Uber versus Trains?
Worldwide Evidence from Transit Expansions*

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Abstract

We study how ride-hailing and public transit interact – an open question with important implications for transportation policy and urban form. We develop a model of mode choice that features three key mechanisms: (i) *substitution*, whereby riders switch from Uber to transit near stations; (ii) *last-mile complementarity*, whereby Uber is used to access transit; and (iii) a dynamic choice-set effect, whereby outbound mode choice constrains return options, giving Uber *option value*. We test the model's implications using a dynamic difference-in-differences design combined with new data on 650 global rail transit expansions and the universe of nearby Uber trips. We document three patterns consistent with each of the above mechanisms: Uber usage rises sharply within 100 meters of new stations (last-mile complementarity), declines locally among nearby residents and workers (substitution), and falls modestly overall for these users as local reductions are partially offset by increased Uber usage elsewhere (option value). Estimating the model on these moments, we find that Uber's option value is quantitatively important and that Uber and transit are net complements. Subsidies to last-mile access provide a targeted tool for increasing transit ridership relative to broader pricing interventions.

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1 Introduction

The rapid global expansion of ride-hailing services has sparked a critical debate over their impact on cities. Policymakers and urban planners are grappling with how best to regulate these services, with some countries – including Denmark, Hungary, and Bulgaria – even banning them outright. A central question in this debate is whether ride-hailing substitutes for or complements public transit. The answer has broad implications. First, declines in transit ridership can lead to budgetary shortfalls for transit agencies. Second, they may reduce social welfare, as transit fares typically exceed marginal social cost due to economies of scale and pricing constraints.[1] Third, if travelers shift away from transit, congestion and pollution may worsen.[2] Finally, changes in transportation technology have historically reshaped urban form: steam railways enabled London's expansion, highways hollowed out U.S. city centers, and ride-hailing may now be altering spatial patterns.[3]

These economic, environmental, and spatial factors underscore the importance of understanding how ride-hailing and public transit interact. Yet the evidence remains unsettled. Estimates of ride-hailing's effect on transit ridership vary widely: some studies find increases of around 5% within two years of Uber's entry (Hall et al., 2018), while others report decreases of 16% after four years (Diao et al., 2021). Moreover, most existing work focuses on aggregate city-level effects, providing limited insight into when, where, or for whom substitution or complementarity occurs. The reverse relationship – how transit expansions affect ride-hailing demand – has been even less studied. Yet this question is central to understanding whether improvements to public transit reduce reliance on ride-hailing, or instead stimulate new demand through mechanisms like last-mile connectivity or the option value of Uber as a flexible backup to transit.

This paper addresses both gaps by combining a dynamic model of travel mode choice with novel data and a new empirical strategy. In the model, travelers choose among car, Uber, and public transit, may use Uber to access transit, and make decisions over multiple trip legs during the day. A key feature is that the outbound mode choice affects the traveler's later options, giving Uber value as a flexible fallback to transit. This framework highlights three channels through which transit improvements can affect ride-hailing demand: substitution (riders switch from Uber to transit), last-mile complementarity (riders use Uber to access transit), and *option value* (Uber is valuable when earlier mode choices constrain later options or transit is unreliable). These mechanisms imply that the effect of a new station on Uber ridership may differ across trips and travelers, both near and far from stations. As a result, aggregate estimates can mask offsetting responses across margins.

We test these predictions using proprietary data on Uber trips across 35 countries and exploit the sharp timing of 650 rail transit station openings. Our identification strategy compares changes in Uber usage within concentric distance bands around newly opened stations, using trips far

[1] Transit fares are usually above marginal cost—though below average cost—due to scale economies. See Parry and Small (2009), Basso and Silva (2014).

[2] See Anderson (2014); Gendron-Carrier et al. (2022).

[3] See Heblich et al. (2020); Baum-Snow (2007); Gorback (2024).

from the station as a local control group. This approach offers several advantages. First, the timing of rail expansions is plausibly exogenous to trends in Uber ridership, as they are planned years in advance – often before Uber even existed. Second, our detailed, geographically precise data enable us to test the mechanisms through which transit and ride-hailing interact locally. Third, our research design allows us to flexibly control for hyper-local, highly variable time trends in Uber ridership. Fourth, we assess the general applicability of our results by examining 650 rail transit openings across 55 cities in 35 countries.

To interpret the spatial and behavioral heterogeneity in responses to new transit, we organize our empirical analysis around three quadrants – each corresponding to a set of mechanisms in the model:

- **Quadrant I** examines how Uber usage responds in space. We estimate large and immediate increases in trip volumes within 100 meters of new stations (48% on average), consistent with first- and last-mile complementarity. However, ridership declines by about 2% at intermediate distances (300–700 meters), consistent with substitution from Uber to transit among travelers within walking distance. Aggregated across the catchment area, these opposing effects balance.

- **Quadrant II** removes last-mile behavior by focusing on travelers with a regular connection to the station area, as in those who might live or work nearby. Holding composition constant, we find substantial declines in their Uber usage near the station post-opening, confirming that substitution away from ride-hailing is a central response among these users.

- **Quadrant III** examines broader behavioral adjustments among the same local travelers as in Quadrant II by tracking their citywide Uber use. We find that while their trips near the station decline, non-local Uber usage increases modestly. This pattern aligns with the model's prediction that travelers who switch away from driving become more reliant on Uber and transit later in the day, reflecting Uber's option value.

Our research design relies on two key identifying assumptions. First, that Uber trips occurring far from the station form an appropriate control group for those occurring near to it. Second, that this control group is sufficiently distant to remain unaffected by the station opening. We test the validity of our research design in three ways. First, we find little evidence for differential trends in Uber ridership between treatment and comparison groups across specifications. Second, the effect on Uber ridership decays towards zero with increasing distance from the station. Third, when leveraging only the variation in timing of rail expansions in an event study framework, we find no effect on Uber trips in our comparison group. This set of evidence is reinforced by our tight study window (six months before and after station openings) and the quasi-exogenous nature of transit expansions. Our results are robust to different geographies, time of the day/week, additional Uber outcomes, as well as alternative controls and placebo studies. We find no evidence that Uber adjusts its pricing structure – fixed costs or cost per kilometer – in response to station openings,

confirming that the ridership patterns we document reflect demand-side rather than supply-side responses.

We then estimate the model using moments from the reduced-form evidence and use it for two purposes. First, the reduced-form results establish that transit expansions generate offsetting responses in Uber ridership across margins –including substitution among nearby riders, last-mile increases near stations, and broader adjustments in citywide Uber use – but they do not separately quantify the contribution of each mechanism or speak to counterfactual environments. The estimated model provides this bridge. We decompose the effect of improved transit quality into direct substitution, last-mile access, and option value. Population-weighted across distance bands, substitution reduces Uber ridership by about 1.0%, while option value increases it by about 1.0%; the last-mile channel is smaller but non-trivial (about 0.2%).

Second, we use the estimated model to evaluate counterfactuals that cannot be recovered from reduced-form variation alone. These counterfactuals show that Uber and transit are complements on net in our setting: new stations increase transit ridership more when Uber is available, and removing Uber from the market reduces overall transit use. The estimated model implies that subsidies targeted to last-mile access can substantially increase transit ridership, more so when marginal access costs are reduced. Ride-hailing taxes, despite being motivated as a way to shift travelers toward transit, can perversely reduce transit ridership by raising the cost of last-mile access and pushing marginal Uber users toward cars rather than transit. Congestion taxes perform better on this dimension because they target cars directly without raising the cost of last-mile access; last-mile subsidies become even more effective at increasing transit ridership in the presence of congestion taxes. A policymaker hoping to increase transit use in a fiscally-neutral way would optimally fund both fixed and marginal cost last-mile subsidies with a congestion tax. However, if direct transit subsidies are also available, they are a more effective tool – raising the attractiveness of transit for both commute and intermediate trips simultaneously.

This paper builds on a quickly growing literature that seeks to determine the conditions under which ride-hailing and public transportation act as complements or substitutes. Most existing studies exploit variation in the timing of Uber's entry across U.S. metropolitan areas to estimate its impact on public transit. Hall et al. (2018) finds that ride-hailing complements public transit on average, whereas Graehler et al. (2019), Erhardt et al. (2021), and Diao et al. (2021) suggest that it serves as a substitute. Other studies, including Nelson and Sadowsky (2018), Babar and Burtch (2020), and Cairncross et al. (2021), report mixed or statistically insignificant results.[4] In contrast to this work, we leverage *within-city* variation in transit access and granular trip data to identify responses with high spatial and temporal precision.[5]

[4]Complementary to this work is (Christensen et al., 2023), who study how travel patterns change with discounts to ride-hailing services in Cairo, Egypt.

[5]There is also a broader literature working to understand the effect of ride-hailing on cities. This includes understanding the effects of surge pricing (Castillo, 2020, 2025) and taxes on ride-hailing (Tarduno, 2025, Leccese, 2025), as well as the impact of ride-hailing on traffic safety (Greenwood et al., 2017, Burgdorf et al., 2019, Barrios et al., 2020, Barreto et al., 2020, Anderson and Davis, 2021, Harmon and Wozniak, 2023) and congestion (Tarduno, 2021). The role of Uber in local labor markets (Angrist et al., 2021, Hall and Krueger, 2018) and housing costs (Gorback, 2024) have

First, we develop a new dynamic model of transit mode choice that formalizes the interaction between ride-hailing and public transit across multiple trip legs and access modes. The model captures three mechanisms – substitution, last-mile complementarity, and option value – and is rich enough to rationalize an array of responses to a new station opening while remaining tractable enough to yield analytical insights. Critically, the model explains why prior estimates of the relationship between ride-hailing and transit vary so widely in sign and magnitude: substitution and complementarity operate simultaneously across different margins, and aggregate estimates mask offsetting responses that depend on user location, trip type, and the relative strength of each mechanism.

We use the model to organize our empirical analysis around three margins that speak to each mechanism, and to document three new empirical facts: large last-mile increases near stations, substitution among nearby residents, and broader citywide adjustments reflecting Uber's option value. This paper is the first to empirically document the role of last-mile trips and option value in the interaction between ride-hailing and transit.[6] Estimating the model on these moments allows us to quantify the relative importance of each mechanism and evaluate counterfactuals. In these counterfactuals, Uber is a net complement to public transit, and subsidies that lower the marginal cost of Uber access are particularly effective at increasing transit ridership.

Second, we introduce a new identification strategy that exploits the sharp timing of rail transit expansions to study how transit access affects ride-hailing demand within cities, and assemble a new dataset of 650 station openings across 55 cities in 35 countries to implement it at scale. Most prior work estimates the effect of Uber entry on transit ridership using city-level variation; we instead use within-city variation in transit access, which offers a clean source of identification. Our design compares outcomes across concentric distance bands around newly opened stations, flexibly controlling for local trends while targeting the catchment area where responses are expected. New stations induce a large improvement in transit access and are independently timed to trends in Uber ridership — most were planned before Uber even existed. Crucially, while our reduced-form estimates identify the effect of transit expansions on Uber usage, our model allows us to invert the relationship and recover the reverse — how Uber availability affects transit ridership — thereby unifying two strands of the literature. The international scope of our data, covering cities across Asia, Europe, and Latin America, also provides the first comparative evidence that the mechanisms we identify operate consistently across highly diverse urban contexts.[7]

The remainder of this paper is structured as follows. Section 2 presents a simple model

also been studied.

[6]The potential for Uber to complement public transit in this way has been theorized (King et al., 2020, Siddiq et al., 2023). Li et al. (2022) find evidence of last-mile complementarity in Austin, while Yan et al. (2019) use survey data to show travelers' willingness to combine ride-hailing with transit. Uber itself introduced a dedicated "last mile" service in Berlin and Munich in 2021 (Uber, 2021, 2023). As discussed before, Agrawal and Zhao (2023) present a theoretical model that includes last-mile complementarities to study the optimal taxation of Uber.

[7]Additionally, we contribute to the growing literature on how public transit shapes urban economic geography more broadly (Billings, 2011, Gonzalez-Navarro and Turner, 2018, Gendron-Carrier et al., 2022, Gupta et al., 2022, Zárate, 2024, Tsivanidis, 2024).

illustrating potential complementarities and substitution effects between Uber and transit following a new station opening. Section 3 details the data sources used in this study. Section 4 discusses our methodology and Section 5 presents our main empirical findings on the effect of transit expansions on Uber ridership. Section 6 estimates the parameters of our model based on our reduced-form evidence and considers counterfactuals. Section 7 concludes.

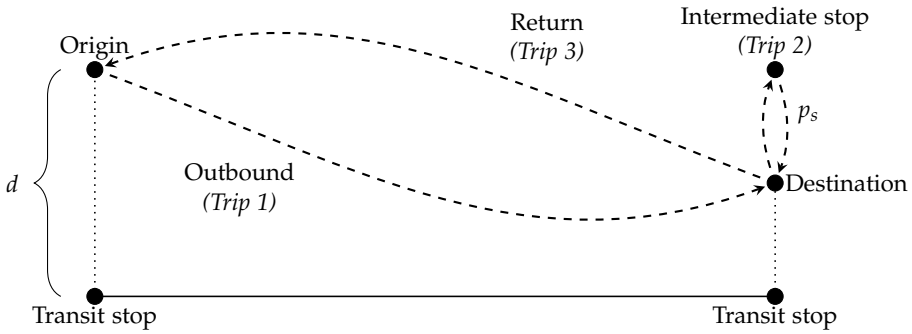
2 Model

We develop a dynamic discrete-choice model of mode selection among public transit, Uber, and private automobile. Our goals are threefold. First, provide insight on how choices vary with distance from the transit station and how they change when transit quality improves. Second, be analytically tractable enough to illustrate three mechanisms by which improved transit can affect Uber ridership — substitution, last-mile complementarity, and option value — and to guide our reduced-form empirical analysis. Third, remain flexible enough to rationalize many different responses of Uber ridership to improvements in public transit, allowing us to combine the model with reduced-form estimates to evaluate counterfactuals.

2.1 Model setup

Consider a single public transit route with two stops and a risk-neutral representative traveler who must travel from an origin d meters from the first stop to a destination near the second. Later in the day, she will make the return trip, and with probability p_s, she will need to make another trip during the day. Figure 1 depicts how trips are linked between origin and destination in our model.

Figure 1: Model geography and trips



Notes: This figure depicts the model geography and the trips that are taken by the representative traveler in our model.

For each trip, the traveler chooses which transportation modes to use, subject to constraints that link her choices across trips. She has three options for her primary mode: personal automobile,

Uber, and public transit. If she uses public transit, she chooses an access mode to travel the d meters to the transit stop: walking or Uber. If she drives her personal automobile for the outbound trip, she must also use the automobile for the return journey, but she may use any mode for the additional trip during the day. If she does not drive for the outbound trip, she cannot use a personal automobile for the remainder of the day's trips.

We define the following parameters. Let the generalized in-vehicle base utility of mode m be denoted by α_m for the outbound and return journeys, and β_m for the additional trip during the day. Using access/egress mode a has fixed cost f_a and marginal cost $c_a \cdot d$. We assume walking has no fixed cost, but has a higher marginal cost than taking Uber to the transit stop ($f_{\text{walk}} = 0;\ c_{\text{walk}} > c_{\text{Uber}}$).

The utility of a one-way trip from the origin to the destination depends on the distance to the transit stop (d), the primary transportation mode chosen ($m_i \in \{\text{car}, \text{transit}, \text{Uber}\}$ for period $l \in \{1,2,3\}$), the access mode chosen if using transit ($a_l \in \{\text{walk}, \text{Uber}\}$ for $l \in \{1,3\}$), and a random shock over transit mode preferences.

We model the shock as additive in a persistent component and a transitory component. The persistent component, η_m, is realized at the start of the day and captures shocks to a traveler's preferences across travel modes that persist across both outbound and return trips. Maybe one traveler has a unique preference for driving, or today's destination is unusually well suited to traveling by public transit. The η_m are independent draws from a normal distribution and η_{car} is normalized to zero.[8]

$$\begin{pmatrix} \eta_{\text{Uber}} \\ \eta_{\text{transit}} \end{pmatrix} \sim \mathcal{N}\left(\begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{pmatrix} \sigma^2_{\text{Uber}} & \phi\, \sigma_{\text{Uber}} \sigma_{\text{transit}} \\ \phi\, \sigma_{\text{Uber}} \sigma_{\text{transit}} & \sigma^2_{\text{transit}} \end{pmatrix} \right), \quad \eta_{\text{car}} \equiv 0.$$

The σ_{Uber}, σ_{transit}, and $\phi \in (-1,1)$ govern the dispersion and correlation of persistent shocks, respectively. A correlation of $\phi > 0$ would indicate that many travelers have strong taste for or against car as a mode choice. A correlation of $\phi < 0$ indicates that travelers that prefer public transit tend to dislike Uber, and vice versa.

The transitory components, ϵ_{mai} for $i \in \{1,3\}$ and ϵ_{m2}, are realized at the start of each period and captures shocks to a traveler's preferences that only affect the current trip. Perhaps the bus is about to arrive, or it is raining, which makes transit unattractive. The transitory shocks are independent and identically distributed random shocks with a type I extreme value distribution.

Thus, the utility for the first period trip is given by

$$U_1(m_1, a_1; d) = \alpha_{m_1} - \mathbb{1}_{m_1 = \text{transit}} \left(f_{a_1} + d \cdot c_{a_1} \right) + \eta_m + \epsilon_{ma1}, \tag{1}$$

[8]When we try to fit the parameters of our model to the data, a more relevant interpretation of the η_m are persistent preferences across the larger population of travelers. Also, we do not explicitly model the fact that travelers' true destinations often lie beyond the public transit terminus. This discrepancy is absorbed by the model's error term.

and the utility of the return trip is similarly given by

$$U_3(m_3, a_3; d) = \alpha_{m_3} - \mathbb{1}_{m_3=\text{transit}} (f_{a_3} + d \cdot c_{a_3}) + \eta_m + \epsilon_{ma3}. \tag{2}$$

The traveler needs to make an additional trip during the day with probability p_s. The utility of the additional trip during the day only depends on the mode chosen and a transitory shock, ϵ_{m2}, which is drawn from the same distribution as the ϵ_{mai}.

$$U_2(m_2) = \beta_{m_2} + \epsilon_{m2} \tag{3}$$

Two features of the model are worth reiterating. First, the traveler has all transit modes available for the additional trip in period 2 only if they chose car in period 1. Otherwise, they can only choose between public transit and Uber for the additional trip. Second, the traveler *must* return via car in period 3 if they drive their car in period 1.

The traveler chooses a sequence of transit options to maximize expected utility. We can derive the expected utility from each period's mode choice using backward induction, and then find conditional choice probabilities using the familiar logit formulation. Unconditional probabilities are calculated by integrating over the persistent shocks η_m. The details of these calculations are in Appendix C.

2.2 Theoretical implications from improving public transit

We use the model to assess how an improvement in public transit affects Uber ridership for the commute trips and a potential additional trip later in the day. In the model, this improvement corresponds to an increase in the parameter α_{transit}, which captures the utility of using transit. While our empirical analysis focuses on the opening of new train stations, many cities already operate bus networks that serve these areas, and a new station opening often bundles several contemporaneous changes – cities may rearrange bus routes, add feeder services, or adjust schedules to complement the new line. We therefore view an improvement in transit quality α_{transit} as a natural and tractable way to model a station opening, one that captures the net effect of these bundled changes on the relative attractiveness of transit over car and Uber.

The dynamic consideration of using Uber is driven by the fact that outbound mode choice constrains the traveler's future choice set. Because travelers are forward-looking, this dependence of future choice sets on the initial decision feeds back into outbound mode choice. There are three alternative names for this effect, each emphasizing a different aspect. One can describe this force as a mode lock-in effect, highlighting the constraint imposed by driving; as an option value effect, emphasizing the ex-ante value of retaining flexibility; or as an insurance effect, highlighting protection against negative shocks to transit. However, these are not distinct mechanisms, but alternative descriptions of the same dynamic consideration: the mode choice for the outbound journey constrains the traveler's choices later in the day. We describe this mechanism throughout the paper as Uber's *option value*.

As we show below, the model generates competing forces – substitution, complementarity, and option value – that determine the net effect of transit improvements on Uber use. Depending on the strength of these forces, Uber ridership may rise or fall. These distinctions will guide our interpretation of empirical results later in the paper.

Uber ridership for outbound trips.

Proposition 1 *The derivative of Uber use in period 1 with respect to the transit utility parameter $\alpha_{transit}$ (conditional on distance d and transit preference η) is:*

$$\frac{\partial}{\partial \alpha_{transit}}\Big(P_1(Uber|d,\eta) + P_1(transit{+}Uber|d,\eta)\Big) = -\underbrace{P_1(Uber|d,\eta)\cdot P_1(transit|d,\eta)}_{\text{Direct substitution effect } (\geq 0)} +$$

$$\underbrace{P_1(transit + Uber|d,\eta)\cdot P_1(transit|d,\eta)\cdot\Big[P_1(Uber|d,\eta) + P_1(car|d,\eta)(1+P_3(transit|m_1\neq car,d,\eta))\Big]}_{\text{Last-mile complementarity } (\geq 0)} +$$

$$\underbrace{P_1(Uber|d,\eta)\cdot P_1(car|d,\eta)\cdot P_3(transit|m_1\neq car,d,\eta)}_{\text{Option value effect } (\geq 0)}$$

The proof can be found in Appendix C.3. The proposition says that the effect on outbound Uber use is indeterminate and can be decomposed into the effect of three competing factors:

1. **Direct substitution effect**: Improved transit quality makes transit more attractive relative to Uber as the primary mode in period 1. Because both Uber and public transit have the same choice set in period 3, the substitution effect does not depend on forward-looking terms.

2. **Last-mile complementarity**: Some of the shift towards transit creates additional demand for Uber as an access mode, partially offsetting the substitution effect. This is captured by the $P_1(\text{Uber}|d,\eta)$ term. The second term $P_1(\text{car}|d,\eta)(1+P_3(\text{transit}|d,\eta))$ captures substitution from car to last-mile trips. Those users benefit from improved transit in the outbound trip as well as access to improved transit in the return trip, hence their dependence on $P_3(\text{transit}|m_1\neq \text{car},d,\eta)$.

3. **Option value effect**: This reflects the traveler's forward-looking behavior where better public transit options for the return trip increase the value of maintaining modal flexibility. Thus, some car users will switch to Uber to access improved public transit in the return trip.

Uber ridership for return trips. We now assess the impact of an improvement in public transit on Uber ridership for the return leg, given in Proposition 2 in Appendix C.3. The proposition says that the effect on return trip Uber use is indeterminate and can be decomposed into the effect of three competing factors, as for the outbound trip. First, there is a direct substitution effect. Second, there is a last-mile complementarity. Third, there is an option value effect, whereby higher α_{transit} shifts travelers away from car in period 1, increasing the fraction with access to Uber in period 3.

Uber ridership far from the station. The additional trip during the day allows us to consider how a local transit improvement affects Uber use elsewhere in the city. We assume that the utility of taking transit for this intermediate trip depends partly on the value of using transit near home, so that an improvement in local access also raises the attractiveness of transit farther away. Formally, this is captured by the condition $\beta'_{\text{transit}}(\alpha_{\text{transit}}) \geq 0$. Intuitively, if a new train station opens near your home, then being on transit downtown is more appealing as well, because you know the network is now better connected for your return trip. However, this is an assumption we can directly test in Section 6.

Proposition 3 in Appendix C.3 gives the main result and the derivation. The proposition says that the effect on Uber ridership elsewhere in the city is directionally indeterminate. It can be decomposed into the effect of two competing and opposite forces. First, a substitution effect, since an increase in β_{transit} makes transit more attractive relative to Uber in period 2, reducing Uber's mode share. Second, an option value effect, since higher α_{transit} shifts travelers from car to transit/Uber in period 1, increasing the fraction with restricted choice sets in period 2, which increases Uber's mode share. The proposition has a natural corollary. If the improvement to public transit in period 1 does not improve the value of transit elsewhere in the city (through β_{transit}), then there is no substitution effect. Consequently, the additional trip Uber mode share will unambiguously increase.[9]

Discussion. The model implies a finite set of mode-switching patterns following an improvement in transit quality. For our purposes, the relevant patterns are those involving Uber either directly or as an access mode to transit. In our setup, transit improvements do not increase car use and do not directly change access-mode preferences conditional on taking transit. As a result, the empirically relevant substitution patterns can be summarized by four transitions, each mapping to one or more of the mechanisms: (1) from car to Uber *(option value effect)*, (2) from Uber to transit-by-walk *(substitution effect)*, (3) from Uber to transit-by-Uber *(substitution + last-mile complementarity)*, and (4) from car to transit-by-Uber *(all three mechanisms)*. Taken together, the theoretical results imply that the net effect on Uber use is ambiguous and depends on the relative strength of substitution, last-mile complementarity, and option value. In the next section, we use simulations to illustrate how different parameterizations generate distinct spatial patterns in Uber ridership following a station opening.

2.3 Model simulations

To illustrate the mechanisms embedded in the model and guide interpretation of our reduced-form estimates, we simulate mode choice responses to improvements in public transit. These simulations trace how Uber usage changes across space and trip types under different parameterizations.

To map the model's predictions onto observed changes in Uber trips at varying distances from a transit station, we assign first- and last-mile trips to the station itself (located at $d = 0$) but allow

[9] Technically, there would be no change in the Uber mode share if $P_1(\text{car}|\eta) \in \{0, 1\}$. So long as the outbound trip does not always or never rely on car, then the Uber mode share will increase for intermediate trips.

for measurement error in the data. Specifically, we assume that the origins and destinations of first- and last-mile trips follow an exponential distribution centered at the station, so that the density of such trips decays with distance.

Figure 2 presents three versions of the model, chosen to illustrate the range of empirical patterns it can rationalize. Each column corresponds to a different parameterization. The first row reports average outbound and return trip mode shares under baseline preferences. The second row shows how those mode shares respond to a 0.5-unit increase in α_{transit}, which captures an improvement in public transit. The third row plots the log change in Uber trips induced by the same transit improvement. All figures report values for locations within 1200 meters of the station. Parameter values for each simulation are described in Section C.5.

In the first model, we set low fixed and marginal costs for using Uber as an access mode, which strengthens the last-mile channel and generates an increase in Uber usage at all distances from the station. In the second model, we shut down the last-mile channel by imposing high fixed access costs and increase the dispersion of persistent preferences over Uber (σ_{Uber}), which strengthens substitution and yields a decline in Uber usage across all distances. The third model combines low access costs with high preference dispersion and predicts a sharp increase in Uber use near the station – driven by first- and last-mile behavior – alongside a decline at intermediate distances, where former Uber users now walk to improved transit. This mixed pattern closely mirrors what we observe empirically in Section 5.

These simulations show why the same transit improvement can generate both complementarity and substitution in Uber ridership depending on the margin observed, and motivate our empirical focus on multiple trip and traveler margins in the next subsection.

2.4 Relating the model to data on Uber trips

The model yields clear, distance-indexed predictions for how Uber ridership should respond to the opening of a new transit station. To bring these predictions into our setting, we must determine which *trips* and which *travelers* to include in our research design.[10]

The model provides two key insights that inform this choice: (i) substitution and complementarity effects are strongest for trips originating near a station, and (ii) these effects are most pronounced among individuals who live or work within the station's catchment area. Accordingly, we classify our empirical margins along the dimensions of where trips and travelers are located:

Table 1: Classification of empirical margins by trip and traveler proximity

Trips/People	Near station	Anyone
Near station	II	I
Everywhere	III	IV

[10]To map model-generated probabilities to our Uber trips data, we aggregate the model's choice probabilities across origins at varying distances from each station, weighting by the geographic area at each distance band. Appendix C.4 describes this mapping in detail.

I: *All trips near station, all travelers.* This margin captures changes in Uber trip volumes geolocated near the new station, irrespective of the traveler's home or work location. It is particularly informative for assessing the extent of last-mile complementarity, as it includes both local and non-local users accessing transit.

II: *Trips near station by travelers near station.* By restricting attention to travelers residing or working within the station's catchment area, this specification isolates behavioral responses among local users. It helps identify substitution from Uber to public transit while minimizing the influence of last-mile effects.

III: *All trips by travelers near station.* This margin examines changes in Uber usage across the entire city for the subset of individuals affected by the new station. It provides insight into how overall Uber reliance adjusts for local residents and workers, reflecting in part broader option value effects (as highlighted in Proposition 3).

IV: *All trips by all travelers.* This specification corresponds to aggregate, citywide effects. As our identification strategy is station-level, we do not focus on this margin directly.

3 Data

To investigate the effect of new transit stations on Uber ridership we require data describing new transit station locations and dates of opening, as well as panel data on Uber ridership and riders near these stations. We use data on Uber ridership constructed from Uber's trip database. Our data on new transit stations are the result of primary data collection. We describe these datasets and their construction below.

3.1 Uber ridership

We use Uber's trip database to calculate the number of trips starting or stopping within a given distance band from the transit station in a month, for example, all trips within 100–200 meters (m). We do this for 12 different 100 m bands from 0–100 m up to 1,100–1,200 m. To avoid double-counting, each Uber pickup or drop-off is allocated to the station to which it is closest. This means the distance bands are not always perfect circles. We use this dataset for the analysis in Quadrant I of Table 1.

We also make use of a fixed area hexagon in robustness exercises as well as to identify individuals with a point-of-interest (POI) near the station. The hexagons have an average edge length of 174 m and an average area of 0.105 km^2. Using these hexagons, we construct what we refer to as our POI sample. These are individuals that had 3 or more trips within a hexagon 12 to 7 months prior to the station opening, where the average location of their trips is within 1200 m of the station. We use this dataset for the analyses in Quadrants II and III of Table 1. Both hexagons and concentric ring spatial units are depicted for train openings in Toronto in Figure

A1.[11] We emphasize that throughout our analysis, as per our data agreement, we have access to data aggregated from the individual trip and rider databases, but not the underlying microdata itself.

Our Uber trip data spans January 2012 to December 2018, but note that Uber was expanding in this time period so that not every city has trip data from 2012. This provides us with between 15 and 79 months of Uber trip data for each transit expansion, with a mean and median of 61 months. We exclude cities where Uber availability began, ended, or paused within six months of the rail expansion. We also excluded New York City and China. Geography-month observations with less than five trips have been set to zero due to privacy concerns.

3.2 Transit stations

To collect data on new transit stations, we start with a list of cities Uber operates in worldwide, and for each city, find all rail transit stations that opened after Uber entered the city. We obtain data on subway openings through 2017 from Gendron-Carrier et al. (2022), and extend this dataset to include light rail and commuter rail, and update it through 2018 using online sources such as www.urbanrail.net, www.wikipedia.org, and news sites. We limit attention to rail stations as these are better documented than bus stops. For each station, we record opening date, latitude and longitude, station name, whether it is the terminal station, city, and country. We define the exact latitude and longitude of each station using Google Maps. We also find the locations of the pre-existing stations that had been the terminal stations before the transit expansion. We restrict our sample to transit that does not interact with traffic. This excludes tram and street car station openings. We are left with 650 station openings across 55 cities and 35 countries.

Figure 3 plots the geographic distribution of cities used in our analysis. The size of each circle is proportional to the number of Uber trips we have in our data from that city. The map reveals that transit openings in our sample are heavily concentrated in India and Southeast Asia, Europe, and North America. Table A1 reports the cities in our sample that expanded their rail transit between the date Uber entered and 2018. Figure A2 shows the time series of rail expansion events and number of stations opened, showing there is a notable drop in openings in January and February, but they are otherwise fairly uniform over time of year.[12]

Our analysis requires us to observe Uber ridership at a transit station for sometime before and after the transit station opens. Thus, we face a trade-off between sample size and the length of time we observe each transit station. We focus on a 13-month window, six months before and after the station opening; excluding any transit stations for which we do not have these data.

Table 2 reports summary statistics for a trip data over the analysis window. The first four

[11] These hexagons are defined using the H3 hexagonal hierarchical geospatial indexing system, designed by Uber. The advantage of hexagons is that they have a uniform area, unlike the concentric rings we use in our main analysis. For more information, see https://h3geo.org/. We have data on all hexagons whose centroids are within 1,200 m of a transit station.

[12] Figure A3 plots the distribution of days and months in our sample, and shows no discernible patterns outside of the drop in transit openings during the winter.

rows report mean and median values for the number of pick-ups, the number of drop-offs, the total kilometers traveled, and average trip length. The fifth row reports the share of distance bin - month observations with zero Uber trips. Rows 6 through 10 report the share of trips that occurred during a weekday morning, a weekday afternoon, Friday and Saturday night, and the weekend during the day, respectively. We report these summary statistics across our entire dataset in Column (1), and across four distance bins in Columns (2) through (5).

On average, our data contain 1,659 Uber pick-ups and 1,652 drop-offs in each 100 m distance band by month cell. Uber trips are on average 11.20 kilometers long. Within 100 m of the station opening, 25% of observations are zeros. That same number is 15% for our 1100–1200 m. The median values show that our data is severely right-skewed towards some larger cities and dense locations. The existence of zeros and outliers motivates our use of the Pseudo-Poisson Maximum Likelihood estimator, which we discuss in further detail in Section 4.

3.3 Additional variables

We use data on city centers to explore heterogeneity in our treatment effects. We define the center of each city using United Nations and Social Affairs (2018). To find the footprint of each city, we use the Global Human Settlement Layer (Schiavina et al., 2023) which defines urban clusters "via a logic of cell clusters population size, population and built-up area densities as defined by the stage I of the Degree of Urbanisation." This is measured for 1 km x 1 km cells. For the purpose of finding average values, we define the footprint of a city as the urban cells within 25 km of the city center. We also use the city center and footprints to determine how close a new train station is to the city center. We measure "closeness" in two ways. First, we measure the straight-line distance, and second, we measure the travel time using public transit.[13]

4 Methodology

Section 2.4 introduced three empirical margins in Table 1 – Quadrants I, II, and III – each corresponding to a distinct set of testable implications from the model. For clarity, we begin by outlining our empirical strategy for Quadrant I, which analyzes the effect of new station openings on *station-adjacent* Uber trips – those that start or end near the station – regardless of the rider's home or work location. In contrast, Quadrants II and III focus on riders with a fixed location near the station, allowing us to study substitution effects and broader behavioral adjustments among the affected population. We then describe how the empirical strategies for Quadrants II and III build on the core design to examine traveler-specific outcomes.

Our identification strategy uses a dynamic difference-in-differences approach, leveraging high-frequency Uber trip data and the precise timing of station openings. The first difference compares Uber ridership before and after a station opens, within a given distance band around the

[13] In calculating this, we remove walking time from the last transit stop and the city center

station. The second difference controls for broader trends in Uber usage over time – an important adjustment, since Uber ridership was growing rapidly throughout our sample period. To flexibly account for these local time trends, we use trips occurring at distances between 1100–1200 meters from the station as a reference group.

Quadrant II applies a similar design but restricts attention to Uber trips taken by individuals with a point of interest (POI) – such as home or work – near the station. This removes last-mile behavior and sharpens our focus on substitution effects. Quadrant III instead tracks citywide Uber use by individuals with a POI near the station, capturing how a new station affects broader Uber usage for the affected population. In both cases, we use Uber trips from individuals with POIs farther from the station as the reference group.

We define the research design for Quadrant I as follows. Let y_{dit} denote the number of station-adjacent trips beginngin or ending in distance band d around transit station i during month t. Denote the month that station i opens as t_i' and define the time since the station opened ("relative time") as $\tau_{it} = t - t_i'$, noting that τ_{it} is negative before the station opens. In the month a station opens, $\tau_{it} = 0$; for stations that open at the start of the month, nearly the entire month is treated, while for stations that open at the end of the month, nearly the entire month is untreated.

We model the effect of a new transit station opening on Uber ridership in distance band d^* using observations from both distance band d^* and the farthest distance band $\bar{d} = 1200$ m. The dynamic difference-in-differences specification is as follows:

$$y_{dit} = \gamma_{it} + \delta_{di} + \sum_{j \in \{-6,-5,\ldots,6\} \setminus \{-2\}} \alpha_{d^* j} \times \mathbb{1}_{\tau_{it}=j} \times \mathbb{1}_{d=d^*} + \left(\beta_{1,d^*} \times \mathbb{1}_{\tau_{it}<-6} + \beta_{2,d^*} \times \mathbb{1}_{\tau_{it}>6}\right) \mathbb{1}_{d=d^*} + \epsilon_{dit}, \quad \forall\, d \in \{d^*, \bar{d}\}, \quad (4)$$

where $\mathbb{1}_{\tau_{it}=j}$ is an indicator function for whether the given observation occurs j months after the station opens, $\mathbb{1}_{d=d^*}$ is an indicator function for whether the given observation is at distance d^*, γ_{it} is a station-time fixed effect, and δ_{di} is a station-distance fixed effect. The index j runs from -6 to 6, excluding -2, so the second month prior to the transit station openings is the reference category.[14]

The coefficients of interest are the $\alpha_{d^* j}$, which in our estimation can be interpreted as the percentage change in Uber trips j months after a new transit station opens. For $j \geq 0$, the $\alpha_{d^* j}$ are the treatment effects we seek to measure at distance d^* in each month after the opening. For $j < 0$, the $\alpha_{d^* j}$ allow us to test whether there are pre-trends in Uber trips before stations open. The coefficients β_{1,d^*} and β_{2,d^*} are event study coefficients for before and after our treatment window. This specification leverages up to 79 months of data per station, while isolating variation around the opening date.

[14] We use the second month prior to the opening as the reference category to test for anticipation effects.

We estimate the following model via Poisson Pseudo-Maximum Likelihood (PPML) (Silva and Tenreyro, 2006, 2011). The PPML estimator has several advantages for our setting. First, it allows for a natural interpretation of our treatment effects as percentage changes. This is an attractive feature for our setting since farther away distance bands are mechanically larger in area, and thus contain more trips. Second, it handles zeros and outliers in the dependent variable well. Many 100 m distance band by month observations will contain zero trips. As evidenced in Table 2, 25% and 15% of observations have zero trips in the 0–100 m and 1100–1200 m distance bands, respectively. Lastly, it handles high-dimensional fixed effects well relative to other non-linear models. Our main specification is fully saturated with station by distance and station by calendar time fixed effects. Throughout, we cluster our standard errors at the station-level.

We often wish to aggregate the treatment effect to a single coefficient, which is helpful when reporting regression results across multiple specifications in a single table or figure. We will want to report these coefficients for each distance band, and so we rely on the following difference-in-difference specification:

$$y_{dit} = \gamma_{it} + \delta_{di} + \sum_{d^* \neq 1200 \text{ m}} \alpha_{d^*} \times \mathbb{1}_{\tau_{it} \in \{1,\ldots,6\}} \times \mathbb{1}_{d=d^*} + \sum_{d^* \neq 1200 \text{ m}} \left(\beta_{1,d^*} \times \mathbb{1}_{\tau_{it}<-6} + \beta_{2,d^*} \times \mathbb{1}_{\tau_{it}>6} + \beta_{3,d^*} \times \mathbb{1}_{\tau_{it} \in \{-2,-1,0\}}\right) \mathbb{1}_{d=d^*} + \epsilon_{dit}, \quad \forall d, \quad (5)$$

In this regression, the omitted category is the third through sixth months before the station opened and the coefficients of interest are the α_{d^*}. The α_{d^*} capture the average percentage effect of a station opening on Uber trips at distance d^* relative to $\bar{d} = 1200$ m, for months $\tau_{it} \in \{1, ..., 6\}$ relative to months $\tau_{it} \in \{-6, -5, -4, -3\}$. We separately control for the effect two months prior through the month of the station opening. This specification mitigates concerns over the partial treatment of month $\tau_{it} = 0$ and soft openings which may have had an impact on Uber usage prior to the station's official open date.

We have two core identifying assumptions. First, we assume that local governments do not time the opening of new transit stations to coincide with a sharp break in Uber ridership. Indeed, Gendron-Carrier et al. (2022) find that it typically takes 11 years between when the plan is approved for a new subway and the opening date. This means that the vast majority, and maybe even all, of the transit openings in our data were approved before Uber existed. Moreover, we have chosen a narrow study window - six months before and after the station opening - for our analysis. Any effects we observe are most likely driven by the sudden opening of public transit, rather than other changes to public policy. Second, we make the standard difference-in-differences assumptions that Uber ridership at all distances would have moved in parallel in the absence of a new transit station opening. A strength of our approach is the granularity of our data, which uses nearby distances to provide a more plausible counterfactual. We will present evidence that

Uber ridership in the 1100-1200 m band moved in parallel to closer distances prior to the station opening.[15]

Given our station openings occur over the period 2013–2018, an additional concern might be whether our setting is subject to the usual issues of difference-in-differences estimators in the presence of staggered treatment timing and treatment effect heterogeneity (Goodman-Bacon, 2021, Callaway and Sant'Anna, 2021, Sun and Abraham, 2021, Borusyak et al., 2021). Our main specification is fully saturated with station by distance and station by month fixed effects. Consequently, the α_{dj} will be a variance weighted-average of each station's individual difference-in-differences estimate at event time j and will not suffer from contaminated control units.[16]

The specification discussed above uses Uber trips far from a station as a control group for trips near to a station that are impacted by its opening. This design is relevant to the analysis in Quadrant I, which considers the effect of a station opening on Uber trip usage for everyone in the city near the station. Quadrants II and III examine how new station openings affect Uber usage among riders with a fixed point of interest (POI) near the station, both locally (II) and across the city (III). To study these effects, we first bin riders into three groups according to the location of their POI relative to the station: 0–500 m, 500–800 m, and 800–1200 m. We then use riders with a POI 800–1200 m away as a control group for riders in our 0–500 m and 500–800 m groups. We pool bins because of the smaller amount of trips in this sample. The specification is the same as above, except observations y_{dit} refer to the number of trips for a rider with a POI in distance group d from station i during month t. Our identifying assumption is now that riders who live or work 800–1200 m away from the station would have behaved similarly to riders who live or work closer to the station in the absence of the station opening.

While our main outcome of interest is Uber trips, we also consider the effects on pick-ups and drop-offs separately. We also study trips that originate or end at certain times of day - for example, weekday morning, weekday afternoon, or the weekend. We also consider other margins of Uber usage, like total distance traveled and total fares. We use average trip distance as an outcome to consider if trips get longer or shorter after the station opening. These alternative outcomes are considered in Section 5.1.

[15] A potential concern is that transit stations are announced well in advance, potentially inducing households to relocate to the area prior to opening. Such sorting could affect Uber usage before service begins or alter the composition of travelers near the station. We believe this channel is unlikely to be important. Residential relocation involves substantial costs and long planning horizons, making it implausible that households would systematically adjust ride-hailing behavior for extended periods before a station opens – especially given that many openings are delayed. More directly, our event-study estimates show no pre-trends in Uber usage in the months leading up to openings, even when we extend the sample to 18 months prior. The results are also robust to restricting attention to non-terminal and centrally-located stations, where residential sorting is less likely.

[16] An alternative way to say this is for each station, each distance is subject to the same, contemporaneous treatment timing - including our control group 1100–1200 m away (Baker et al., 2022). This is equivalent to a "stacked" stagge red adoption specification (Cengiz et al., 2019).

5 The Effect of a New Station on Uber Ridership

This section presents our core empirical results and interprets them through the lens of the model. We organize the analysis around the three empirical quadrants introduced in Table 1, each speaking to a different behavioral margin. Quadrant I analyzes changes in Uber usage near the station for all riders and is indicative of last-mile Uber usage. Quadrant II focuses on station-adjacent Uber trips taken by individuals with a fixed POI near the station, allowing us to identify substitution behavior between Uber and transit. Finally, Quadrant III examines citywide Uber usage among the same POI sample, which indicates the importance of option value. We begin with a detailed analysis of Quadrant I, whose moments are important for the modeling exercise in Section 6 and forms the basis for several key robustness exercises, before turning to Quadrants II and III.

5.1 Last-mile and substitution responses to transit openings (Quadrant I)

We begin by estimating how overall Uber trips respond to the opening of a new transit station, focusing on variation in distance from the station. Panel A of Figure 4 plots the estimated effect on trips within 0–100 meters of a station, relative to trips within 1100–1200 meters. These estimates correspond to the $\alpha_{0\text{–}100\text{ m},j}$ in Equation 4. We find a large and statistically significant increase in ridership of 42% within one month of the opening (0.35 log points). In the two months prior to opening, there were an average of 650 trips within 100 m of a station, so the estimated effect corresponds to roughly 273 additional trips. Six months after opening, trips had increased by 0.45 log points, and we can rule out increases smaller than 0.33 log points at the 95% level. This effect is persistent and shows no signs of decay over the six-month window.

The smaller increase in month 0 likely reflects partial exposure: stations do not always open on the first day of the month. In addition, travelers may take time to adjust their travel behavior. We also observe a modest effect one month prior to opening, consistent with "soft" openings or early access at some stations. Overall, we find a swift and large rise in Uber trips within 100 m of a new transit station.

The immediacy of the ridership response also helps rule out alternative explanations. For example, it is unlikely that new restaurants or retail developments – whose impacts typically unfold gradually – could account for such a sharp jump. While businesses may attempt to coordinate openings with new stations, doing so precisely is difficult. The high frequency of our data allows us to isolate the effects of sudden infrastructure shocks from slower-moving neighborhood change.

The figure also provides evidence in support of our identification strategy. There are no signs of pre-trends in Uber trips from six to three months before the opening, and the large increase in ridership only occurs once the station opens. Our estimates are precise: we can reject pre-treatment differences between the 0–100 m and 1100–1200 m groups greater than 5.8% at the 95% level.

To assess substitution responses, we next examine effects slightly farther from the station, where the model suggests substitution responses may dominate. Panel B of Figure 4 presents the event study for trips 300–400 m from the station, where we do not expect last-mile trip effects to occur. Unlike the sharp increases observed in the immediate vicinity, we observe a moderate but statistically significant decline in Uber usage beginning shortly after the station opens. This pattern is consistent with substitution away from Uber toward improved public transit access, particularly for travelers within comfortable walking distance of the station.

Figure 5 summarizes the average effect during months 1–6 of a new transit station on Uber ridership changes with distance. The reported coefficients are those from the model in Equation 5. On average, a new station opening increases Uber trips by 48% or 0.39 log points (s.e. 0.045) within 100 m. Farther out, we find that a new transit station opening increases Uber ridership at 100–200 m by 0.05 log points (a 5% effect, significant at the 95%-level). For distances 200–700 m, we find evidence that new rail openings *decrease* Uber trips (though insignificantly at 400–500 m and 600–700 m). We find significant effects on the order of a 2% decline in trips at these distances. Thus, while Uber users show strong evidence of complementarities at the station, we do find evidence of substitution away from Uber at intermediate distances. This is a point we take up in more detail in the next section.

Beyond these distances there is no detectable effect. Moreover, the magnitude of the estimates converges towards zero. For example, we can rule out an effect of the station opening on Uber trips at 1000–1100 m of greater than 2.1%. We take this as additional evidence in favor of our identification assumption: that 1100–1200 m is sufficiently far from the station as to be unaffected by its opening. Appendix Figure A4 plots the coefficients for the full dynamic difference-in-differences specification for each distance. Importantly, the plots consistently show no pre-trends in the months leading up to the station opening across each distance band.

Together, these findings indicate that new station openings trigger a discrete shift in Uber demand – consistent with strong last-mile complementarities near the station and moderate substitution at intermediate distances.

Stability of the control group 1100–1200 m

Our finding of no effect beyond 600 m, relative to the 1100–1200 m band, suggests that transit–Uber interactions at these distances are minimal. An alternative possibility is that effects are constant across 600–1200 m and thus net out in our design. To test this, we estimate an event study at 1100–1200 m as a placebo check on our identifying assumptions.

This test is motivated by our model, which highlights the importance of the catchment area. If riders are willing to walk long distances to access public transit, then even those far from a station may substitute away from Uber. In North American transportation planning, a 1/2-mile (approximately 800 m) radius is widely used as the default catchment area for rail transit stations (Guerra, 2012). Empirical studies show that ridership tends to decline sharply beyond this range (Agrawal et al., 2008, Daniels and Mulley, 2013). Our control group lies well outside this threshold,

but we formally assess its validity below.

We estimate an event study using only observations from the 1100–1200 m band, treating not-yet-treated locations as controls. We follow the estimator of de Chaisemartin and D'Haultfœuille (2024) and include city-by-month fixed effects to absorb secular trends. We use a linear model with the inverse hyperbolic sine of trips (in hundreds) as the outcome.[17] Full specification details are provided in Appendix Section D.1. This design isolates variation at a single distance band and serves as a validity test: we expect no treatment effect at 1100–1200 m if our identifying assumptions hold.

Results are shown in Figure 6. Consistent with our identifying assumptions, we find no significant changes in Uber trips before or after the opening. While this specification is less precise than our main difference-in-differences design, it reinforces the validity of the 1100–1200 m band as a comparison group. Appendix Figures A5 and A6 confirm similar results when using a basic two-way fixed effects model estimated by a PPML regression and an IHS-transformed linear model, respectively.

Aggregate effect within 700 m

While we find large increases in Uber ridership very close to new transit stations and small declines at intermediate distances, it is not immediately clear which effect dominates in aggregate. Although the impact is strongest within 0–100 m, that zone covers a much smaller area – for example, the 300–400 m band is seven times larger. Table 2 shows that, on average, the 300–400 m band sees 3.7 times more Uber trips than the 0–100 m zone.

To assess the net effect, we aggregate trips within 700 m and estimate a difference-in-differences model using 1100–1200 m as the control group (as in Equation 4). Appendix Figure 8 plots the estimated treatment effects. We find no statistically significant differences between the treated and control groups, either before or after the station opening. This implies that the positive effects near the station are offset by substitution at intermediate distances. Appendix Figure A18 shows this balance holds across most cities in our sample.

Effects across other ridership margins

Our main outcome thus far has been the total number of Uber trips that either originated or terminated near the station. We now explore whether our results hold across alternative ride metrics. Appendix Figure A15 shows that the effects are nearly identical when estimating impacts on pickups and dropoffs separately. We also find consistent results when examining total fares paid and kilometers traveled, as shown in Appendix Figure A16.

[17] To our knowledge, a PPML-style estimator along the lines of de Chaisemartin and D'Haultfœuille (2024) has not been developed. Our compromise is to use linear regression with a transformed outcome so that we can interpret treatment effects as log changes. We normalize by 100 so that estimated treatment effects near to the station are comparable to those from our PPML specifications. However, estimated effects using inverse hyperbolic sine-transformed outcomes are not scale-invariant (Chen and Roth, 2023).

Given our broad sample of 55 cities across four continents, we next test whether the average effects mask regional heterogeneity. Appendix Figure A17 shows that the pattern of last-mile increases and intermediate-distance substitution holds across continents, with the strongest effects observed in Asian cities and attenuated patterns in Europe. To explore this further, we estimate city-specific treatment effects within 0–100 m and 300–400 m of a station and plot the results in funnel graphs (Figure 7). Estimates are centered around the aggregate treatment effect, with most cities – especially those with larger Uber markets – falling within standard confidence bounds. While a handful of smaller cities show outlier responses,[18] the core pattern is remarkably consistent across the global sample. These findings reinforce the external validity of our main findings and highlight their applicability across the variety of contexts in our sample.

Effects depend on quality of transit improvements

We test whether the magnitude of our estimated effects depends on the quality of the transit improvement. In particular, we expect that openings which meaningfully improve transit access – by offering faster or more reliable service – are more likely to induce last-mile complementarities near the station and substitution from Uber use farther away.

As a test, we analyze a set of 378 station openings for transit modes that interact with traffic, such as trams and streetcars. While these systems expand public transit coverage, they generally do not offer speed advantages over cars or Uber due to shared road use. These transit openings are not included in our main analysis. Appendix Figure A19 presents the results. Panel A plots dynamic estimates from Equation 4, showing no pre-trends in Uber trips. Panel B reports average effects by distance from Equation 5. We find a modest increase in Uber trips at 200–300 m, but no significant effects at other distances. These findings suggest that the findings in our main sample are indeed driven by substantive improvements in transit accessibility, rather than confounding neighborhood changes.

Last mile behavior

Uber is a natural complement to public transit for last-mile travel. If the increase in ridership near stations reflects last-mile use, we would expect Uber trips in those areas to be shorter on average. To test this, we compute the average kilometers per trip across all station-month observations (excluding those with zero trips). Estimates from our main specification are shown in Figure 9.

Consistent with last-mile behavior, we find that average trip length declines sharply near the station. Within 100 meters, trips are 0.15 log points (16%) shorter, corresponding to a reduction of 1.8 kilometers. At 100–200 m, trips are 5% shorter. In contrast, trip length increases slightly at intermediate distances – for example, by 0.02 log points (2%) at 400–500 m. This pattern is consistent with substitution away from previous last-mile trips: if travelers previously took Uber

[18] Negative effects are concentrated in a few cities, including Panama City, Prague, and Lisbon.

for longer trips to access a farther station, but now switch to the new one nearby, the remaining trips at those distances will appear longer on average.

We next examine whether these patterns are stronger for stations where last-mile behavior is likely more important. Terminal stations – those at the end of a transit line – are natural candidates. Appendix Figure A20 reports treatment effects by distance band for terminal and non-terminal stations. Though noisier, estimates for terminal stations are substantially larger. We find an 82% increase in Uber ridership within 100 m (0.60 log points), more than double the 38% increase (0.32 log points) observed near non-terminal stations. At 100–200 m, terminal stations induce an additional 0.30 log point increase in trips relative to non-terminal ones.

Stations far from the city core are also locations where we might expect last-mile behavior to be strongest. To that end, we examine whether ridership gains are larger for stations on the urban periphery. Appendix Figure A21 shows that effects within 100 m are significantly larger for more peripheral stations, both when measured by travel time and by kilometers from the central business district (significant at the 5% and 10% levels, respectively).

Finally, we assess whether these increases are concentrated among riders less likely to live or work near the station – those more likely to require a last-mile connection. We explore this directly in the next section by examining Uber usage for individuals with persistent activity near stations using our POI data.

5.2 Substitution for travelers with nearby POIs (Quadrant II)

Quadrant I showed that Uber usage increases sharply within 100 meters of a new transit station and declines modestly at intermediate distances. While these patterns are consistent with a mix of complementarity and substitution, the evidence is inherently aggregated and may conflate shifts in who uses Uber with changes in individual behavior. To better isolate substitution responses, we now turn to a sample of riders with a persistent connection to a specific location near the station.

This section focuses on a subset of Uber trips taken by users whose regular activity (either home, work, or habitual travel) is near the station – what we refer to as the POI sample. These riders have a fixed relationship to the treated area, allowing us to hold composition constant and directly observe how their mode choice responds to improved transit access. This setting corresponds closely to the substitution mechanism in our model. In the presence of a new transit option, users who previously relied on Uber for travel to or from their POI may now substitute toward transit.

We begin by examining how Uber usage changes across distance bands for users with a fixed point of interest (POI) near the station, following the structure of our main difference-in-differences analysis. Specifically, we compare trips taken 0–500 meters from the station by users with a POI in that zone to trips taken 800–1200 meters from the station by users with a POI in that corresponding outer zone.[19] Because the sample size is smaller, we pool distance band for the control group. We

[19]Due to data constraints, we observe Uber trips for POI samples only in two distance bands: 0–500 m and 500–1200 m. However, trips taken 800–1200 m from the station by users with a POI 500–1200 m away will primarily come from

also pool the 0–100 m and 100–200 m groups due to the resolution of our POI hexes, which are approximately 174 meters in width.[20]

Dynamic estimates from Equation 4 for each distance bin through 700–800 m are presented in Table 5. We generally find balanced trends in Uber usage prior to the station opening. While Uber trips are 2% higher within 0–300 m four months before opening, the magnitude is small relative to the post-treatment effects. We also observe some evidence of anticipation effects 200–400 m from the station, consistent with soft openings.

Following the opening, we find a significant and sustained decline in Uber usage. Uber trips fall by 9% at 200–300 m, 8% at 300–400 m, and 6% at 400–500 m. The effects taper off beyond this range, becoming smaller at 500–600 m and nearly disappearing by 600–700 m. To confirm that the treatment effect dissipates beyond the immediate catchment area, we estimate the same model using 1100–1200 m as the control group for 800–900 m, 900–1000 m, and 1000–1100 m bands. We find no significant effects at these distances, as shown in Figure A22. These results provide strong evidence of substitution away from Uber following transit improvements among travelers with persistent ties to the treated area.

Outbound vs. return trips: heterogeneity by time/day of week

The model highlights why Uber use may persist in the presence of better transit access. For outbound trips, travelers take Uber to preserve flexibility for the return leg. Fewer outbound car trips, in turn, lead to more Uber trips on the return leg. If substitution away from Uber is symmetric across outbound and return trips, then differences across time-of-day can help reveal the relative strength of these two dynamic considerations.

To investigate this, we explore heterogeneity in our estimated effects by time of day and day of week. We focus on the 300–400 meter band, which exhibited the strongest substitution effects in the previous analysis, and estimate Equation 4 separately for different types of trips. Table 6 reports these results. Column (1) replicates our baseline estimate. Columns (2) and (3) isolate weekday morning (AM) and weekday evening (PM) trips, respectively, which are likely to reflect work-related outbound and return travel. Columns (4) and (5) focus on leisure travel: Friday and Saturday nights, and weekend daytime trips. Column (6) covers other remaining periods.

Across all groups, we find consistent evidence of substitution: Uber usage declines by 6–10% for users with POIs near the station, with limited variation across time blocks. Weekday afternoon trips fall by 12%, compared to a 7.6% decline in weekday morning trips. However, these differences – averaged over the 1–6 months following the station opening – are not statistically significant at conventional levels. To test for differential responses between morning and afternoon trips across all distances within 0–500 meters, we estimate an average difference of 0.2 percentage points (s.e.

those located closer to the 800–1200 m range. While this approximation may introduce some attenuation bias, we do not expect it to materially affect the results.

[20] Even with these adjustments, 110–115 stations (depending on the specification) are ommitted from the regression due to sparsity of the data and our saturated fixed effects.

0.9). This confirms that substitution patterns are statistically indistinguishable across the two periods.

These results suggest that substitution away from Uber occurs across a broad range of travel contexts. Importantly, we find no meaningful difference between periods likely to capture outbound versus return trips. This pattern is consistent with similar magnitudes of the option value effect on outbound and return trips. We next turn to Quadrant III, which expands the analysis beyond the local area to examine how Uber usage changes citywide for the same set of individuals – allowing us to evaluate broader responses.

5.3 Citywide Uber ridership (Quadrant III)

We now turn to Quadrant III, focusing on how the opening of a new transit station affects overall Uber usage among individuals that live or work near the station. Using the same POI sample from the previous section, we examine the total number of Uber trips taken by each user across the city – what we refer to as *citywide* Uber ridership. To better understand the nature of these changes, we disaggregate trips into those that are *local* (originating or ending near the new station) and *non-local* (all other trips).

We assign each user to one of three groups based on the distance between their primary POI and the new station: 0–500 meters, 500–800 meters, and 800–1200 meters. Following the strategy used in the previous section, we treat users whose POI is 800–1200 meters from the station as a control group, under the identifying assumption that – absent the transit expansion – they would have experienced similar trends in Uber use as the closer groups.

Table 7 presents estimates from Equation 4. The first three columns report results for users with POIs within 0–500 meters of the station. Column (1) shows that, prior to the station opening, citywide Uber usage trends for this group track closely with the control group. Table A2 shows that these findings are robust across alternative controls. After the station opens, however, citywide trips decline significantly by 3.3%. Disaggregating this effect, Column (2) shows a 7.5% decline in local trips – the same drop in station-adjacent travel observed in the previous section. Column (3) shows that non-local trips increase modestly, with an average post-opening effect of 3.8% (significant at the 10% level), although this estimate should be interpreted cautiously due to pre-treatment imbalances.

The next three columns focus on users with POIs located 500–800 meters from the station. Here, we find little evidence of change in citywide or local Uber usage following the station opening. However, non-local trips rise steadily over time, increasing from 1.7% one month after the opening to 4.4% after six months. The average effect is a 3.4% increase in non-local trips for this group.

These findings speak to the relative magnitude of the substitution and option value effects, as outlined in our model. The increase in non-local trips – especially among users located 500–800 meters from the new station – mirrors the dynamics described in our analysis of intermediate trips in Proposition 3 and points to the importance of Uber's option value. In particular, some

users may choose not to drive in the morning so they can take advantage of improved transit options for the return leg later in the day. As a result, they rely on both transit and Uber more for midday or intermediate trips that arise. Importantly, while the value of transit access declines with distance, the relevance of the option value effect increases: users farther from the station are more likely to drive by default due to higher access costs, and thus more likely to change their travel mode when transit is improved. This helps explain why the option value effect – reflected in increased non-local Uber trips – is more stable across distance.

In contrast, the decline in local Uber trips is sharper for those located 0–500 meters from the new station, producing a net decrease in citywide Uber usage for that group. This pattern is consistent with substitution effects being strongest where access costs are lowest and the gains from transit improvements are greatest. While our reduced-form evidence cannot fully isolate the substitution and option value effects, the model estimated in Section 6 allows us to formally disentangle their relative contributions.

5.4 Robustness

We conduct a series of robustness checks focused on Quadrant I, where statistical power is greatest and behavioral responses aggregate across all margins. Importantly, Quadrant I is the only setting that captures last-mile behavior, making these estimates especially relevant for the model-based analysis in Section 6. We show that the results are consistent across alternative specifications, placebo tests, and variations in geography and event timing.

Placebo tests. We assign each station a fake opening date randomly drawn from the set of dates with sufficient pre/post data (6 months on each side) and re-estimate our main specification 100 times. Appendix Figure A7 compares the distribution of placebo coefficients to the true estimates (blue circles), confirming that transit expansions increase Uber trips near the station and reduce them farther away.

Alternative specifications. Tables 3 and 4 show results at 0–100 m and 300–400 m using different sets of fixed effects. Column (3) is our main design, which includes station-by-distance and station-by-month fixed effects to flexibly control for unobserved heterogeneity and hyper-local trends. Column (1) omits these controls, and Column (2) adds city-by-month fixed effects. Despite these variations, treatment effects remain stable and pre-trends are absent, reinforcing the importance of exogenous timing variation for identification. Column (4) adds distance-bin-by-month fixed effects to address concerns about broader neighborhood change. Results are consistent across all specifications. Figures A8 and A9 show event study estimates using not-yet-treated periods as controls, using PPML and linear regression, respectively. Both specifications show little evidence of pre-trends and similar effects to the main design.

Structural break test. We follow Andrews (1993, 2003) in estimating the treatment effect under shifted "placebo" opening dates. Appendix Figure A10 shows that the estimated effect is most significant at the true opening date, with a Wald statistic of 66.59, rejecting the null of no structural

break at conventional levels.

Adjacent distance comparisons. We re-estimate effects using adjacent 100-meter bands as controls, following a discrete version of the gradient estimator in Diamond and McQuade (2019). Appendix Figure A11 shows both the marginal and aggregate effects of station openings. The results closely track our main estimates in shape, magnitude, and significance.

Uber fare structure. If Uber were strategically repricing near new stations – for example, by lowering fares to compete with transit or experiencing surge pricing from the demand shock near the station – this could confound our interpretation of the ridership patterns as demand-side responses. To test this possibility, we estimate our main specification using fare per trip as the outcome, and interact the treatment effect with kilometers per trip to separately identify changes in the fixed and marginal cost components of fares. These estimates are depicted in Figure A12. We find no meaningful change in either component following a station opening, ruling out pricing adjustments as a driver of our results.

Geographic robustness. To address concerns about ring geometry, we replicate our analysis using fixed-area hexagonal bins (Appendix Figure A13). Results are muted, as expected, due to spatial averaging within bins, but show similar qualitative patterns.

Time window. Expanding the analysis to an 18-month window (Appendix Figure A14) reveals no pre-trends and, if anything, stronger post-opening effects. Uber trips within 0–100 m increase by 0.60 log points (82%) sixteen months after opening.

6 Model Estimation and Counterfactuals

While our reduced-form findings depict substitution and complementarity across trips and user types, they do not isolate the relative contributions of specific mechanisms and cannot evaluate how transit behavior might change under alternative policy environments – such as the effect of Uber exiting the market, or subsidizing last-mile trips. To that end, we estimate the parameters of the model introduced in Section 2 to match key reduced-form moments from Section 5 using the method of simulated moments. Our goal is not to recover a fully structural model of travel demand, but to organize the reduced-form evidence, quantify mechanisms, aggregate effects, and conduct counterfactuals which cannot be done using the findings in Section 5 alone.

6.1 Approach and moments matched

We estimate the model by matching its predictions to the causal estimates from Section 5 using the method of simulated moments. The goal is not to recover a fully structural model of travel demand, but to select parameter values consistent with our empirical patterns and use them to quantify mechanisms and evaluate counterfactuals.

As outlined in Section 2, the parameter vector θ includes baseline mode preferences for primary and intermediate trips, persistent preference heterogeneity, Uber access costs (with walking fixed

costs normalized to zero). To this set, we include two additional parameters capturing how the station opening shifts transit utility for primary trips ($\Delta^{\alpha}_{\text{transit}}$) and intermediate trips ($\Delta^{\beta}_{\text{transit}}$). We also estimate two spatial parameters: an exponential kernel rate λ governing the spatial dispersion of first- and last-mile trips around the station, and a population density gradient κ capturing the decline in potential last-mile travelers with distance. In total, θ contains 14 parameters. Technical details of the simulation procedure and spatial assignment of last-mile trips are provided in Appendix E.

We match 24 reduced-form moments drawn from the three empirical quadrants, plus two calibration targets, to discipline these 14 parameters. We estimate θ by minimizing the weighted distance between data and model-implied moments, with an additional penalty for deviations from the calibration targets; the objective function and standard error formula are reported in Appendix E. The moments and the parameters they primarily discipline are as follows.

Quadrant I (13 moments): station-adjacent Uber usage. These moments include the estimated change in Uber trips across distance bands near the station, along with changes in average trip length within 0–100 m and 100–200 m. They are primarily informative about first- and last-mile access costs (f_{Uber}, c_{Uber}, c_{walk}), the magnitude of the transit quality improvement ($\Delta^{\alpha}_{\text{transit}}$), and the spatial parameters (κ, λ). These moments, in combination with the spatial patterns elsewhere, also inform the distribution of preferences ($\sigma_{\text{transit}}, \sigma_{\text{Uber}}, \phi$).

Quadrant II (7 moments): station-adjacent Uber usage for local travelers. These moments are the average treatment effects on station-adjacent Uber usage for POI travelers (0–500 m and 500–800 m from the station) across distance bins from 0–200 m through 700–800 m. By conditioning on a stable set of travelers, they remove last-mile trips and isolate the substitution channel.

Quadrant III (4 moments): citywide and non-local Uber usage for local travelers. These moments are the estimated changes in citywide and non-local Uber usage for the 0–500 m and 500–800 m POI samples. They correspond directly to the option value mechanism and primarily discipline the intermediate-trip utilities β_{Uber} and β_{transit}, as well as $\Delta^{\beta}_{\text{transit}}$.

Calibration targets. Because our moments are differences in ridership levels, mean mode shares are not well identified without additional structure. We therefore impose two calibration targets. First, a public transit mode share of 40% within 800 m of stations, based on observed mode shares in dense transit-oriented cities.[21] This share helps identify mode preferences α_{transit} and α_{Uber}. Second, the ratio of Uber trips per square kilometer at 1000–1100 m to 1100–1200 m prior to opening (equal to 1.08), which helps pin down κ separately from c_{Uber}, since both parameters otherwise have similar effects on the spatial pattern of first- and last-mile trips.

[21] The Center for Transit-Oriented Development (2024) data show transit mode shares within 1/2 mile of stations range from 15% in Los Angeles to 50% in New York. We target near the New York benchmark as the density and transit quality in that city more closely resemble the Asian and European cities in our sample.

6.2 Estimation results

Before reporting parameter estimates, we describe how we convert utility units to willingness-to-pay (WTP). Let ρ denote the marginal utility of income, which governs the mapping between utility units and dollar-valued WTP. Our identification exploits transit expansions rather than price variation, so we cannot separately identify mode utilities from ρ without additional structure. Moreover, we found that Uber's pricing structure – fixed costs and cost per kilometer – does not change in response to station openings (Figure A12). We therefore calibrate ρ using an external Uber demand elasticity of $\varepsilon^D = -0.6$ from Cohen et al. (2016) and Castillo (2025). Appendix Proposition 4 derives the mapping from the elasticity target to ρ in our mode-choice model. This yields $\hat{\rho} = 0.41$, so that one utility unit corresponds to approximately \$2.43 in WTP.

Improvement in transit quality. Parameter estimates and standard errors are reported in Table 8. The station opening corresponds to an improvement in outbound/return utility from public transit of $\Delta^{\alpha}_{\text{transit}} = 0.47$ (s.e. 0.03), corresponding to a \$1.14 improvement in WTP per primary trip – roughly 15% of the mean Uber fare in our sample. Public transit is a more attractive mode than car for those that live near the station by \$3.89, with 29% of that value coming from the new station itself. The station opening also induces a small but significant decline in intermediate-trip transit utility ($\Delta^{\beta}_{\text{transit}} = -0.02$, s.e. 0.01), corresponding to \$0.05 in WTP. On a base intermediate-trip utility of $\beta_{\text{transit}} = 0.47$ (s.e. 0.08), this change has limited effect on transit decisions, and is consistent with improved local access not substantially raising the attractiveness of transit for trips elsewhere in the city. At the station itself ($d = 0$), the opening increases the probability of choosing transit from 66% to 71%, with gains coming equally from substitution away from driving and direct Uber trips. The increase in transit use and decline in car use peak at 6 pp and 5 pp respectively at 500 m from the station.

Access costs and last-mile behavior. The fixed cost of using Uber for station access is estimated at $f_{\text{Uber}} = 5.37$ (s.e. 0.20), corresponding to approximately \$13.05 in WTP. Marginal access costs imply each additional 100 meters imposes disutility equivalent to \$1.14 by walking and \$0.23 by Uber. While last-mile trips remain rare at any given location – accounting for 2.6% of total trips at peak – they aggregate across the catchment area to produce the substantial 48% increase in station-adjacent Uber ridership documented in Section 5.1. The estimated spatial dispersion parameter λ implies an average measurement error in last-mile trip geo-locations of 43 m. The estimated population density gradient $\kappa = 0.63$ (s.e. 0.19) implies that the pool of potential last-mile travelers nearly halves every kilometer from the station, reflecting the declining share of residents for whom the new station is the closest transit option.[22]

Mode preferences and heterogeneity. The estimated baseline utilities imply that, adjacent to the station, transit is preferred to car use, which in turn is preferred to direct Uber, for both

[22]The estimated costs imply travelers are willing to walk up to 1440 m before Uber becomes the preferred access mode. Beyond 800 m, transit mode share falls below 25%, consistent with standard 1/2-mile catchment areas (Guerra, 2012, Agrawal et al., 2008, Daniels and Mulley, 2013). By 1200 m the model predicts less than 1% change in Uber ridership, providing theoretical justification for our control group choice.

commute and intermediate trips. The estimated standard deviations of persistent preference shocks are $\sigma_{\text{Uber}} = 2.72$ (s.e. 0.19) and $\sigma_{\text{transit}} = 2.24$ (s.e. 0.20), reflecting substantial heterogeneity in preferences over both modes relative to private car use. This is consistent with Uber serving a mix of travelers for whom it is highly convenient and those for whom it is rarely used, and similarly with public transit serving travelers ranging from those with strong preferences for it to those who find it costly or inconvenient. This heterogeneity helps explain why aggregate effects of transit improvements on Uber ridership are moderate even when individual behavioral responses are large: the population contains many travelers near the margin of switching, but also many who are far from it in either direction.

The estimated correlation between Uber and transit preferences is strongly negative ($\phi = -0.69$, s.e. 0.08), indicating that travelers who prefer ride-hailing over driving tend to dislike transit, and vice versa. This suggests that Uber and transit draw from different segments of the non-driving population, which helps explain why pro-transit policies can generate limited substitution toward ride-hailing even when both are alternatives to car use.

Model fit. Table A3 compares model-implied moments to their empirical counterparts. Importantly, the model predicts negligible changes in Uber ridership within our control groups: a 0.00 log point change at 1100–1200 m for Quadrant I, and 0.00 for local POI trips at 800–1200 m for Quadrant II. These predictions support our identifying assumption that treatment effects are negligible sufficiently far from the station. For Quadrant III, the model predicts log point increases of 0.03 and 0.015 for non-local and citywide trips among the 800–1200 m POI sample – suggesting if anything that our reduced-form estimates of the non-local trip increase are biased downward. Turning to the matched moments, the model performs well overall, with an RMSE of 1.7 pp. The main discrepancies are at intermediate distances: the model predicts a 0.05 log point decline in Uber trips at those distances compared with a 0.03 log point decline in the reduced-form estimates, and a 0.05 log point decline for the POI sample at 200–300 m compared with a 0.10 log point decline in the data. Both discrepancies suggest the model slightly overpredicts substitution at intermediate distances and underpredicts it close to the station.

6.3 Decomposition of mechanisms

Propositions 1, 2, and 3 provide a framework for decomposing the change in Uber ridership induced by an improvement in transit quality. We use these results to decompose the effect of a new station opening on Uber ridership in the model. Population-weighted across distance bands, substitution and option value are equal in magnitude and opposite in sign: substitution decreases Uber ridership by 1.0% in aggregate, while option value increases it by 1.0%. Both forces are larger on the return leg, when outbound mode choice constrains the subsequent choice set. By comparison, the last-mile mechanism increases Uber ridership by only 0.2%, making it roughly five times smaller than either the substitution or option-value effect. Thus, the last-mile mechanism accounts for 17% of the positive forces increasing Uber ridership in response to better transit access. The net effect of the three mechanisms is positive. Spatially, the substitution effect

is concentrated near the station, whereas the option-value and last-mile effects are more diffuse.

For intermediate trips, the decomposition implies an average increase in Uber ridership of 0.6%: the option-value effect outweighs the negative substitution effect (which arises because $\Delta^{\beta}_{\text{transit}} = -0.02$). At 600 m from the station, option-value considerations are strongest and account for a 2.3% increase in Uber ridership. The decomposition also supports our interpretation of the reduced-form evidence: the near-station positive effect is driven primarily by last-mile trips, the intermediate-distance negative effect arises from the substitution channel, and the citywide non-local increase reflects Uber's option value.

These derivative-based estimates are local linear approximations and therefore need not aggregate exactly to the total effect of a station opening. We therefore also compute the exact model-implied change in Uber ridership under the station-opening counterfactual. Under this calculation, outbound/return-trip Uber use increases by 0.6% on average, and intermediate-trip Uber use increases by 2.0% after the station opens. Aggregating across trip types, a new station opening increases average Uber ridership by 0.9% in the model. Taken together, these results imply that improved public transit complements Uber ridership on net.

6.4 Counterfactuals

Policymakers often seek to increase public transit use to reduce driving externalities. The effectiveness of these policies depends on how transit interacts with other modes, including ride-hailing and personal vehicles. We use the estimated model to evaluate counterfactual policies that target different margins of travel behavior. Because we do not explicitly value reductions in congestion and pollution, our welfare and fiscal measures should be interpreted as the direct costs required to induce higher transit ridership.

Uber entry/exit. Section 6.3 showed that in our setting, a new train station increases Uber ridership. Here we probe this complementarity further. First, we examine how the station-opening effects vary with Uber availability. Second, we examine how transit ridership changes if Uber exits the market. Throughout, we treat Uber as representative of the broader ride-hailing market. In cities where Uber competes with other ride-hailing platforms, the effects of Uber exit would be attenuated to the extent that competing services substitute for Uber's last-mile and direct trip functions. In our sample however, Uber was the dominant, and often sole, ride-hailing platform making this assumption more palatable.

Table 9 reports model-predicted changes in mode shares, welfare, and fiscal costs across counterfactual scenarios. Panel A focuses on the impact of a new station opening under three Uber environments: baseline (row 1), no direct Uber trips (row 2), and no Uber at all (including last-mile access; row 3). Under the baseline, the station opening increases transit ridership by 1.60 pp. When direct Uber trips are removed, the increase in transit ridership is slightly larger (1.69 pp), consistent with reduced mode competition. In contrast, eliminating Uber entirely reduces the transit increase to 1.36 pp: walk access does not fully substitute for Uber-enabled access, and some travelers instead shift toward cars. In percentage terms, transit ridership responds more to a

station opening when Uber is present – increasing 6.73% when Uber is available as compared to 6.50% when Uber is not.

Panel B considers Uber exit more directly. When direct Uber trips are removed, transit use on intermediate trips falls sharply (4.49 pp). Rather than switching into transit, former Uber users substitute primarily toward cars, consistent with (i) negatively correlated preferences for Uber and transit and (ii) high access costs at longer distances. As a result, aggregate transit ridership declines by 0.75 pp. When last-mile Uber access is also removed, the decline is larger: commute transit falls as access trips disappear, and intermediate-trip transit declines further (4.69 pp), yielding a total transit reduction of 1.61 pp. Taken together, these counterfactuals show that last-mile access is critical: removing Uber reduces transit use in this setting, consistent with Uber and transit being complements on net.

Subsidizing last-mile trips. Panel C considers subsidies to first/last-mile access, a commonly proposed tool to expand station catchment areas. We evaluate three subsidy policies relative to a baseline with no subsidy. The first is a purely fixed subsidy: we implement this by reducing the Uber access fixed cost f_{Uber} by \$4. The second is an equal-value hybrid subsidy that reduces marginal access costs c_{Uber} by 50% and allocates the remaining value to a fixed subsidy, so that the total offered value is \$4. The third fully subsidizes marginal Uber access costs (i.e., sets the marginal price of Uber access to zero); we include a small fixed subsidy so that, by construction, the total offered value is again \$4. These policies are therefore equal in offered value, but not in fiscal cost, since total program spending depends on take-up and trip distances.

Among these equal-value subsidies, fully subsidizing marginal access costs is most effective at increasing transit use. Relative to the no-subsidy baseline, commuter transit use increases by 6.82 pp, largely driven by Uber-accessed transit trips, and intermediate-trip transit increases by 1.18 pp. However, the fiscal costs are large: average spending is \$1.04 per traveler for willingness-to-pay gains totaling only \$0.41. Fixed subsidies are less powerful at expanding ridership but more targeted. A purely fixed subsidy increases average commuter transit use by 3.78 pp, partially by shifting access from walking to Uber among travelers who would have used transit anyway. The hybrid 50% marginal-cost subsidy produces a larger increase in commuter transit use (4.77 pp), with fiscal costs of \$0.60 per traveler and willingness-to-pay gains of \$0.29. Intuitively, fixed components primarily reallocate access from walking to Uber among existing transit users, whereas marginal-cost subsidies are more effective at inducing new transit use – especially at longer distances, where access costs are high but marginal subsidies are also most expensive.

Ride-hailing taxes. Ride-hailing taxes are often motivated as a way to shift trips from ride-hailing to public transit. However, because ride-hailing is also used for last-mile access, such taxes can reduce transit use by raising the cost of accessing transit. Panel D evaluates a \$1 ride-hailing tax. The tax induces a large substitution away from direct Uber and toward personal vehicles: direct Uber use falls by 5.48 pp, while car use rises by a similar magnitude. This response is driven by negatively correlated preferences for Uber and transit: the marginal Uber users who are most sensitive to the tax are more likely to switch into cars rather than into transit, especially at longer

distances where access costs are high. The tax increases transit-by-walk only slightly (0.19 pp) and reduces transit use via Uber access, yielding a net decline in aggregate transit use. The shift toward car commuting also spills over into intermediate travel, reducing intermediate-trip transit use by 0.14 pp.

Panel D also shows that pairing the tax with a last-mile subsidy (policy II, row 2) can more than offset the transit losses from the tax alone, though the implied increase in last-mile transit access is smaller than under the stand-alone subsidy policies in Panel C.

Congestion taxes. While the model is formulated for a general point of interest, we now interpret it through the lens of a commuter traveling from home on the periphery to a job in the dense CBD. Congestion pricing is increasingly used to reduce automobile traffic in city centers, typically via a cordon charge. We model this policy as a tax applied to commute trips by car and by direct Uber, and for simplicity apply it to both outbound and return legs. We assume last-mile access trips do not enter the cordon, and that intermediate trips occur within the cordon, so neither is taxed.

Panel E reports the results. A congestion tax of \$0.50 each way increases commute transit use, raising transit-by-walk by 0.54 pp and transit-by-Uber by 0.24 pp, largely at the expense of cars. The tax also induces modest increases in transit use for intermediate trips within the cordon. Because congestion pricing discourages automobile use without directly penalizing last-mile access, it creates scope for complementary last-mile subsidies. Row 2 adds a last-mile subsidy (policy II), leading to a much larger increase in commute transit use (6.22 pp) and a 1.08 pp increase in intermediate-trip transit use within the cordon, again primarily offset by reduced car travel. Direct Uber use is largely unchanged: although the tax discourages Uber on the commute margin, the improved relative attractiveness of transit sustains demand for Uber through its option value.

Congestion pricing is effective in this setting because it is broad – it directly targets cars, the primary substitution channel away from transit, while leaving last-mile access incentives intact. Consistent with this mechanism, the marginal impact of a last-mile subsidy is larger under congestion pricing than in the baseline, highlighting that these policies can reinforce one another.

Fiscally-neutral policy mix. Finally, we solve for a fiscally neutral policy that increases aggregate transit use by 5 pp while minimizing welfare losses, financing last-mile subsidies with ride-hailing and congestion taxes. Panel F reports the resulting optimal policy mix. The model selects a marginal last-mile subsidy of \$0.69 per km, a fixed last-mile subsidy of \$3.09, a \$0.38 congestion tax, and zero ride-hailing tax. While optimal levels will vary across cities and institutional settings, the relative magnitudes are informative. In particular, the congestion tax dominates the ride-hailing tax as a revenue instrument for increasing transit use at lower welfare cost, and the optimal last-mile subsidies are sizable relative to baseline access costs: the marginal subsidy is about 61% of estimated marginal access costs and the fixed subsidy is about 24% of fixed access costs. The fixed last-mile subsidy is also large relative to the congestion charge, underscoring the importance of reducing access frictions in achieving the transit-use target.

Table A4 shows the distribution of welfare losses from the optimal policy across distance

bins. At the farthest distances, most travelers bear the congestion tax with limited scope to adjust behavior. Across most distances, the 25th percentile of welfare losses corresponds to paying the full congestion charge, consistent with strong preference heterogeneity and limited switching for some travelers. Welfare losses are smallest near the station, where many travelers already use transit, and are mitigated at intermediate distances by the last-mile subsidies.

We conclude by solving for the fiscally neutral optimal policy when the policymaker can additionally subsidize transit directly. Row 2 of Panel F reports the results. The optimal policy shifts markedly: a direct transit subsidy of \$1.49 replaces last-mile subsidies entirely, paired with a congestion tax of \$0.53 and a small ride-hailing tax of \$0.04. The intuition is straightforward. First, direct transit subsidies raise the attractiveness of transit for both commute and intermediate trips simultaneously, whereas last-mile subsidies operate primarily through the commute margin and reach intermediate trips only indirectly through the option value channel. Second, last-mile subsidies are a costly policy to attract distant travelers. When the policymaker has access to a more direct instrument, last-mile subsidies are no longer attractive.

6.5 Policy implications

Our results suggest that the policy question is not just whether ride-hailing and public transit are complements or substitutes in general, but how and where they interact. The same transit improvement can generate both substitution away from Uber (through improved direct transit service) and complementarity with Uber (through last-mile access and option value). The net effect depends on the relative strength of these mechanisms across trip types and distance from the station. Related to this point, there is an active debate over the impact of Uber entry and exit on public transit ridership. Existing estimates range from increases of up to 5% after two years (Hall et al., 2018) to declines of 16% after four years (Diao et al., 2021). Our findings help reconcile the mixed evidence in the existing literature; in our sample of 55 cities, we find that on net, transit improvements increase Uber ridership, and Uber entry increases transit use.

A first implication is for transit agencies planning station openings or service expansions. Changes in ride-hailing demand around new stations is not solely evidence of competition with transit. In our setting, increases in Uber use near stations reflects greater use of Uber as an access mode to transit. At the same time, improved transit quality can reduce direct Uber use for riders who live or work near the station. This implies that station-area planning should account for both margins simultaneously. In practice, this points to the importance of curb management, pickup/dropoff design, and enforcement near stations. It also highlights that new transit access as a policy to reduce local congestion may have the unintended consequence of *increasing* congestion.

A second implication concerns the design of transit–ride-hailing partnerships. For example, Berlin and Munich piloted partnerships with Uber in 2021 that offered a flat-fee subsidy for trips that began or ended at U-Bahn stations, and these programs were later expanded to additional stations (with Berlin expanding in 2023 to some S-Bahn stations). Our counterfactuals show that subsidy policies with the same offered value can have markedly different effects on transit

ridership depending on how the subsidy is delivered. In particular, subsidies that reduce the marginal cost of Uber access (our flat-fee policy) generate larger increases in transit use than equal-valued subsidies that reduce the fixed cost of Uber access. Intuitively, marginal-cost subsidies more directly target the last-mile access margin, whereas fixed subsidies shift some access from walking to Uber conditional on already taking transit. At the same time, marginal-cost subsidies become fiscally expensive as they induce travelers farther from stations to switch to transit, providing a rationale for distance caps on eligible last-mile trips (such as the 2.5 km limit in the Berlin/Munich pilot).

Importantly, when policymakers can also subsidize transit directly, last-mile subsidies are no longer optimal. Direct transit subsidies dominate because they raise the attractiveness of transit for both commute and intermediate trips simultaneously, whereas last-mile subsidies reach intermediate trips only indirectly through the option value channel and become fiscally expensive as they induce distant travelers to switch to transit. This suggests that last-mile subsidies are most valuable precisely in settings where direct transit subsidization is politically or fiscally constrained. More broadly, our results complement Agrawal and Zhao (2023) by showing that whether ride-hailing complements public transit depends critically on the policy instruments that affect last-mile access.

Our findings also have implications for transportation policies such as ride-hailing taxes (Tarduno, 2025, Leccese, 2025) and congestion pricing (Cook et al., 2025). These policies are typically motivated by the goal of reducing automobile externalities, including congestion (Currie and Walker, 2011, Yang et al., 2020), emissions (Anderson, 2020), noise (Moretti and Wheeler, 2025), and safety (Ashenfelter and Greenstone, 2004).[23] A central implication of our framework is that policies targeting ride-hailing or driving inevitably affect multiple behavioral margins: it is difficult to tax substitution away from transit without also changing complementary channels such as last-mile access and option value.

In our setting, ride-hailing taxes reduce total transit use because they raise the cost of last-mile access, and the marginal riders who switch out of Uber substitute primarily toward cars rather than toward transit. This suggests that ride-hailing taxes may be particularly poorly targeted in peripheral station catchment areas, where last-mile access is critical, or in settings with unreliable transit service, where Uber's option value is important. Congestion pricing performs better on this dimension because it more directly targets cars – the primary substitute away from transit – while leaving last-mile access outside the cordon largely unaffected. Even so, congestion pricing can dampen some transit use among commuters who value Uber's option value for the return trip. Because congestion pricing is broader and does not directly tax last-mile access, it can be effectively complemented by last-mile subsidies.

[23] For a survey of automobile externalities, see Parry et al. (2007). Kashner and Ross (2025) provides recent evidence quantifying traffic externalities.

7 Conclusion

The question of whether ride-hailing complements or substitutes for public transit has generated substantial debate and a wide range of empirical estimates. Our results suggest that the disagreement is not only a matter of measurement or context: substitution and complementarity operate simultaneously, on different margins, for different travelers, and at different distances from transit infrastructure. Aggregate estimates often conflate these forces, and the sign of the net effect depends on which margins are observed and which policies shape interactions between modes.

In this paper, we developed a model of transit mode choice to formalize these mechanisms and estimate it using a new dataset of 650 rail station openings across 55 cities in 35 countries. Our identification strategy exploits the sharp timing of station openings – planned years in advance, typically before Uber existed – to compare changes in ride-hailing across concentric distance bands. This design allows us to document three patterns simultaneously: a 48% increase in Uber trips within 100 meters of new stations, consistent with first- and last-mile complementarity; among travelers with a persistent connection to station areas, substitution away from Uber use near the station by 6–10%; among these same travelers, increased Uber use elsewhere in the city, consistent with the model's option-value mechanism.

Estimating the model on these moments, we find that substitution and option value are similar in magnitude and opposite in sign on average, while the last-mile channel is smaller but still accounts for roughly one-sixth of the positive forces acting on Uber ridership. In counterfactuals, Uber is a net complement to public transit in our setting: allowing Uber access raises transit ridership, removing it reduces transit use, and subsidies that lower last-mile access costs increase transit ridership. The counterfactual analysis also reveals that policies meant to spur transit ridership, like ride-hailing taxes and congestion pricing, operate through distinct channels. Ride-hailing taxes can reduce transit use by raising the cost of last-mile access and pushing marginal Uber users toward cars rather than transit. By contrast, congestion pricing is more effective in our setting at increasing transit ridership because it targets cars directly while leaving last-mile access largely intact, and its effectiveness is amplified when paired with last-mile subsidies.

These findings imply that the net effect of any intervention on transit ridership depends not just on which mode it targets, but on how it interacts with last-mile access and the option value of ride-hailing for return trips. As a result, a $1 ride-hailing tax and a $0.50 congestion charge can have opposite effects on transit use despite similar stated goals. More broadly, our results suggest that the key policy question is not whether ride-hailing competes with transit, but how the two modes interact across space and across margins of behavior.

Several limitations remain. Our estimates capture short-run behavioral responses within six months of station openings and may not reflect longer-run adjustments in residential location, car ownership, or travel patterns. Those longer run changes could also include supply-side responses – such as changes in ride-hailing pricing or transit frequency – that could amplify or dampen the mechanisms we identify. And while our international sample provides unusually broad external

validity, the estimated parameters reflect an average across contexts that vary substantially in transit quality, urban density, and car ownership.

These limitations point to productive directions for future work. As autonomous vehicles enter urban markets – altering the cost structure of both ride-hailing and car ownership – the same mechanisms we identify will shape how travelers respond. Whether autonomous vehicles reinforce last-mile complementarity by lowering access costs, or undermine it by making car use more attractive, will depend on the same forces emphasized here: access costs, preference heterogeneity, and the option value of flexible return modes. Understanding these interactions is essential for designing transportation infrastructure and policy that works alongside, rather than against, the modes that travelers actually use.

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Tables

Table 2: Uber trips descriptive statistics

	Summary Statistics				
	Full: $t \in [-6, 6]$	*0-100m*	*3-400m*	*7-800m*	*11-1200m*
Uber trips	mean [median]	mean [med.]	mean [med.]	mean [med.]	mean [med.]
Pickups	1,659 [188]	417 [47]	1,527 [181]	1,858 [255]	2,106 [227]
Dropoffs	1,652 [187]	423 [47]	1,580 [188]	1,824 [247]	2,088 [227]
Kilometers	29,113 [3,979]	7,698 [940]	28,592 [3,882]	31,616 [5,275]	35,722 [5,003]
Km/trip	11.20 [10.06]	10.24 [9.10]	11.31 [10.12]	11.33 [10.23]	11.32 [10.12]
Fare/trip (USD)	7.84 [5.48]	6.98 [4.78]	7.92 [5.48]	7.96 [5.58]	7.89 [5.60]
Zero Trips Shr	0.16	0.25	0.15	0.14	0.15
Weekday AM Shr	0.09 [0.09]	0.08 [0.08]	0.09 [0.09]	0.09 [0.09]	0.09 [0.09]
Weekday PM Shr	0.11 [0.13]	0.11 [0.12]	0.12 [0.13]	0.12 [0.13]	0.11 [0.13]
Fri-Sat Night Shr	0.08 [0.07]	0.06 [0.06]	0.08 [0.07]	0.09 [0.07]	0.08 [0.08]
Weekend Day Shr	0.11 [0.11]	0.10 [0.11]	0.11 [0.11]	0.11 [0.12]	0.11 [0.12]
N	100,032	8336	8336	8336	8336

Notes: This table contains summary statistics on Uber trips in our sample. All data is from the study window of 6 months prior and after the station opening. Each column contains means and medians (in brackets) for some relevant Uber trip outcomes. Column (1) is for our full sample through 1200 meters away from the station. Columns (2) through (5) disaggregate those means by four 100 meter distance bands. Rows (1) through (4) contains average counts for the number of pick-ups, drop-offs, kilometers travelled, and average trip length. Row (5) contains the share of month-distance band cells that had zero trips in them. This includes true zeros as well as those that had fewer than 5 trips, and so were censored. Rows (6) through (9) contain the share of trips during different parts of the week. Row (10) contains observation counts.

Table 3: Difference-in-differences estimates for 0–100 m with varied fixed effects

	(1) Uber trips	(2) Uber trips	(3) Uber trips	(4) Uber trips
-6 months after	-0.00966	0.00671	0.00676	0.0399
	(0.0262)	(0.0260)	(0.0259)	(0.0304)
-5 months after	-0.00417	0.00506	-0.00327	0.0239
	(0.0223)	(0.0212)	(0.0234)	(0.0263)
-4 months after	0.0177	0.00980	0.00756	0.0229
	(0.0211)	(0.0181)	(0.0194)	(0.0205)
-3 months after	0.0125	0.00807	0.0124	0.0201
	(0.0157)	(0.0141)	(0.0160)	(0.0169)
-1 months after	0.0324	0.0365*	0.0482**	0.0478**
	(0.0233)	(0.0188)	(0.0225)	(0.0211)
Month of expansion	0.141***	0.161***	0.180***	0.177***
	(0.0285)	(0.0266)	(0.0292)	(0.0296)
1 months after	0.328***	0.343***	0.350***	0.342***
	(0.0415)	(0.0417)	(0.0428)	(0.0429)
2 months after	0.336***	0.366***	0.366***	0.350***
	(0.0437)	(0.0440)	(0.0432)	(0.0432)
3 months after	0.353***	0.379***	0.372***	0.351***
	(0.0459)	(0.0470)	(0.0456)	(0.0460)
4 months after	0.391***	0.410***	0.396***	0.375***
	(0.0494)	(0.0488)	(0.0454)	(0.0459)
5 months after	0.407***	0.427***	0.406***	0.386***
	(0.0605)	(0.0584)	(0.0556)	(0.0560)
6 months after	0.436***	0.469***	0.451***	0.423***
	(0.0629)	(0.0624)	(0.0603)	(0.0610)
Observations	72,618	70,998	58,298	58,298
Station Openings	635	634	608	608
Station x Dist FE	✓	✓	✓	✓
Cal. and Evt. Time FE	✓	✓	✓	✓
City x Date FE		✓		
Station x Date FE			✓	✓
Dist x Date FE				✓

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Notes: This table contains coefficient estimates and standard errors from equation (4) for trips 0–100 meters from the station under varying fixed effects. These coefficients estimate the effect of a new train station opening on Uber trips 0–100 meters away in every month leading up to and after the station opening relative to Uber trips 1100–1200 meters away. Coefficients are relative to two months prior to the station opening. All specifications include station and calendar and event time fixed effects. Column (2) adds city by calendar time fixed effects. Column (3) adds station by date fixed effects, and is our main specification. Column (4) includes distance by date fixed effects. All errors are clustered at the station-level.

Table 4: Difference-in-differences estimates for 300–400 m with varied fixed effects

	(1) Uber trips	(2) Uber trips	(3) Uber trips	(4) Uber trips
-6 months after	-0.0117	0.000533	0.00584	-7.43e-06
	(0.0137)	(0.0107)	(0.0113)	(0.0114)
-5 months after	0.00198	0.00527	0.00755	0.00394
	(0.0118)	(0.00843)	(0.00873)	(0.00892)
-4 months after	0.00400	0.00563	0.00864	0.00817
	(0.0119)	(0.00935)	(0.00979)	(0.00998)
-3 months after	0.00527	0.00476	0.00603	0.00609
	(0.00813)	(0.00627)	(0.00658)	(0.00650)
-1 months after	-0.00716	-0.00964	-0.00998	-0.00825
	(0.0120)	(0.00854)	(0.00674)	(0.00690)
Month of expansion	-0.0297***	-0.0251**	-0.0163*	-0.0134
	(0.0110)	(0.0104)	(0.00918)	(0.00927)
1 months after	-0.0472***	-0.0431***	-0.0255**	-0.0208**
	(0.0130)	(0.0120)	(0.0110)	(0.0106)
2 months after	-0.0562***	-0.0447***	-0.0299**	-0.0235*
	(0.0152)	(0.0139)	(0.0130)	(0.0125)
3 months after	-0.0533***	-0.0437***	-0.0340**	-0.0267**
	(0.0148)	(0.0140)	(0.0135)	(0.0132)
4 months after	-0.0444**	-0.0385**	-0.0302**	-0.0220
	(0.0180)	(0.0157)	(0.0140)	(0.0152)
5 months after	-0.0654***	-0.0627***	-0.0632***	-0.0546***
	(0.0229)	(0.0167)	(0.0154)	(0.0159)
6 months after	-0.0732***	-0.0556***	-0.0482***	-0.0381**
	(0.0234)	(0.0150)	(0.0135)	(0.0151)
Observations	73,407	71,706	60,624	60,624
Station Openings	637	637	620	620
Station x Dist FE	✓	✓	✓	✓
Cal. and Evt. Time FE	✓	✓	✓	✓
City x Date FE		✓		
Station x Date FE			✓	✓
Dist x Date FE				✓

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Notes: This table contains coefficient estimates and standard errors from equation (4) for trips 300–400 meters from the station under varying fixed effects. These coefficients estimate the effect of a new train station opening on Uber trips 300–400 meters away in every month leading up to and after the station opening relative to Uber trips 1100–1200 meters away. Coefficients are relative to two months prior to the station opening. All specifications include station and calendar and event time fixed effects. Column (2) adds city by calendar time fixed effects. Column (3) adds station by date fixed effects, and is our main specification. Column (4) includes distance by date fixed effects. All errors are clustered at the station-level.

Table 5: Difference-in-differences estimates for station-adjacent trips in POI sample

	(1) Log Uber trips	(2) Log Uber trips	(3) Log Uber trips	(4) Log Uber trips	(5) Log Uber trips	(6) Log Uber trips	(7) Log Uber trips
-6 months after	0.0199*	0.0109	0.00415	0.00766	-0.0151***	-0.000494	-0.00732
	(0.0118)	(0.0149)	(0.01000)	(0.00727)	(0.00551)	(0.00542)	(0.00515)
-5 months after	0.0135	0.0159**	0.00385	0.00343	-0.00946*	-0.00558	-0.00423
	(0.00917)	(0.00736)	(0.00634)	(0.00589)	(0.00555)	(0.00552)	(0.00431)
-4 months after	0.0204**	0.0205**	-0.00208	-0.00257	-0.00648	-0.00409	-0.00709*
	(0.00952)	(0.0102)	(0.00679)	(0.00633)	(0.00535)	(0.00488)	(0.00418)
-3 months after	0.00923	0.0165	0.00422	0.00208	-0.00244	-0.00190	0.00456
	(0.00764)	(0.0130)	(0.00545)	(0.00457)	(0.00403)	(0.00366)	(0.00294)
-1 months after	-0.00651	-0.0287**	-0.0225***	-0.00672	-0.00201	-0.00183	0.00388
	(0.00889)	(0.0119)	(0.00575)	(0.00471)	(0.00465)	(0.00393)	(0.00372)
Month of expansion	-0.0281***	-0.0526***	-0.0384***	-0.0228***	-0.00790*	-0.00706	-0.00582
	(0.00839)	(0.0133)	(0.00814)	(0.00515)	(0.00476)	(0.00502)	(0.00423)
1 months after	-0.0457***	-0.0848***	-0.0688***	-0.0520***	-0.0158***	-0.0120**	-0.00556
	(0.0110)	(0.00821)	(0.00688)	(0.00571)	(0.00523)	(0.00531)	(0.00431)
2 months after	-0.0334***	-0.0829***	-0.0641***	-0.0523***	-0.0184***	-0.00873	0.00101
	(0.0119)	(0.00939)	(0.00741)	(0.00679)	(0.00648)	(0.00563)	(0.00492)
3 months after	-0.0512***	-0.0832***	-0.0685***	-0.0530***	-0.00895	-0.00140	0.00955**
	(0.0129)	(0.0106)	(0.00869)	(0.00749)	(0.00654)	(0.00590)	(0.00470)
4 months after	-0.0511***	-0.0973***	-0.0827***	-0.0635***	-0.0121	-0.00771	-0.00208
	(0.0159)	(0.0133)	(0.00899)	(0.00901)	(0.00754)	(0.00598)	(0.00587)
5 months after	-0.0460**	-0.0890***	-0.0784***	-0.0544***	-0.0141*	-0.00339	-0.00533
	(0.0181)	(0.0112)	(0.0106)	(0.0105)	(0.00781)	(0.00735)	(0.00677)
6 months after	-0.0503**	-0.0941***	-0.0902***	-0.0645***	-0.0126	-0.00368	-0.00868
	(0.0199)	(0.0143)	(0.0121)	(0.0105)	(0.00801)	(0.00655)	(0.00688)
Observations	135,470	116,321	117,025	117,361	118,835	118,267	117,787
Distance	0–200 m	200–300 m	300–400 m	400–500 m	500–600 m	600–700 m	700–800 m
Station Openings	540	539	542	538	539	536	535
Station x Dist FE	✓	✓	✓	✓	✓	✓	✓
Station x Date FE	✓	✓	✓	✓	✓	✓	✓

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Notes: This table contains coefficient estimates and standard errors from equation (4) for station-adjacent trips in 100 meter bins from the station in the POI sample. These coefficients estimate the effect of a new train station opening on POI sample Uber trips in 100 meter bins from the station in every month leading up to and after the station opening relative to POI sample Uber trips 800–1200 meters away. Coefficients are relative to two months prior to the station opening. All specifications include station by distance, station by date and event time fixed effect. All errors are clustered at the station-level.

Table 6: DD estimates for station-adjacent trips in POI sample by time/day of week

	(1)	(2)	(3)	(4)	(5)	(6)
	Log Uber trips	Log Uber trips	Log Uber trips	Log Uber trips	Log Uber trips	Log Uber trips
-6 months after	0.00415	0.0122	0.00346	0.0233	-0.00808	0.00314
	(0.01000)	(0.0142)	(0.0157)	(0.0162)	(0.0124)	(0.0106)
-5 months after	0.00385	0.00741	0.00304	0.00688	0.00974	0.00329
	(0.00634)	(0.0139)	(0.0108)	(0.0129)	(0.0121)	(0.00673)
-4 months after	-0.00208	-0.00648	0.000129	0.00221	-0.00328	-0.00208
	(0.00679)	(0.0126)	(0.0121)	(0.0129)	(0.0107)	(0.00683)
-3 months after	0.00422	0.00739	0.00414	0.00857	-0.00734	0.00601
	(0.00545)	(0.0101)	(0.0101)	(0.0119)	(0.0114)	(0.00586)
-1 months after	-0.0225***	-0.0106	-0.0287***	-0.0288**	-0.0287**	-0.0210***
	(0.00575)	(0.0101)	(0.00986)	(0.0128)	(0.0117)	(0.00636)
Month of expansion	-0.0384***	-0.0390***	-0.0384***	-0.0354**	-0.0418***	-0.0383***
	(0.00814)	(0.0112)	(0.0126)	(0.0146)	(0.0119)	(0.00931)
1 months after	-0.0688***	-0.0696***	-0.0708***	-0.0526***	-0.0887***	-0.0671***
	(0.00688)	(0.0136)	(0.0130)	(0.0132)	(0.0119)	(0.00759)
2 months after	-0.0641***	-0.0607***	-0.0725***	-0.0602***	-0.0791***	-0.0612***
	(0.00741)	(0.0142)	(0.0133)	(0.0134)	(0.0117)	(0.00845)
3 months after	-0.0685***	-0.0577***	-0.0853***	-0.0564***	-0.0884***	-0.0662***
	(0.00869)	(0.0155)	(0.0117)	(0.0156)	(0.0142)	(0.00983)
4 months after	-0.0827***	-0.0778***	-0.0962***	-0.0755***	-0.0779***	-0.0831***
	(0.00899)	(0.0179)	(0.0128)	(0.0136)	(0.0136)	(0.00982)
5 months after	-0.0784***	-0.0768***	-0.0962***	-0.0660***	-0.0810***	-0.0772***
	(0.0106)	(0.0177)	(0.0154)	(0.0184)	(0.0152)	(0.0117)
6 months after	-0.0902***	-0.0756***	-0.116***	-0.0845***	-0.0888***	-0.0892***
	(0.0121)	(0.0200)	(0.0157)	(0.0200)	(0.0181)	(0.0133)
Observations	117,025	80,816	84,739	81,045	81,108	108,821
Distance	300–400 m	300–400 m	300–400 m	300–400 m	300–400 m	300–400 m
Time Block	All	Weekday AM	Weekday PM	Fri/Sat night	Weekend day	Rest of week
Station Openings	542	451	449	446	450	516
Station x Dist FE	✓	✓	✓	✓	✓	✓
Station x Date FE	✓	✓	✓	✓	✓	✓

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Notes: This table contains coefficient estimates and standard errors from equation (4) for trips 300–400 meters from the station across various times/days of the week in the POI sample. These coefficients estimate the effect of a new train station opening on POI sample Uber trips in 300–400 meters from the station in every month leading up to and after the station opening relative to POI sample Uber trips 800–1200 meters away. Coefficients are relative to two months prior to the station opening. All specifications include station by distance, station by date and event time fixed effect. All errors are clustered at the station-level.

Table 7: Difference-in-differences estimates for citywide, local and non-local trips in POI sample

	(1) Log Uber trips Citywide	(2) Log Uber trips Local	(3) Log Uber trips Non-Local	(4) Log Uber trips Citywide	(5) Log Uber trips Local	(6) Log Uber trips Non-Local
-6 months after	-0.00183	0.0102	-0.0355**	-0.00466	-0.00739**	-0.00312
	(0.00608)	(0.00877)	(0.0171)	(0.00311)	(0.00373)	(0.00895)
-5 months after	-0.00435	0.00913*	-0.0346**	-0.00521*	-0.00621*	-0.0136*
	(0.00393)	(0.00496)	(0.0171)	(0.00294)	(0.00369)	(0.00734)
-4 months after	-8.02e-06	0.00718	-0.0162	-0.00365	-0.00571	-0.00713
	(0.00409)	(0.00616)	(0.0125)	(0.00294)	(0.00374)	(0.00707)
-3 months after	0.00347	0.00832	-0.00873	-0.000744	-0.000188	-0.00524
	(0.00414)	(0.00604)	(0.00968)	(0.00223)	(0.00249)	(0.00565)
-1 months after	-0.00979***	-0.0165***	0.00471	-0.00227	1.44e-05	0.00221
	(0.00358)	(0.00533)	(0.00930)	(0.00266)	(0.00322)	(0.00600)
Month of expansion	-0.0187***	-0.0359***	0.00740	-0.00618**	-0.00725**	0.00484
	(0.00418)	(0.00633)	(0.0105)	(0.00294)	(0.00328)	(0.00722)
1 months after	-0.0348***	-0.0629***	0.00529	-0.00609*	-0.0112***	0.0168**
	(0.00421)	(0.00512)	(0.0132)	(0.00318)	(0.00355)	(0.00782)
2 months after	-0.0310***	-0.0587***	0.0112	-0.00367	-0.00891**	0.0262***
	(0.00519)	(0.00639)	(0.0140)	(0.00335)	(0.00404)	(0.00943)
3 months after	-0.0332***	-0.0634***	0.00428	0.000762	0.000107	0.0170*
	(0.00527)	(0.00653)	(0.0157)	(0.00311)	(0.00412)	(0.00912)
4 months after	-0.0338***	-0.0745***	0.0207	-0.00271	-0.00754	0.0303***
	(0.00482)	(0.00721)	(0.0196)	(0.00433)	(0.00494)	(0.0111)
5 months after	-0.0328***	-0.0680***	0.0211	-0.00234	-0.00795	0.0392***
	(0.00553)	(0.00815)	(0.0261)	(0.00509)	(0.00568)	(0.0140)
6 months after	-0.0349***	-0.0778***	0.0263	-0.00153	-0.00852*	0.0437***
	(0.00619)	(0.00922)	(0.0223)	(0.00526)	(0.00516)	(0.0138)
Observations	49,830	48,568	49,434	51,346	49,938	50,326
Distance	0–500 m	0–500 m	0–500 m	500–800 m	500–800 m	500–800 m
Avg. Effect (%)	-3.26***	-7.54***	3.78*	0.09	-0.23	3.43***
Station Openings	508	522	508	533	539	530
Station x Dist FE	✓	✓	✓	✓	✓	✓
Station x Date FE	✓	✓	✓	✓	✓	✓

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Notes: This table contains coefficient estimates and standard errors from equation (4) for citywide, local, and non-local trips, for those with a POI 0–500 meters and 500–800 meters from the station. These coefficients estimate the effect of a new train station opening on citywide, local, and non-local POI sample Uber trips in every month leading up to and after the station opening relative to POI sample Uber trips 800–1200 meters away. Coefficients are relative to two months prior to the station opening. All specifications include station by distance, station by date and event time fixed effect. All errors are clustered at the station-level.

Table 8: Model estimates

Parameter	Estimate	Std. Error
α_{transit}	1.13^{***}	(0.11)
α_{Uber}	-1.02^{***}	(0.31)
β_{transit}	0.47^{*}	(0.26)
β_{Uber}	-1.96^{***}	(0.29)
$\Delta^{\alpha}_{\text{transit}}$	0.47^{***}	(0.03)
$\Delta^{\beta}_{\text{transit}}$	-0.02^{***}	(0.01)
f_{Uber}	5.37^{***}	(0.20)
c_{walk}	4.68^{***}	(0.30)
c_{Uber}	0.94^{***}	(0.23)
σ_{transit}	2.24^{***}	(0.20)
σ_{Uber}	2.72^{***}	(0.19)
ϕ	-0.69^{***}	(0.08)
λ	23.10^{***}	(0.37)
κ	0.63^{***}	(0.19)
Number of moments	24	
Number of parameters	14	
Degrees of freedom	10	
RMSE	0.0171	

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Notes: This table contains coefficient estimates and standard errors from the model estimated in Section 6. The probability of an intermediate trips p_s is set to 0.5. Errors are computed using numerical gradients with $N = 650$ station openings.

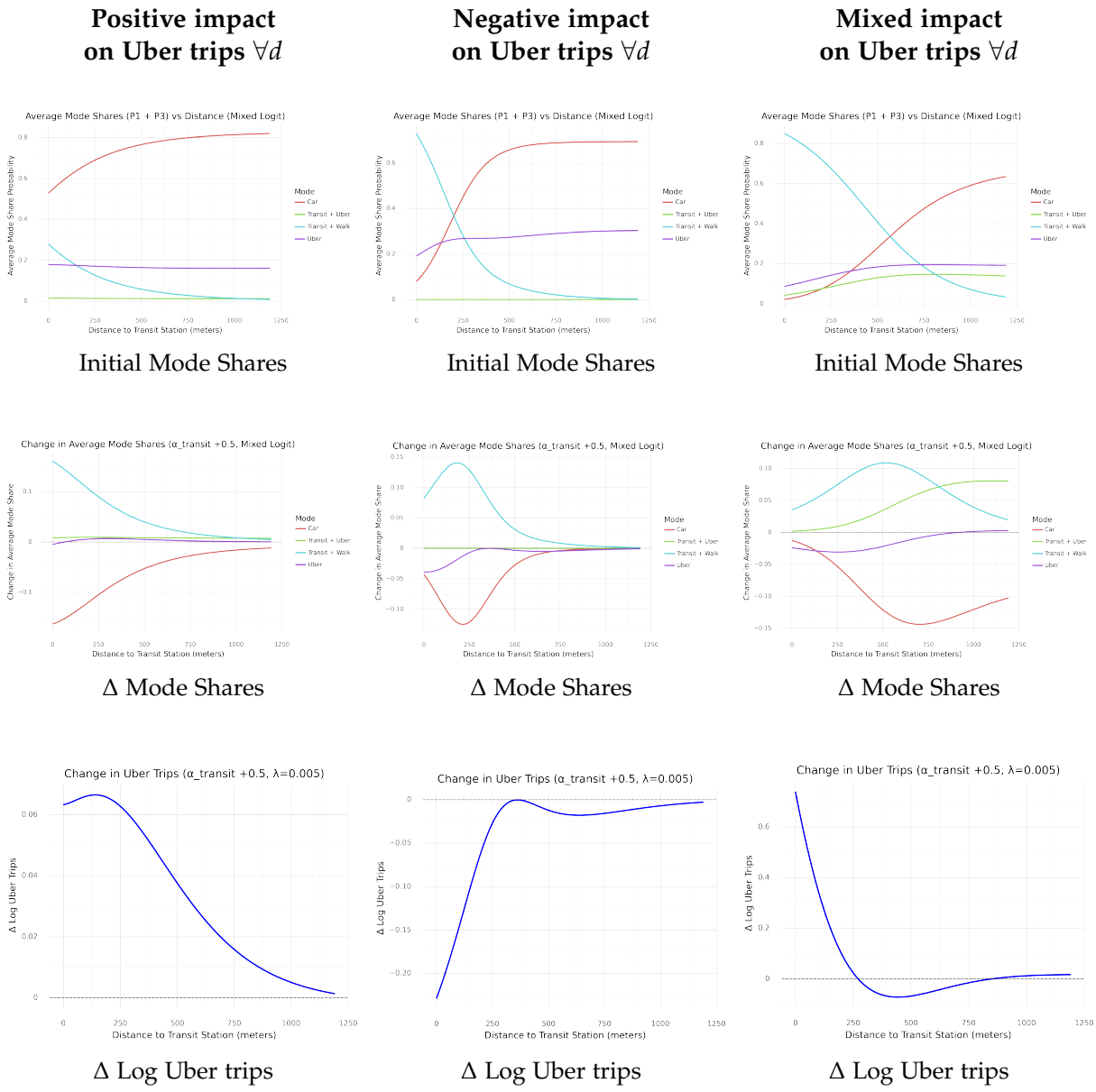
Table 9: Counterfactuals

Scenario	Commute (pp)				Intermediate (pp)			Transit, welfare, & fiscal			
	Tr. walk	Tr. Uber	Dir. Uber	Car	Transit	Uber	Car	Δ Tr. (%)	ΔW (%)	ΔW ($)	Fiscal ($)
Panel A: Transit station opening											
Transit station opening	+1.16	+0.44	-0.14	-1.45	+0.10	+0.07	-0.16	+6.73	+1.94	+0.14	—
Station opening, no direct Uber	+1.29	+0.40	+0.00	-1.70	+0.13	+0.00	-0.13	+7.92	+3.97	+0.15	—
Station opening, no Uber at all	+1.36	+0.00	+0.00	-1.36	+0.07	+0.00	-0.07	+6.50	+3.49	+0.13	—
Panel B: Uber exit											
Uber exit (direct only)	+0.32	-0.14	-37.35	+37.17	-4.49	-3.28	+7.77	-7.94	-48.57	-3.67	—
Uber exit (direct + last-mile)	+0.49	-1.33	-37.35	+38.19	-4.69	-3.28	+7.97	-12.19	-49.29	-3.72	—
Panel C: Last-mile subsidies											
LM subsidy I: fixed ($4)	-0.73	+4.51	+0.03	-3.82	+0.65	+0.06	-0.70	+15.75	+3.32	+0.25	-0.47
LM subsidy II: 50% marg. + fixed ($4)	-0.48	+5.25	+0.11	-4.88	+0.82	+0.07	-0.90	+19.86	+3.84	+0.29	-0.60
LM subsidy III: 100% marg. + fixed ($4)	-0.31	+7.13	+0.17	-6.98	+1.18	+0.11	-1.29	+28.38	+5.46	+0.41	-1.04
Panel D: Ride-hailing taxes											
RH tax ($1)	+0.19	-0.47	-5.48	+5.76	-0.14	-1.12	+1.26	-1.33	-9.80	-0.74	+0.68
RH tax ($1) + LM sub. II	-0.16	+3.35	-5.35	+2.16	+0.49	-1.08	+0.58	+13.18	-7.19	-0.54	+0.33
Panel E: Congestion pricing											
Congestion ($0.50)	+0.54	+0.24	-0.07	-0.72	+0.12	+0.01	-0.13	+3.26	-12.16	-0.92	+0.91
Congestion ($0.50) + LM sub. II	-0.03	+6.25	+0.03	-6.25	+1.06	+0.09	-1.15	+25.87	-7.65	-0.58	+0.17
Panel F: Fiscally-neutral policy mix											
Δ Transit = 5 pp	-0.30	+6.06	+0.02	-5.78	+0.98	+0.09	-1.06	+23.96	-4.87	-0.37	-0.00
$s_c^{\text{LM}} = 0.69$, $s_f^{\text{LM}} = 3.09$, $t^{\text{RH}} = 0$, $t^{\text{cong.}} = 0.38$											
Δ Transit = 5 pp, with s^{Tr}	+2.43	+1.28	+0.03	-3.75	+5.07	-1.28	-3.78	+23.96	-1.51	-0.11	-0.00
$s^{\text{Tr}} = 1.49$, $s_c^{\text{LM}} = s_f^{\text{LM}} = 0$, $t^{\text{RH}} = 0.04$, $t^{\text{cong.}} = 0.53$											

Notes: This table contains counterfactual estimates under different scenarios using the model estimates in Table 8. Each row corresponds to a different scenario, compared to a baseline in which that scenario did not occur. For example, row 1 shows changes in traveler behavior in response to a transit station opening, compared to a baseline where the station did not open. Columns (2) through (5) calculate the percentage point change in different mode shares averaged across outbound and return legs. Columns (6) through (8) calculate percentage point changes in intermediate trip mode shares. Columns (9) and (10) calculates the welfare change in percentage and WTP terms respectively, relative to the baseline. Column (11) calculates the fiscal cost of a policy change per traveler, summed across all trip types. All columns are averaged over distances through 5000 m from the station using the κ-population weights.

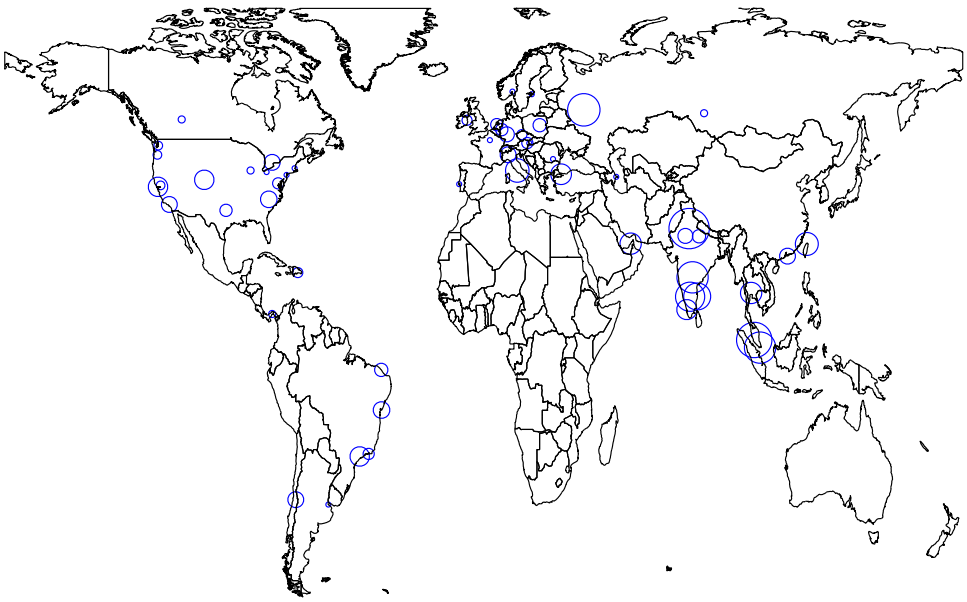
Figures

Figure 2: Model simulations of the response to an improvement in public transit



Notes: This panel contains figures from three separate model simulations. Each model simulation corresponds to a column of figures. Row 1 contains average initial mode shares for outbound and return trips plotted by distance from the transit station. Row 2 contains changes in average outbound and return trip mode shares by distance from the transit station. Row 3 contains log changes in the number of trips at each distance from the transit station. First- and last-mile trips are assumed to be located at $d = 0$ but have some measurement error, following an exponential distribution with scale parameter $\lambda = 0.005$. Details of the model and calculations are included in the text and Appendix C.

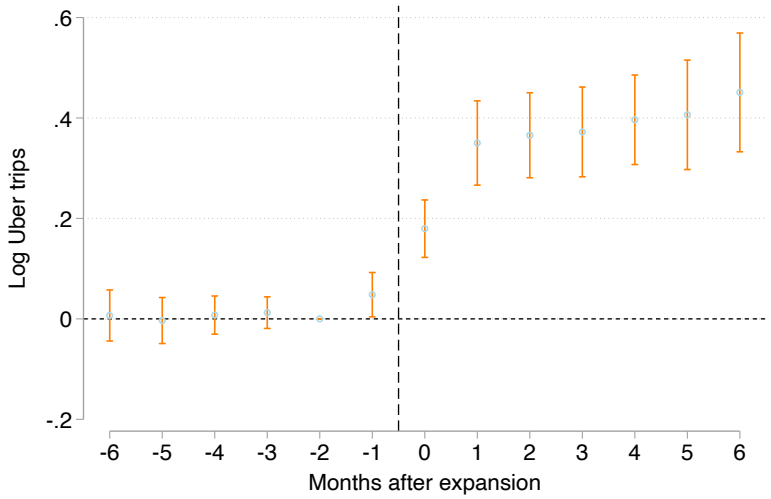
Figure 3: Locations of transit expansions in our data



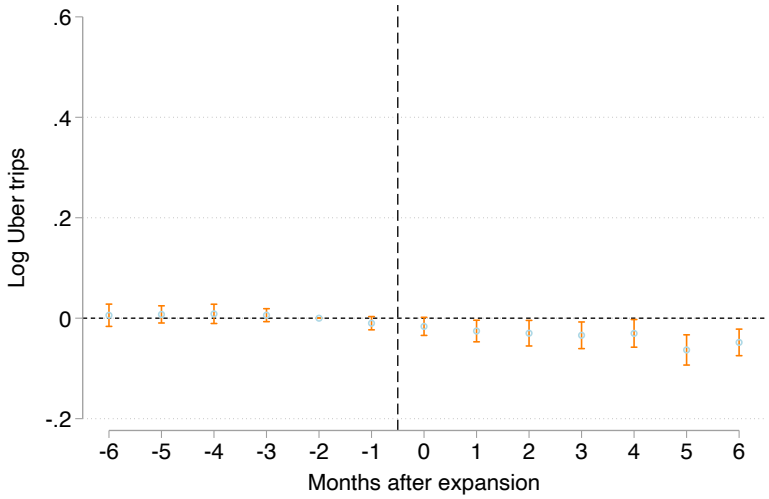
Notes: This map plots the locations of new transit openings in our data. The size of each circle is proportional to the number of new stations that opened between Uber's entry date and 2018.

Figure 4: Dynamic difference-in-difference estimates relative to 1100–1200 m

Effects 0–100 m from the station

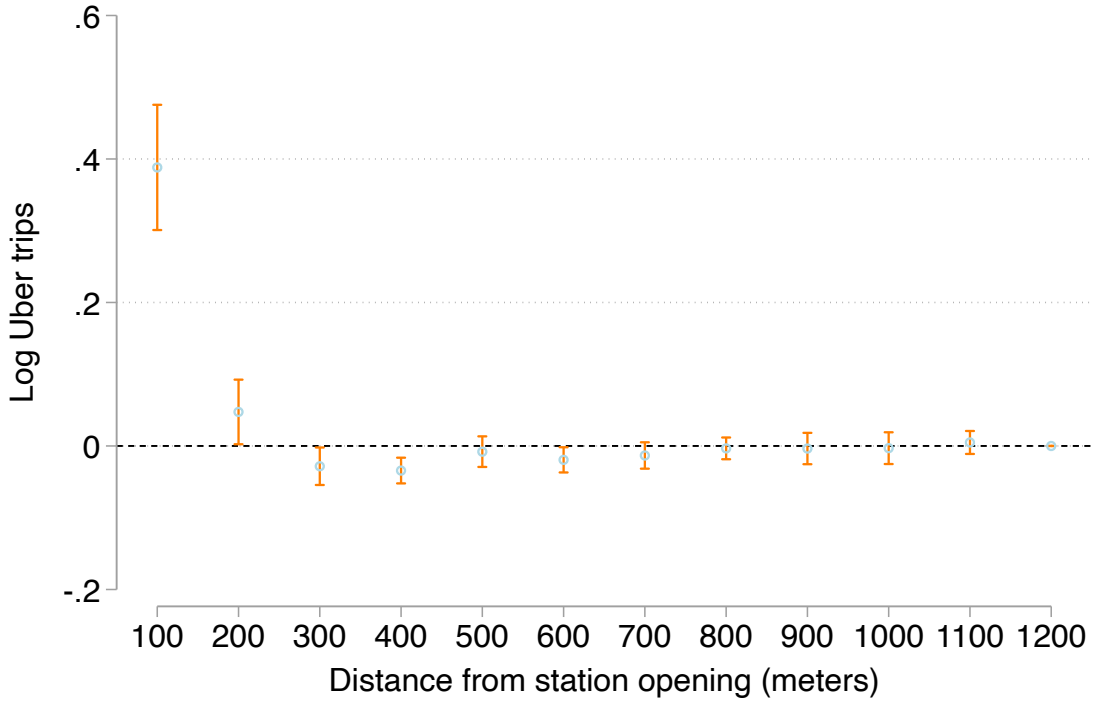


Effects 300–400 m from the station



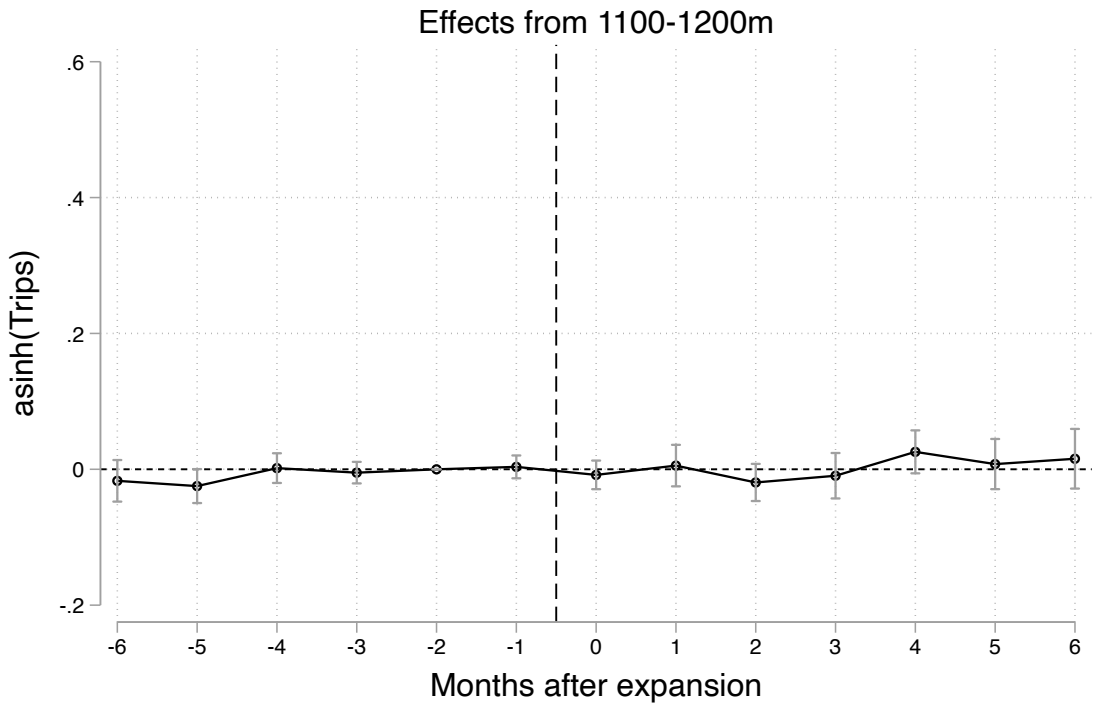
Notes: This figure plots the coefficients (circles) and 95% confidence intervals (bars) for the percentage effect of a new train station opening on Uber trips 0–100 m away (Panel A) and 300–400 m (Panel B), relative to 1100–1200 m away. The coefficients are plotted for each month between six months prior and six months after an expansion. The PPML estimation follows a dynamic difference-in-differences model of station openings on Uber trips that either originated or terminated at a given distance band from the opening. The model contains station by distance band and station by time fixed effects; additionally, fixed effects for distance band by more than 6 months before or after an expansion are included. All errors are clustered at the station-level.

Figure 5: Relative effect by distance of new train stations on Uber trips



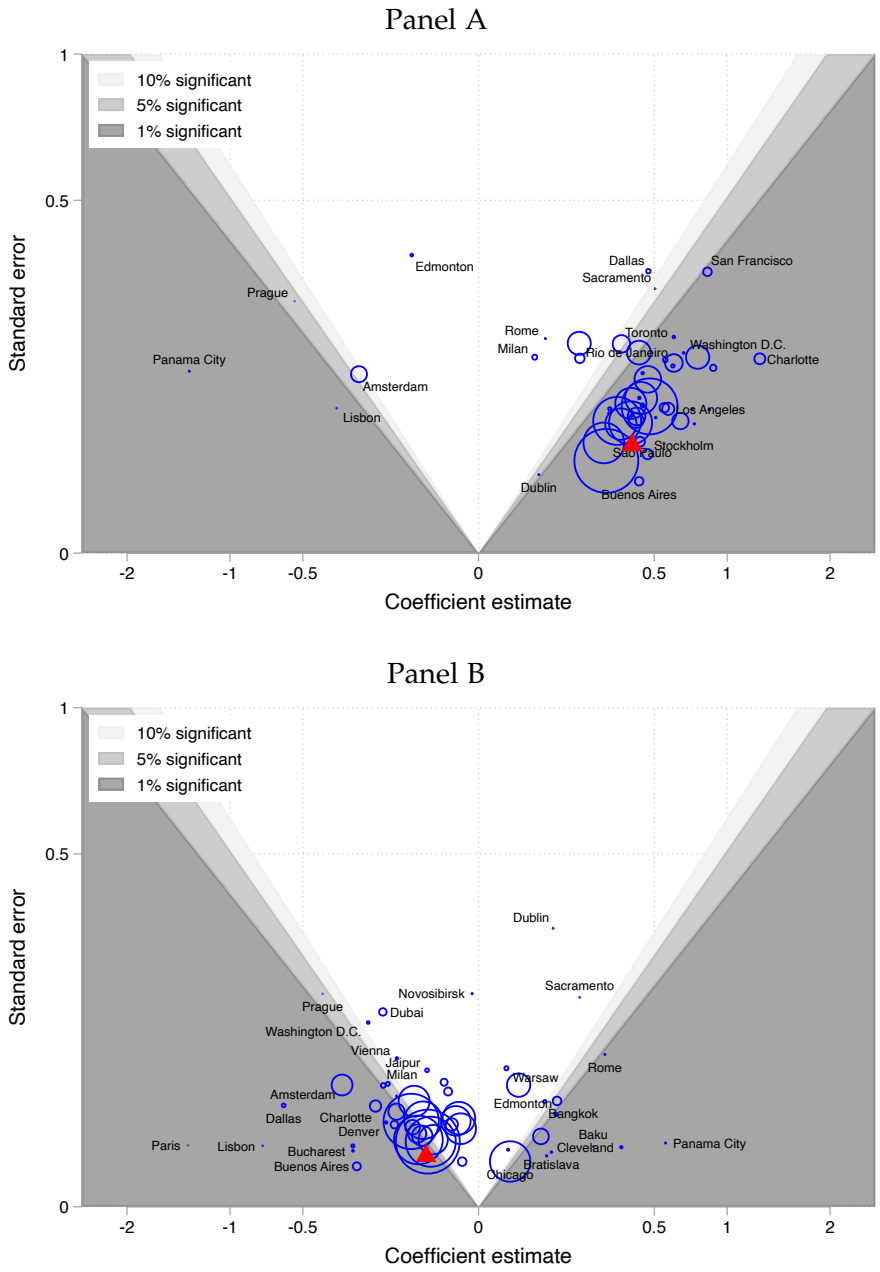
Notes: This figure plots the coefficients (circles) and 95% confidence intervals (bars) from estimating equation (5). These coefficients estimate the effect of a new train station opening on Uber trips at varying distances from the train station during months 1 through 6, relative to the farthest distance band 1100–1200 m, and relative to months -6 through -3. Each distance is measured over a 100 m band ending at the given distance; for example, the coefficient at 400 m reports the change in trips between 300 and 400 m away from a train station.

Figure 6: Event study estimates for 1100–1200 m



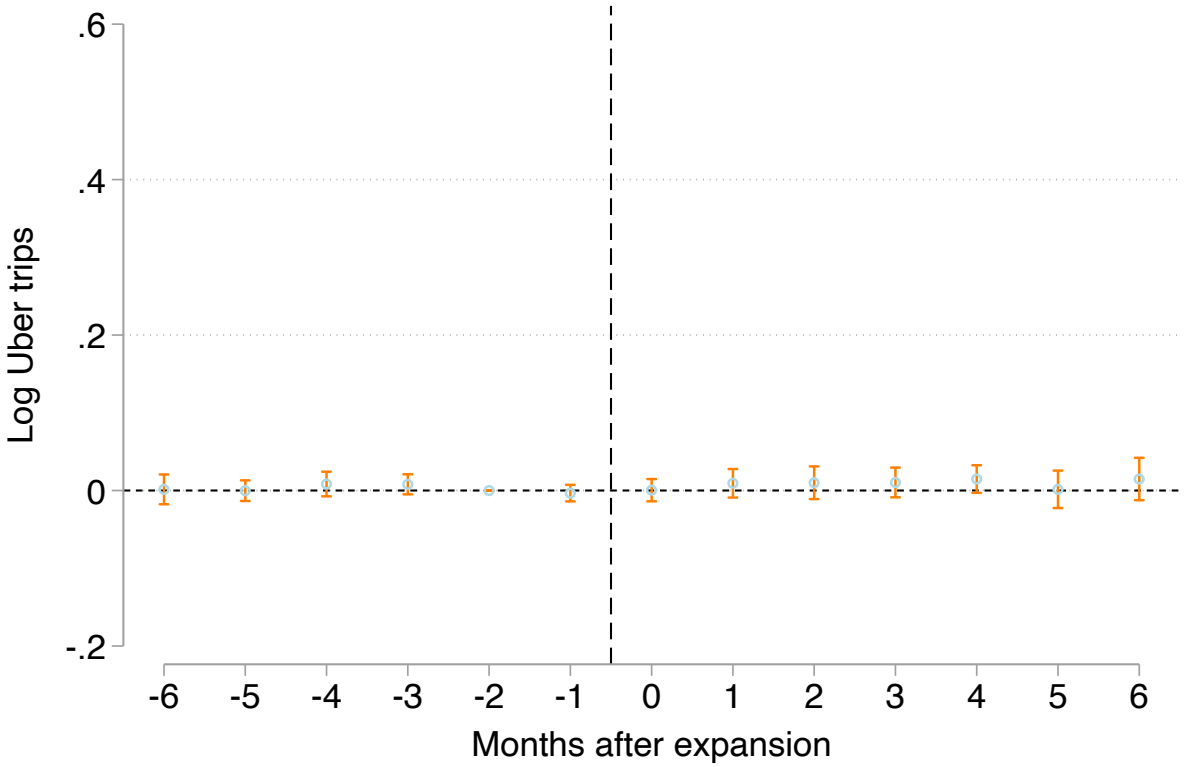
Notes: This figure plots the coefficients (circles) and 95% confidence intervals (bars) for the percentage effect of a new train station opening on Uber trips 1100–1200 m away. The coefficients are plotted for each month between six months prior and six months after an expansion. The regression is an event study model of station openings on the inverse hyperbolic sine of Uber trips (in 100s) that either originated or terminated at a given distance band from the opening. The model contains station and city by time fixed effects; additionally, fixed effects for more than 6 months before or after an expansion are included. The model is estimated using (de Chaisemartin and D'Haultfœuille, 2024). All errors are clustered at the station-level.

Figure 7: Heterogeneous effect by city, 0–100 m and 300–400 m



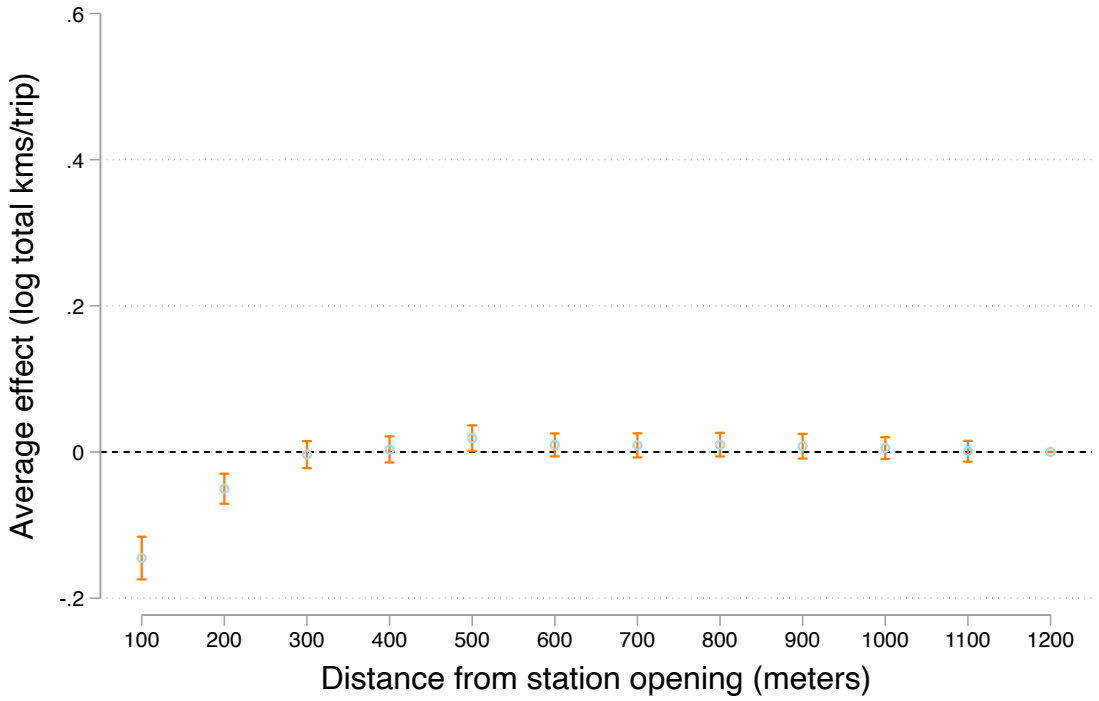
Notes: This funnel graph shows city-specific treatment effects based on equation (5) where the coefficient α is allowed to vary by city. Panel A contains estimates for 0–100 m whereas Panel B contains estimates for 300–400 m. The x-axis shows coefficient estimates, the y-axis shows standard errors. The region in white contains estimates that are not statistically different from zero. The light, medium, and dark gray regions contain estimates that are statistically different from zero at 10%, 5%, and 1%, respectively. The size of each circle is proportional to baseline Uber ridership. The large red triangle indicates the average effect reported in Figure 5.

Figure 8: Aggregate 0 – 700 m effect



Notes: This figure plots the coefficients (circles) and 95% confidence intervals (bars) for the percentage effect of a new train station opening on Uber trips 0–700 m away, relative to 1100–1200 m away. The coefficients are plotted for each month between six months prior and six months after an expansion. The PPML estimation follows a dynamic difference-in-differences model of station openings on Uber trips that either originated or terminated at a given distance band from the opening. The model contains station by distance band and station by time fixed effects; additionally, fixed effects for distance band by more than 6 months before or after an expansion are included. All errors are clustered at the station-level.

Figure 9: Effect by distance of new train stations on kilometers per Uber trip



Notes: This figure plots the coefficients (circles) and 95% confidence intervals (bars) from estimating equation (5) for the effect of a new train station opening on kilometers travelled per Uber trip at varying distances from the train station. Each distance is measured over a 100 m band ending at the given distance; for example, the coefficient at 400 m reports the change in trips between 300 and 400 m away from a train station.

Online Appendix

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A Supplemental tables

A.1 Descriptives

Table A1: City-level descriptive statistics

City	# Exp.	# Stn.	Light	Heavy	Subway	First Yr	Last Yr	Uber Yr.
Amsterdam	1	6	0	0	6	2018	2018	2012
Baku	1	1	0	0	1	2016	2016	2015
Bangalore	5	34	0	0	34	2014	2017	2013
Bangkok	4	18	0	0	18	2016	2017	2014
Boston	1	1	0	0	1	2014	2014	2012
Bratislava	1	1	1	0	0	2016	2016	2015
Bucharest	1	1	0	0	1	2017	2017	2015
Buenos Aires	1	1	0	0	1	2018	2018	2016
Charlotte	1	11	11	0	0	2018	2018	2013
Chennai	5	29	0	0	29	2015	2018	2014
Chicago	2	2	0	0	2	2015	2017	2012
Cleveland	1	1	0	0	1	2015	2015	2014
Dallas	3	6	6	0	0	2014	2016	2012
Delhi	13	65	0	0	65	2014	2018	2013
Denver	2	15	15	0	0	2013	2017	2012
Dubai	5	18	10	0	8	2014	2017	2013
Dublin	1	4	4	0	0	2017	2017	2014
Dusseldorf	1	6	6	0	0	2016	2016	2014
Edmonton	1	2	2	0	0	2015	2015	2014
Fortaleza	3	7	6	0	1	2017	2018	2016
Frankfurt	1	9	0	0	9	2016	2016	2014
Hong Kong	4	10	0	0	10	2014	2016	2014
Hyderabad	2	39	0	0	39	2017	2018	2014
Istanbul	5	17	0	0	17	2015	2017	2014
Jaipur	1	9	0	0	9	2015	2015	2014
Kochi	2	16	0	0	16	2017	2017	2014
Kuala Lumpur	5	50	22	0	28	2015	2017	2013
Lisbon	1	1	0	0	1	2016	2016	2014
Los Angeles	2	10	10	0	0	2016	2016	2012
Lucknow	1	7	0	0	7	2017	2017	2016
Milan	7	10	0	0	10	2014	2015	2013
Moscow	13	42	0	0	42	2014	2017	2013
New Jersey	1	1	0	1	0	2016	2016	2013
Novosibirsk	1	2	2	0	0	2016	2016	2015
Oslo	1	1	0	0	1	2016	2016	2014
Panama City	2	2	0	0	2	2015	2015	2014
Paris	1	1	0	0	1	2013	2013	2012
Portland	1	3	3	0	0	2015	2015	2014
Prague	1	4	0	0	4	2015	2015	2014
Rio de Janeiro	1	5	0	0	5	2016	2016	2014
Rome	3	22	0	0	22	2014	2015	2013
Sacramento	1	3	3	0	0	2015	2015	2013
Salvador	4	11	0	0	11	2016	2018	2016
San Francisco	5	15	0	11	4	2014	2018	2012
Santiago	1	10	0	0	10	2017	2017	2013
Santo Domingo	1	4	0	0	4	2018	2018	2015
Sao Paulo	9	15	0	0	11	2017	2018	2014
Seattle	2	3	3	0	0	2016	2016	2012
Singapore	9	39	6	0	33	2013	2017	2013
Stockholm	1	1	0	1	0	2017	2017	2013
Taipei	3	21	0	0	21	2014	2017	2013
Toronto	2	10	0	4	6	2015	2017	2012
Vienna	1	5	0	0	5	2017	2017	2014
Warsaw	1	7	0	0	7	2015	2015	2014
Washington D.C.	1	5	0	0	5	2014	2014	2012

Notes: This table contains summary statistics on the 650 stations in our sample. Column (1) contains the 55 cities in our sample. Columns (2) through (6) count the number of expansions, the number of stations associated with those expansions, and whether they were for light rail, heavy rail, or subways, respectively. Column (7) and (8) denote the first and last year we have Uber data for that city. Column (9) contains the year that Uber entered the market.

A.2 Robustness of POI sample findings

Table A2: Difference-in-differences estimates for 0–500 m POI sample

	(1) Uber trips	(2) Uber trips	(3) Uber trips	(4) Uber trips
-6 months after	-0.0109	-0.00332	-0.00183	0.00927
	(0.00852)	(0.00714)	(0.00608)	(0.00816)
-5 months after	-0.0110*	-0.00708	-0.00447	0.00470
	(0.00579)	(0.00472)	(0.00393)	(0.00524)
-4 months after	-0.00637	-0.00430	-8.52e-05	0.00720
	(0.00561)	(0.00474)	(0.00408)	(0.00509)
-3 months after	0.00149	0.00189	0.00345	0.00770
	(0.00485)	(0.00422)	(0.00413)	(0.00474)
-1 months after	-0.00751	-0.0106**	-0.00988***	-0.0144***
	(0.00527)	(0.00425)	(0.00358)	(0.00480)
Month of expansion	-0.0215***	-0.0205***	-0.0188***	-0.0264***
	(0.00666)	(0.00450)	(0.00418)	(0.00548)
1 months after	-0.0399***	-0.0363***	-0.0349***	-0.0438***
	(0.00793)	(0.00490)	(0.00421)	(0.00514)
2 months after	-0.0401***	-0.0340***	-0.0311***	-0.0420***
	(0.00919)	(0.00619)	(0.00519)	(0.00546)
3 months after	-0.0453***	-0.0360***	-0.0332***	-0.0464***
	(0.0101)	(0.00626)	(0.00527)	(0.00630)
4 months after	-0.0523***	-0.0372***	-0.0338***	-0.0508***
	(0.0115)	(0.00636)	(0.00482)	(0.00734)
5 months after	-0.0493***	-0.0349***	-0.0327***	-0.0532***
	(0.0119)	(0.00616)	(0.00552)	(0.00921)
6 months after	-0.0511***	-0.0379***	-0.0349***	-0.0591***
	(0.0129)	(0.00773)	(0.00619)	(0.00955)
Observations	62,202	59,897	49,946	49,946
Station Openings	566	563	510	510
Station FE	✓	✓	✓	✓
Cal. and Evt. Time FE	✓	✓	✓	✓
City x Date FE		✓		
Station x Date FE			✓	✓
Dist x Date FE				✓

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Notes: This table contains coefficient estimates and standard errors from equation (4) for individuals with a POI near the station, and with varying fixed effects. These coefficients estimate the effect of a new train station opening on *city-wide* Uber trips in every month leading up to and after the station opening, for those with a POI within 500 m of the station opening relative to those with a POI within 800–1200 meters. Coefficients are relative to two months prior to the station opening. All specifications include station and calendar and event time fixed effects. Column (2) adds city by calendar time fixed effects. Column (3) adds station by date fixed effects, and is our main specification. Column (4) includes distance by date fixed effects. All errors are clustered at the station-level.

A.3 Model estimates

Table A3: Model fit

Moment	Data	Model
Ia: Trips near station		
0–100 m	0.388	0.386
100–200 m	0.047	0.033
200–300 m	−0.028	−0.049
300–400 m	−0.034	−0.042
400–500 m	−0.008	−0.031
500–600 m	−0.019	−0.021
600–700 m	−0.013	−0.014
700–800 m	−0.003	−0.008
800–900 m	−0.004	−0.004
900–1000 m	−0.003	−0.001
1000–1100 m	0.005	0.000
1100–1200 m	-	0.001
Ib: Trip length near station		
0–100 m	−0.168	−0.169
100–200 m	−0.063	−0.085
1100–1200 m	-	−0.000
II: Local trips (POI)		
0–200 m	−0.064	−0.076
200–300 m	−0.103	−0.053
300–400 m	−0.078	−0.038
400–500 m	−0.059	−0.026
500–600 m	−0.004	−0.014
600–700 m	−0.003	−0.005
700–800 m	0.002	0.002
800–1200 m	-	0.014
IIIa: Non-Local trips (POI)		
0–500 m	0.033	0.033
500–800 m	0.039	0.039
800–1200 m	-	0.030
IIIb: Citywide trips (POI)		
0–500 m	−0.033	−0.048
500–800 m	0.001	−0.003
800–1200 m	-	0.015

Notes: This table compares the moments used in estimation with those implied by the model. Each Panel corresponds to a different set of moments. Column (1) indicates the relevant distance group for that moment. Column (2) shows the estimate from the reduced-form results in Section 5. Column (3) shows the model-implied equivalent moment.

A.4 Counterfactuals

Table A4: Distribution of welfare changes in "optimal" policy mix

Distance (m)	Percentiles ($)					Mean ($)
	P10	P25	Median	P75	P90	
0	-0.72	-0.34	-0.02	+0.05	+0.06	-0.17
500	-0.76	-0.69	-0.33	+0.28	+0.41	-0.23
1000	-0.76	-0.74	-0.65	-0.03	+1.61	-0.17
1500	-0.76	-0.75	-0.70	-0.41	+0.96	-0.18
2000	-0.76	-0.75	-0.72	-0.57	+0.23	-0.28
2500	-0.76	-0.76	-0.74	-0.63	-0.13	-0.39
3000	-0.76	-0.76	-0.74	-0.67	-0.35	-0.48
3500	-0.76	-0.76	-0.75	-0.70	-0.47	-0.55
4000	-0.76	-0.76	-0.75	-0.72	-0.59	-0.61
4500	-0.76	-0.76	-0.76	-0.73	-0.65	-0.65
5000	-0.76	-0.76	-0.76	-0.74	-0.69	-0.69

Notes: This table calculates welfare changes in WTP terms for the optimal policy in the last row of Table 9. The policy mix solves for the fiscally neutral set of last-mile subsidies, ride-hailing taxes, and congestion taxes that would deliver a 5 pp increase in average transit use, while minimizing welfare losses. Each column shows a different percentile of the welfare change distribution. Each row shows a different distance from the station those distributions are calculated at.

B Supplemental figures

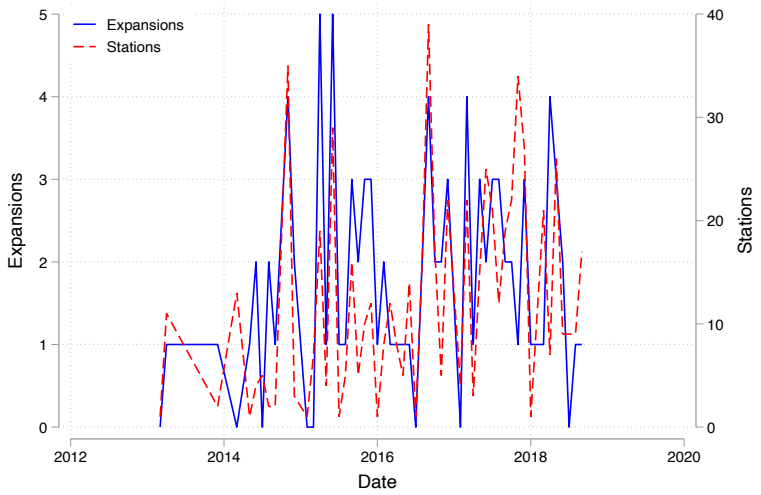
B.1 Descriptives



Figure A1: Spatial sampling for Toronto-York Spadina subway extension in 2017

Notes: These maps depict two ways to sample Uber trips in our data. Blue dots indicate the locations of 6 subway openings along the 1-line in Toronto's subway system. The map on the left uses concentric rings of 100 meter width from the location of the station. Our main specifications rely on data sampled in this manner. The map on the right uses fixed width hexagons at varying distances from the new station. We use these to determine points-of-interest (POIs) for individual riders, as well as in some robustness exercises.

Figure A2: Transit expansions in our data over time



Notes: This figure plots the time series of expansions and station openings in our sample. The left-side y-axis contains counts of rail expansions, which are plotted in blue. The right-side y-axis contains counts of stations associated with those expansions, which are plotted in red.

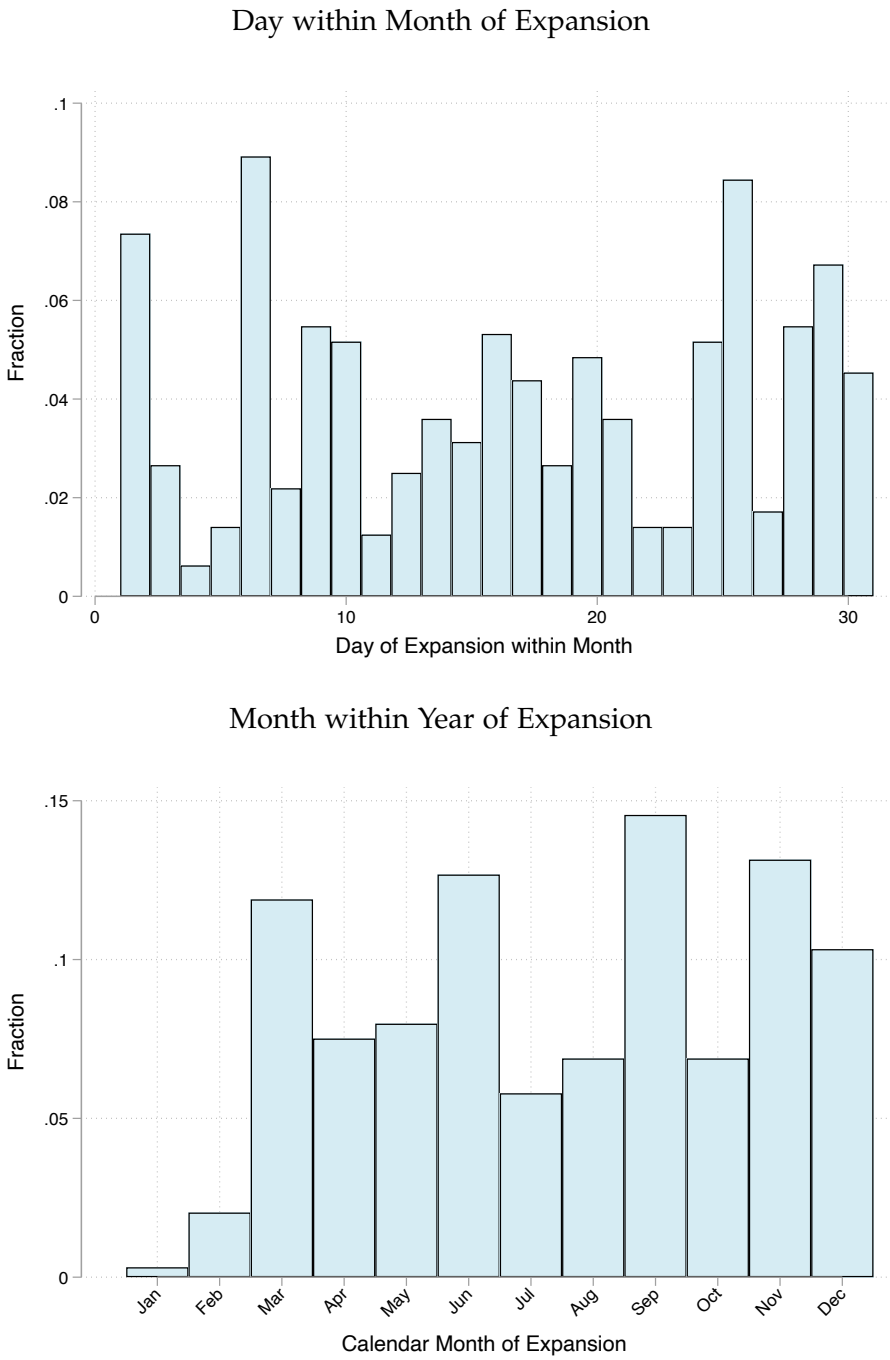


Figure A3: Distribution of days and months of station openings

Notes: These histograms plot the temporal distribution of station openings. The x-axis is the fraction of station openings in our sample that fall within a certain day/month. The top figure plots the distribution of numeric day within the month of expansion. The bottom figure plots the distribution of month within year of expansion.

B.2 Robustness

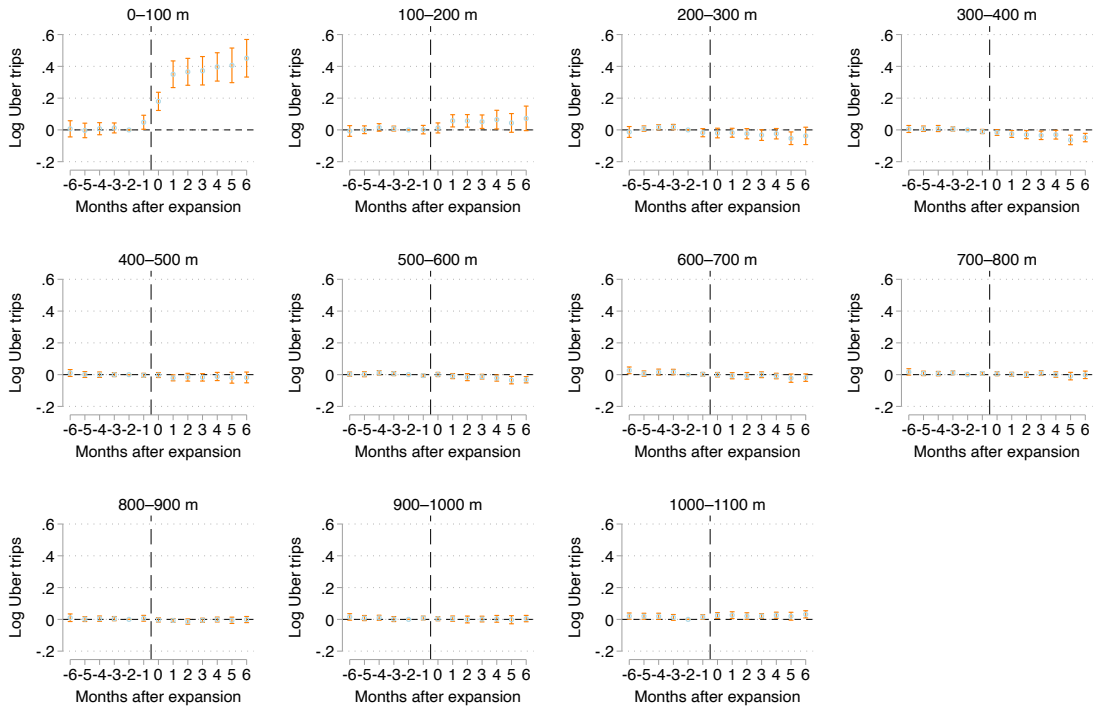


Figure A4: Difference-in-differences estimates, using the farthest distance band as the control group, from 0–100 m to 1000–1100 m

Notes: These subfigures plot the coefficients (circles) and 95% confidence intervals (bars) for the percentage effect of a new train station opening on Uber trips for the labeled distance bands. The coefficients are plotted for each month between six months prior and six months after an expansion. The regression is a dynamic difference-in-differences model of station openings on Uber trips that either originated or terminated at a given distance band from the opening, and the regression equation is given by equation (4). The model contains station by distance band and station by time fixed effects; additionally, fixed effects for distance band by more than 6 months before or after an expansion are included. All errors are clustered at the station-level.

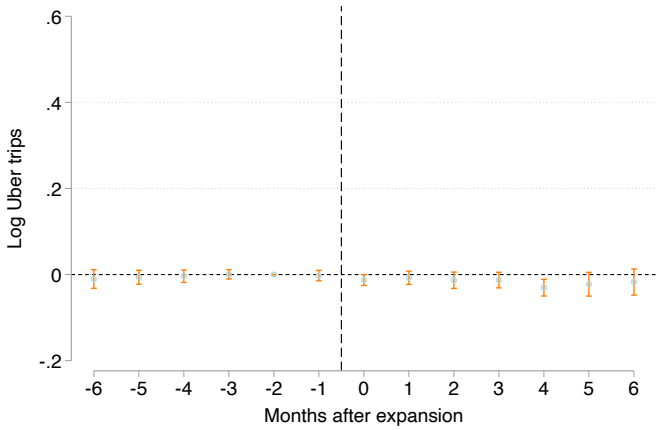


Figure A5: Event study estimates for 1100–1200 m using PPML estimator

Notes: This figure plots the coefficients (circles) and 95% confidence intervals (bars) for the percentage effect of a new train station opening on Uber trips at our farthest distance band: 1100–1200 meters. It is a complement to the event study analysis depicted in Figure 6. The coefficients are plotted for each month between six months prior and six months after an expansion. The PPML estimates follow an event study model of station openings on Uber trips that either originated or terminated at a given distance band from the opening. The model contains station and city by time fixed effects; additionally, fixed effects for more than 6 months before or after an expansion are included. All errors are clustered at the station-level.

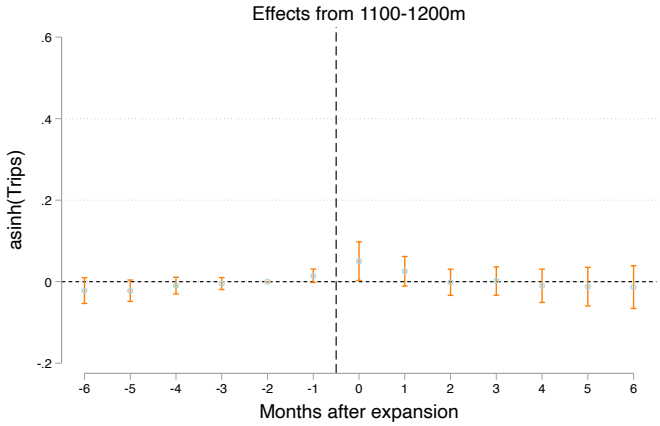


Figure A6: Event study estimates for 1100–1200 m using two-way fixed effects linear regression and inverse hyperbolic sine transformed Uber trips (in hundreds)

Notes: This figure plots the coefficients (circles) and 95% confidence intervals (bars) for the percentage effect of a new train station opening on Uber trips at our farthest distance band: 1100–1200 meters. It is a complement to the event study analysis depicted in Figure 6, and corresponds to the simpler two-way fixed effects linear regression model. The coefficients are plotted for each month between six months prior and six months after an expansion. The regression is an event study model of station openings on Uber trips that either originated or terminated at a given distance band from the opening. The model contains station and city by time fixed effects; additionally, fixed effects for more than 6 months before or after an expansion are included. All errors are clustered at the station-level.

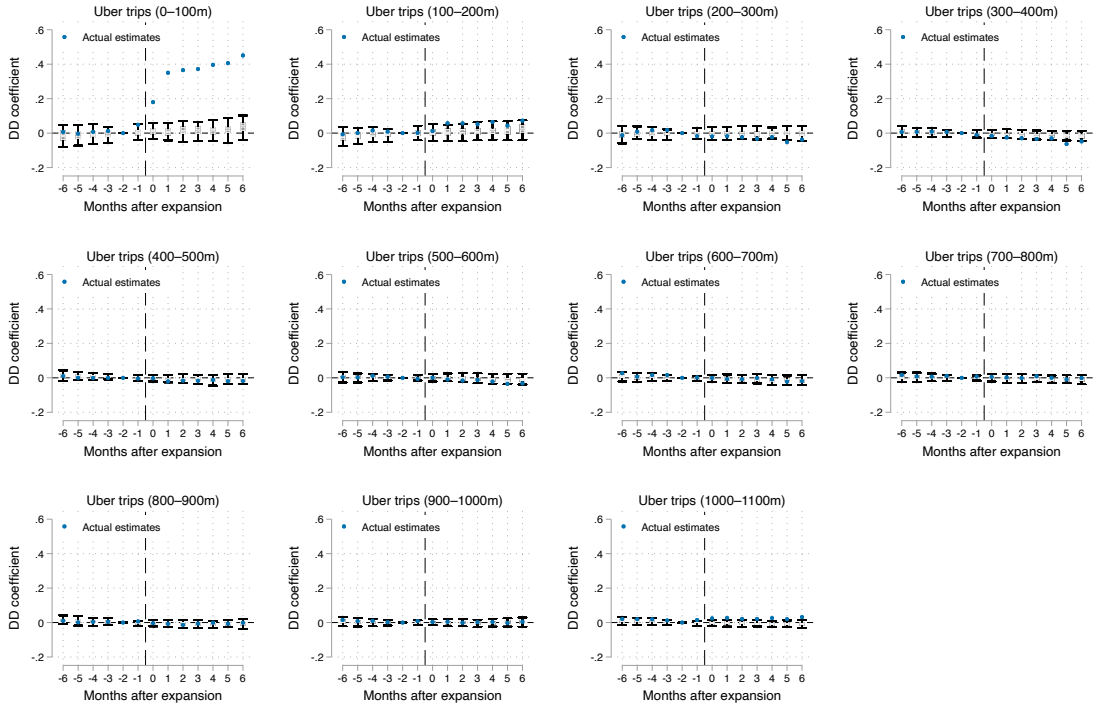


Figure A7: Placebo tests for all 100 m distance bands, up through 1000–1100 m

Notes: This figure plots the results of a placebo test where we randomly assign placebo opening dates to each transit station. To implement this test, we randomly assign each station a new opening date with uniform probabilities from 6 months after the station's first observation to 6 months prior to the station opening. This ensures that we have sufficient observations to estimate the event-time specific coefficients above. Also, it ensures that the new station opening is prior to any actual effects on Uber trips. We then re-estimate our baseline model using the "fake" opening dates. We perform this 100 times and use a box-whisker plot to depict the distribution of these estimates. The blue circle denotes estimates from the true station opening dates. We perform this placebo analysis for each distance band.

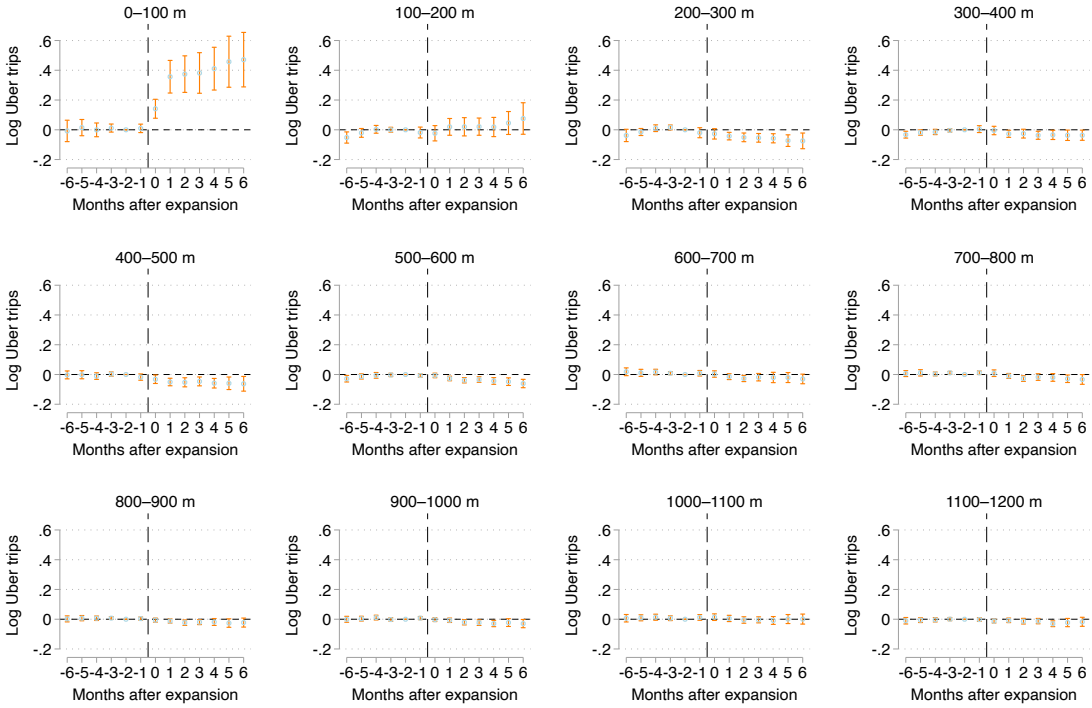


Figure A8: Event study estimates on Uber trips estimated via PPML

Notes: These figures plot the coefficients (circles) and 95% confidence intervals (bars) for the percentage effect of a new train station opening on Uber trips for each 100 meter distance band. It relies on the simpler two-way fixed effects PPML regression model. The coefficients are plotted for each month between six months prior and six months after an expansion. The regression is an event study model of station openings on Uber trips that either originated or terminated at a given distance band from the opening. The model contains station and city by time fixed effects; additionally, fixed effects for more than 6 months before or after an expansion are included. All errors are clustered at the station-level.

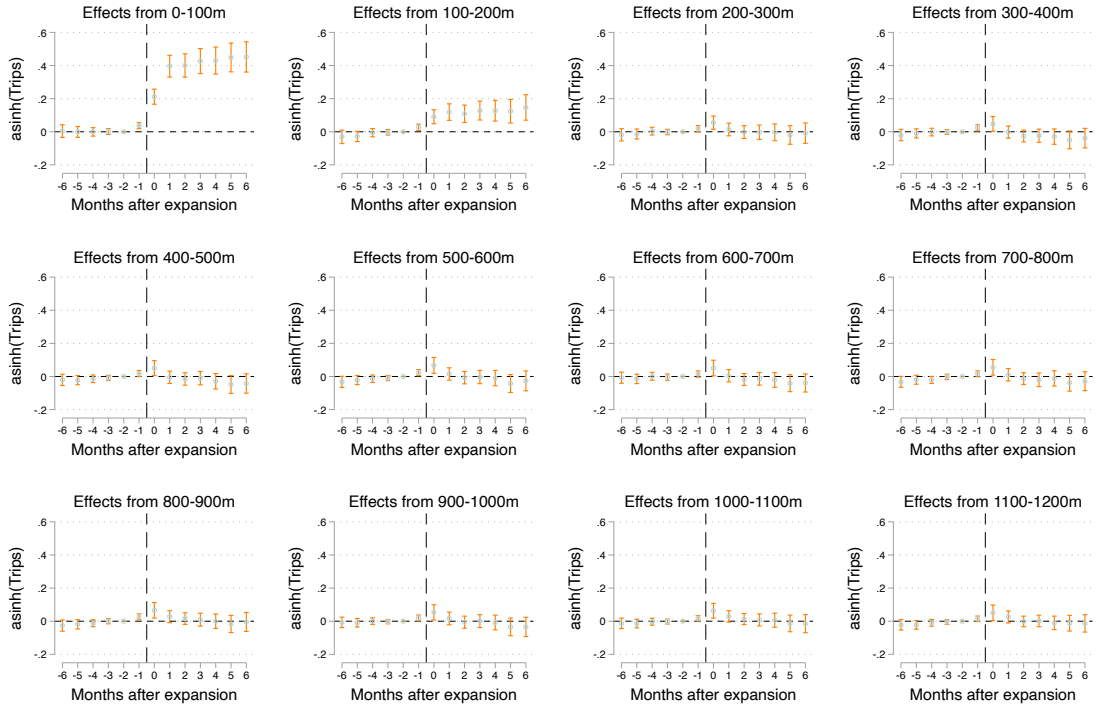


Figure A9: Event study estimates estimated via linear regression with the inverse hyperbolic sine transformed Uber trips (in hundreds) as the outcome

Notes: These figures plot the coefficients (circles) and 95% confidence intervals (bars) for the percentage effect of a new train station opening on Uber trips for each 100 meter distance band. It relies on the simpler two-way fixed effects linear regression model and the inverse hyperbolic sine transformation of the outcome Uber trips. The coefficients are plotted for each month between six months prior and six months after an expansion. The regression is an event study model of station openings on Uber trips that either originated or terminated at a given distance band from the opening. The model contains station and city by time fixed effects; additionally, fixed effects for more than 6 months before or after an expansion are included. All errors are clustered at the station-level.

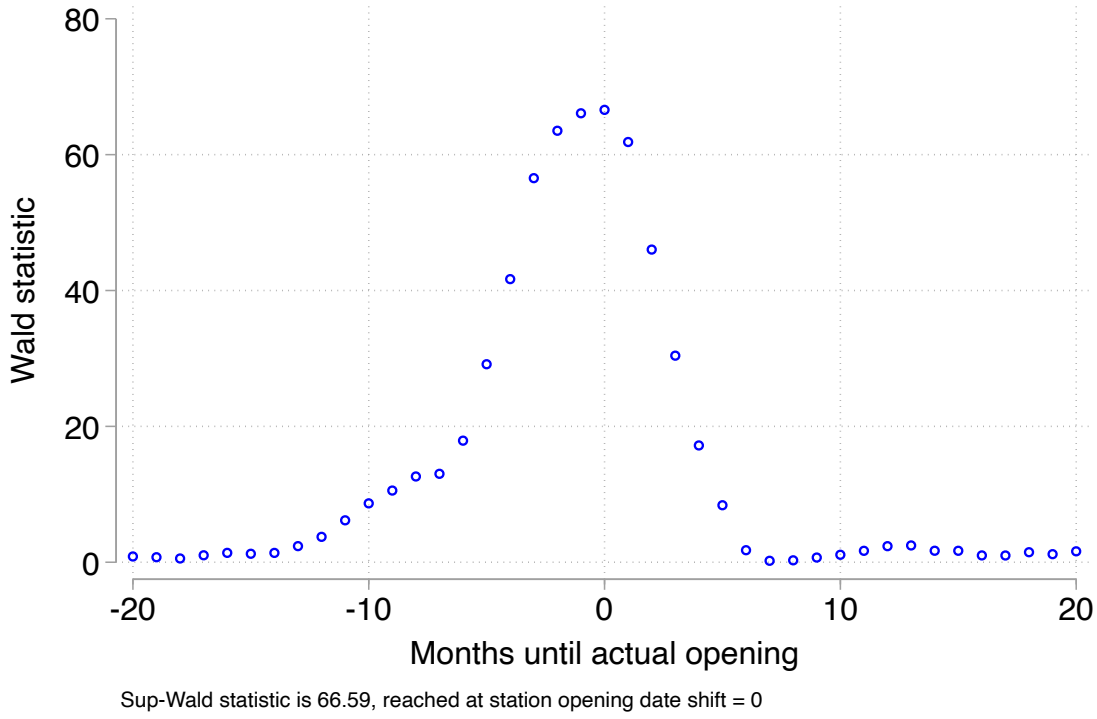


Figure A10: Wald test for 0–100 m difference-in-difference estimate

Notes: This figure plots the results of a structural break test on the effect of a station opening on Uber trips 0–100 meters away. The test follows Andrews (1993, 2003). To implement this test, we re-estimate the average effect for our main difference-in-differences specification as if the opening date were any number of months before or after the true station opening. We estimate this model for each event time, and plot the Wald-statistic of those estimates on the chart above. The sup-Wald statistic is achieved at the true station opening. Moreover, our model supports a structural break in Uber usage at any conventional level (Andrews, 2003). All errors are clustered at the station-level.

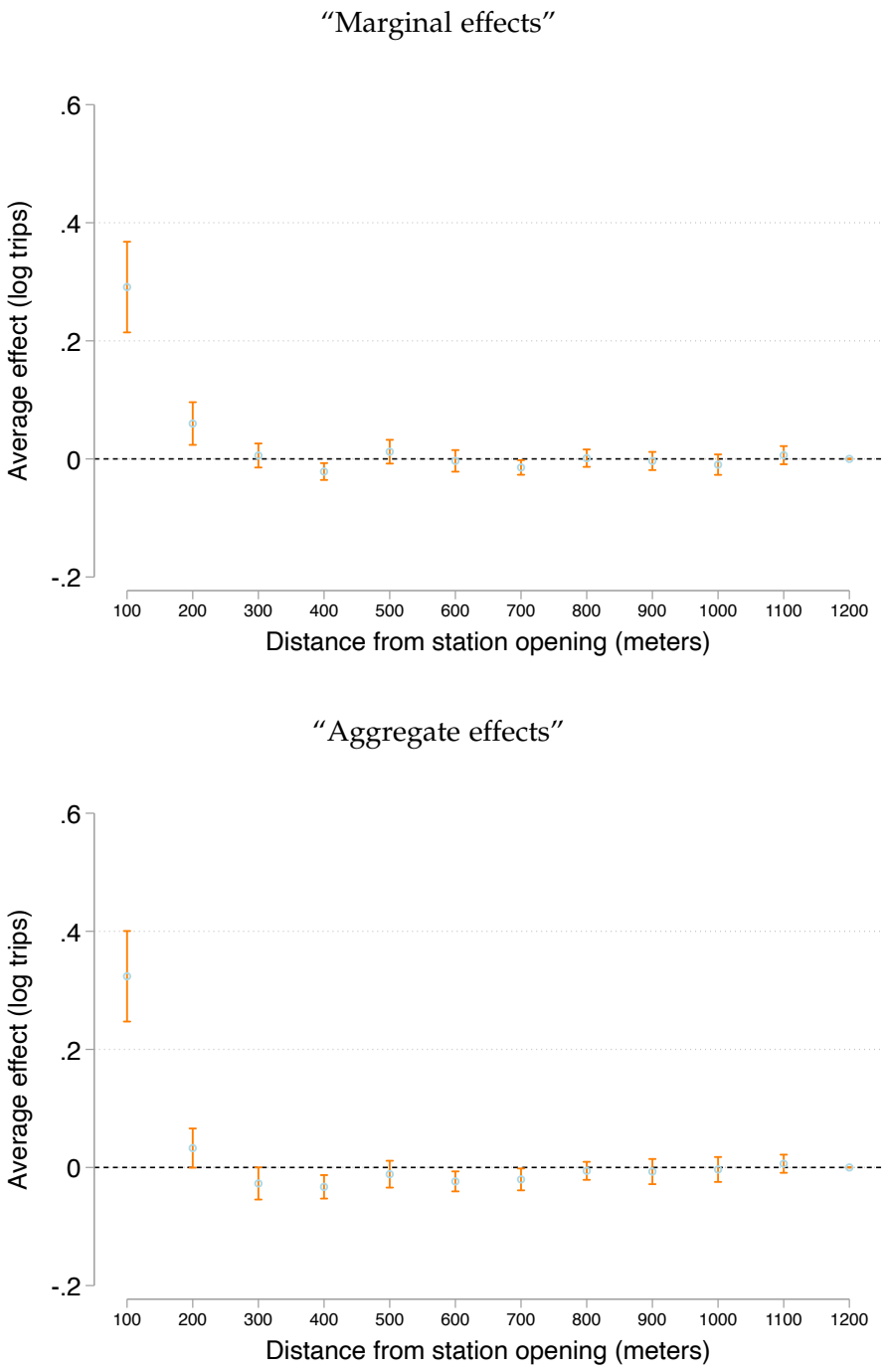


Figure A11: Difference-in-differences estimates using the adjacent bin as a control group

Notes: These figures plot the coefficients (circles) and 95% confidence intervals (bars) from estimating a version of equation (5) that relies on adjacent distance bins as the control group. In the top figure, these coefficients estimate the effect of a new train station opening on Uber trips at varying distances from the train station during months 1 through 6, relative to the *next* farthest distance band, and relative to months -6 through -3. Each distance is measured over a 100 m band ending at the given distance; for example, the coefficient at 400 m reports the change in trips between 300 and 400 m away from a train station relative to 400 and 500 m away. In the bottom figure, those coefficients are summed over the entire range to account for effect the new station opening has on the "control" group at close enough distances. This procedure is described in Section 5 as well as Appendix D.2. All errors are clustered at the station-level.

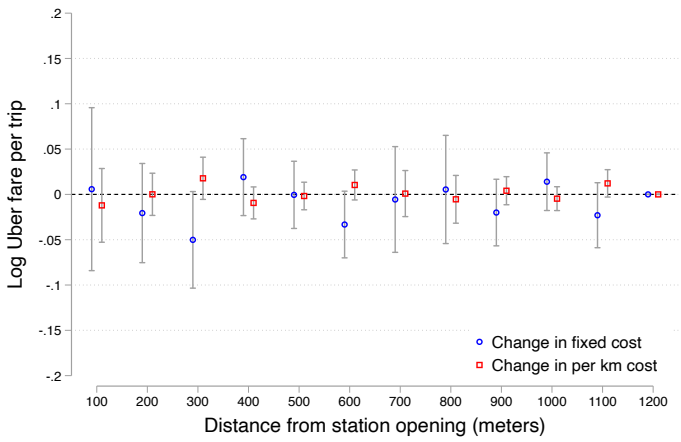


Figure A12: Difference-in-differences estimates for fare per trip

Notes: This figure plots the coefficients (circles and squares) and 95% confidence intervals (bars) from estimating equation (5) for the Uber fare in USD per trip. We look at a change in the fixed cost (the main effect, in blue) and the marginal cost per kilometer (the interacted effect with kilometers per trip, in red). These coefficients estimate the change in fare structure from a new train station opening at varying distances from the train station during months 1 through 6, relative to the farthest distance band, and relative to months -6 through -3. Each distance is measured over a 100 m band ending at the given distance; for example, the coefficient at 400 m reports the change in trips between 300 and 400 m away from a train station. All errors are clustered at the station-level.

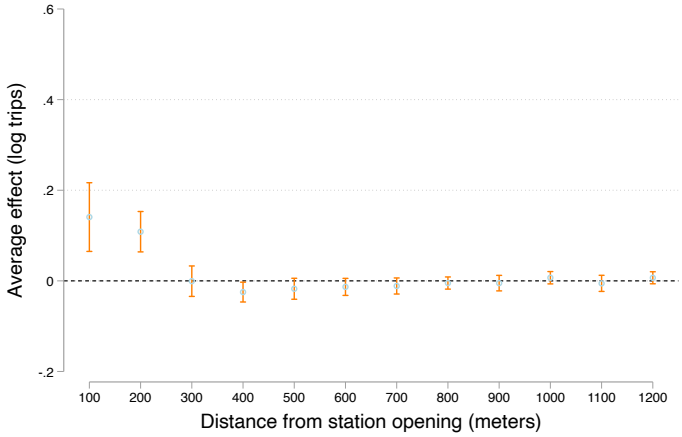


Figure A13: Difference-in-differences estimates across distances using hexagons

Notes: This figure plots the coefficients (circles) and 95% confidence intervals (bars) from estimating a version of equation (5) estimated on data aggregated to the hexagon level. Hexagons are assigned distances from the station according to their centroid. These coefficients estimate the effect of a new train station opening on Uber trips at varying distances from the train station during months 1 through 6, relative to the farthest distance band, and relative to months -6 through -3. Each distance is measured over a 100 m band ending at the given distance; for example, the coefficient at 400 m reports the change in trips between 300 and 400 m away from a train station. All errors are clustered at the station-level.

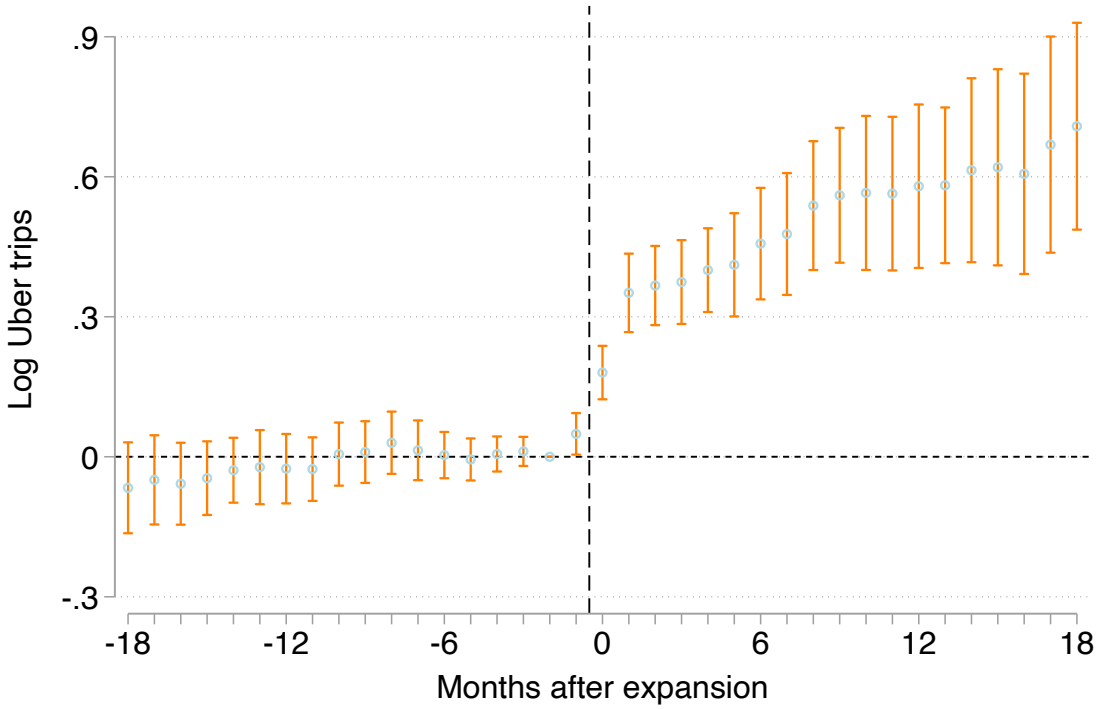


Figure A14: Difference-in-differences estimates using an 18-month window

Notes: This figure plots the coefficients (circles) and 95% confidence intervals (bars) for the percentage effect of a new train station opening on Uber trips 0–100 m from the station. The coefficients are plotted for each month between 18 months prior and 18 months after an expansion. The regression is a dynamic difference-in-differences model of station openings on Uber trips that either originated or terminated at a given distance band from the opening, and the regression equation is given by equation (4). The model contains station by distance band and station by time fixed effects; additionally, fixed effects for distance band by more than 18 months before or after an expansion are included. All errors are clustered at the station-level.

B.3 Additional outcomes

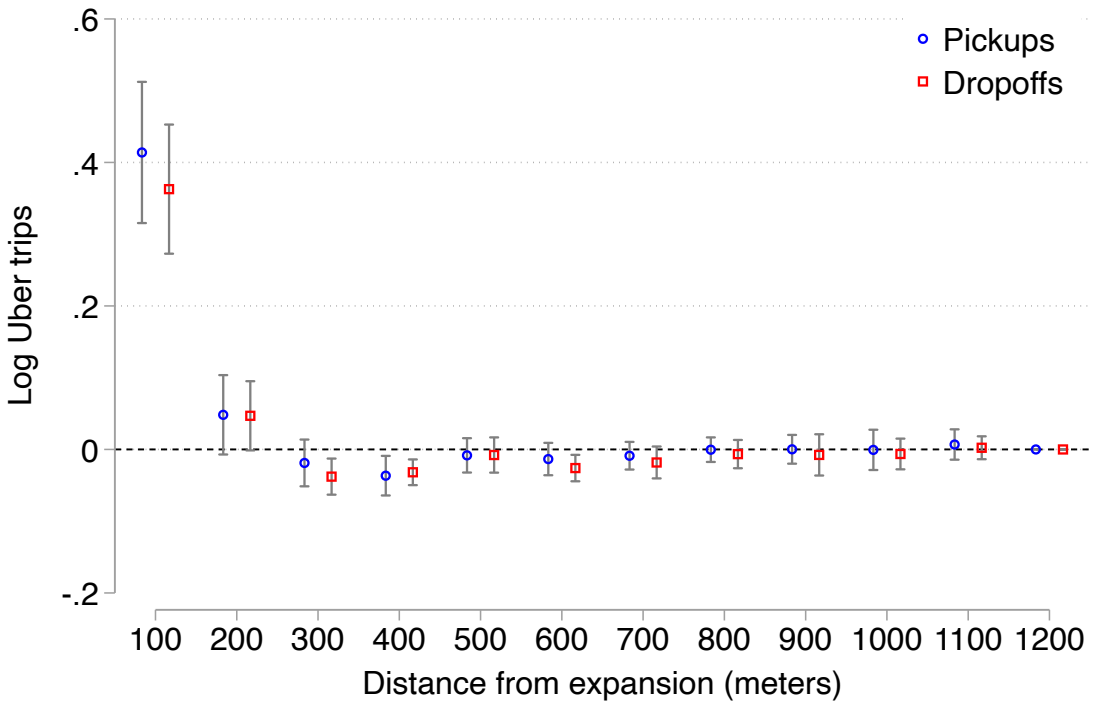


Figure A15: Estimates for pick-ups and drop-offs

Notes: This figure plots the coefficients (circles) and 95% confidence intervals (bars) from estimating equation (5) separately for pick-ups and drop-offs. These coefficients estimate the effect of a new train station opening on Uber pick-ups and drop-offs at varying distances from the train station during months 1 through 6, relative to the farthest distance band, and relative to months -6 through -3. Each distance is measured over a 100 m band ending at the given distance; for example, the coefficient at 400 m reports the change in trips between 300 and 400 m away from a train station. All errors are clustered at the station-level.

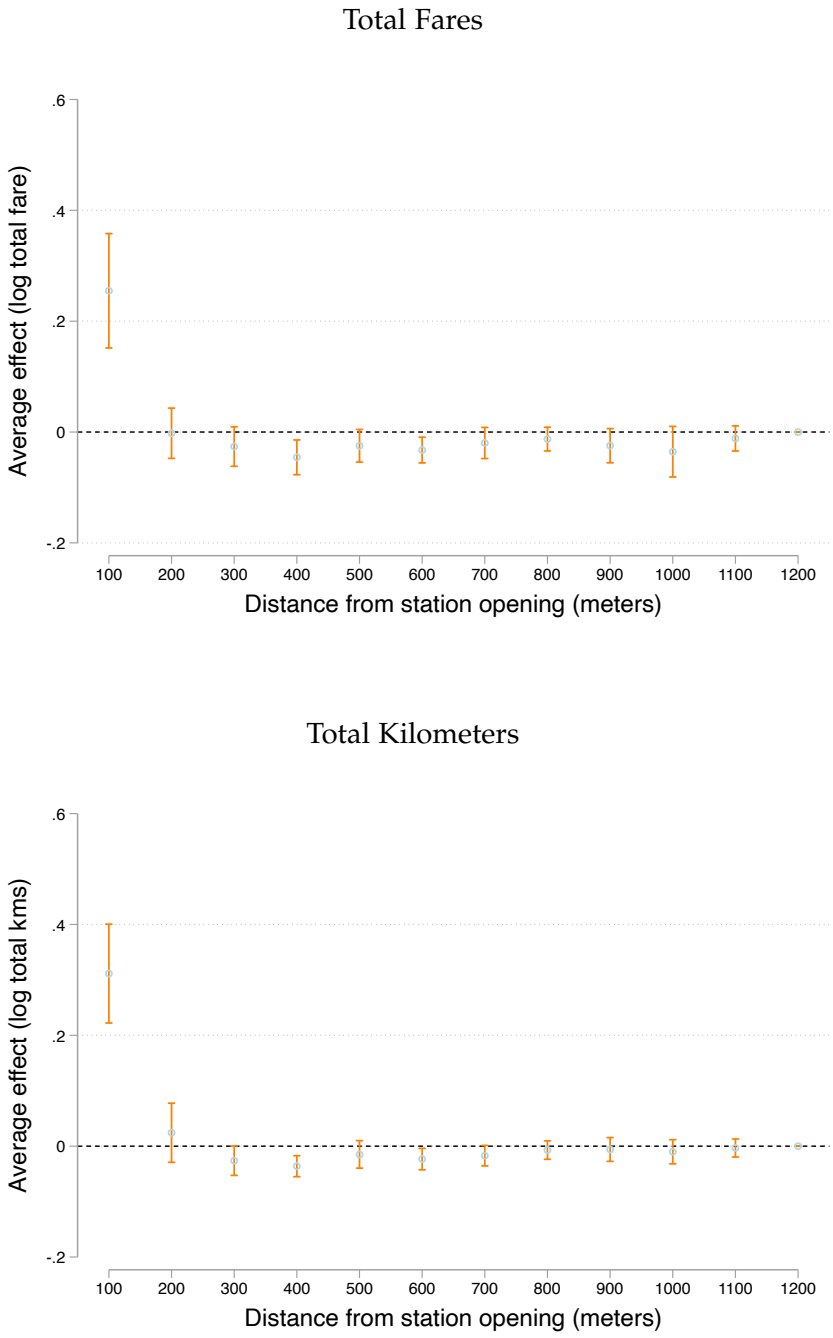


Figure A16: Estimates for total kilometers and fare of trips

Notes: This figure plots the coefficients (circles) and 95% confidence intervals (bars) from estimating equation (5) for the total fare paid (top figure) and kilometers travelled (bottom figure) along Uber trips. These coefficients estimate the effect of a new train station opening on Uber fare and trip length at varying distances from the train station during months 1 through 6, relative to the farthest distance band, and relative to months -6 through -3. Each distance is measured over a 100 m band ending at the given distance; for example, the coefficient at 400 m reports the change in trips between 300 and 400 m away from a train station. All errors are clustered at the station-level.

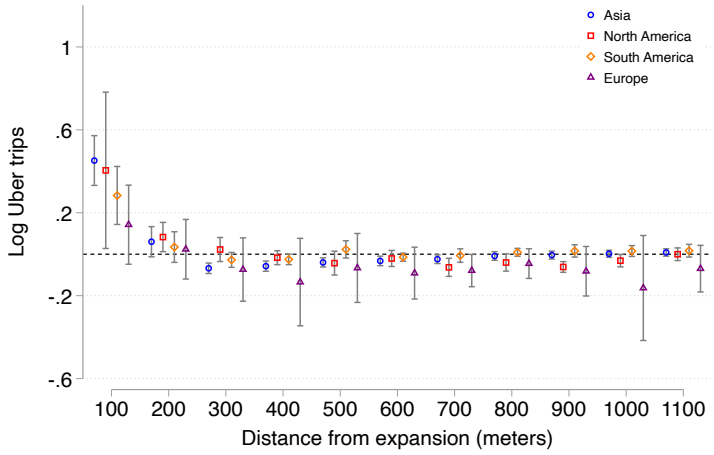


Figure A17: Estimates across continents

Notes: This figure plots the coefficients (circles) and 95% confidence intervals (bars) from estimating equation (5) separately for each continent: Asia, North America, South America, and Europe. These coefficients estimate the effect of a new train station opening on Uber pick-ups and drop-offs at varying distances from the train station during months 1 through 6, relative to the farthest distance band, and relative to months -6 through -3. Each distance is measured over a 100 m band ending at the given distance; for example, the coefficient at 400 m reports the change in trips between 300 and 400 m away from a train station. All errors are clustered at the station-level.

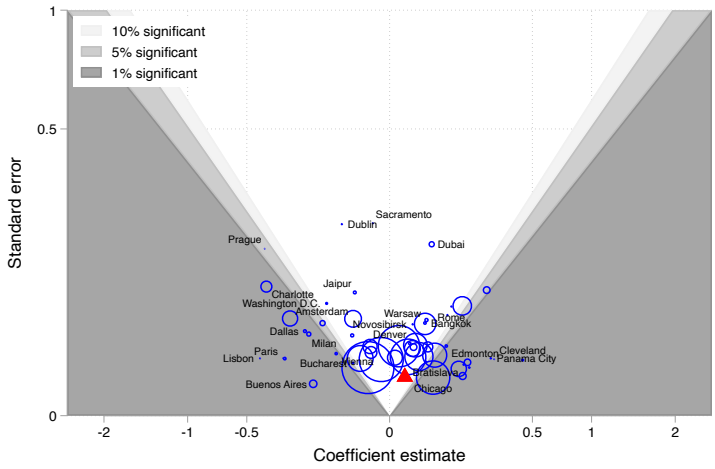
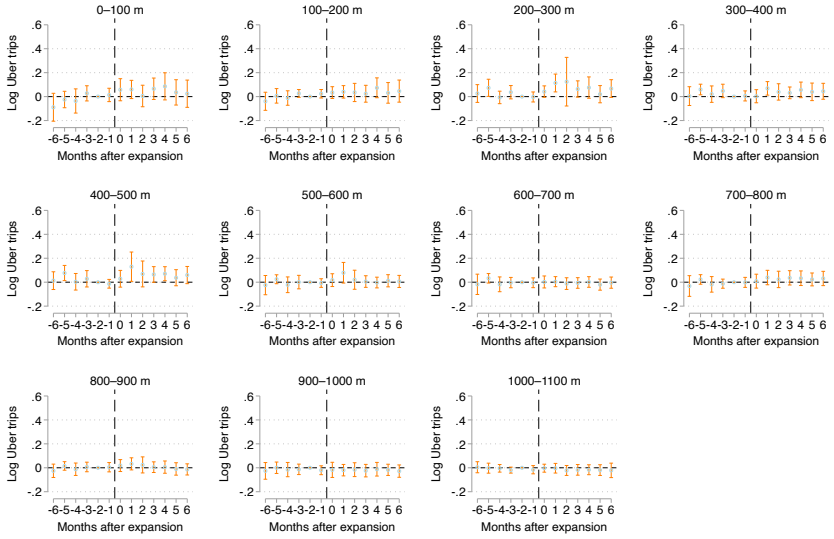


Figure A18: Aggregate 0 – 700 m effect by city

Notes: This funnel graph shows city-specific treatment effects based on equation (5) for Uber trips within 700 meters of the station opening, and where the coefficient α is allowed to vary by city. The x-axis shows coefficient estimates, the y-axis shows standard errors. The region in white contains estimates that are not statistically different from zero. The light, medium, and dark gray regions contain estimates that are statistically different from zero at 10%, 5%, and 1%, respectively. The size of each circle is proportional to baseline Uber ridership. The large red triangle indicates the average effect reported in Figure 5. All error are clustered at the station-level.

B.4 Heterogeneity in transit quality / location

Panel A: Dynamic effects



Panel B: Average effect by distance

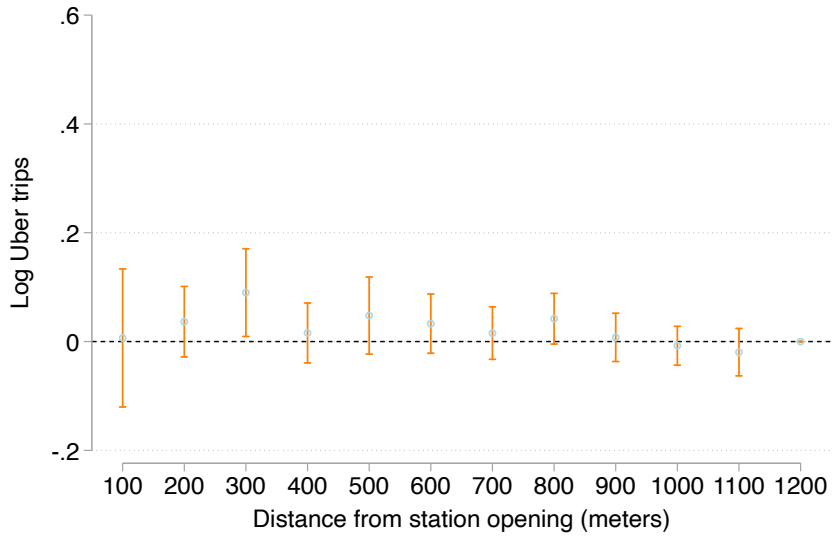


Figure A19: Dynamic and average effects for station openings that interact with traffic

Notes: This figure plots the coefficients (circles) and 95% confidence intervals (bars) from estimating equations (4) and (5) for stations whose transit interacts with traffic. These estimates are contained in Panel A and Panel B, respectively. These coefficients estimate the effect of a new train station opening on Uber trips at varying times and distances from the train station opening. All errors are clustered at the station-level.

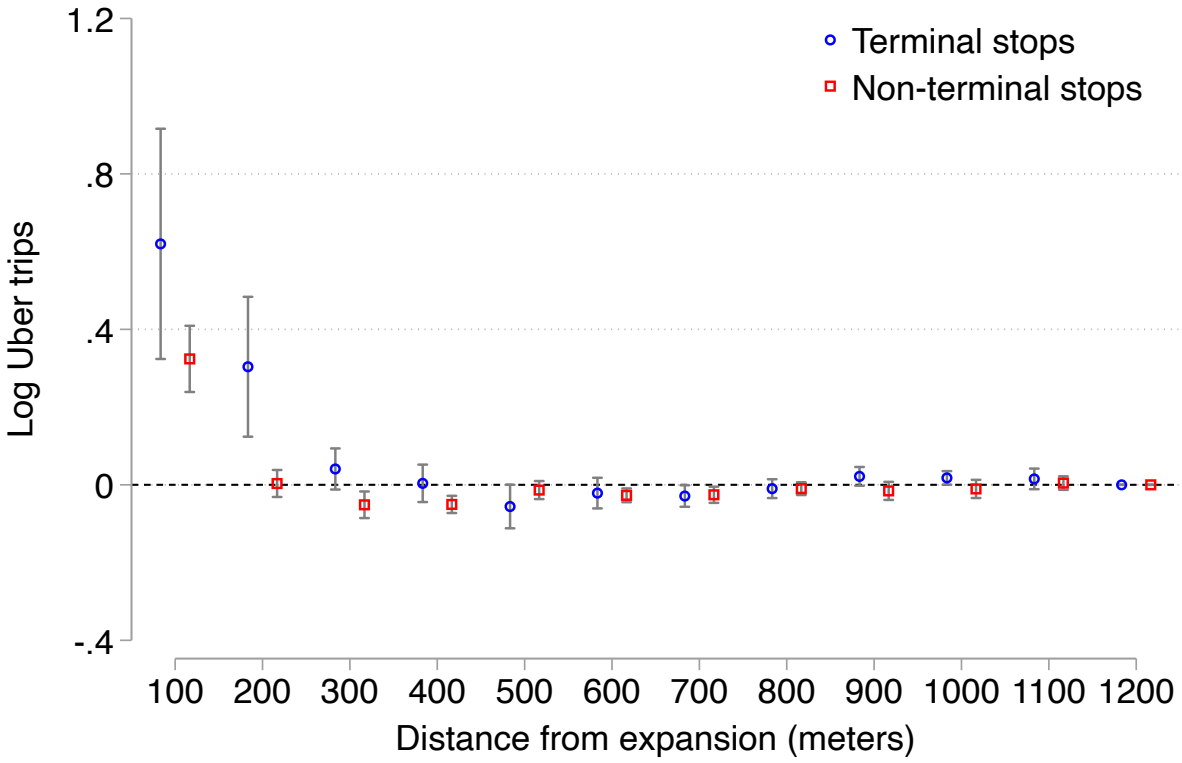
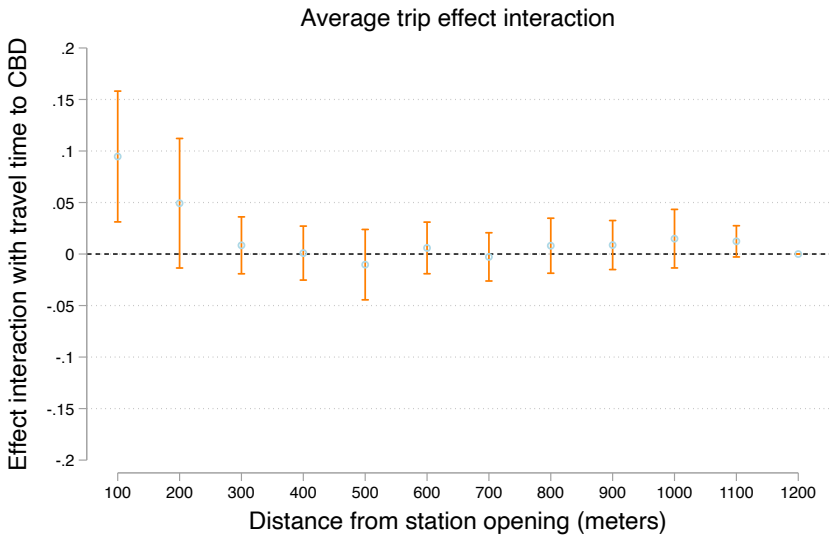


Figure A20: Differential effects for terminal versus non-terminal stations

Notes: This figure plots the coefficients (circles) and 95% confidence intervals (bars) from estimating equation (5) separately for stations that were a terminal stop on their train line. The coefficients estimate the effect on Uber trips at varying distances from the train station opening, separately for each type of train station. All errors are clustered at the station-level.

Panel A: Interaction of effect by with normalized travel time from CBD



Panel B: Interaction of effect by distance with normalized travel time from CBD

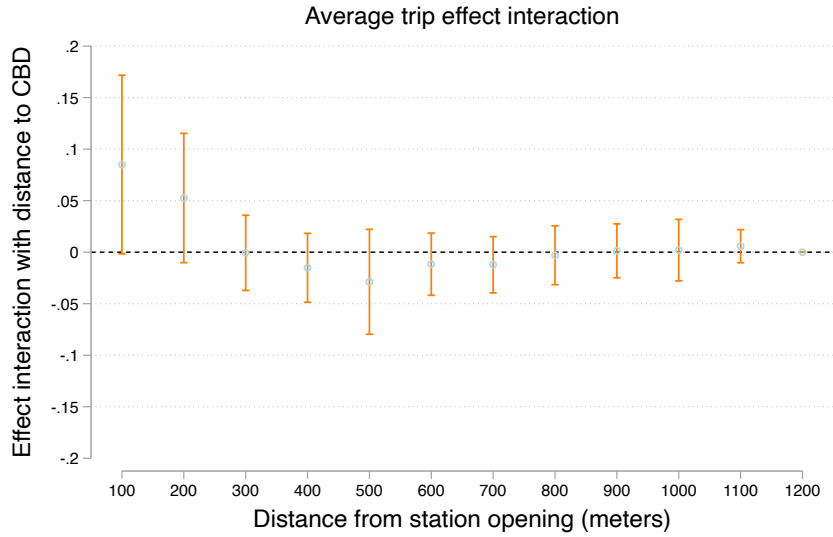


Figure A21: Differential effects for peripheral stations

Notes: This figure plots the coefficients (circles) and 95% confidence intervals (bars) from estimating a version of equation (5) that interacts each effect with a normalized measure of distance from the CBD. The measure uses travel time in Panel A and physical distance in Panel B. The coefficients estimate the different effect on Uber trips at varying distances from the train station opening. All errors are clustered at the station-level.

B.5 POI sample

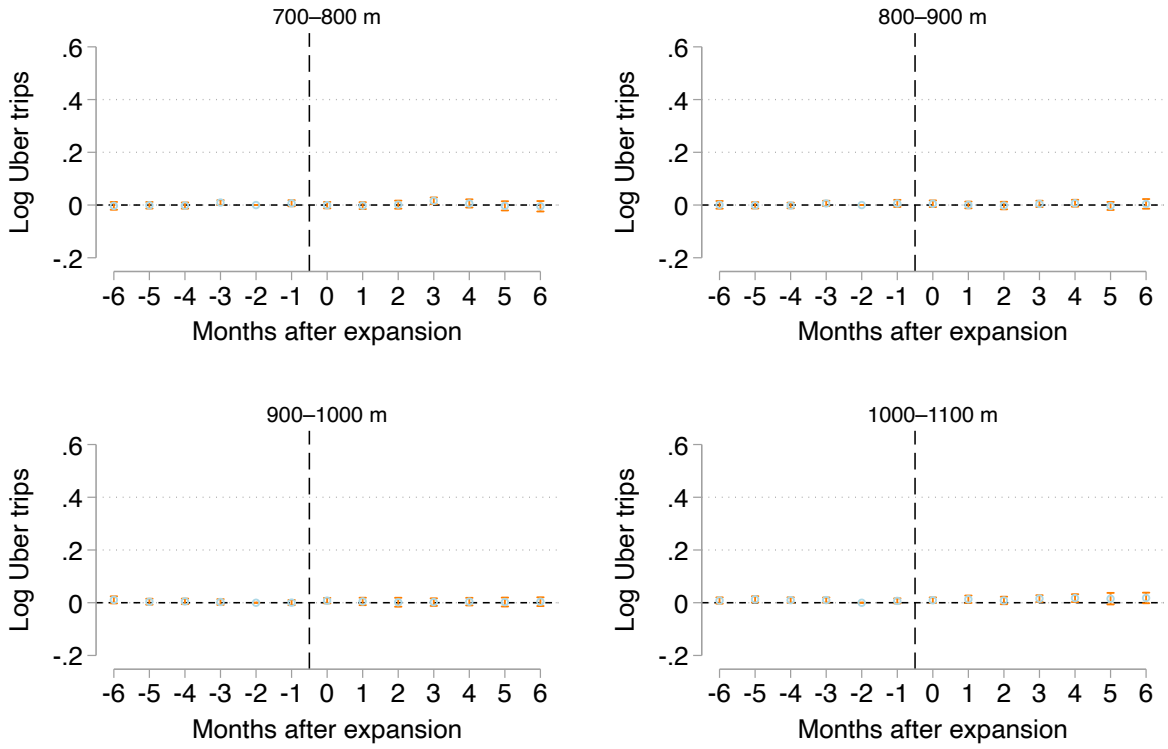


Figure A22: Dynamic effects for the POI sample 800–1100 m

Notes: This figure plots the coefficients (circles) and 95% confidence intervals (bars) from estimating equations (4) for individuals with a POI within 500–1200 m of the opening, calculated using trip data from 12 to 7 months prior to the station opening. These coefficients estimate the effect of a new train station opening on Uber trips at varying distances from the train station opening for this sample of Uber riders, relative to trips taken 1100–1200 m away. All errors are clustered at the station-level.

C Model appendix

Finding choice probabilities

In this section we first derive the expected utility from each period's mode choice using backward induction and then find choice probabilities using the familiar logit formulation. Both calculations are conditional on the permanent preference shock η_m, which is known to the traveler prior to deciding on transit. We then calculate unconditional probabilities by aggregating over the distribution of η_m.

C.1 Solving the model

Return Journey (Period 3)

When making the return journey, the traveler is constrained by whether or not they drove for the outbound journey: $m_3 = \text{car}$ if and only if $m_1 = \text{car}$. If she did not drive, she chooses between transit and Uber.

Transit involves choosing the egress mode. The inclusive value for transit is:

$$IV_3^{\text{transit}}(d, \eta) = \ln\left[\exp(\alpha_{\text{transit}} - d \cdot c_{\text{walk}} + \eta_{\text{transit}}) + \exp(\alpha_{\text{transit}} - f_{\text{Uber}} - d \cdot c_{\text{Uber}} + \eta_{\text{transit}})\right]. \tag{6}$$

The expected utility from the return journey, conditional on the outbound mode, is:

$$V_3(m_1, d, \eta) = \begin{cases} \alpha_{\text{car}} & \text{if } m_1 = \text{car} \\ \ln[\exp(IV_3^{\text{transit}}(d, \eta)) + \exp(\alpha_{\text{Uber}} + \eta_{\text{Uber}})] + \gamma & \text{if } m_1 \in \{\text{transit}, \text{Uber}\} \end{cases} \tag{7}$$

where $\gamma \approx 0.5772$ is Euler's constant, which arises from the expected maximum of Type I extreme value random variables.

Intermediate Trip (Period 2)

With probability p_s, the traveler needs to make an intermediate trip. If she didn't take her personal automobile already, she cannot do so now. This gives the following expected utility for the second period.

$$V_2(m_1) = p_s \cdot \begin{cases} \ln[\exp(\beta_{\text{car}}) + \exp(\beta_{\text{transit}}) + \exp(\beta_{\text{Uber}})] + \gamma & \text{if } m_1 = \text{car} \\ \ln[\exp(\beta_{\text{transit}}) + \exp(\beta_{\text{Uber}})] + \gamma & \text{if } m_1 \in \{\text{transit}, \text{Uber}\} \end{cases} \tag{8}$$

Outbound Journey (Period 1)

For the outbound journey, transit users choose an access mode. The inclusive value is:

$$IV_1^{\text{transit}}(d,\eta) = \ln\left[\exp(\alpha_{\text{transit}} - d \cdot c_{\text{walk}} + \eta_{\text{transit}}) + \exp(\alpha_{\text{transit}} - f_{\text{Uber}} - d \cdot c_{\text{Uber}} + \eta_{\text{transit}})\right] \quad (9)$$

The total expected utility for each outbound mode is:

$$V(m_1,d,\eta) = \begin{cases} \alpha_{\text{car}} + V_2(\text{car}) + V_3(\text{car},d,\eta) & \text{if } m_1 = \text{car} \\ IV_1^{\text{transit}}(d,\eta) + \gamma + V_2(\text{transit}) + V_3(\text{transit},d,\eta) & \text{if } m_1 = \text{transit} \\ \alpha_{\text{Uber}} + \eta_{\text{Uber}} + V_2(\text{Uber}) + V_3(\text{Uber},d,\eta) & \text{if } m_1 = \text{Uber} \end{cases} \quad (10)$$

Note that, per (8) and (7), $V_2(\text{transit}) = V_2(\text{Uber})$ and $V_3(\text{transit},d,\eta) = V_3(\text{Uber},d,\eta)$.

C.2 Conditional choice probabilities

We can now use the familiar logit formulation to derive choice probabilities conditional on the preference shock η_m.

Outbound Journey (Period 1)

The probability of choosing mode m_1 for the outbound journey is:

$$P_1(m_1 \mid d,\eta) = \frac{\exp(V(m_1,d,\eta))}{\sum_{m' \in \{\text{car,transit,Uber}\}} \exp(V(m',d,eta))} \quad (11)$$

For travelers who choose transit, the probability of using access mode a_1 is:

$$P_1(a_1 \mid m_1 = \text{transit},d,\eta) = \frac{\exp(\alpha_{\text{transit}} - f_{a_1} - d \cdot c_{a_1} + \eta_{\text{transit}})}{\sum_{a' \in \{\text{walk,Uber}\}} \exp(\alpha_{\text{transit}} - f_{a'} - d \cdot c_{a'} + \eta_{\text{transit}})}. \quad (12)$$

Intermediate Trip (Period 2)

Conditional on needing an intermediate trip (which occurs with probability p_s), the mode choice probabilities depend on the outbound mode:

For travelers who drove outbound:

$$P_2(m_2 \mid m_1 = \text{car}) = \frac{\exp(\beta_{m_2})}{\sum_{m' \in \{\text{car,transit,Uber}\}} \exp(\beta_{m'})} \quad \text{for } m_2 \in \{\text{car},\text{transit},\text{Uber}\} \quad (13)$$

For travelers who used transit or Uber outbound:

$$P_2(m_2 \mid m_1 \in \{\text{transit},\text{Uber}\}) = \begin{cases} \frac{\exp(\beta_{m_2})}{\exp(\beta_{\text{transit}}) + \exp(\beta_{\text{Uber}})} & \text{if } m_2 \in \{\text{transit},\text{Uber}\} \\ 0 & \text{if } m_2 = \text{car} \end{cases} \quad (14)$$

Return Journey (Period 3)

We start by noting that for travelers who drove outbound, the return mode is deterministic:

$$P_3(m_3 \mid m_1 = \text{car}) = \begin{cases} 1 & \text{if } m_3 = \text{car} \\ 0 & \text{otherwise} \end{cases} \tag{15}$$

The conditional choice probabilities for the return journey for those who did not drive outbound are

$$P_3(m_3 \mid m_1 \in \{\text{transit}, \text{Uber}\}, d, \eta) = \begin{cases} \frac{\exp(IV_3^{\text{transit}}(d,\eta))}{\exp(IV_3^{\text{transit}}(d,\eta))+\exp(\alpha_{\text{Uber}}+\eta_{\text{Uber}})} & \text{if } m_3 = \text{transit} \\ \frac{\exp(\alpha_{\text{Uber}}+\eta_{\text{Uber}})}{\exp(IV_3^{\text{transit}}(d,\eta))+\exp(\alpha_{\text{Uber}}+\eta_{\text{Uber}})} & \text{if } m_3 = \text{Uber} \\ 0 & \text{if } m_3 = \text{car} \end{cases} \tag{16}$$

For travelers who choose transit for the return journey, the egress mode probabilities are

$$P_3(a_3 \mid m_3 = \text{transit}, d, \eta) = \frac{\exp(\alpha_{\text{transit}} - f_{a_3} - d \cdot c_{a_3} + \eta_{\text{transit}})}{\sum_{a' \in \{\text{walk,Uber}\}} \exp(\alpha_{\text{transit}} - f_{a'} - d \cdot c_{a'} + \eta_{\text{transit}})} \tag{17}$$

Unconditional choice probabilities

The unconditional choice probabilities can be found by integrating over possible realizations of η_m. Let $F(\eta)$ denote the joint distribution over all preference shocks η_m. Then the unconditional choice probabilities for the outbound trip and access modes are

$$P_1(m_1 \mid d) = \int P_1(m_1 \mid d, \eta) \mathrm{d}F(\eta)$$

$$P_1(a_1 \mid m_1 = \text{transit}, d) = \int P_1(a_1 \mid m_1 = \text{transit}, d, \eta) \mathrm{d}F(\eta)$$

Similarly, the unconditional choice probabilities for the return trip and access modes are

$$P_3(m_3 \mid m_1, d) = \int P_3(m_3 \mid m_1, d, \eta) \mathrm{d}F(\eta)$$

$$P_3(a_3 \mid m_3 = \text{transit}, d) = \int P_3(a_3 \mid m_3 = \text{transit}, d, \eta) \mathrm{d}F(\eta)$$

C.3 Theoretical results

Proposition 1 *Consider the three-period mode choice model described in the text. The derivative with respect to the transit utility parameter $\alpha_{transit}$ of Uber use in period 1 conditional on the traveler's distance d and persistent transit preference η is:*

$$\frac{\partial}{\partial \alpha_{transit}}\Big(P_1(Uber|d,\eta) + P_1(transit{+}Uber|d,\eta)\Big)$$
$$= -\underbrace{P_1(Uber|d,\eta)\cdot P_1(transit|d,\eta)}_{\text{Direct substitution effect } (\geq 0)} +$$
$$\underbrace{P_1(transit + Uber|d,\eta)\cdot P_1(transit|d,\eta)\cdot\Big[P_1(Uber|d,\eta) + P_1(car|d,\eta)(1+P_3(transit|m_1\neq car,d,\eta))\Big]}_{\text{Last-mile complementarity } (\geq 0)} +$$
$$\underbrace{P_1(Uber|d,\eta)\cdot P_1(car|d,\eta)\cdot P_3(transit|m_1\neq car,d,\eta)}_{\text{Option value effect } (\geq 0)}$$

Proof. The total Uber usage in period 1 consists of two components: direct Uber usage and Uber as an access mode to transit. We know that:

$$P_1(\text{transit+Uber}|d,\eta) = P_1(a_1 = \text{Uber}|m_1 = \text{transit},d,\eta)\times P_1(m_1=\text{transit}|d,\eta)$$

Taking the derivative of total Uber usage:

$$\frac{\partial}{\partial \alpha_{\text{transit}}}\Big(P_1(\text{Uber}|d,\eta) + P_1(\text{transit+Uber}|d,\eta)\Big)$$

$$= \frac{\partial P_1(\text{Uber}|d,\eta)}{\partial \alpha_{\text{transit}}} + \frac{\partial}{\partial \alpha_{\text{transit}}}\Big[P_1(a_1=\text{Uber}|m_1=\text{transit},d,\eta)\times P_1(\text{transit}|d,\eta)\Big]$$

$$= \frac{\partial P_1(\text{Uber}|d,\eta)}{\partial \alpha_{\text{transit}}} + P_1(a_1=\text{Uber}|m_1=\text{transit},d,\eta)\times\frac{\partial P_1(\text{transit}|d,\eta)}{\partial \alpha_{\text{transit}}}$$

The last line follows since the access mode choice depends only on the relative costs of walking versus Uber for accessing transit, not on α_{transit} directly:

$$\frac{\partial P_1(a_1=\text{Uber}|m_1=\text{transit},d,\eta)}{\partial \alpha_{\text{transit}}} = 0$$

Step 1: Period 1 derivatives. From the multinomial logit model and backward induction:

$$\frac{\partial V(\text{car},d,\eta)}{\partial \alpha_{\text{transit}}} = 0$$
$$\frac{\partial V(\text{transit},d,\eta)}{\partial \alpha_{\text{transit}}} = 1 + P_3(\text{transit}|m_1\neq\text{car},d,\eta)$$
$$\frac{\partial V(\text{Uber},d,\eta)}{\partial \alpha_{\text{transit}}} = P_3(\text{transit}|m_1\neq\text{car},d,\eta)$$

Using properties of multinomial logit derivatives:

$$\frac{\partial P_1(\text{transit}|d,\eta)}{\partial \alpha_{\text{transit}}} = P_1(\text{transit}|d,\eta) \times [1 + P_3(\text{transit}|m_1 \neq \text{car}, d, \eta) - \bar{V}']$$

$$\frac{\partial P_1(\text{Uber}|d,\eta)}{\partial \alpha_{\text{transit}}} = P_1(\text{Uber}|d,\eta) \times [P_3(\text{transit}|m_1 \neq \text{car}, d, \eta) - \bar{V}']$$

$$\frac{\partial P_1(\text{car}|d,\eta)}{\partial \alpha_{\text{transit}}} = P_1(\text{car}|d,\eta) \times [0 - \bar{V}'] = -P_1(\text{car}|d,\eta) \times \bar{V}'$$

where

$$\bar{V}' = P_1(\text{transit}|d,\eta) \times [1 + P_3(\text{transit}|m_1 \neq \text{car}, d, \eta)] + P_1(\text{Uber}|d,\eta) \times P_3(\text{transit}|m_1 \neq \text{car}, d, \eta)$$

Step 2: Substitute and combine terms. Substituting the expressions in, we get:

$$\begin{aligned}\frac{\partial P_1(\text{Uber}|d,\eta)}{\partial \alpha_{\text{transit}}} = {} & P_1(\text{Uber}|d,\eta) \times P_3(\text{transit}|m_1 \neq \text{car}, d, \eta) - \\ & P_1(\text{Uber}|d,\eta) \times P_1(\text{transit}|d,\eta) \times [1 + P_3(\text{transit}|m_1 \neq \text{car}, d, \eta)] - \\ & P_1(\text{Uber}|d,\eta)^2 \times P_3(\text{transit}|m_1 \neq \text{car}, d, \eta)\end{aligned}$$

$$\begin{aligned}\frac{\partial P_1(\text{transit}|d,\eta)}{\partial \alpha_{\text{transit}}} = {} & P_1(\text{transit}|d,\eta) \times [1 + P_3(\text{transit}|m_1 \neq \text{car}, d, \eta)] - \\ & P_1(\text{transit}|d,\eta) \times P_1(\text{transit}|d,\eta) \times [1 + P_3(\text{transit}|m_1 \neq \text{car}, d, \eta)] \\ & - P_1(\text{transit}|d,\eta) \times P_1(\text{Uber}|d,\eta) \times P_3(\text{transit}|m_1 \neq \text{car}, d, \eta)\end{aligned}$$

Take the first derivative. We can rewrite this expression as:

$$\begin{aligned}\frac{\partial P_1(\text{Uber}|d,\eta)}{\partial \alpha_{\text{transit}}} = {} & P_1(\text{Uber}|d,\eta) \times \\ & \Big[P_3(\text{transit}|m_1 \neq \text{car}, d, \eta) \times (1 - P_1(\text{transit}|d,\eta) - P_1(\text{Uber}|d,\eta)) - P_1(\text{transit}|d,\eta)\Big] \\ = {} & P_1(\text{Uber}|d,\eta) \times \Big[P_3(\text{transit}|m_1 \neq \text{car}, d, \eta) \times P_1(\text{car}|d,\eta) - P_1(\text{transit}|d,\eta)\Big]\end{aligned}$$

The second derivative can be rewritten as:

$$\frac{\partial P_1(\text{transit}|d,\eta)}{\partial \alpha_{\text{transit}}} = P_1(\text{transit}|d,\eta)\times \left[P_1(\text{Uber}|d,\eta) + P_1(\text{car}|d,\eta)(1+P_3(\text{transit}|m_1 \neq \text{car},d,\eta))\right]$$

Combining the terms with the original product-rule derivative for total Uber use gives the expression in the proposition. ■

Proposition 2 *Consider the three-period mode choice model described in the text. The derivative of the conditional Uber use in period 3 with respect to the transit utility parameter $\alpha_{transit}$ is:*

$$\begin{aligned}
&\frac{\partial}{\partial \alpha_{transit}}\Big(P_3(Uber|d,\eta) + P_3(transit{+}Uber|d,\eta)\Big) \\
&\quad = \underbrace{-(1-P_1(car|d,\eta))\cdot P_3(Uber|m_1 \neq car,d,\eta)\cdot P_3(transit|m_1 \neq car,d,\eta)}_{\text{Direct substitution effect } (\geq 0)} + \\
&\underbrace{(1-P_1(car|d,\eta))\cdot P_3(Uber|m_1 \neq car,d,\eta)\cdot P_3(transit|m_1 \neq car,d,\eta)\cdot P_3(a_3 = Uber|m_3 = transit,d)}_{\text{Last-mile complementarity } (\geq 0)} + \\
&\quad \underbrace{P_1(car|d,\eta)\cdot\Gamma\cdot[P_3(Uber|m_1 \neq car,d,\eta) + P_3(transit + Uber|m_1 \neq car,d,\eta)]}_{\text{Option value effect } (\geq 0)}
\end{aligned}$$

where:

- $\Gamma = P_1(transit|d,\eta) + (1-P_1(car|d,\eta))\cdot P_3(transit|m_1 \neq car,d,\eta) \geq 0$

Proof. The overall Uber mode share in period 3 consists of direct Uber trips and Uber used as the egress mode for transit.

$$\begin{aligned}
&P_3(\text{Uber}|d,\eta) + P_3(\text{transit+Uber}|d,\eta) = \\
&\qquad (1-P_1(\text{car}|d,\eta))\cdot[P_3(\text{Uber}|m_1 \neq \text{car},d,\eta) + P_3(\text{transit + Uber}|m_1 \neq \text{car},d,\eta)]
\end{aligned}$$

Taking the derivative with respect to α_{transit}:

$$\begin{aligned}
&\frac{\partial}{\partial \alpha_{\text{transit}}}\Big(P_3(\text{Uber}|d,\eta) + P_3(\text{transit+Uber}|d,\eta)\Big) = \\
&\quad -\frac{\partial P_1(\text{car}|d,\eta)}{\partial \alpha_{\text{transit}}}\cdot[P_3(\text{Uber}|m_1 \neq \text{car},d,\eta) + P_3(\text{transit + Uber}|m_1 \neq \text{car},d,\eta)] \\
&\quad + (1-P_1(\text{car}|d,\eta))\cdot\left[\frac{\partial P_3(\text{Uber}|m_1 \neq \text{car},d,\eta)}{\partial \alpha_{\text{transit}}} + \frac{\partial P_3(\text{transit + Uber}|m_1 \neq \text{car},d,\eta)}{\partial \alpha_{\text{transit}}}\right]
\end{aligned}$$

Step 1: Period 1 derivatives. From the multinomial logit model and backward induction:

$$\begin{aligned}
\frac{\partial V(\text{car}, d, \eta)}{\partial \alpha_{\text{transit}}} &= 0 \\
\frac{\partial V(\text{transit}, d, \eta)}{\partial \alpha_{\text{transit}}} &= 1 + P_3(\text{transit} | m_1 \in \{\text{Uber, transit}\}, d, \eta) \\
\frac{\partial V(\text{Uber}, d, \eta)}{\partial \alpha_{\text{transit}}} &= P_3(\text{transit} | m_1 \in \{\text{Uber, transit}\}, d, \eta)
\end{aligned}$$

Using the multinomial logit derivative formula:

$$\begin{aligned}
\frac{\partial P_1(\text{car}|d,\eta)}{\partial \alpha_{\text{transit}}} &= -P_1(\text{car}|d,\eta) \cdot [P_1(\text{transit}|d,\eta) \cdot (1 + P_3(\text{transit}|m_1 \in \{\text{Uber, transit}\}, d, \eta)) \\
&\quad + P_1(\text{Uber}|d,\eta) \cdot P_3(\text{transit}|m_1 \in \{\text{Uber, transit}\}, d, \eta)] \\
&= -P_1(\text{car}|d,\eta) \cdot [P_1(\text{transit}|\eta) + (1 - P_1(\text{car}|d,\eta)) \cdot P_3(\text{transit}|m_1 \in \{\text{Uber, transit}\}, d, \eta)] \\
&= -P_1(\text{car}|d,\eta) \cdot \Gamma
\end{aligned}$$

Step 2: Period 3 conditional probability derivatives. For travelers who did not drive in period 1, from the multinomial logit model for period 3:

$$\frac{\partial P_3(\text{Uber}|m_1 \neq \text{car}, d, \eta)}{\partial \alpha_{\text{transit}}} = -P_3(\text{Uber}|m_1 \neq \text{car}, d, \eta) \cdot P_3(\text{transit}|m_1 \neq \text{car}, d, \eta)$$

For the transit + Uber combination, we need to consider both the choice of transit as primary mode and Uber as egress mode.

$$P_3(\text{transit + Uber}|m_1 \neq \text{car}, d, \eta) = P_3(a_3 = \text{Uber}|m_1 = \text{transit}, d, \eta) \cdot P_3(\text{transit}|m_1 \neq \text{car}, d, \eta)$$

Taking the derivative:

$$\begin{aligned}
\frac{\partial P_3(\text{transit + Uber}|m_1 \neq \text{car}, d, \eta)}{\partial \alpha_{\text{transit}}} &= \frac{\partial P_3(a_3 = \text{Uber}|m_3 = \text{transit}, d, \eta)}{\partial \alpha_{\text{transit}}} \cdot P_3(\text{transit}|m_1 \neq \text{car}, d, \eta) + \\
&\quad P_3(a_3 = \text{Uber}|m_3 = \text{transit}, d, \eta) \cdot \frac{\partial P_3(\text{transit}|m_1 \neq \text{car}, d, \eta)}{\partial \alpha_{\text{transit}}}
\end{aligned}$$

The egress mode choice depends only on the fixed and marginal costs. However, improving transit quality (α_{transit}) makes transit more attractive relative to Uber as the primary mode, so:

$$\frac{\partial P_3(a_3 = \text{Uber}|m_3 = \text{transit}, d, \eta)}{\partial \alpha_{\text{transit}}} = 0$$

$$\frac{\partial P_3(\text{transit}|m_1 \neq \text{car}, d, \eta)}{\partial \alpha_{\text{transit}}} = P_3(\text{transit}|m_1 \neq \text{car}, d, \eta) \cdot P_3(\text{Uber}|m_1 \neq \text{car}, d, \eta)$$

Therefore:

$$\frac{\partial P_3(\text{transit + Uber}|m_1 \neq \text{car}, d, \eta)}{\partial \alpha_{\text{transit}}} =$$
$$P_3(a_3 = \text{Uber}|m_3 = \text{transit}, d, \eta) \cdot P_3(\text{transit}|m_1 \neq \text{car}, d, \eta) \cdot P_3(\text{Uber}|m_1 \neq \text{car}, d, \eta)$$

Step 3: Combining terms. Substituting into the main derivative:

$$\frac{\partial}{\partial \alpha_{\text{transit}}}\Big(P_3(\text{Uber}|d, \eta) + P_3(\text{transit+Uber}|d, \eta)\Big) =$$
$$P_1(\text{car}|d, \eta) \cdot \Gamma \cdot [P_3(\text{Uber}|m_1 \neq \text{car}, d, \eta) + P_3(\text{transit + Uber}|m_1 \neq \text{car}, d, \eta)]$$
$$+ (1 - P_1(\text{car}|d, \eta)) \cdot [-P_3(\text{Uber}|m_1 \neq \text{car}, d, \eta) \cdot P_3(\text{transit}|m_1 \neq \text{car}, d, \eta)$$
$$+ P_3(a_3 = \text{Uber}|m_3 = \text{transit}, d, \eta) \cdot P_3(\text{transit}|m_1 \neq \text{car}, d, \eta) \cdot P_3(\text{Uber}|m_1 \neq \text{car}, d, \eta)]$$

Rearranging:

$$\frac{\partial}{\partial \alpha_{\text{transit}}}\Big(P_3(\text{Uber}|d, \eta) + P_3(\text{transit+Uber}|d, \eta)\Big) =$$
$$P_1(\text{car}|d, \eta) \cdot \Gamma \cdot [P_3(\text{Uber}|m_1 \neq \text{car}, d, \eta) + P_3(\text{transit + Uber}|m_1 \neq \text{car}, d, \eta)]$$
$$- (1 - P_1(\text{car}|d, \eta)) \cdot P_3(\text{Uber}|m_1 \neq \text{car}, d, \eta) \cdot P_3(\text{transit}|m_1 \neq \text{car}, d, \eta)$$
$$+ (1 - P_1(\text{car}|d, \eta)) \cdot P_3(\text{Uber}|m_1 \neq \text{car}, d, \eta) \cdot P_3(\text{transit}|m_1 \neq \text{car}, d, \eta) \cdot P_3(a_3 = \text{Uber}|m_3 = \text{transit}, d, \eta)$$

■

Proposition 3 *Consider the three-period mode choice model described in the text, where* $\beta_{transit} = \beta_{transit}(\alpha_{transit})$ *is a differentiable function with* $\beta'_{transit}(\alpha_{transit}) \geq 0$*. The derivative of the Uber mode share in period 2 (conditional on period 2 occurring) with respect to the transit utility parameter* $\alpha_{transit}$ *is:*

$$\frac{\partial P_2(Uber|d, \eta)}{\partial \alpha_{transit}} = -\underbrace{\beta'_{transit}(\alpha_{transit}) \cdot \Omega}_{\text{Substitution effect } (\geq 0)} +$$
$$\underbrace{P_1(car|d, \eta) \cdot \Gamma \cdot [P_2(Uber|m_1 \in \{Uber,\ transit\}) - P_2(Uber|m_1 = car)]}_{\text{Option value effect } (\geq 0)}$$

where:

- $\Gamma = P_1(transit|d, \eta) + (1 - P_1(car|d, \eta)) \cdot P_3(transit|m_1 \in \{Uber, transit\}, d, \eta) \geq 0$
- $\Omega = P_1(car|d, \eta) \cdot P_2(Uber|m_1 = car) \cdot P_2(transit|m_1 = car) + [1 - P_1(car|d, \eta)] \cdot P_2(Uber|m_1 \in \{Uber,\ transit\}) \cdot P_2(transit|m_1 \in \{Uber,\ transit\}) \geq 0$

The derivative is non-negative if and only if:

$$\beta'_{transit}(\alpha_{transit}) \leq \frac{P_1(car|d,\eta) \cdot \Gamma \cdot [P_2(Uber|m_1 \in \{Uber,\ transit\}) - P_2(Uber|m_1 = car)]}{\Omega}$$

Proof. The overall Uber mode share in period 2 is:

$$P_2(\text{Uber}|d,\eta) = P_1(\text{car}|d,\eta) \cdot P_2(\text{Uber}|m_1 = \text{car}) + [1 - P_1(\text{car}|d,\eta)] \cdot P_2(\text{Uber}|m_1 \in \{\text{Uber, transit}\})$$

where we use the fact that $P_1(\text{transit}) + P_1(\text{Uber}) = 1 - P_1(\text{car})$ since travelers who don't drive have the same choice set in periods 2 and 3. Also note that conditional on period 1 mode choices, intermediate trip probabilities do not depend on d or η.

Taking the derivative with respect to α_{transit}:

$$\begin{aligned}\frac{\partial P_2(\text{Uber}|d,\eta)}{\partial \alpha_{\text{transit}}} = \frac{\partial P_1(\text{car}|d,\eta)}{\partial \alpha_{\text{transit}}} \cdot [P_2(\text{Uber}|m_1 = \text{car}) - P_2(\text{Uber}|m_1 \in \{\text{Uber, transit}\})] \\ + P_1(\text{car}|d,\eta) \cdot \frac{\partial P_2(\text{Uber}|m_1 = \text{car})}{\partial \alpha_{\text{transit}}} + [1 - P_1(\text{car}|d,\eta)] \cdot \frac{\partial P_2(\text{Uber}|m_1 \in \{\text{Uber, transit}\})}{\partial \alpha_{\text{transit}}}\end{aligned}$$

Step 1: Period 1 derivatives. *See Step 1 of the proof for Proposition 2.*

Step 2: Period 2 conditional probability derivatives. From the multinomial logit model:

$$\begin{aligned}\frac{\partial P_2(\text{Uber}|m_1 = \text{car})}{\partial \alpha_{\text{transit}}} &= \frac{\partial P_2(\text{Uber}|m_1 = \text{car})}{\partial \beta_{\text{transit}}} \cdot \beta'_{\text{transit}}(\alpha_{\text{transit}}) \\ &= -P_2(\text{Uber}|m_1 = \text{car}) \cdot P_2(\text{transit}|m_1 = \text{car}) \cdot \beta'_{\text{transit}}(\alpha_{\text{transit}})\end{aligned}$$

Similarly:

$$\begin{aligned}\frac{\partial P_2(\text{Uber}|m_1 \in \{\text{Uber, transit}\})}{\partial \alpha_{\text{transit}}} = -P_2(\text{Uber}|m_1 \in \{\text{Uber, transit}\}) \\ \times P_2(\text{transit}|m_1 \in \{\text{Uber, transit}\}) \cdot \beta'_{\text{transit}}(\alpha_{\text{transit}})\end{aligned}$$

Step 3: Combining terms. Substituting into the main derivative:

$$\begin{aligned}\frac{\partial P_2(\text{Uber}|d,\eta)}{\partial \alpha_{\text{transit}}} = -P_1(\text{car}|d,\eta) \cdot \Gamma \cdot [P_2(\text{Uber}|m_1 = \text{car}) - P_2(\text{Uber}|m_1 \in \{\text{Uber, transit}\})] \\ - \beta'_{\text{transit}}(\alpha_{\text{transit}}) \cdot [P_1(\text{car}|d,\eta) \cdot P_2(\text{Uber}|m_1 = \text{car}) \cdot P_2(\text{transit}|m_1 = \text{car}) \\ + [1 - P_1(\text{car}|d,\eta)] \cdot P_2(\text{Uber}|m_1 \in \{\text{Uber, transit}\}) \\ \cdot P_2(\text{transit}|m_1 \in \{\text{Uber, transit}\})]\end{aligned}$$

Since $P_2(\text{Uber}|m_1 \in \{\text{Uber, transit}\}) > P_2(\text{Uber}|m_1 = \text{car})$ when $\beta_{\text{car}} > -\infty$, we can rewrite

this as:

$$\frac{\partial P_2(\text{Uber}|d,\eta)}{\partial \alpha_{\text{transit}}} = P_1(\text{car}|d,\eta)\cdot\Gamma\cdot[P_2(\text{Uber}|m_1\in\{\text{Uber, transit}\}) - P_2(\text{Uber}|m_1=\text{car})] - \beta'_{\text{transit}}(\alpha_{\text{transit}})\cdot\Omega$$

The condition for non-negativity follows immediately. ■

Corollary 1 *The derivative of the overall Uber market share at distance d in period 2 (conditional on period 2 occurring) with respect to the transit utility parameter $\alpha_{transit}$ is:*

$$\frac{\partial P_2(Uber|d)}{\partial \alpha_{transit}} = \underbrace{-\int(\beta'_{transit}(\alpha_{transit})\cdot\Omega)dF(\eta)}_{\text{Aggregate substitution effect } (\geq 0)} + \underbrace{\int P_1(car|d,\eta)\cdot\Gamma\cdot[P_2(Uber|m_1\in\{Uber,\ transit\}) - P_2(Uber|m_1=car)]dF(\eta)}_{\text{Aggregate option value effect } (\geq 0)}$$

Proof. The unconditional choice probability for Uber in period 2 comes from integrating over η.

$$P_2(\text{Uber}|d) = \int P_2(\text{Uber}|d,\eta)\text{d}F(\eta)$$

Because the domain of integration does not depend on α_{transit} and the integrand is sufficiently well-behaved, we can differentiate under the integral sign.

$$\frac{\partial P_2(\text{Uber}|d)}{\partial \alpha_{\text{transit}}} = \int \frac{\partial P_2(\text{Uber}|d,\eta)}{\partial \alpha_{\text{transit}}}\text{d}F(\eta)$$

The integrand for each of the substitution and option value effects is positive for each η by the prior result, and so integrating over the distribution of η will also be positive. ■

Proposition 4 *Assume $\alpha_m = \tilde{\alpha}_m - \rho(d,\eta)\cdot\pi_m$ and $\beta_m = \tilde{\beta}_m - \rho(d,\eta)\cdot\pi_m$, for average mode prices π_m and for a traveler at distance d and with preferences η. Let $\varepsilon^D(d,\eta)$ be the elasticity of demand for Uber trips with respect to Uber price π_{Uber}. Let $Q(Uber|d,\eta)$ be total expected direct Uber trips over the outbound, intermediate, and return trips. Then $\rho(d,\eta)$ can be expressed as*

$$\rho(d,\eta) = -\frac{\varepsilon^D(d,\eta)}{\pi_{Uber}}\cdot\frac{Q(Uber|d,\eta)}{Z(d,\eta)}$$

where $Z(d,\eta)$ is a function of model probabilities given in the proof. In particular, if the elasticity of demand is constant and if distances are distributed according to $G(d)$, then the average price coefficient is

$$\bar{\rho} = -\frac{\varepsilon^D}{\pi_{Uber}}\iint\frac{Q(Uber|d,\eta)}{Z(d,\eta)}dG(d)dF(\eta)$$

Proof. Overall direct Uber trips are given by

$$Q(\text{Uber}|d,\eta) = P_1(\text{Uber}|d,\eta) + p_s P_2(\text{Uber}|d,\eta) + P_3(\text{Uber}|d,\eta)$$

By properties of logit:

$$\begin{aligned}
&\frac{\partial P_1(\text{Uber}|d,\eta)}{\partial \pi_{\text{Uber}}} = \\
&-\rho(d,\eta)\cdot P_1(\text{Uber}|d,\eta)\Big[(1-P_1(\text{Uber}|d,\eta))\big[1+p_s\cdot P_2(\text{Uber}|m_1=\text{Uber},d,\eta)+P_3(\text{Uber}|m_1=\text{Uber},d,\eta)\big] \\
&\qquad - P_1(\text{transit}|d,\eta)\big[p_s\cdot P_2(\text{Uber}|m_1=\text{transit},d,\eta)+P_3(\text{Uber}|m_1=\text{transit},d,\eta)\big] \\
&\qquad\qquad - P_1(\text{car}|d,\eta)\big[p_s\cdot P_2(\text{Uber}|m_1=\text{car},d,\eta)\big]\Big]
\end{aligned}$$

$$\begin{aligned}
\frac{\partial P_2(\text{Uber}|d,\eta)}{\partial \pi_{\text{Uber}}} &= \frac{\partial P_1(\text{car}|d,\eta)}{\partial \pi_{\text{Uber}}}\cdot[P_2(\text{Uber}|m_1=\text{car},d,\eta) - P_2(\text{Uber}|m_1\neq\text{car},d,\eta)] \\
&+ P_1(\text{car}|d,\eta)\cdot\frac{\partial P_2(\text{Uber}|m_1=\text{car},d,\eta)}{\partial P_{\text{Uber}}} + (1-P_1(\text{car}|d,\eta))\cdot\frac{\partial P_2(\text{Uber}|m_1\neq\text{car},d,\eta)}{\partial \pi_{\text{Uber}}} \\
&= \rho(d,\eta)\cdot P_1(\text{car}|d,\eta)[P_1(\text{Uber}|d,\eta)+p_s\cdot P_2(\text{Uber}|d,\eta)+P_3(\text{Uber}|d,\eta)] \\
&\qquad\times[P_2(\text{Uber}|m_1=\text{car},d,\eta)-P_2(\text{Uber}|m_1\neq\text{car},d,\eta)] \\
&- \rho(d,\eta)\Big[P_1(\text{car}|d,\eta)\cdot P_2(\text{Uber}|m_1=\text{car},d,\eta)[1-P_2(\text{Uber}|m_1=\text{car},d,\eta)] \\
&\qquad + (1-P_1(\text{car}|d,\eta))\cdot P_2(\text{Uber}|m_1\neq\text{car},d,\eta)[1-P_2(\text{Uber}|m_1\neq\text{car},d,\eta)]\Big]
\end{aligned}$$

$$\begin{aligned}
\frac{\partial P_3(\text{Uber}|d,\eta)}{\partial \pi_{\text{Uber}}} &= -\frac{\partial P_1(\text{car}|d,\eta)}{\partial \pi_{\text{Uber}}}\cdot P_3(\text{Uber}|m_1\neq\text{car},d,\eta) \\
&\qquad + (1-P_1(\text{car}|d,\eta))\cdot\frac{\partial P_3(\text{Uber}|m_1\neq\text{car},d,\eta)}{\partial \pi_{\text{Uber}}} \\
&= -\rho(d,\eta)\cdot P_1(\text{car}|d,\eta)[P_1(\text{Uber}|d,\eta)+p_s\cdot P_2(\text{Uber}|d,\eta)+P_3(\text{Uber}|d,\eta)] \\
&\qquad\times P_3(\text{Uber}|m_1\neq\text{car},d,\eta) \\
&- \rho(d,\eta)\cdot(1-P_1(\text{car}|d,\eta))\cdot P_3(\text{Uber}|m_1\neq\text{car},d,\eta)[1-P_3(\text{Uber}|m_1\neq\text{car},d,\eta)]
\end{aligned}$$

Taken together, this means

$$\frac{\partial Q(\text{Uber}|d,\eta)}{\partial \pi_{\text{Uber}}} = -\rho(d,\eta)\cdot Z(d,\eta)$$

With terms in $Z(d,\eta)$ coming from the above expressions. And so

$$\rho(d,\eta) = -\frac{\partial Q(\text{Uber}|d,\eta)}{\partial \pi_{\text{Uber}}} \cdot \frac{1}{Z(d,\eta)} = -\frac{\varepsilon^D(d,\eta)}{\pi_{\text{Uber}}} \cdot \frac{Q(\text{Uber}|d,\eta)}{Z(d,\eta)}$$

The integral for $\bar{\rho}$ follows immediately. ■

C.4 Mapping the model to the data

It will be simpler to discuss the choice of transit plus an access mode as a single choice, and so note that

$$\begin{aligned} &P_1(\text{transit + Uber} \mid d) = P_1(a_1 = \text{Uber} \mid m_1 = \text{transit}, d) \times P_1(m_1 = \text{transit} \mid d), \\ &P_3(\text{transit + Uber} \mid m_1 \neq \text{car}, d) = P_3(a_3 = \text{Uber} \mid m_3 = \text{transit}, d) \times P_3(m_3 = \text{transit} \mid m_1 \neq \text{car}, d). \end{aligned} \tag{18}$$

In our data we observe the number of Uber trips near a transit stop and the number of Uber trips in the rest of the city. If N is the total number of travelers within $\bar{d}$ meters of the transit stop, then the number of Uber trips occurring between d_1 and d_2 meters of the transit stop is

$$\begin{aligned} \int_{d=d_1}^{d_2} \Big(&P_1(\text{Uber} \mid d) + P_1(\text{transit + Uber} \mid d) \\ &+ \big[1 - P(\text{car} \mid d)\big] \big[P_3(\text{Uber} \mid m_1 \neq \text{car}, d) \\ &+ P_3(\text{transit + Uber} \mid m_1 \neq \text{car}, d) \big] \Big) f(d)\, \mathrm{d}d, \end{aligned} \tag{19}$$

where $f(d)$ is the population density function. Assuming uniform population density, $f(d)$ simplifies to $2Nd/\bar{d}^2$.

The number of Uber trips happening in the rest of the city by people living between d_1 and d_2 meters of the transit stop is

$$\begin{aligned} \int_{d=d_1}^{d_2} \Big(&P_2(\text{Uber} \mid m_1 = \text{car}) \times P_1(\text{car} \mid d) \\ &+ P_2(\text{Uber} \mid m_1 \neq \text{car}) \times P_1(m_1 \neq \text{car} \mid d) \Big) f(d)\, \mathrm{d}d \end{aligned} \tag{20}$$

C.5 Model simulations

Table A5: Model parameters for simulation in Figure 2

Parameter	Positive impact on Uber trips	Negative impact on Uber trips	Mixed impact on Uber trips
α_{car}	0	0	0
α_{transit}	-1	0.7	1.5
α_{Uber}	-1.5	-1.4	-2
β_{car}	0	0	0
β_{transit}	0.5	0.2	0.5
β_{Uber}	-1.5	-1.4	-2
f_{Uber}	3	10	3
c_{walk}	0.003	0.007	0.004
c_{Uber}	0.0001	0.004	0.0003
p_s	0.75	0.50	0.50
p_r	1	1	1
$\sigma_{\alpha_{\text{transit}}}$	0	0.5	0.5
$\sigma_{\alpha_{\text{Uber}}}$	1	2	2
ϕ	0	0	0
n_{sim}	1000	1000	1000

Notes: Each model simulates 1000 individuals with random preferences over modes, and uses distance bands from 0 to 5000 meters for probability calculations. However, all plots are restricted to 0–1200 meters from the station. Parameter definitions are discussed in Section 2.

D Empirics appendix

D.1 Event study for far distances

We adapt our empirical approach slightly to assess the validity of our control group. Because we can no longer use a farther distance band as a control, we instead use untreated observations across all stations and rely on city-by-month fixed effects to absorb secular trends. We implement the estimator of de Chaisemartin and D'Haultfœuille (2024), using a linear model with the inverse hyperbolic sine of trips (in hundreds) as the outcome.[24] The event-study specification for a given distance d^* is:

$$y_{dit} = \gamma_{c(i)t} + \delta_{di} \sum_{j \in \{-6,-5,\ldots,6\} \setminus \{-2\}} \alpha_{d^*,j} \times \mathbb{1}\{\tau_{it} = j\} \times \mathbb{1}\{d = d^*\} + \left(\beta_{1,d^*} \times \mathbb{1}\{\tau_{it} < -6\} + \beta_{2,d^*} \times \mathbb{1}\{\tau_{it} > 6\}\right) \mathbb{1}\{d = d^*\} + \epsilon_{dit}, \quad \text{where } d = d^*$$

D.2 Adjacent distance bins methodology

Total effects by distance calculation

Our main difference-in-differences estimates come from (5), given by

$$y_{dit} = \gamma_{it} + \delta_{di} + \alpha_{\tilde{d}} \times \mathbb{1}_{\tau_{it} \in \{1,\ldots,6\}} \times \mathbb{1}_{d=\tilde{d}} + \left(\beta_{1,\tilde{d}} \times \mathbb{1}_{\tau_{it} < -6} + \beta_{2,\tilde{d}} \times \mathbb{1}_{\tau_{it} > 6} + \beta_{3,\tilde{d}} \times \mathbb{1}_{\tau_{it} \in \{-2,-1,0\}}\right) \mathbb{1}_{d=\tilde{d}} + \epsilon_{dit},$$
$$\forall\, d \in \{\tilde{d}, \tilde{d}+1\}.$$

Each regression is estimated separately by $\tilde{d}$, producing an array of expansion effects at varying distances relative to the next distance band $\tilde{d}+1$. The α_d can be estimated jointly by stacking all such distance pairs p, where $p \in \{100, \ldots., 1100\}$ refers to the "treated" distance in each pair. In the new data set, distance bands 0–100 m and 1100–1200 m will appear once, while all others will appear twice (once in the control group and once in the treatment group). The specification can then be written as follows.

$$y_{dipt} = \gamma_{ipt} + \delta_{dip} + \sum_{\tilde{d}} \alpha_{\tilde{d}} \times \mathbb{1}_{\tau_{it} \in \{1,\ldots,6\}} \times \mathbb{1}_{d=\tilde{d}} \times \mathbb{1}_{p=\tilde{d}} + \sum_{\tilde{d}} \left(\beta_{1,\tilde{d}p} \times \mathbb{1}_{\tau_{it} < -6} + \beta_{2,\tilde{d}p} \times \mathbb{1}_{\tau_{it} > 6} + \beta_{3,\tilde{d}p} \times \mathbb{1}_{\tau_{it} \in \{-2,-1,0\}}\right) \mathbb{1}_{d=\tilde{d}} \times \mathbb{1}_{p=\tilde{d}} + \epsilon_{dipt}$$

As before, the α estimate the effect at one distance relative to another. In order to estimate the total effect of an expansion on Uber trips at a given distance, we sum all estimates from farther

[24] Log or IHS transformations are not scale-invariant (Chen and Roth, 2023); we normalize trips by 100 so that estimated effects at 0–100 m align with our PPML estimates.

distances. To implement this, we simplify the above regression as follows.

$$y_{dipt} = \gamma_{ipt} + \delta_{dip} + \sum_{\tilde{d}} \alpha^*_{\tilde{d}} \times \mathbb{1}_{\tau_{it} \in \{1,\ldots,6\}} \times \mathbb{1}_{d=\tilde{d}}$$
$$+ \sum_{\tilde{d}} \left(\beta_{1,\tilde{d}} \times \mathbb{1}_{\tau_{it} < -6} + \beta_{2,\tilde{d}} \times \mathbb{1}_{\tau_{it} > 6} + \beta_{3,\tilde{d}} \times \mathbb{1}_{\tau_{it} \in \{-2,-1,0\}} \right) \mathbb{1}_{d=\tilde{d}} + \epsilon_{dipt}$$

We no longer estimate the α's by comparisons within distance-pairs. By not fully-saturating on pairs p, we allow the treatment effect from one distance to pass through into the next, closer distance. Numerically, $\alpha^*_{\tilde{d}} = \sum_{d \geq \tilde{d}} \alpha_d$. Additionally, the regression implementation of summing the coefficients correctly calculates standard errors. The average effect for 1-6 months after the transit opening are reported in Figure A11.

E Model estimation and counterfactuals appendix

This appendix provides technical details on the implementation of the GMM estimation procedure described in Section 6.

Simulation procedure

The model includes permanent unobserved preference heterogeneity for transit and Uber (η_{transit} and η_{Uber}), drawn from a joint normal distribution with mean zero and variance-covariance matrix:

$$\Sigma_\eta = \begin{pmatrix} \sigma^2_{\text{Uber}} & \phi\, \sigma_{\text{Uber}}\sigma_{\text{transit}} \\ \phi\, \sigma_{\text{Uber}}\sigma_{\text{transit}} & \sigma^2_{\text{transit}} \end{pmatrix} \tag{21}$$

These preference shocks affect utility for outbound (Period 1) and return (Period 3) trips but not intermediate (Period 2) trips.

To simulate the model, we draw $N_{\text{sim}} = 1000$ realizations of base shocks $\tilde{\eta} = (\tilde{\eta}_{\text{Uber}}, \tilde{\eta}_{\text{transit}})' \sim \mathcal{N}(0, I)$ once and hold them fixed across all parameter evaluations. For a given parameter vector θ, we recover correlated preference shocks via the Cholesky decomposition of Σ_η. Specifically, let $L(\theta)$ denote the lower-triangular Cholesky factor such that $L(\theta)L(\theta)' = \Sigma_\eta(\theta)$. The simulated preference shocks are then:

$$\begin{pmatrix} \eta_{\text{Uber}} \\ \eta_{\text{transit}} \end{pmatrix} = L(\theta) \begin{pmatrix} \tilde{\eta}_{\text{Uber}} \\ \tilde{\eta}_{\text{transit}} \end{pmatrix} \tag{22}$$

This common random numbers approach ensures that the same underlying draws are used across all parameter evaluations, with only the scale and correlation parameters changing as θ varies (Train, 2009). As a result, the simulated objective function is smooth in θ, which improves the numerical stability of the optimization. For each simulated individual, we compute optimal mode choices via backward induction as described in Appendix C.

Spatial assignment of last-mile trips

Quadrant I moments capture Uber trips observed near the station, which include both direct trips by nearby residents and last-mile trips from residents throughout the catchment area. Last-mile trips originate at the traveler's home but terminate near the station. We model the spatial distribution of these trip endpoints using an exponential density with rate parameter λ.

Formally, let $T^{\text{direct}}(d)$ denote Uber trips by residents at distance d, and $T^{\text{last-mile}}(\delta)$ denote last-mile trips by residents at distance δ. The observed Uber usage at distance d is:

$$T^{\text{observed}}(d) = T^{\text{direct}}(d) + \int_0^{D_{\max}} T^{\text{last-mile}}(\delta) \cdot \rho(d)\, \mathrm{d}\delta \tag{23}$$

where $\rho(d) = \frac{\lambda e^{-\lambda d}}{1 - e^{-\lambda D_{\max}}}$ is the exponential density giving the probability a last-mile trip terminates at distance d from the station, normalized over $[0, D_{\max}]$ with $D_{\max} = 5000$ m. We discretize this

integral using 100 m distance bins, weighting last-mile trips from each origin distance bin by annulus area to account for radial population density.

Population density and price heterogeneity

We model the residential population around each station as exponentially declining with distance: $\exp(-\kappa \cdot d)$, where κ is the population density gradient (per km) estimated within a 5 km radius. We calibrate κ using the ratio of Uber trips per square kilometer at 1000–1100 m to trips at 1100–1200 m prior to opening, which equals 1.08. This separates κ from c_{Uber}, which would otherwise have similar effects on the pattern of first- and last-mile trips.

To convert utility estimates to willingness-to-pay, we calibrate the marginal utility of income ρ using a demand elasticity of $\varepsilon^D = -0.6$ (Cohen et al., 2016, Castillo, 2025). The expression for ρ implied by the model is given in Proposition 4. Average prices vary widely across our sample: the 10th percentile city by average fare is Novosibirsk at \$2.84 per trip, while the 90th percentile is Stockholm at \$21.80. The mean fare of \$7.84 is similar to prices in Rio de Janeiro and Panama City. While using a single price masks this heterogeneity, it allows us to assign a dollar value for the average context in our setting.

Estimation and standard errors

We minimize the GMM objective using L-BFGS-B with box constraints on parameters:

$$\hat{\theta} = \arg\min_{\theta} \; [m^{\text{data}} - m(\theta)]' W [m^{\text{data}} - m(\theta)] + \mu [n^{\text{calibrated}} - n(\theta)]' [n^{\text{calibrated}} - n(\theta)]$$

where W is the identity matrix and $\mu = 1$. Initial values are set based on the simulations in Section 2. We estimate $\log \lambda$ to ensure positivity and apply the delta method to report standard errors in natural units.

Standard errors are computed using the standard one-step GMM formula:

$$\text{Var}(\hat{\theta}) = \frac{1}{N} (G'WG)^{-1} G'W\Sigma WG (G'WG)^{-1} \tag{24}$$

where $N = 650$ station openings, G is the Jacobian of moments with respect to parameters computed via numerical differentiation, and Σ is the variance-covariance matrix of empirical moments from the first-stage PPML regressions.