Public and Private Transit: Evidence from Lagos

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Private minibuses dominate transport in many developing country cities. They serve 62% of trips in Lagos, the largest city in sub-Saharan Africa. We collect panel data to measure how private minibuses respond to the rollout of a new public bus network. When the government enters a route, minibuses depart less frequently, driver profits fall, and drivers switch to connected routes, reducing prices. We develop a custom app to estimate how commuters trade off prices and wait times in an RCT. The private response harms commuters on treated routes, who wait longer, but benefits those on connected routes, who face only lower prices. Overall, 10% of the commuter welfare gains of building the public transit system arise from the response of private transit. Drivers lose welfare equal to half of the commuter gains.

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1. Introduction

Developing country cities are growing rapidly, and their governments are making large investments in mass public transit systems.[1] But in these contexts, transit services are already provided by the private sector—typically by a decentralized network of private minibuses. Standard approaches to evaluating the impacts of public transit infrastructure consider public transit in isolation, such as time it saves (Small and Verhoef 2007) or how it changes accessibility (Tsivanidis 2023; Zárate 2024). But public systems are unlikely to completely displace private systems anytime soon, given the scale of these cities and the cost of building infrastructure.[2] Public entry is thus likely to have important indirect impacts; for example, it may crowd out the supply of private transit, leading to longer wait times for travelers, or intensify competition, driving down private prices.

We consider this interaction in sub-Saharan Africa's largest city, Lagos. Before our study period, most of Lagos's 22 million residents relied on private minibuses, known as danfo, for transportation. In the late 2010s, as part of a modernization plan, the government launched the Bus Reform Initiative (BRI) to establish a new public bus network. The system overall opened 64 new routes served by 820 buses that were larger and more modern than the incumbent minibuses.[3] The policy aimed to provide higher-quality service, attract potential car users, and integrate with future rail services as part of a long-term intermodal transportation network.

This paper examines the private sector response to public entry, and its implications for commuters and minibus drivers in four steps. First, we collect new data during the staggered rollout of 13 of the new public transit routes that opened during our sample period. Second, we estimate how this public entry affected prices and departure frequencies in the private market. Third, we estimate how these changes are valued through a field experiment measuring how commuters value time. And finally, we quantify the distributional impacts of public entry using a sufficient statistics approach based on a queuing model of private transit.

Our first step confronts the fact that there is little data with which to estimate the impacts of infrastructure investments in low income cities. In our setting, the public transit system can be measured by smartcard swipes when each commuter boards a bus. However, no up-to-date data on the private minibus market existed prior to the study. The government lacked even an accurate map of routes, let alone information on market characteristics over time. We therefore conduct a large-scale data collection effort. We hired enumerators to document the locations of minibus routes by discovering and riding 759 routes throughout the city, traveling nearly 30,000 km. We stationed enumerators at the start of 278 routes across 13 survey rounds to measure

[1] 60% of World Bank spending within cities is on transport projects (The World Bank (2025a), The World Bank (2025b)).

[2] For example, even Dar-es-Salaam's celebrated BRT system accounts for only 1.3% of trips: around 60% are still taken by private minibuses.

[3] Most routes operate on regular roadways and offer similar in-vehicle travel times to minibuses but differ in wait times, fares, and other amenities.

fares, bus queues and bus departures over a 15 month period. We capture these on treated routes (sharing both endpoints with a new public route), connected routes (sharing one endpoint), and control routes (sharing neither endpoint). We additionally conducted a panel survey of 854 minibus drivers across 5 survey rounds. Due to changes in government opening plans, we captured data on 13 of 35 routes that opened in our sample period. These reveal several facts about this underdocumented system: minibuses depart frequently (every 8 minutes on average), buses are in excess supply (91% of routes have a bus waiting in its queue, with an average of 4.8 buses waiting) and leave when full so that departures are determined by how quickly passengers arrive and load minibuses, and drivers switch routes frequently (59% of drivers change routes over a year, mostly within the same terminal).

The second step of the paper estimates how the private market responds to public entry by comparing outcomes on routes as their service status changes. When the government enters a route, minibuses departure frequencies fall by 22%, and there is suggestive evidence that prices fall, by 5-10%.[4] There is no change in congestion, which is not surprising, as the new buses use the same roads as minibuses. When a driver's route is treated, he or she makes fewer trips and earns less revenue, and is more likely to switch to other routes at the same terminal. Corroborating this, we find that the queue of minibuses waiting to fill with passengers decreases when a route is treated.

These effects on treated routes are similar regardless of which of two research designs we use. A within-terminal design compares changes as a route is treated to changes on connected routes. This uses terminal-by-survey-round fixed effects that account for differences in trends between the larger terminals where the government entered and smaller terminals without public service. A spillover design instead compares how outcomes shift when a route is treated, or receives a connection to a treated route, relative to control routes, but requires taking a stand on the form of spillovers.

These latter spillover specifications provide more color on the nature of spillovers: when a private route becomes connected to a new public route, it absorbs new minibus drivers, increasing minibus queue lengths and decreasing prices. This suggests that government entry indirectly reduces the profits of minibus drivers. We do not see corresponding spillover effects on demand. The estimated spillover effects are relatively small, which is why they do not greatly bias our within-terminal estimates, but because there are so many more connected routes, we will find they are economically important in aggregate. Our specifications assume that treatment affects only routes that share an endpoint connection; in a robustness test we show that our results are not affected by overlap along the route itself.

We assess whether these effects could be due to confounds by measuring impacts on 'placebo' routes that were planned but never opened. Following a fatal police shooting at Lekki Tollgate, groups of protesters burned a public television station and the Oyingbo public bus terminal in

[4]In our baseline within-terminal design, prices fall by about 5% (though not statistically significant), whereas in our spillover specifications, prices drop by a statistically significant 10%.

October 2020. This terminal had been slated to receive 8 new routes at the end of October and late November, which were subsequently canceled. Our empirical strategy finds no phantom effects on these routes, nor on routes whose opening was scrapped during changes in opening plans across 22 variants of the rollout plan we digitized over our sample period.

Our results suggest that some commuters have to wait longer for minibus transit, and may face lower prices. Our third step estimates how commuters value wait time and prices. Recent approaches have used digital interactions with ride-sharing platforms to measure how commuters trade-off time and price (e.g., Goldszmidt et al. 2020; Buchholz et al. 2022). However, these applications—and even the smartphones they require—are not widely used in developing countries. Data from smartphones can thus yield biased estimates of population parameters in low income settings (Milusheva, Bjorkegren, and Viotti 2021). Moreover, users endogenously select when to request a rideshare–if they request rideshare when in a hurry, approaches that do not correct for this selection will yield biased estimates of the value of time.

We instead design a custom application to measure commuter values of price and time in a randomized experiment that explicitly addresses potential selection bias from endogenous participation. Over multiple weeks, enrolled commuters arriving at their local bus stop receive random monetary offers to wait. We provide enumerators stationed at these stops during commuting hours a custom app that displays a new cryptographic code each minute. Participants check in by texting the current code, then receive both a check-in payment and a random offer to wait a specified number of minutes. To accept the offer, they wait and text the new code. To reject, they continue on their way. Participants need only a basic phone. We recruit participants at home on the weekends to aim for a representative sample, since people with high value of time are likely to ignore a recruitment request at a bus stop. Commuters are less likely to participate on days when they are rushed. We address this by modeling the two-stage decision process for each day—first, whether to participate, and second, whether to accept an offer once participating. To shift participation exogenously, we randomize the check-in payment across individuals. Users with higher check-in offers are more likely to participate but conditional on checking in are less likely to accept offers, consistent with selection based on the value of time. By tracking which offers are accepted, we obtain a selection-corrected estimate of the disutility of waiting of ₦18.94 per minute ($1.42 per hour). A naïve estimation strategy that does not account for imperfect compliance undervalues the hassle of waiting by 56%. A stated preference approach that asks participants at baseline to make hypothetical choices between transport options—a common approach in the transportation literature—overvalues the value of time by 145%.

The final step of the paper uses a model to derive sufficient statistics that combine our reduced-form estimates with structural parameters to measure changes in commuter and driver surplus throughout the network. We develop a simple queuing model of private transit. In the model, individuals arrive each period and choose among available transit modes. Drivers then select a route and join its bus queue. As passengers arrive, they fill the bus from the front of the queue; the time each driver spends in the queue—and thus their expected number of daily trips—depends on both the queue length and the passenger arrival rate. Prices and driver entry costs are set by a drivers' association that maximizes its revenue.

Using the sufficient statistics approach, we show that the private sector response matters for understanding the aggregate and distributional effects of the public transit intervention. The private response accounts for 10% of the total commuter surplus generated by public transit. However, its benefits are unevenly distributed across the network: on treated routes, the private response reduces benefits by 12% because commuters dislike the increased wait times more than they value the reduction in fares. Yet on connected routes, commuters benefit from lower prices without any change in wait times. Given the large number of commuters on connected routes, the net effect of the private response is to increase the overall benefits of the public system. Overall, the investment generates an additional $1.47 million in commuter surplus per month.

Failing to account for the private sector response also ignores the impact on drivers. We find drivers lose an average of $2.98 per day, or around 25% of baseline surplus. These losses are the same for drivers on treated and connected routes, because driver mobility equalizes expected profits. In fact, route switching among drivers drives most of these losses, which total $0.75 million per month—about half the magnitude of the commuter surplus gains.

Our results suggest that when governments enter markets dominated by private incumbents in interconnected network settings, they can have nuanced distributional effects. They suggest the world's fastest growing cities should carefully consider the interplay of public and private transit when planning transit systems.

Related Literature. A body of previous work measures the impacts of transit reforms in cities. Existing work focuses primarily on centralized public transit (Tsivanidis 2023; Kreindler et al. 2023; Almagro et al. 2024), subways (Gibbons and Machin 2005; Glaeser, Kahn, and Rappaport 2008), or roads (Baum-Snow 2007). However, much of the world's population relies on decentralized private transit. There are various case studies of these systems (Cervero and Golub 2007), but few well-identified studies. An emerging literature has begun to investigate various aspects of decentralized minibus systems. Mbonu and Eaglin (2024) analyses the impacts of fragmentation between driver's associations in Johannesburg. Kelley, Lane, and Schönholzer (2021) introduces a monitoring technology to minibus owners in Kenya and finds that it improves contracting with drivers. Conwell (2023) develops a model of matching between minibuses and commuters, measures commuters' value of waiting using stated preferences, and sets other parameters with calibrations. We contribute to this literature by measuring the response of a minibus network to the rollout of a new public network using a quasi-experiment, developing a sufficient statistics approach to measure its welfare implications using a queuing model of transit markets, and a randomized experiment to measure how commuters value price and wait time for transport options.[5]

Our paper is one of few that causally estimates commuters' value of time in a developing country setting. Recent work in this literature has used experiments to identify how travelers trade off time and money. Kreindler (2023) conducts a field experiment that measures value of time and scheduling for drivers in Bangalore. There is a large literature studying travelers value of time in wealthier settings. As discussed above, a recent literature uses experiments to measure value of time for rideshare apps in the US. Our contribution is to develop a methodology suitable for low-income settings with basic phones to measure value of time for public transport users, using an approach that accounts for endogenous participation.

The paper also relates to work on the impacts of public good provision in developing country contexts where the good or service is already provided by private firms.[6] Recent work focuses on insurance (e.g. Mobarak and Rosenzweig (2013)) and education, where public sector investments can crowd-in or crowd-out private schools in different contexts (Dinerstein, Neilson, and Otero 2020; Andrabi et al. 2023; Dinerstein and Smith 2021). We show a response by private sector incumbents to government entry in the market for a different public good—mobility—and measure the (indirect) surplus generated by this response.

2. Public Transit in Lagos

Previous to the period we study, the public transit system consistent of a single Bus Rapid Transit (BRT) route and a handful of regular routes that phased in and out of existence. As of 2009, only 5% of trips in Lagos were by government public transit (Lagos Travel Survey, described below).

As part of a modernization plan, the Lagos state government developed a Bus Reform Initiative to introduce a new public bus network. The network serves 64 routes, mapped in Figure 1A. The routes were served by 820 new buses, most of which have a capacity of 70 passengers; a smaller number have a capacity of 30. These buses offer amenities such as air conditioning. Users pay for service by tapping an electronic card on entry to the bus (a 'Cowry' card), which can be topped up at stations or online.

The Lagos Metropolitan Area Transport Authority (LAMATA) was responsible for supervising the rollout, which contracted out operations of the routes to four operators. In addition to the bus routes, new terminal infrastructure was built at major interchanges. Our study focuses on the large buses connecting these terminals on high demand axes. Most routes, and the routes we study, are standard buses without dedicated lanes (shown in solid lines in Figure 1A). Public

[5]In studying decentralized transport, we also connect with a recent strand of work studying this in contexts such as shipping and taxicab markets (Buchholz 2022; Brancaccio, Kalouptsidi, and Papageorgiou 2020; Fréchette, Lizzeri, and Salz 2019). Also related is Roberts et al. (2024), which finds that requests for motorcycle ride hailing increases in Jakarta around a recently opened mass transit line. An earlier, mostly theoretical literature considers how minibuses might interact with public transit in wealthy cities (Walters 1982; Mohring 1983; Bly and Oldfield 1986).

[6]There is a long tradition of similar work in developed countries, such as Brown and Finkelstein (2008) in health insurance.

buses travel alongside existing traffic, and as a result have similar travel times. The plan did include a handful of bus rapid transit routes with dedicated lanes (shown in dotted lines in Figure 1A). Many passengers ride buses from the origin to the final terminal: 57% of boardings are at the origin of the route.

Since 2019, a total of 64 routes have opened, with 35 launching during our sample period (late 2020 to the end of 2021). Route opening plans changed frequently due to the COVID-19 pandemic and operational challenges. This includes some shocks; for example, one terminal was burned during the EndSARS protests against police brutality in October 2020, resulting in the cancellation of 8 routes scheduled to open that month. Consequently, we collected data on only 13 routes that eventually opened, since we finalized our sample in September 2020.

The bus expansion we study was followed by two other expansions. One was a series of 'First and Last Mile' routes connecting terminals to nearby neighborhoods, operated by smaller 7-seater vehicles (some via narrow and muddy roads). A second was two rail lines connecting Lagos Island to the west and north. The rail lines and most of the smaller routes opened after our period of study.[7]

2.1. Data

We rely on two data sources to measure the public network.

Electronic Ticketing. We observe every tap in to the system with the associated fare, timestamp, and origin (though not destination). From this data we derive passenger volumes.

Opening Plans. To track the changes in public rollout plans, we collected a sequence of 22 route opening plans from LAMATA at regular dates between March 2020 and December 2021.

3. Private Transit in Lagos

Like many other fast growing cities, the backdrop of transportation in Lagos is dominated by private minibuses, which are locally called danfo (similar to matatus, or dala dalas). In 2009, 62% of motorized trips were via private minibus, as reported by the Lagos Travel Survey.

The minibus network is organized around major terminals (motorparks), a subset of which are near public terminals. Although public buses run on existing routes, they serve different stops—with public and private stops for the same origin or destination averaging 180m apart.[8]

Most drivers begin a journey by queueing at a terminal, to depart along a particular route. Once the vehicles in the front of the queue have departed and a driver's vehicle is next in line, it

[7] The rail lines opened September 2023 and September 2024, respectively.

[8] This is computed for 36 pairs of public and private stops, for which we were able to locate both stops on Google Earth.

may load passengers until full, at which point it may depart. The most common size of minibus holds 14 passengers, although this can range from 7 to 22 passengers.[9]

The system tends to operate from terminal to terminal, and does not provide great service at intermediate stops. Minibuses tend to leave their origin terminals full, so passengers may not be able to board at intermediate stops.[10]

The industry is overseen by bus drivers' associations, also known as unions. The National Union of Road Transport Workers (NURTW) controls most terminals in Lagos; some are also controlled by the Road Transport Employers' Association of Nigeria (RTEAN).[11] The government grants these associations the authority to regulate the industry by setting fares and collecting fees, ostensibly in exchange for organizing the sector, managing shared infrastructure, and enforcing rules (CPCS 2024). In practice, however, these groups have evolved into complex entities characterized by revenue extraction, political patronage, and street-level authority. A small share of union revenue is remitted to the government, while most flows upward through the association hierarchy.[12] Drivers often perceive these fees as exploitative—often forced under threat of violence—even though the unions are nominally established to protect their interests. Indeed, over 70% of drivers view association dues as extortion, and critics argue that the NURTW functions more as a "street bureaucracy" and a grassroots mobilization tool for political elites than as a representative body for drivers (Fourchard 2023). Notable figures like MC Oluomo and current president Bola Tinubu have been reported to use links with the associations for political patronage and voter mobilization (Republic 2023). At bus stops outside terminals there is less oversight, and drivers have more leeway on setting prices in response to factors such as demand or weather.

3.1. Data

There are few existing statistics on this incumbent minibus network. Our main task is to collect data to better understand Lagos' private transit network—and how it responds to the expansion in public transit.

Network Map. We commissioned a network mapping, which aimed to identify and georeference every usual private transit route in the Lagos Metropolitan area. It was conducted by a specialized firm, WhereIsMyTransport, during the winter of 2022 by sending enumerators

[9]For simplicity we refer to all private shared transit vehicles as minibuses, including larger size buses (locally called molue) and smaller size vehicles (locally called korope).

[10]Data collected during our network mapping suggest 92% of passengers along minibus routes board at the origin terminal.

[11]The Lagos chapters have recently been renamed to Lagos State Parks and Garages Management and Lagos State Park and Garage Administration, respectively.

[12]In 2021, the NURTW was estimated to collect N123 billion annually in Lagos, yet local governments receive only around N200 per park each day (ICIR Nigeria 2021).

to identify and ride minibus routes while using a GPS tracker.[13] A total of 759 routes, and almost 30,000 km, were mapped. These represent a dense, comprehensive network spanning the metropolitan area; we plot the routes discovered in Figure 1B.

Bus Stop Observations. We hired observers to count bus departures and passengers throughout the network as the public system was rolled out, from October 2020 until December 2021. Our team collected 13 rounds of data, spaced approximately every month. At terminals, enumerators collected data on departures, fares, and driver queues in half-hourly windows during morning peak, midday offpeak, and afternoon peak times.[14] Terminal observations covered 278 routes. We also collected similar data at 79 bus stops (where our enumerators could not identify the exact route, since it is not always displayed on vehicles).

We focused data collection on routes that constituted part of the government's long term bus network plan. Around 85% of routes were selected from the Lagos State Government's planned future bus system. The remaining 15% were adjacent routes which our team was able to collect data on while standing from a single position in a terminal.

We classify our sampled routes into three categories: *treated* routes that share both endpoints with a public bus route that opened within our observation period, *connected* routes that share one endpoint, and *control* routes that share neither endpoint.[15] Among our 278 routes, 13 are treated (representing 37% of all 35 routes receiving public transit during this period). However, some of the untreated routes had originally been planned for opening during our period: 55 of our sampled routes appeared in any deployment plans for 2020-2021, and 41 appeared in the March 2020 deployment plan closest to opening.[16]

Figure 1C maps sampled routes according to these categories.[17] Figure 2 shows the timing of public route openings on our sampled routes, and the dates of our bus stop observations. Routes that are not connected at endpoints may partially overlap on roads, but it tends to be difficult to transfer at intermediate stops.

[13]For this mapping, a commuter route was defined as a route used by passengers to travel between home and work on a daily basis, whereby a passenger can travel the full length of the route from origin to destination and back within one day, with multiple trips available per day.

[14]Corresponding to 7-9 a.m., 1-2 p.m., and 4-6 p.m., respectively. Queue lengths and fare were recorded as of the start of the observation window; departures were measured cumulatively over the window.

[15]We consider routes as opened if they served passengers for at least 3 months. While we only collect data on a subset of treated routes, we use the full set of opened public routes to measure private routes' public transit connections.

[16]We had planned to begin data collection in February 2020, which was delayed due to the COVID-19 pandemic. Analysis of Google mobility data (Figure S3) showed that travel patterns reverted to January 2020 levels by late July 2020, prompting the collection of baseline data in October 2020.

[17]For the 83% of sampled routes that we could match to our GIS data.

FIGURE 1. Transit in Lagos

A. New Public Transit Network

exhibits/maps/all_public2.pdf

B. Private Transit Network

exhibits/maps/all_private2.pdf

C. Sampled Private Transit Routes

exhibits/maps/tsc4.pdf

Note: The first panel shows the new public transit routes. Bus rapid transit (BRT) routes are shown with a dotted line. The second panel shows the existing private transit routes, as discovered in our network mapping exercise. The final panel shows the private transit routes we monitored for our study, including routes treated by public transit, connected routes that share an endpoint with a public transit terminal, and control routes that do not share an endpoint with public transit terminals. This final panel plots the 83% of sampled routes that we were able to match to the GIS database of routes. Base layer color shows population density.

FIGURE 2. Sampled Routes Served by Public Transit and Bus Stop Observations

exhibits/supplyside/fig/desc/RouteOpenings-eps-converted-to.pdf

Note: Plots the number of routes served by public transit in our monitored sample. The timing of our bus stop observations are shaded as vertical boxes.

Driver Surveys. We conducted a panel survey of 854 minibus drivers, starting with a baseline survey and following up in four subsequent rounds. Drivers were sampled while waiting in queues at terminals, and outside terminals, on treated, connected, and control routes. The baseline survey was administered during recruitment, and drivers were asked for permission to participate in follow-up surveys by phone. This sampling method is less likely to capture drivers who often skip terminals (drive sole). We correct for this by asking the drivers who we survey what fraction of the time they skip terminals, and use that to reweight the sample, as described in Appendix S1.1. The reweighted sample includes 849 drivers, as 5 drivers (recruited near terminals) had not worked in the past seven days and could not provide the information needed to construct these weights.

Wait Time Experiment. We additionally ran an experiment on sensitivity to wait time for minibus commuters which included its own data collection. It included a baseline survey at the time of onboarding, daily interaction with an enumerator recorded via an app at bus stops, and an endline survey. This data is described in more detail in Section 6.2.

Other Sources. We also use the Lagos Travel Survey—a representative 2009 survey of 12,274 individuals commissioned by LAMATA—and a dataset of live travel times collected from Google Maps multiple times per day throughout the study period.

3.2. Features of Private Transit in Lagos

Here we use our data to document several features of private transit in Lagos. We draw from baseline driver statistics presented in Appendix Table S2, and additional statistics generated from our baseline observation data.

Incentives to Adjust. Most drivers are residual claimants on fare payments they collect. On the last day worked, the average net income was ₦5,140, net of fuel, payments to conductors, fees paid at terminals, and any side payments. Fuel is a substantial expense: ₦3,766 on average in the last day worked. 31% of drivers hired a conductor to collect fares and help passengers board, paid an average of ₦2,531.

Margins of Adjustment. Drivers can change routes: 85% of drivers report that they choose the routes they operate. However, switching terminals is costly: drivers must pay the association a one time ₦15,494 on average to register to pick up passengers at a terminal. After paying that, drivers pay an average of ₦691 per day in additional fees to the association. 87% of drivers drive a single route, resulting in an average number of routes per driver close to one. As we discuss in Section 5.2.3, route switching is fairly frequent: 59% of drivers change routes over the year we monitor, with 86% of these changes coming within the same terminal.

It may be challenging for drivers to switch industries. The average driver surveyed has driven minibuses in Lagos for 12.7 years. Some have sunk investments: 51% of drivers own their buses; the remainder either rent or pay for their vehicle on installments (rent to own). Only 60% of drivers have completed secondary education.

Excess Supply. In 91% of our terminal route observations, there was a minibus waiting for passengers to load, and on average, 4.75 buses were waiting in queue. And in the baseline driver survey, drivers report that 42% of working time is spent waiting in queues. That buses are queuing for passengers is suggestive of excess entry. It also suggests that minibus departure frequencies will mostly be determined by passenger arrival rates, and will tend to not be affected by marginal changes in supply of minibuses, since almost buses (96%) wait until they are full before departing.

Some drivers skip terminals and the queue to start driving along a route with an empty bus (locally this is called driving 'sole'); our survey suggests this constitutes a minority (21%) of driver trips.

Challenging Job. Drivers complete 9.2 trips per day on average. Minibuses frequently break down, with 92% of drivers reporting a repair in the last month. Also in the last month, 83% of drivers report paying a fine, commonly for being caught driving without proof of paying the terminal fee (sole), or parking/picking up/dropping off in an inappropriate location. The work entails conflict: 48% of drivers report having disputes with passengers weekly, and 37% report having disputes with other drivers weekly, reported in Appendix Table S7.

Limited Expectations About Rollout. As of 2020, only 57% of drivers had heard about the public transit rollout. Of those, 79% correctly predicted whether it would open on their route (omitting those whose main route had already seen the introduction of public transit by the time of the survey), although none correctly predicted the month of entry. 36% expected public transit would reduce their passengers. See Appendix Table S8.

3.3. Comparison of Public and Private Service

We next compare public and private transit service. Table 1 compares characteristics of public transit to private transit, before and after entry of public transit. We restrict the sample to routes on which public transit entered. Statistics are reported for journeys beginning at a terminal.

Private Transit is More Frequent. The first pair of rows of Table 1 shows departure frequencies. Private minibuses had frequent departures: before public entry, 3.8-4.5 minibuses passed per half hour on average, and this declined slightly to 3.7-3.8 after entry. In contrast, we estimate that after entry only 0.2-0.6 public buses passed per hour.[18] Overall, the public buses constituted 6-14% of all departures. Because the two services serve different stops, commuters must decide which type of bus to wait for–it would be difficult to monitor arrivals and hop on the first departing bus.

Minibuses Fill Before Departing Terminals. The second pair of rows of Table 1 compares passenger counts. Minibuses tend to fill up to near capacity before departure: 96% of minibuses leave when full (most buses have 14 seats). In contrast, the public buses were not always full to capacity, especially during the midday offpeak times.

Public and Private Fares are Similar. The next pair of rows of Table 1 compares fares for traversing from the origin terminal to the route's endpoint. On private buses, the fare is lower if you get off at an earlier stop. For most public routes the fare is flat regardless of distance; only a handful of public routes have distance based fares. Fares are the same on both systems during peak periods, while public fares are slightly lower during off peak (₦212 vs ₦224). Fares across the entire system rose over time in line with inflation in the country; we report the average fare across all measured private transit routes in the final row which shows this overall trend. Because of the difference in fare structure, minibus transit tends to be relatively more attractive

[18] Commuters seldom queue to board the minibus system; however, during the morning peak there may be queues to board public buses.

for shorter trips. Transfers are fairly common. However, there is no discount for transferring: on both systems, one must pay the independent fare on each leg.

TABLE 1. Private vs. Public Service on the Same Route

	Before Public Entry		After Public Entry	
	Private Transit	Public Transit	Private Transit	Public Transit
Departures per 30 min				
Peak	4.47	-	3.78	0.62
	(2.46)		(2.70)	(0.33)
Off peak	3.79	-	3.66	0.23
	(1.93)		(2.35)	(0.19)
Passengers at Departure				
Peak	13.63	-	12.94	25.66
	(4.44)		(5.61)	(6.02)
Off peak	13.88	-	13.60	10.40
	(4.74)		(6.03)	(5.33)
Fare (₦)				
Peak	202.13	-	223.50	223.45
	(74.92)		(90.57)	(110.40)
Off peak	199.47	-	223.96	211.95
	(60.07)		(72.86)	(116.75)
Average fare across all routes (₦)	284.69	-	300.78	

Notes: Table reports means across routes for a given time of day for routes that are eventually served by public transit. We separately report means before and after public transit commences on the route. Standard deviations reported in parentheses. Computed for the 9 (of 13) treated private transit routes in our sample that can be matched to public transit e-ticketing data. Peak hours are defined as 7-9 a.m. and 4-6 p.m., and off-peak 1-2 p.m. Passengers counted upon departure from the origin terminal; additional passengers may board at later stops. For private transit we compute the route average over all our terminal observations before public transit began on that route, and after. For public transit, we compute the route average from e-ticketing data, using only the time periods and months that coincide with our private transit route observations. We then compute the average across routes, weighting routes based on the average volume of private transit passengers prior to rollout. For public transit, a bus departure is defined using the last swipe at a route endpoint, which is not followed by another swipe at the same endpoint within 30 minutes. Passenger counts are aggregated at each departure, calculated as the total swipes for the same bus, route, and endpoint up to and including the last swipe.

4. A Model of Hybrid Transit Markets

This section develops a model of transit markets. Its aim is to characterize how commuters and incumbent minibus drivers are affected by government entry, and deliver a set of sufficient statistics to measure the impacts on their surplus. The key addition relative to models of decentralized transport (Brancaccio et al. 2023; Conwell 2023) is a model of queuing and route choice of shared transit providers. Full details are provided in Online Appendix S3.1.

Time is discrete and the horizon is infinite. There are I locations, $i \in \{1, \ldots, I\}$. A pair of locations ij is called a route.

4.1. Commuters

Each period, new commuters arrive at i intending to travel to j according to a Poisson process with arrival rate μ_{ij}. Commuters select a mode $m \in \mathcal{M}$ to travel the route, and exit the model upon arrival at the destination. Prior to government entry, $\mathcal{M} = \{M, 0\}$ includes minibus (M) and an outside option (0) capturing other modes such as walking or automobile. When the government enters, treated routes face the additional option of public buses (P; $m \in \mathcal{M}' = \{M, P, 0\}$).[19]

The utility of commuter n traveling from i to j using mode m is given by

$$u_{ijmn} = u_{ijm} + \epsilon_{ijmn} \tag{1}$$

where ϵ_{ijmn} is a preference shock idiosyncratic to commuter n distributed type 1 extreme value with scale parameter $1/\theta$. The fraction of commuters who choose mode m is therefore

$$s_{ijm} = \frac{\exp\left(\theta u_{ijm}\right)}{\sum_{m' \in \mathcal{M}} \exp\left(\theta u_{ijm'}\right)}. \tag{2}$$

Average utility of travelers on route ij is

$$\bar{U}_{ij} = \frac{1}{\theta} \ln\left(\sum_{m' \in \mathcal{M}} \exp\left(\theta u_{ijm'}\right)\right). \tag{3}$$

We are agnostic about the utility provided by public buses u_{ijP}, and normalize the mean utility of the outside option $u_{ij0} = 0$. To account for the changing utility provided by minibuses, we explicitly model the dynamic process of waiting and traveling in Online Appendix S3.1.1. This yields utility

$$u_{ijM} = \alpha_M - \gamma p_{ijM} - \eta t_{ijM} \tag{4}$$

where α_M is an amenity (such as comfort or safety) and p_{ijM} is the fare. Travel time t_{ijM} in minutes is the sum of the waiting time $\bar{t}^W_{ijM}$ and in-vehicle travel time t^T_{ij}. While wait times are equilibrium objects, we take travel times as exogenous for all modes since road speeds were unaffected by government entry (see Section 5.2.1). In this setup, γ and η represent the price and time sensitivity conditional on mode choice; $\theta\gamma$ and $\theta\eta$ represent the sensitivity when mode

[19] The primary other options are walking and cars with 9% and 12% of trips in the 2009 travel survey respectively. We collapse these and the handful of other modes into the outside option since the payoffs to these are unlikely to be affected by the reform: in Section 5.2.1 we show no effect on road speeds (which would affect payoffs for drivers). Formally the set of modes varies by route, yet we abstract from this to economize on notation.

choice is allowed for.

4.2. Supply

Minibus Drivers. Each period, B_i drivers enter terminal i. After entry, each chooses a route ij to ply and joins that route's queue. Minibuses in the queue fill on a first-in-first-out basis: passengers load into the bus at the top of the queue. Once full with $\bar{n}$ passengers, buses travel to the destination, and probabilistically either return to queue ij, or exit the model.[20] Each commuter pays a fare of p_{ijM}, which drivers take as given, and the bus incurs a travel cost of c_{ij}.

Drivers have idiosyncratic productivities on different routes. If driver φ enters route ij, they obtains expected profit $\nu_{ij\varphi} \cdot V_{ij}^Q$, where $\nu_{ij\varphi}$ is a shock distributed Fréchet with shape parameter σ and V_{ij}^Q is the expected common value. The dynamic model suggests this common value is the expected number of trips times the profit per trip,

$$V_{ij}^Q = \underbrace{\frac{T}{t_{ij}^Q + t_{ij}^T}}_{N_{ij}^{\text{Trips}}} \times \underbrace{\left[p_{ijM}\bar{n} - c_{ij}\right]}_{\pi_{ij}}. \tag{5}$$

where t_{ij}^Q is minutes spent in queue, and T is the minutes in the day. Queue times are the key margin through which drivers steal business from each other: the more drivers enter a route, the longer each will have to queue, lowering the number of trips each driver can complete and their resulting profits.

The proportion of drivers at terminal i choosing route ij is

$$\rho_{ij} = \frac{\left(V_{ij}^Q\right)^\sigma}{\sum_k \left(V_{ik}^Q\right)^\sigma} = \frac{\left(N_{ij}^{\text{Trips}} \times \left[p_{ijM}\bar{n} - c_{ij}\right]\right)^\sigma}{\sum_k \left(N_{ik}^{\text{Trips}} \times \left[p_{ikM}\bar{n} - c_{ik}\right]\right)^\sigma}. \tag{6}$$

Properties of the Fréchet distribution imply that average profits of each driver at terminal i are equalized across routes, and given by

$$\Pi_i = \underbrace{\Gamma\left(\frac{\sigma - 1}{\sigma}\right)\left[\sum_k \left(N_{ik}^{\text{Trips}} \times \left[p_{ikM}\bar{n} - c_{ik}\right]\right)^\sigma\right]^{1/\sigma}}_{\Pi_i^V} - F_i \tag{7}$$

where Π_i^V are average variable profits, $\Gamma(\cdot)$ is the gamma function, and F_i is the registration fee charged by the association. We assume that the number of entrants, B_i, is determined by free entry to capture a long-run equilibrium; however, the model can also accommodate a fixed number of entrants (see below).

[20] We abstract from the return leg of trips. We assume drivers make the route choice decision only at entry since 87% of drivers drive from an origin to a destination and back again in our driver survey.

Minibus Association. The minibus association chooses the price p_{ijM} on each route and registration fee F_i at each terminal to maximize aggregate variable driver profits, $B_i \Pi_i^V$, which the association is able to capture through registration fees.

Public Buses. Public buses charge a price p_{ijP} which is taken to be exogenous. But in contrast to minibuses, public buses leave on an exogenous schedule regardless of passenger arrivals.

4.3. Minibus Equilibrium and the Effects of Public Entry

An equilibrium reconciles the choices of commuters, drivers, and the association, and implies steady state conditions on queues and waiting times. Government entry affects equilibrium by lowering the market share of minibuses, s_{ijM}. Here we summarize equilibrium waits and queues, and discuss how outcomes change when s_{ijM} declines.[21] Because minibuses pool passengers and depart dynamically rather than on a fixed schedule, departures (and wait times) depend on the arrival rates of both buses and passengers.

Commuter Wait Times. With probability $\beta_{ij} = \frac{\lambda_{ij}\bar{n}}{s_{ijM}\mu_{ij}}$ there is a bus on the queue when a commuter arrives. This is increasing in the arrival rate of buses λ_{ij} into the queue and decreasing in the arrival rate of minibus passengers $s_{ijM}\mu_{ij}$, as this increases the rate of departures from the queue.

Commuters face expected wait times of

$$\bar{t}_{ij}^{W} = \beta_{ij} \underbrace{\frac{1}{s_{ijM}\mu_{ij}} \left(\frac{\bar{n}}{2} - 1\right)}_{t_{ij}^{F}} + (1 - \beta_{ij}) \underbrace{\frac{1}{\lambda_{ij}}}_{t_{ij}^{W}}$$

If there is a bus waiting on the queue, the commuter waits the $t_{ijM}^F = \frac{1}{s_{ijM}\mu_{ij}} \left(\frac{\bar{n}}{2} - 1\right)$ minutes it takes for the bus to fill with the remaining $\frac{\bar{n}}{2} - 1$ passengers (each bus is half full in expectation). If there is no bus on the queue the passenger expects waits $t_{ijm}^W = 1/\lambda_{ij}$ for the next one to arrive.[22]

When the minibus market share s_{ijM} declines, waiting buses take longer to fill as passengers arrive more slowly. The impact on expected commuter wait times is ambiguous in general. However, in our baseline data, minibuses were waiting in the queue in 96% of treated route observations. In the limit where there is always a bus waiting ($\beta_{ij} \to 1$), commuter wait times

[21] Precise comparative statics are not possible given the many interactions in the model. Appendix Section S3.2.7 presents the large system of equations that must be solved simultaneously to assess the impact of reduced minibus demand caused by the new public option. Rather than offering clear qualitative predictions, the objective of the model is to deliver a quantitative framework for welfare analysis.

[22] In steady state, there will be at least $\bar{n}$ passengers waiting by the time this bus arrives, so it will immediately fill and depart.

increase, because they do not depend on bus arrival times: commuters wait only for other commuters to fill the bus so it can depart.

Minibus Queue Times and Route Choices. When entering a queue with N_{ij}^Q buses, a driver will wait for all buses ahead of them plus the bus itself to depart:

$$t_{ij}^Q = \frac{\bar{n}}{s_{ijM}\mu_{ij}}\left(\frac{1}{\frac{\mu_{ij}s_{ijM}}{\lambda_{ij}\bar{n}} - 1} + 1\right) = \frac{\bar{n}}{s_{ijM}\mu_{ij}}(N_{ij}^Q + 1) \tag{8}$$

When the minibus market share falls, buses take longer to fill. However, some drivers may cease to serve the route, reducing the number of buses in the queue in equilibrium, N_{ij}^Q. If the former effect dominates, queue times will rise and we would expect to see drivers on the route making fewer trips in a day.

If minibus queue times rise on routes the government enters, then fewer trips per day reduce the profitability of the route. According to the route choice probabilities in (6), drivers will switch away from route ij, decreasing ρ_{ij} and increasing ρ_{ik} for connected routes. This shift increases the number of drivers on connected routes ik, which, in turn, reduces the number of daily trips per driver on those routes due to longer queue times.

Minibus Fares. When associations set prices, they trade off that higher prices raise driver profits but also depress demand. This leads to an optimal markup

$$p_{ijM} - c_{ij}/\bar{n} = \frac{1}{\frac{t_{ij}^Q}{t_{ij}^Q + t_{ij}^T}\left(\frac{B_{ij}}{B_i}\right)^{-1/\sigma}\underbrace{\left[\left|\frac{\partial \ln s_{ijM}}{\partial p_{ij}}\right| + \frac{N_{ij}^Q}{1+N_{ij}^Q}\frac{\partial \ln N_{ij}^Q}{\partial p_{ij}}\right]}_{\frac{\partial \ln t_{ij}^Q}{\partial p_{ij}}}}. \tag{9}$$

The cost of higher prices to drivers is longer queue times. As shown in equation (8), queue times are influenced directly by demand (the first term in $\partial \ln t_{ij}^Q/\partial p_{ij}$) and indirectly through equilibrium effects on queue length (the second term). As the share of minibus users decreases, demand becomes more (semi-)elastic through $|\partial \ln s_{ijM}/\partial p_{ij}| = \gamma(1 - s_{ijM})$, due to the greater variety of options available to commuters. While there is no parameter restriction that determines the overall sign of the queue time semi-elasticity, if the direct effect dominates, minibus prices would decline on routes where the public system enters. The association also internalizes that changing prices affects the average productivity of drivers through the selection term $(B_{ij}/B_i)^{-1/\sigma}$. This price setting equation holds under both free and fixed entry.

4.4. Changes in Surplus from New Government Transit

The model provides a set of sufficient statistics that easily map empirical elasticities into changes in commuter and minibus driver surplus. We also show in Online Appendix S3.2.7 how the model can be use to conduct counterfactual analysis in general equilibrium.

Change in Consumer Surplus. Entry of public bus mode P on route ij that expands the set of transit modes to $\mathcal{M}' = \{M, P, 0\}$ changes consumer surplus by

$$\Delta CS_{ij} = \frac{\mu_{ij}}{\gamma\theta} \ln\left(\frac{1}{1 - s'_{ijP}}\right) + \frac{\mu_{ij}}{\gamma\theta} \ln\left(s_{ij0} + s_{ijM} \exp\left(-\theta\eta\Delta t_{ijM} - \theta\gamma\Delta p_{ijM}\right)\right), \tag{10}$$

The first line represents the direct change from accessing a new mode of transport, based on its market share of trips in the post-entry period (as in love-of-variety models; Feenstra 1994). The second line accounts for the fact that those who continue to use the private mode are indirectly affected if its attributes change (trip times and prices). Both are scaled by the elasticity θ that controls how easily commuters substitute between alternative modes.[23] The total change in consumer surplus $\Delta CS = \sum_{ij} \Delta CS_{ij}$ simply aggregates this across routes.

Change in Producer Surplus. Defining $\hat{x} \equiv x'/x$ as the relative change in a variable between pre- and post-government entry equilibria, the change in variable profits is

$$\hat{\Pi}_i^V = \left[\sum_j \rho_{ij} \left(\hat{N}_{ij}^{\text{Trips}}\right)^{\sigma} \left[\hat{p}_{ijM}\pi_{ij}^{rev} + 1 - \pi_{ij}^{rev}\right]^{\sigma}\right]^{1/\sigma} \tag{11}$$

where $\pi_{ijM}^{rev} = p_{ijM}\bar{n}/(p_{ijM}\bar{n} - c_{ij})$ is the ratio of gross to net revenues. The change in driver surplus depends on two forces. First, government entry can directly affect profitability for drivers on the routes it enters by influencing prices and reducing the number of daily trips drivers can make due to longer queue times. Second, public transit entry may indirectly affect untreated routes at i if drivers switch from treated to untreated routes, leading to longer queue times (and fewer daily trips) and potentially affecting prices too.

The change in aggregate producer surplus is given by $\Delta\Pi = \sum_i B_i \Pi_i^V (\hat{\Pi}_i^V - 1)$. How this surplus is shared between drivers and the association depends on whether minibus entry and association fees change after government entry. We assume free entry initially to capture long-run equilibrium; if this persisted post-entry, the surplus would go to the association. However,

[23] See Appendix Section S3.2.6 for a derivation. This model omits demand-side linkages across markets: while government entry on one route could affect minibus demand on connected routes, we find no evidence of this in Section 5.3. Equation (10) still accounts for changes in consumer surplus that flow through supply-side linkages, for instance if prices change routes connected to treated routes in response to expanded supply.

our data show no significant changes in driver exit or association fees during the sample period. We interpret this as a medium-run response, and under these conditions $\Delta\Pi$ accrues to drivers. Thus, we refer to this change as driver surplus, noting that under different assumptions, it could be shared with the association.

Empirics. The sufficient statistics in equations (10) and (11) can be computed with three categories of empirical objects. First, descriptive statistics: traveller arrival rates (μ_{ij}),pre-entry minibus market share (s_{ijM}), post-entry public bus market share (s'_{ijP}), pre-entry route choices of minibus drivers (B_i and ρ_{ij}) and driver profit margins (π_{ij}^{rev}). These are obtained from the data we describe in Sections 2.1 and 3.1. Second, elasticities: how government entry affected commuter wait times (Δt_{ijM}), fares (Δp_{ijM} and $\hat{p}_{ijM}$), and driver trips ($\hat{N}_{ij}^{\text{Trips}}$). We estimate these exploiting the staggered government entry in the following section. Third, commuter and driver preference parameters (θ, γ, η, and σ). We identify these using the response of driver route choices to government entry, as well as the response of commuter trips to abrupt price changes on the public system and a wait time field experiment as described in Section 6.

5. How Private Transit Responds to Public Rollout

This section uses the panel data we collected on minibus supply to measure how incumbents responded to the opening of the new public system. We are primarily interested in impacts on minibus departure frequencies (which determine wait times), prices, and driver queues. We will also assess impacts on additional outcomes using our survey of drivers.

5.1. Descriptive Evidence

Figure 3 compares overall public transit ridership with that on our three categories of private routes: *treated* routes that share both endpoints with a public bus route that opened within our observation period, *connected* routes that share one endpoint, and *control* routes that share neither endpoint.

In this sample of routes, three patterns are evident. First, public transit ridership (blue dot-dashed line) increases over this period as it is rolled out over more routes. Second, private transit ridership on those routes (treated: orange dashed line) sees a commensurate decline. Third, there appears to be no meaningful trend on connected or control private transit routes. This suggests that most of the impact of public transit on overall ridership appears to be local to treated routes, and justifies a specification that identifies effects on treated routes by comparing them to other private transit routes. We will more finely investigate impacts on connected routes at the end of the section, and find some evidence of supply-side spillover effects. Finally, note that despite the large investment in public transit, it remains a smaller share of trips than minibuses on the routes we sampled.

FIGURE 3. Trends in Trips

exhibits/fig/tsc_pass_log.png

Note: Plots show the total passenger counts in private and public transit. Public transit ridership comes from electronic ticketing data and covers the same 13 routes we observe in the private treated sample. Private transit ridership comes from our terminal observations. Not all routes were monitored in all survey rounds: we impute missing route observations with the average number of passengers in routes of the same group (public, private treated, private control, or private connected) in that round. Vertical axis shown in logarithmic scale.

The three categories of private routes were similar at baseline, as shown in Appendix Table S12. Treated routes had similar route distances and driver queue lengths to connected and control routes, but were slightly higher volume routes (they had more frequent minibus departures and passengers). Overall, we fail to reject tests of joint equality of these attributes between treated and either connected or control routes. However, *terminals* that had at least one treated route tend to be better connected and have higher passenger volumes than terminals that have no public transit connections, as shown in Appendix Table S13. We reject a test of joint equality between the characteristics of these two groups of terminals (F-stat 5.26).

Because the two groups of terminals are different, we will begin with specifications that absorb differential trends at the terminal level, using terminal-by-survey-round fixed effects. However, because this approach compares routes within terminals, it could be biased if untreated routes within a terminal are affected, such as through driver substitution or other spillovers (a violation of Stable Unit Treatment Value Assumption or SUTVA). In Section 5.3, we remove these fixed effects and estimate specifications that account for spillovers of particular forms. We find small supply-side spillovers between routes at a terminal but show that the estimated effect on treated routes is similar whether we control for terminal trends or spillovers. Finally, Section 5.3.4 provides evidence that possible higher-order spillovers beyond those modeled do not appear to be at play in our setting.

5.2. Impact on Treated Routes

We begin by estimating how minibuses respond to public transit entry on their routes, with terminal-by-survey-round fixed effects.

Base Regression Specification. Outcomes are at the level of route r, survey round t, and time of day τ (30 minute intervals within morning peak, afternoon peak, and afternoon off peak). Our main estimating equation is

$$Y_{rt\tau} = \beta \mathbb{I}\{\text{Open}_{rt}\} + \gamma_{m(r\tau)} + \delta_{i(r)t} + \boldsymbol{\eta}_t{}' X_{rt\tau} + \epsilon_{rt\tau}. \tag{12}$$

which includes an indicator for whether route r served by public buses as of survey round t as well as a variety of controls including fixed effects and observable controls $X_{rt\tau}$. The coefficient of interest is β which represents the impact of public transit entry.

Commuting patterns in Lagos are highly asymmetric, with the same route varying significantly by time of day.[24] We define a 'transit market' $m(r\tau)$ as a route segmented into three periods: morning peak, afternoon peak, and afternoon off-peak. Transit market fixed effects $\gamma_{m(r\tau)}$ are included to control for time-invariant unobservables and to identify β from changes in outcomes driven by public entry. Control variables $X_{rt\tau}$, which include day of week, hour of departure fixed effects, and a set of fixed trip characteristics such as trip length, are interacted with survey round fixed effects to allow their effects to be time-varying. Specifications in this section include terminal-by-survey-round fixed effects $\delta_{i(r)t}$, with $i(r)$ representing the origin terminal of route r. These will absorb time-varying shocks at the terminal level.[25]

Our identification strategy compares how private transit shifts when public transit serves its route, relative to other routes. In our focal specifications, this comparison is made relative to other routes sharing a terminal endpoint. This is because terminal-by-survey-round fixed effects absorb terminal wide shocks. As a result, this relies primarily on comparisons between changes in treated versus connected routes serving the same terminals. Standard errors are clustered by route and terminal since treatment is at the route level but our sampling was at the terminal level.

5.2.1. Departure Observations

We estimate the effect of public transit entry on outcomes observed in our departure observations at terminals, with results shown in Table 2. We focus on log outcomes to lower impacts of outliers;

[24] Lagos' patterns are typical: morning travel flows from the outskirts to the center, and the reverse in the afternoon.

[25] In theory one might also wish to include fixed effects for the destination terminal of route r, but empirically that would absorb most of our variation. That is because we observe departures on sampled routes at each terminal: we capture many routes with the same origin, but few with the same destination. The vast majority of our origin-destination pairs are not treated (13 routes treated out of a sample of 278), largely alleviating the recently highlighted issues when using yet-to-treated units as a comparison group (e.g., de Chaisemartin and D'Haultfoeuille 2022).

results are similar in levels as shown in Appendix Table S15.

Introducing public buses on a route decreases the departure rate of minibuses by 11-22%, as shown in Panel A. In the simplest specification in column (1), departures fall by 11% after public entry. Since on each route there are typically minibuses waiting for passengers to depart, these reductions reflect a decline in passengers. Because shared transport works by pooling passengers, less frequent departures mean higher waits for those who continue to use minibuses, as they will spend longer waiting in a bus as it fills to depart when full. This effect grows stronger as we add controls. Column (2) adds the terminal of observation-by-survey round fixed effects, allowing for aggregate shocks to locations, which sharpens up these effects. Column (3) adds controls for trip distance interacted with survey round fixed effects (to allow for differential trends by trip distance). Column (4) adds an indicator for whether the route was ever included in one of the government's opening plans for this phase of the system, again interacted with a time indicator. Column (5) adds controls for whether a route ends in one of Lagos' business districts. Column (6) adds flexible controls for origin and destination characteristics through a 3rd order polynomial in their longitude and latitude. Finally, column (7) adds origin and destination region fixed effects interacted with time indicators. We define region by the local government area (LGA), which partition Lagos into 20 administrative units. Overall, the estimate of largest magnitude (22% decline in departures) comes from our most restrictive specification in column (7).

Introducing public buses on a route has a suggestive negative effect on private fares, shown in Panel B. Our point estimates suggest a reduction in fares between 2-7% across our various specifications; these estimates are negative in all specifications but are not statistically significant. Our confidence intervals can rule out declines larger than 15%.

Combined, the slower arrival of passengers and possible reductions in fares make treated routes less desirable for drivers to serve. Correspondingly, we see declines in the number of minibuses waiting in queues for passengers of 23-29% depending on specification, as shown in Panel C. This suggests drivers on treated routes must be leaving those routes, which we will turn to in the next section.

We treat column (7) as the preferred specification going forward since it includes the richest set of controls.

TABLE 2. Effect of Public Transit on Private Transit

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A: log(Departures)							
Open	-0.114***	-0.182***	-0.180***	-0.189***	-0.186***	-0.215***	-0.221***
	(0.041)	(0.037)	(0.056)	(0.057)	(0.058)	(0.078)	(0.075)
N	21,284	21,284	21,284	21,284	21,284	21,284	21,284
R^2	0.58	0.64	0.64	0.64	0.64	0.65	0.66
Panel B: log(Fare)							
Open	-0.031	-0.051	-0.037	-0.055	-0.059	-0.066	-0.024
	(0.047)	(0.050)	(0.051)	(0.049)	(0.047)	(0.040)	(0.035)
N	23,067	23,067	23,067	23,067	23,067	23,067	23,067
R^2	0.92	0.94	0.94	0.94	0.94	0.94	0.95
Panel C: log(Queues)							
Open	-0.228***	-0.282***	-0.266***	-0.270***	-0.254***	-0.277***	-0.289***
	(0.062)	(0.095)	(0.078)	(0.079)	(0.086)	(0.078)	(0.072)
N	22,290	22,290	22,290	22,290	22,290	22,290	22,290
R^2	0.47	0.55	0.56	0.56	0.56	0.58	0.59
Route X Period FE	X	X	X	X	X	X	X
Day of Week X Survey Round FE	X	X	X	X	X	X	X
Hour of Dep X Survey Round FE	X	X	X	X	X	X	X
Terminal X Survey Round FE		X	X	X	X	X	X
Trip Dist Controls X Survey Round FE			X	X	X	X	X
Dep. Plan X Survey Round FE				X	X	X	X
CBD Controls X Survey Round FE					X		
O & D Lat-Lon Poly X Survey Round FE						X	
O & D LGA X Survey Round FE							X

Notes: The rows at the bottom of the tables reflect control variables added to each specification. Route X Period FE are the 3 "transit market" fixed effects for each route. The remaining rows interact survey round fixed effects with the following variables. Rows 2 and 3 add fixed effects for each day of the week and hour of departure. Row 4 adds a fixed effect for each origin terminal. Row 5 adds dummies for each quartile of trip distance. Row 6 adds a dummy for whether the route ever appears in a LAMATA deployment plan, reflecting whether they planned to open public transit on that route at some point. Row 7 adds dummies for whether the route ends on Lagos Island or Lagos Island, containing the city's two main central business districts. Row 8 adds a third-order polynomial in origin and destination latitude and longitude. Row 9 adds fixed effects for the LGA of each origin and destination. Standard errors clustered by route and terminal reported in parentheses. * $p<0.1$; ** $p<0.05$; *** $p<0.01$.

Placebo Tests. We conduct a falsification test by applying the same strategy to estimate effects on two sets of planned routes that never became operational. Using the dates the government planned to open these routes, we construct hypothetical Open_{rt} dummies which turn on when these routes were scheduled to be operational. If the main treatment effects are driven by public entry itself, rather than pre-existing trends on targeted routes, these planned opening dummies should have no impact on outcomes.

The EndSARS Protests and Fire at Oyingbo Terminal. The new Oyingbo terminal was slated to open and host 8 new public bus routes starting in late October and early November 2020. However, weeks before opening, a protest against police brutality swept Nigeria, illuminating abuses by a police unit called the Special Anti-Robbery Squad (SARS). Following a fatal police shooting at Lekki Tollgate on October 20, groups of protesters burned a television station and the Oyingbo public bus terminal (see Appendix Figure S4), which canceled the planned routes.

Evolving Opening Plans. The government's rollout plans evolved over time. We digitized 22 versions of the rollout plans shared with us by the government over 2020 and 2021, allowing us to observe routes that were planned to be opened during this period but were suspended or delayed due to operational considerations.

TABLE 3. Placebo Tests

	log(Departures)			log(Fare)			log(Queues)		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Open	-0.221***	-0.221***	-0.208***	-0.024	-0.024	-0.029	-0.289***	-0.289***	-0.282***
	(0.075)	(0.075)	(0.078)	(0.035)	(0.035)	(0.035)	(0.072)	(0.072)	(0.075)
Open ENDSARS		-0.012			0.185*			0.087	
		(0.149)			(0.104)			(0.164)	
Open Cancelled			0.088			-0.036			0.044
			(0.078)			(0.022)			(0.100)
N	21,284	21,284	21,284	23,067	23,067	23,067	22,290	22,290	22,290
R^2	0.66	0.66	0.66	0.95	0.95	0.95	0.59	0.59	0.59

Notes: Specification is the same as column 7 of Table 2. Standard errors clustered by route and terminal reported in parentheses. * p<0.1; ** p<0.05; *** p<0.01.

Results. Table 3 shows the results. The first three columns report results for departures. Column (1) repeats the baseline specification (column (7) in Table 2). Column (2) adds the event-time indicator that turns on when a route at Oyingbo would have opened, had it not been cancelled after the fire. Column (3) does the same for planned openings that were canceled due to changes in government deployment plans. Columns (4-6) repeat these specifications for fares, and columns (7-9) for queues.

We do not see evidence of effects after planned but canceled public transit entry. The effects on departures and queues are both economically small and statistically insignificant. Over all outcomes, four out of the 6 coefficients go in the opposite direction of the main effect on actually opened routes. On fares the ENDSARS coefficient is statistically significant at the 10% level but is in the opposite direction of the effect on actually opened routes. These results support the notion that our main treatment effects are due to entry itself, and not differential trends on routes the government planned to enter.

Robustness. Our estimates are also robust to a number of adjustments. Coefficients of the baseline specification are similar whether estimated with a two-way fixed effects estimator or a

Sun and Abraham (2021) estimator that is more robust to treatment effect heterogeneity, shown in Appendix Table S14. Results are qualitatively similar when outcomes reported in levels rather than logs, as shown in Appendix Table S15. Wild cluster bootstrap (Cameron, Gelbach, and Miller 2008) may be more trustworthy in small samples, and suggests lower statistical precision but still support declines in departures and queues with median p-value 0.06 for departures and 0.07 for queues (fare impacts remain imprecise). See Appendix Table S16.

Impacts on Congestion. We find no impact of public transit rollout on measures of traffic congestion derived from Google Maps (log road speed and travel time), reported in Appendix Table S17. This is not surprising given that the public buses we study share the roadways, and did not pack passengers much more densely than minibuses on average (Table 1).

5.2.2. Departure Observations: Dynamics

To assess dynamics, we replace the binary treatment indicator with indicators for whether public buses have been running for less than 3 months (associated coefficient β_1), 3 to 6 months (β_2), or longer than 6 months (β_3) on route r by survey round t. This results in estimating equation

$$
\begin{aligned}
Y_{rt\tau} = &\beta_1 \mathbb{I}\{\text{Open}_{rt} < 3 \text{ months}\} + \beta_2 \mathbb{I}\{\text{Open}_{rt} \text{ 3-6 months}\} + \\
&\beta_3 \mathbb{I}\{\text{Open}_{rt} > 6 \text{ months}\} + \gamma_{m(r\tau)} + \delta_{i(r)t} + \boldsymbol{\eta}_t{}' X_{rt} + \epsilon_{rt\tau}. \qquad (13)
\end{aligned}
$$

Results are shown in Appendix Table S3, repeating the specifications of Table 2. There is evidence of a slight decline in departures within 3 months, which grows stronger and persists after 3 months, as shown in Panel A. Fare effects are always negative but are imprecisely measured and do not show a clear time trend, shown in Panel B. Queues decline much more after 3 months, shown in Panel C. A delay between the adjustment of departures and queues would be consistent with drivers adjusting to reduced passenger flows after a delay. We present dynamic results visually in Appendix Figure S6, showing event studies for our main results using both two-way fixed effects and Sun and Abraham (2021) estimates.

Taking stock, we find that on treated routes, departures decrease, and there is suggestive evidence that fares decrease. Driver queues also shorten. This raises the question: where do affected drivers go? We assess this in the next two subsections.

5.2.3. Drivers

We next turn to our panel of driver surveys to understand how individual drivers are affected when public transit rolls out on their primary route.

Drivers are a challenging group to track down for follow up surveys: they are highly mobile, do not have defined work locations, and work long and erratic hours around the week, with unpredictable breaks. We followed a protocol to call multiple times and arrange to call back at convenient times. We recruited 854 drivers at baseline; 82% could be reached for at least one follow up but only 34% could be reached for all 4 follow ups.[26] Older drivers are more likely to participate in follow up rounds, but we do not find differential attrition based on whether the driver's main route at baseline was treated, whether the driver owned their bus, or income. We present these results in Appendix Table S11. Since only driver age appears correlated with attrition we will control for it, although our results are not sensitive to this choice.

We return to the base regression specification, equation (12), and run it on outcomes from the driver survey. We compare drivers whose main route, as reported in the baseline survey, has the public service operating at the survey date ($\text{Open}_{r(d)t} = 1$ for driver d) with those whose main route does not. Results are shown in Table 4. Drivers whose baseline routes become served by public transit complete fewer trips (column (1)) and earn less revenue (column (4)) compared to other drivers operating from the same terminal at baseline. They do not report significant differences in fares (column (2)) or the fee paid to the association for each trip (column (3)), and do not work fewer days (column (5)).[27] This reduction in the quantity of trips made aligns with the terminal observation results. In response, drivers are more likely to change routes. On average, 59% of drivers change routes over the year we monitor, and treatment results in an increase of 7.2 percentage points (column (6)). The vast majority of these changes are drivers selecting different routes from the same terminal (51% of all drivers, or 86% of all switchers): column (7) reports a sharper 11.6 percentage point increase in the likelihood a driver switches routes within the same terminal after the public service enters on their main route.

These findings support the main terminal-level results and suggest that changes in drivers' route choices may have affected other routes serving the same terminal. We explore this possibility next.

TABLE 4. Effect of Public Transit on Minibus Drivers

	N Trips	log(AvgFare)	Log(Assoc Fee)	log(Rev)	log(DaysWork)	Change Route Any	Change Route Same Terminal
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Open	-1.550***	-0.037	-0.039	-0.115**	0.003	0.072	0.116***
	(0.503)	(0.033)	(0.055)	(0.051)	(0.038)	(0.045)	(0.038)
N	2,161	1,991	2,015	1,943	2,166	1,383	1,383
R^2	0.76	0.87	0.78	0.76	0.53	0.83	0.79
Mean Outcome (Levels)	9.58	197.26	580.88	17474.65	4.41	0.59	0.51

Notes: All columns include driver fixed effects, and survey round fixed effects interacted with terminal of recruitment, dummies for each quartile of driver age, the number of trips the driver reports in the previous workday at baseline, and a dummy for whether they own their vehicle or not at baseline. Number of trips and revenue are winsorized at 99th percentile due to large outliers. Regressions are weighted by the sampling weights discussed in Section 3.1. Standard errors clustered by driver and terminal of recruitment reported in parentheses. * p<0.1; ** p<0.05; *** p<0.01.

[26] Appendix Table S9 reports the number of completed surveys in each round, and Appendix Table S10 reports the distribution of number of survey rounds completed.

[27] We only asked the per-trip payments to the association in all survey rounds; the terminal registration fee was asked only in the baseline survey since it is paid infrequently.

5.3. Impact on Connected Routes

We next test for the presence of spillover effects on private routes not directly exposed to public sector competition. On routes where the government enters, departure frequencies fall and there is some suggestion that prices fall. This suggests a reduction in driver profits, and increased incentives to reallocate to alternative routes. Indeed we see driver queues on treated routes shorten and drivers report switching to other routes within the same terminal. It is also possible that connected routes experience a change in demand: more passengers might take private buses to connect with public buses, or passengers who were previously connecting between private routes may opt to change the mode of one of the legs.

To test for spillovers, we drop terminal-by-survey-round fixed effects and run regressions that compare treated, connected, and control routes. Connected routes are more likely to experience driver substitution, as the primary fee drivers pay the association is to serve a specific terminal, making it cheaper to switch to a route with the same origin or destination.[28] Conceptually, if a new public route opens on ij, the effect of treatment is identified by comparing changes on the treated route (ij) with those on untreated routes serving terminals with no public service (control routes, for example, lm). The spillover effect is identified by comparing how untreated routes change when their terminal receives new public service (connected routes, for example, ik) with those on untreated routes at terminals without public service (e.g., lm).

5.3.1. Departure Observations

Our spillover specifications omit terminal-by-survey round fixed effects, and take the form

$$Y_{rt\tau} = \beta \mathbb{I}\{\text{Open}_{rt}\} + \alpha \text{ Connections to public transit}_{rt} + \gamma_{m(r\tau)} + \boldsymbol{\eta}_t{}' X_{rt} + \epsilon_{rt\tau}.$$

where Connections to public transit$_{rt}$ describes route r's connections to public transit. In our main specifications this is the number of running public routes that share an endpoint with route r; we consider alternative specifications of public transit connections in robustness checks. We define these connection measures based on the max of the variable at the origin and destination, and set them to zero if route r itself ever receives public transit. This ensures the connection coefficients are estimated using variation in exposure on untreated routes rather than as treated routes are connected to more public bus routes. The impact of treating route r on treated route r is captured by β, and the impact on connected route r' is captured by α.

Results are shown in Table 5. Odd columns replicate the main specification (column (7) of Table 2), while even columns report the spillover specification which omit terminal-by-survey

[28] Drivers could experience lower switching costs within terminals for other reasons, such as familiarity, and reports suggest that drivers are indeed "often tied to a single origin-destination (or sometimes a set of origin-destination), which are connected to a corresponding park" (CPCS 2024). 'Higher-order' spillovers could also affect control routes—for instance, if they interact with the public service at points along the route rather than at either endpoint. We will revisit this possibility in Section 5.3.4.

round fixed effects and add the connection measure.

TABLE 5. Effect of Public Transit on Connected Private Transit Routes

	log(Departures)		log(Fare)		log(Queues)	
	(1)	(2)	(3)	(4)	(5)	(6)
Open	-0.221***	-0.163*	-0.024	-0.108**	-0.289***	-0.163*
	(0.075)	(0.090)	(0.035)	(0.052)	(0.072)	(0.093)
Number of open routes at terminal		0.002		-0.016***		0.029*
		(0.013)		(0.006)		(0.017)
N	21,284	21,284	23,067	23,067	22,290	22,290
R^2	0.66	0.63	0.95	0.94	0.59	0.55
Terminal X Survey Round FE	X		X		X	
p-val: Same estimate on Open	0.59		0.05		0.30	

Notes: All columns include the same controls as the main specification (column (7) of Table 2), except for terminal-by-survey round fixed effects which are omitted in even columns. Number of open routes at a terminal is defined as the maximum of the number of public routes open at a minibus routes origin and destination, and is non-zero only for routes that never receive public service themselves. Final row shows the estimated p-value on a hypothesis test of equality between the coefficient on Open in the corresponding odd and even columns. Standard errors clustered by route and terminal reported in parentheses.* $p<0.1$; ** $p<0.05$; *** $p<0.01$.

The first two columns test for demand-side spillovers: when buses are waiting in queues (observed in 84% of spillover route observation windows at baseline), the departure rate of buses depends on the passenger arrival rate. The results show a precise zero effect of a route without new public service becoming connected to more public routes at either endpoint on its bus departure rate. This indicates that the introduction of new public service does not affect minibus passenger demand on untreated routes.

The last two columns test for supply side spillovers by examining the effects of new public service on the length of driver queues on connected routes. As a route receives public transit, driver queues on that route shorten but queues to drive connected routes increase as shown in column (6). This is consistent with drivers substituting to serve other routes at the same terminal, affecting the supply of buses there and the number of daily trips drivers can make.

The effect of public transit connections on minibus fares reflects the net impact of shifts in supply and demand. With only the supply of drivers increasing, any observed price changes are driven by the greater availability of drivers on these routes. Column (4) demonstrates that minibus fares decline on routes with new public transit connections. According to equation (9), the model predicts that prices will decrease if queue lengths become more sensitive to prices as driver supply expands. While the total change in this elasticity is theoretically ambiguous (as detailed in Appendix Section S3.2.7), a negative relationship between prices and supply is plausible since this elasticity scales linearly with the length of the driver queue. The effect of public entry on minibus fares on treated routes also sharpens in this specification, with a 10% reduction significant at the 5% level.

5.3.2. Drivers

Table 6 presents estimates of driver outcomes accounting for spillover effects. Results for treated drivers remain consistent with the previous specification using terminal-by-survey round fixed effects, so we focus on connected routes. We find suggestive evidence that drivers on connected routes experience similar effects as treated drivers, but to a smaller extent, consistent with second-order effects from the movement of drivers from treated to connected routes. Drivers on connected routes are more likely to switch routes within the same terminal (column (7)) and receive lower average fares across their daily trips (column (2)). While there is no significant effect on the number of daily trips, multiplying the point estimate by the average of 5.1 open public routes at terminals with public service implies an effect for connected drivers approximately 10% as large as for treated drivers.

TABLE 6. Effect of Public Transit on Connected Minibus Drivers

	N Trips (1)	log(AvgFare) (2)	Log(Trip Fee) (3)	log(Rev) (4)	log(DaysWork) (5)	Change Route Any (6)	Change Route Same Terminal (7)
Open	-1.319***	-0.064*	-0.025	-0.145**	-0.007	0.091**	0.169***
	(0.478)	(0.036)	(0.053)	(0.056)	(0.036)	(0.036)	(0.047)
Number of routes open at terminal	-0.028	-0.006*	-0.002	-0.015	-0.005	0.006	0.020**
	(0.083)	(0.004)	(0.008)	(0.009)	(0.004)	(0.008)	(0.008)
Mean Outcome (Levels)	9.58	197.26	580.88	17474.65	4.41	0.59	0.51
N	2,173	2,011	2,026	1,966	2,178	1,405	1,405
R^2	0.71	0.84	0.72	0.69	0.41	0.80	0.76

Notes: All columns include driver fixed effects, and survey round fixed effects interacted with: dummies for each quartile of driver age, the number of trips the driver reports in the previous workday at baseline, and a dummy for whether they own their vehicle or not at baseline. Open and Number of open routes are defined analogously to the terminal observation specifications, but based on a driver's main route from the baseline survey. Regressions are weighted by the sampling weights discussed in Section 3.1. Standard errors clustered by driver and terminal of recruitment reported in parentheses.* p<0.1; ** p<0.05; *** p<0.01.

5.3.3. Robustness

Placebo Spillover Specifications. In Appendix Table S18 we repeat the placebo regressions, finding that neither type of canceled route yields phantom effects in the spillover specification.

Alternative Spillover Specifications. Columns (2) and (3) of Appendix Table S19 present specifications with alternative measures of connections to public transit. Column (2) uses two dummies binning the number of open public transit connections (the baseline measure) into two groups above and below 5 routes (the average number of open routes is 5.1), and column (3) uses a dummy for whether the route has any public connections. The findings of supply side and fare spillovers are robust to these alternative functional forms, with effects becoming larger on routes with more new public transit connections. For departures, we see some mixed effects but not convincing evidence of demand spillovers. Although there is a negative departure effect when a route receives any connection in column (3), column (2) suggests that the effect is stronger at terminals that are less affected, suggesting it may be picking up noise.

Alternative Driver Specifications. Appendix Table S20 runs an unweighted version of the driver spillover specification, and a version replacing the continuous measure of transit connections with a dummy for whether a route has any connections. The results are generally similar to the main specifications, although the spillover effects are larger when using a dummy to capture public connections.

5.3.4. Discussion

Reconciling the Baseline and Spillover Estimates. We estimate two families of specifications in the previous analysis. Since terminals with treated routes differ from those without, our first specification includes terminal-by-survey round fixed effects to flexibly control for unobservable terminal-level trends. The drawback is that treatment effects are identified through within-terminal comparisons, which may be subject to spillovers. Our second specification compares outcomes on routes at treated terminals (both treated and connected routes) with routes that do not interact with the new public system at either endpoint. This reduces concerns about spillovers but requires selecting a functional form, and sacrifices control over unobserved terminal-level trends. Thus a key question is whether our conclusions are sensitive to the approach.

Appendix Table S19 presents three alternative functional forms for spillovers in columns (1–3). For each, we reports p-values for whether the coefficient on Open_{rt} differs from that in the specification with terminal-by-survey round fixed effects in column (4). In only two of the nine regressions do we reject equality at the 5% level—those where fare is the outcome. For queue length, coefficients are smaller in two of the three spillover specifications but not significantly so.

Overall, our results remain consistent regardless of whether the specification accounts for spillovers. This suggests that SUTVA violations are relatively minor in the terminal-by-survey-round fixed effects specifications, aligning with the small point estimates on the number of connected routes in Table 5. Small treatment effects on connected routes do not greatly influence our estimation strategy, but could still be quantitatively important when aggregated across many routes.

Higher Order Spillovers. The specifications from the previous section remain valid in the presence of spillovers only if there are no 'higher-order' spillovers beyond interactions at origin or destination terminals, as captured by our measure of connections. While most trips in Lagos begin at route origins, some routes may interact with the public transit system at intermediate stops beyond their origin or destination.[29] Such interactions could violate SUTVA by exposing control group routes to the treatment. In Appendix Section S4.1, we provide evidence that our estimates are not substantially affected by higher-order spillovers.

Testing Profit Equalization Across Routes. Our theory predicts that after public entry, drivers will reallocate between routes until expected profits are equalized. Appendix Section S3.2.8 tests this formally. The combination of departure, queue length, and price impacts imply a reduction of profits of approximately 0.376 log points on treated routes and 0.334 on connected routes, which are statistically indistinguishable (p=0.78).

6. How Commuters Value Changes in Transit Attributes

Next we estimate how commuters value wait time and price changes. We use quasiexperimental price variation in public buses to estimate how trips respond to prices. We use an RCT to estimate how commuters value the changes in minibus prices and wait times.

6.1. Price Elasticity

We compute medium run price sensitivity from a sequence of abrupt price changes in the public transit system, using an event study approach, in Appendix S1.2. We find a value of the composite demand elasticity $\theta\gamma = 0.0021$. We separate the substitution elasticity θ by estimating γ in the field experiment described below.

6.2. Wait Time Experiment

We estimate utility parameters using an experiment: we measure sensitivity to prices (γ) and waiting (η) by providing commuters offers to wait for random times before boarding a minibus. This experiment was preregistered in the AEA RCT registry (AEARCTR-0010283).[30]

Implementation. Our team developed a text message service which allows us to estimate commuters' value of time at minibus stops, and deployed it between June and August, 2023. We sampled 18 bus stops, and in the surrounding areas recruited 640 commuters at their homes on weekends.[31] We informed them that on weekdays morning when they commute over the next 3-5 weeks, they will find an enumerator waiting at their registered bus stop. The enumerator

[29] 92% of minibus passengers board at the origin (from our network mapping microdata), while 88% of public passengers do so (based on electronic ticketing data).

[30] Deviations are detailed in Online Appendix S2.2.

[31] If we had alternately attempted to recruit at bus stops, it is likely that the only commuters who would be willing to go through our intake process would be only those with low value of time.

holds a phone or tablet, which displays a random code which changes every minute. The participant texts this code to our shortcode phone number (see Appendix Figure S5 for a photo of this interaction). For individual n at day and time t, the service sends an immediate airtime reward of $s_n^{checkin}$ for checking in, as well as a randomized offer to wait Δt_{nt} minutes for a payment of s_{nt} Naira. To accept the offer, a participant may wait at the bus stop, and after at least Δt_n minutes text back the new code that the enumerator's tablet then displays. This code allowing us to verify they had waited the requisite amount of time. If the participant does not accept the offer, they can continue with their day. By observing the combinations of wait time and payments that are accepted and rejected, we are able to identify participants' value of time. Check in offers $s_n^{checkin}$ were randomized between individuals (₦200, 400, 700, or 1000) and then held fixed over the experiment. Wait offers $(\Delta t_{nt}, s_{nt})$ were randomized for each individual-day. Individuals were told summary statistics about the distribution of wait offers.[32] Under the first three days checking in, participants were given shorter (or no) waits and higher offers, to get them accustomed to checking in and to get a baseline on their typical arrival time at the bus stop.[33] Further details on implementation are provided in Online Appendix S2.

Theory. Because engaging with our experiment represents a hassle, we model the decision to participate. After a commuter has arrived at a bus stop, having already chosen a travel mode (minibus), she decides whether to check in, and then whether to accept an offer to wait. We work backwards, based on utility defined in equations (1) and (4).

Conditional on checking in, she will accept an offer to wait Δt_{nt} for payment s_{nt} if

$$\alpha_m - \gamma(p_m - s_{nt}) - \eta(t_m + \Delta t_{nt}) + \epsilon_{mnt+\Delta t_{nt}} > \alpha_m - \gamma p_m - \eta t_m + \epsilon_{mnt}.$$

where we omit route subscripts (ij) and allow the idiosyncratic error ϵ_{mnt} to depend on time. Decomposing the idiosyncratic error into a component that is stable across short waits and one that may vary yields $\epsilon_{mnt} = \nu_{mn} + \nu_{nt}$. Then the commuter will wait if

$$D_{nt}^* = \gamma s_{nt} - \eta \Delta t_{nt} + \nu_{nt}^{wait} > 0,$$

where we define $\nu_{nt}^{wait} = \nu_{nt+\Delta t_{nt}} - \nu_{nt}$.

Checking in incurs a time cost of $t^{checkin}$ but provides immediate payment $s_n^{checkin}$ plus any expected benefit of wait offer, captured by utility

$$C_{nt}^* = \gamma s_n^{checkin} - \eta t^{checkin} + \mathbb{E}[D_{nt}^* | D_{nt}^* > 0] \Pr(D_{nt}^* > 0) + \nu_{nt}^{checkin}$$

[32] They were informed, "You'll also get an opportunity to earn ₦20-1250 more by waiting between 3-25 minutes. The average offer will be ₦150 for 10 min."

[33] Participants were randomly assigned to either have one or two initial days with zero wait, and then high offers for the rest of this initial period.

where $\nu_{nt}^{checkin}$ captures idiosyncratic utility.

Estimation Procedure. We assume that the idiosyncratic errors are jointly normally distributed

$$\begin{bmatrix} \nu_{nt}^{wait} \\ \nu_{nt}^{checkin} \end{bmatrix} \sim N\left(\mathbf{0}, \begin{bmatrix} 1 & \rho\sigma^{checkin} \\ \rho\sigma^{checkin} & (\sigma^{checkin})^2 \end{bmatrix}\right),$$

fixing $\sigma^{wait} = 1$. In our data we observe the decision to check in $C_{nt} = \mathbb{I}\{C_{nt}^* > 0\}$ and, only if the person checks in ($C_{nt} = 1$), the decision to accept $D_{nt} = \mathbb{I}\{D_{nt}^* > 0\}$. Because $s_n^{checkin}$ is excluded from the waiting decision, we can use it as an instrument for the decision to check in. We calibrate the average hassle cost of checking in, $t^{checkin} = 1.31$ minutes, by having each enumerator time how long it took to walk to their spot, text the code, and wait for a response.[34] We estimate using maximum likelihood and cluster standard errors at the commuter level.

FIGURE 4. Wait Experiment

exhibits/experiment_waittime/sampleAcceptRejectDotPlotunscheduled.pdf

A. Offer Acceptances

exhibits/experiment_waittime/selection_plannedChec

B. Selection into Checking In

Note: Panel (A) plots offers (₦: y-axis) to wait (minutes: x-axis), with the proportion accepted shaded. The size of each point scales with the number of observations given that particular offer. Offers were randomly drawn from a weighted distribution that gave higher probability to lower times and offers. Panel (B) plots various outcomes by check in offer (₦: x-axis).

Results. We plot the experimental data in Figure 4. Figure 4A shows the distribution of offers and acceptances. We drew from a distribution where shorter times were more likely, with offer values tending to increase with time, but still include variation in both. Participants are much more likely to wait for shorter times and higher payments, though there is idiosyncratic

[34] Each enumerator timed the following sequence using a stopwatch: beginning at the bus stop, walk to the location where the enumerator typically stands, type in and send the random code, and then walk back to the bus stop. These estimates ranged between 28 and 144 seconds; we took the average.

variation, which depends on the individual and day. Figure 4B illustrates the selection issue. On average, respondents report planning to travel 91% of weekdays in the first week, and this does not vary by the (randomly assigned) check in offer. However, the proportion of days checked in is 55%, suggesting that participants are not engaging with the experiment every time they travel. But participants randomly assigned higher check in offers are more likely to check in, confirming that we may use this as an instrument. We also find that although respondents given higher check in offers check in more frequently, they are less likely to accept the subsequent wait offer, which would be consistent with them being induced to check in on days they have particularly high value of time.

Estimated parameters using our selection-corrected maximum likelihood procedure are shown in Table 7. We obtain $\hat{\eta} = 0.0464$ and $\hat{\gamma} = 0.0025$; combined these suggest a disutility of waiting of ₦18.94 per minute. This corresponds to 2.9 times the average wage in our sample, or 2.6 times the civil service minimum wage closely following the study's conclusion.[35]

TABLE 7. Commuting Utility Parameter Estimates

γ (utils/₦)	0.0025***
	(0.0002)
η (utils/min)	0.0464***
	(0.0031)
$\frac{\eta}{\gamma}$ (₦/min)	18.9357***
	(1.7123)
$\sigma^{checkin}$	14.3662***
	(3.901)
ρ	0.5163***
	(0.0588)
N	8640
Avg. Log Likelihood	-8720.18

Notes: Standard errors clustered at the user level. Estimation fixes $\sigma^{wait} = 1$.
* p<0.1; ** p<0.05; *** p<0.01.

We estimate a positive ρ, suggesting a positive correlation of wait and checkin shocks, which is consistent with participants being less likely to both accept and check in on days they are rushed. We also find that the estimate of $\sigma^{checkin}$ is substantially larger than $\sigma^{wait} = 1$, suggesting

[35] Respondents reported monthly income in nine categories; we use each category's midpoint to compute an average monthly income of ₦61,289. While Lagos civil servants' minimum wage was ₦35,000 in 2023 (unchanged since 2019), it increased to ₦70,000 in 2024. We use the updated figure, as the 2023 wage likely lagged contemporary levels. Calculations assume 40 hours per week and 4 weeks per month.

the decision to commute and check in is more idiosyncratic than that to accept waits.

Comparison to Other Estimation Procedures. In Appendix Table S6 column (2), we show that a model that assumes perfect compliance estimates a value of time of ₦8.33 per minute: undervaluing the hassle of waiting by 56% relative to the selection-corrected estimate. This corresponds to 1.3 times the average wage in our sample or 1.1 times the average civil service wage closely following the study's conclusion.

Transportation studies commonly infer the value of time from hypothetical choices or stated preferences. In the baseline survey we asked participants to make hypothetical choices between options with varying costs and wait times.[36] The value of time estimated from hypothetical choices is ₦46.46 per minute–overstating our main estimate by a factor of 2.5, as shown in Appendix Table S6, column (3). Other work also finds hypothetical choices can greatly overstate valuations (Kremer et al. 2011).

Our implied value of time is higher than some estimates in the literature. For example, Wardman, Neki, and Humphreys (2023) finds an average estimate of the valuation of wait time of 1.13 times the wage in low- and middle-income countries, in a meta-analysis of which 83% of estimates come from hypothetical evaluations. Several factors could contribute to a higher disutility of waiting in our setting, such as perceptions of safety or that many private bus stops lack comfortable shelter, which can affect perceived wait times (Fan, Guthrie, and Levinson 2016).

Robustness. We assess several notions of robustness in Online Appendix S2.5. We assess alternate specifications in Appendix Table S23. When we allow separate η parameters by income, we estimate that commuters with above median income value time at ₦20.62 per minute, relative to ₦18.17 for those with below median income (column (2)). We find slight diminishing disutility when we allow utility to include a squared term for waiting time (column (3)). Given that the heterogeneity and curvature we estimate are both slight, we focus on the simple specification as our main specification. Estimates are similar under alternate sample definitions, shown in Appendix Table S24. Given that our estimated value of time is large relative to wages, we will also asses sensitivity in welfare exercises.

We evaluate the possibility that participants arrive to the bus stop earlier to take advantage of waiting offers in Online Appendix S2.5.2. If that were the case, one could adjust the model to account for the scheduling friction. However, we do not find consistent evidence of such schedule adjustments.

Estimates are also similar under a model that accounts for the possibility that, regardless of their hurry, participants accept a wait offer if a bus does not arrive. To limit this possibility, we asked our enumerators to stand away from bus stops, not in direct line of sight. Online

[36]We asked about 5 pairs of offers.

Appendix S2.5.3 estimates a model in which the decision to accept a wait offer depends on whether a bus arrives. For the range of arrival frequencies we observe in our data, this does not meaningfully affect our estimates.

7. Welfare Effects

Finally, we combine our estimates of treatment effects and parameters to assess how the rollout of public transit affected the welfare of different groups of commuters and drivers. We compute welfare impacts on commuters following equation (10) and on minibus drivers following equation (11) and using the point estimates from Table 5. Results are shown in Table 8. 95% confidence intervals are reported in parentheses. Appendix Section S3.3 provides details.

Commuters. At baseline, each commuter earns an average of $0.86 surplus per day from the preexisting system, as shown in the first row of Panel A. Overall, public transit increases the surplus of commuters on treated routes by $0.20 per day (23%), as shown in Column (1). The following three rows decompose this effect using equation (10). The benefit of introducing the new variety, without accounting for impacts on private transit, is $0.22 per day. But longer wait times cost travelers $0.04 per day, and lower fares would add $0.02 per day in benefits (taking our point estimates). Although the treatment effect on fares were not statistically significant, we find that both welfare adjustments are statistically significant, with zero excluded from the confidence intervals. Ultimately, commuters' disutility from increased wait times outweighs the benefits of reduced fares, so private market impacts harm treated commuters. The net loss from the private response is 12% of the total impact on treated routes.[37]

Commuters on connected routes also benefit from the price reductions we document in Table 5. Each commuter on a connected route gains $0.01 in surplus per day arising from price reductions (column (2)). Although small individually, there are around four times as many commuters on connected routes as on treated routes.

The third column aggregates these effects and reports the change in total commuter surplus in millions of dollars per month. Ignoring the private sector's response yields an estimated increase of $1.33 million per month. However, longer wait times for private transit reduce total surplus by $0.26 million per month, while lower prices on both treated and connected routes boost surplus by $0.41 million per month. Three quarters of the surplus from price reductions comes from connected routes, demonstrating how small diffuse impacts add up across the network. On aggregate, the private sector's response raises aggregate commuter surplus from public entry by $0.14 million per month to $1.47 million per month—accounting for 10% of the total commuter welfare gains from public transit.

[37]This is also the amount we would overestimate the benefits to commuters on treated routes if we ignored the private response. 95% confidence intervals for this ratio are [-3%,37%]. We also note the quantification includes all routes that were opened, not just the sample we collected panel data on.

Drivers. While commuters benefit from public transit entry, minibus drivers face significant losses from increased competition. At baseline, each minibus driver earned an average surplus of $11.87 per day, as shown in the first row of Panel B. Overall, drivers lose an average of $2.98 in surplus per day (25%, second row). These losses are the same for drivers on treated and connected routes, because driver mobility equalizes expected profits.

TABLE 8. Welfare Effects of Introducing Public Transit

		Individuals ($/individual/day)		**Aggregate** ($mn/month)
		Treated	Connected	
Panel A: Commuters	*Number:*	**252,004**	**919,579**	**1,171,583**
Baseline surplus from private transit		0.86	0.86	24.01
		[0.67,1.19]	[0.67,1.19]	[18.76,33.13]
Effect of introducing public transit		+0.20	+0.01	+1.47
		[0.14,0.29]	[0.00,0.03]	[0.94,2.16]
Direct benefit of public transit		+0.22	0	+1.33
		[0.17,0.31]		[1.04,1.83]
Additional impact from decrease in private departures		-0.04	0	-0.26
		[-0.07,-0.02]		[-0.42,-0.12]
Additional impact from decrease in private prices		+0.02	+0.01	+0.41
		[0.00,0.04]	[0.00,0.03]	[0.02,0.80]
Panel B: Minibus Drivers	*Number:*	**1,800**	**10,040**	**11,840**
Baseline surplus from private transit		11.87	11.87	2.97
		[9.01,13.36]	[9.01,13.36]	[2.25,3.34]
Effect of introducing public transit		-2.98	-2.98	-0.75
		[-4.25,-1.12]	[-4.25,-1.12]	[-1.06,-0.28]
Accounting for decrease in private departures, ignoring route switching		-2.35	0	-0.09
		[-3.42,-1.04]		[-0.13,-0.04]
Accounting for prices and private departures, ignoring route switching		-4.76	0	-0.18
		[-6.85,-2.10]		[-0.26,-0.08]
Additional impact of allowing route switching		+1.78	-2.98	-0.57
		[0.97,2.61]	[-4.25,-1.12]	[-0.80,-0.20]
Panel C: Public Bus Drivers	*Number:*	**1,640**	**0**	**1,640**
Wages		-	-	+0.21
Panel D: Costs				
Operating Costs (Buses)		-	-	+2.15
Operating Costs (Terminals)		-	-	+0.11

Notes: 95% Confidence intervals reported using a bootstrap procedure which draw 1000 values of $\gamma, \eta, \theta, \sigma, \Delta t^{W}_{ijM}, \Delta p_{ijM}, \hat{N}^{\text{Trips}}_{ij}$ from a normal distribution with mean equal to each parameter's point estimate and a standard deviation equal to its standard error. Driver surplus at baseline is measured using driver income net of all fees and expenses on the last day traveled in the baseline survey. Operating costs provided by LAMATA, and include fuel, maintenance and insurance for buses.

The subsequent rows decompose this loss in three steps. If prices and route choices were fixed, the drop in demand (i.e., fewer daily trips) would lower drivers' profits on treated routes by \$2.35 per day, while drivers on connected routes would remain unaffected (since their demand is unchanged). When the price decline on treated routes is incorporated, the loss for these drivers nearly doubles to \$4.76 per day while those on connected routes remain unaffected.[38] Finally, accounting for changes in routes benefits those on treated routes by \$1.78 per day, as they can shift to untreated alternatives, while it hurts drivers on connected routes by \$2.98 per day due to longer queues and lower fares. In aggregate, minibus drivers lose \$0.75 million per month, as shown in column (3) of Panel B.

Net Return. On net, commuters gain \$1.47 million per month, while minibus drivers lose \$0.75 million, resulting in a net benefit of \$0.72 million. Public bus drivers earn wages of \$0.29 million per month (an upper bound for their surplus, shown in Panel C). If one includes those wages, the combined surplus of \$1.01 million falls short of the \$2.26 million in operating costs, mostly fuel expenses, reported in Panel D. These calculations exclude other factors, such as emissions, that may affect societal surplus. However, ignoring the private response would meaningfully change the net return: commuter benefits of \$1.33 million per month—with no driver losses—would come much closer to operating costs.[39]

Robustness. Appendix Table S30 replicates the results using wild bootstrapped standard errors for the changes in departures and prices when computing confidence intervals. Although the confidence intervals widen slightly, zero remains excluded from most intervals—except for the contribution of price changes to individuals in columns (2) and (3), where zero is marginally included. Appendix Table S31 presents key quantitative results using different parameter values across columns. In column (2), we use the lower value of $\sigma = 2.04$ estimated via PPML; the driver results are very similar. Columns (3) and (4) adjust the estimated value of θ upward and downward by 25%. This adjustment notably affects the estimate of the direct effect, as evidenced by the scaling of the first line in equation (10), though the results remain qualitatively similar overall. Finally, column (5) evaluates the impact of a time valuation that is 25% lower than that estimated in our wait time experiment—reflecting a scenario where participants value airtime less than cash. In this case, commuter benefits are reduced (since commuters are more averse to longer private wait times), but only by 4%.

8. Conclusion

Despite ambitious policy goals to replace decentralized private transit with centralized public transit, many developing country cities will have hybrid systems. This paper analyzes the

[38] We observe changes in supply but not demand on connected routes, and so assume the change in driver trips and fares on connected routes is generated by drivers switching from treated to connected routes.

[39] Mass transit systems in large cities London, New York and Paris receive subsidies equal to 50-75% of operating costs, so the gap between societal benefits and costs is smaller here if we consider only commuters and about the same once drivers are accounted for.

interplay of public and private transit in Africa's largest city. We combine extensive data collected from observations, surveys, and ticketing, with quasiexperimental variation on the rollout of new public routes and an experiment on wait times with commuters at bus stops. We find that public entry partially displaces private minibuses, impacts fares, and causes drivers to reallocate across the system. We find that commuters have a high value of time. Altogether, we find that building a public transit system affects even commuters who continue to use the private network. Our analysis illuminates one particular design decision: Lagos' public system serves different stops from the private system, which prevents passengers from pooling into the first passing bus, and results in larger wait times (Bly and Oldfield 1986).

Quantifying these impacts may be important for better understanding resistance governments face by incumbents when introducing these types of reforms. Our results also suggest indirect impacts represent an important component of the total return to infrastructure investments. Our results suggest that distributional effects of government entry can be in network markets dominated by private incumbents.

Many further questions remain. When public transit is built, will private transit automatically rearrange into a socially useful structure (e.g., feeders), or does special care need to be taken? How should the design of public transit systems account for the service that can be provided by private networks? Are the regulations that are sufficient for a completely private system sufficient for one where private and public systems potentially connect and overlap? What combination of public and private transit best serve these growing cities?

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Online Appendix: Public and Private Transit

Contents

Appendix S1. Additional Details

S1.1. Minibus Driver Survey Sampling

Minibus drivers are difficult to sample. We found that terminal queues were a natural place to recruit drivers into our survey, but drivers travel frequently and some skip terminal queues. We attempt to obtain representative statistics on the population of minibus drivers using two sampling streams and a reweighting correction.[40]

We recruit most of our drivers (632) from terminal queues. For these drivers we apply a sampling correction. We seek to estimate the average value of a characteristic x in a population. However, each individual i may be in different states: although we sample individuals in a queue, the likelihood that i is in the queue is W_i. We ask our sampled drivers what proportion of their trips begin at terminals (w_i; that is one minus the proportion skipping the terminal start).[41] This yields an estimate of W_i: w_i. We apply this sampling probability in an inverse probability weight for our results using the driver survey. Note that if individuals are in the queue with the same probability ($w_i \equiv w$), this would not reweight individuals in this sample relative to one another. Alternately, note that this correction cannot help us for individuals who are *never* observed in the queue: if $w_i = 0$, we would never observe the individual in this sample.

To attempt to capture some of these drivers who queue less, we specified that a portion of our sample was to be recruited from drivers waiting outside terminals. These drivers (217 in number) are more likely to skip terminals starts: 12% report always skipping the terminal start. We had initially planned to apply the above correction in reverse for this sample, which would have assumed that a driver outside the terminal was planning on skipping the queue; however, 50% of these drivers report never skipping the queue in the past workday. So some of these drivers may be simply taking an extended break. For that reason, we do not apply a sampling correction to these drivers; we include them in the sample each with a weight of 1 (equivalent to a 100% probability of being sampled).

Online Appendix Table S7 compares the weighted statistics to their unweighted counterparts.

S1.2. Price Sensitivity

This section estimates the substitution parameter θ by estimating trip responses to unexpected public bus fare changes. If public buses follow the same indirect utility structure as minibuses (equation (4)), the commuter model implies we can recover $\theta = -\frac{\partial \ln N_{rt}}{\partial p_{rt}} \frac{1}{\gamma \mathbb{E}[(1-s_{ijP})]}$ using the semi-elasticity of the number of trips to price (estimated here), combined with our field experiment's estimate of γ and the observed share $\mathbb{E}[(1 - s_{ijP})]$.

S1.2.1. Background on Price Changes

The government implemented several changes to public bus prices in 2023 and 2024, in response to pressure arising from rising fuel prices and macroeconomic conditions. On August 2, 2023, the government

[40] This reweighting procedure was inspired by a conversation with Rob Jensen.

[41] We compute this proportion based on the trip diary for the previous day (including up to 8 trips) plus the trip they are about to complete on the day of survey (where we count them as beginning at the queue if they are sampled in the queue).

announced a 50% subsidy on public transit. Alongside this first price change, the government said it had arranged with minibus operators to reduce prices by 25%, but it has limited control over minibus fares so it is not clear whether minibus fares changed. We will treat this first price change separately from changes that followed. On November 7 the public transit subsidy was reduced to 25%.[42] On January 29, 2024, the public transit subsidy was eliminated, and on February 26, 2024, it was reinstated at 25%. This provides four changes in price for public buses, all of which were unexpected.

We illustrate the price changes by route in Figure S1. Each panel shows a different price change date, plotting the price two weeks prior (x-axis) and and two weeks after (y-axis), with a point for each combination of route and entry point. The size of the point is scaled to the number of boardings over those days. The plots include two reference lines: one corresponding to the announced price change (dashed blue) and the 45° line corresponding to no price change (dotted red). The observed prices broadly coincide with the announced price changes; however in some cases, prices were rounded to convenient currency multiples, and some smaller routes did not follow the overall price changes. As a result of these discrepancies, the first change in particular lowered prices by less than 50% on average.

FIGURE S1. Public Bus Price Changes

exhibits/priceelasticity/PRICE_change_fare_plots.pdf

Note: Plots show the fares the two weeks before (x-axis) and after (y-axis) designated price changes on public bus routes. Each point represents a combination of an initial fare and final fare, with size scaled to the number of boardings on routes and boarding locations facing those corresponding fares during those days. Dashed blue line corresponds to the announced price change; dotted red line corresponds to no price change.

We next show descriptively the trends in prices, ridership, and number of public buses in Figure S2. The dates of the price changes are designated with dashed blue lines. The sharp changes in average fare paid are evident in the top panel. These changes coincide with changes in the total number of trips on public transit, as shown in the second panel. However, price is not the only factor affecting the number of trips. Some changes in trips coincide with changes in service, as shown in the final panel, which shows the number of unique buses used each week. We note that although service is relatively stable around price changes, there is a slight increase in buses following the first price change (which would reduce wait times for passengers). For this reason, in addition to the coincident announcement about minibus fares, we exclude the first price change from our preferred estimates, but report results for all changes. Our specifications will focus on relatively narrow windows around each price change to minimize the risk of other minibus fare and supply adjustments. Demand will end up responding

[42]On November 6, the public transit subsidy was eliminated for a single day. We will include fixed effects in our specifications for this particular day.

quickly, suggesting that despite these narrow windows, we can still capture the full adjustment.

Overall these results suggest an empirical strategy that focuses on the variation in ridership around the sharp fare changes, accounting for slight deviations in the implemented fare changes between routes.

FIGURE S2. Public Transit Bus Trends 2023-2024

exhibits/priceelasticity/PRICE_trends.pdf

Note: Panels show the trend in average fares, total trips, and number of buses in the public bus system, per the electronic ticketing data, with a 7 day rolling average. Dotted lines indicate dates of fare changes. The major dropoff in travel and supply around 2023-12 to 2024-01 begins around Christmas.

S1.2.2. Estimation

We estimate the impact on prices around the discontinuities, and relate this to the corresponding impact on ridership. This allows us to account for the deviations in implementations. We assemble a dataset from e-ticketing at the route-day (rt) level, and include only observations within a designated number of days of a price change.[43]

Dynamics. To assess what time window is relevant for measuring the change, we first estimate the response of trips after different windows of time. We focus on the second price change (7 November 2023), because it is furthest from changes in the supply of buses and from other price changes. We jointly

[43] There are some route-days that have no boardings. Many of these appear to be idiosyncratic, suggesting they result from missing data. For that reason, we omit route-days that contain no boardings. We compute the mean price for each route-day, to account for minor variation in the recorded fare. In the log price specifications we omit a small number of observations that have a recorded price of zero.

estimate the system of seemingly unrelated linear regressions on price and log ridership,

$$p_{rt} = \boldsymbol{\zeta} Window_t + \phi_r + \psi_{DoW(t)} + \nu_{rt}$$

$$logN_{rt} = \boldsymbol{\alpha} Window_t + \mu_r + \xi_{DoW(t)} + \epsilon_{rt}$$

where $Window_t$ is a vector of indicator variables, which is 1 if t lies within a given window of days of the price change and 0 otherwise. We include fixed effects for route and day of week ($DoW(t)$). The price semi-elasticity for window k is then given by $\frac{\partial \ln N_{rt}}{\partial p_{rt}} = \frac{\alpha_k}{\zeta_k}$ (in log trips per ₦).

We also estimate a detrended version to account for possible trends in ridership. Using data from only the period before the price change, we estimate the trend equation

$$logN_{rt} = \beta \cdot t + \lambda_r + \chi_{DoW(t)} + e_{rt}.$$

We then predict the ridership for all periods $\hat{logN}_{rt}$, and estimate the detrended regression

$$logN_{rt} - \hat{logN}_{rt} = \boldsymbol{\alpha} Window_t + \mu_r + \xi_{DoW(t)} + \epsilon_{rt}$$

We estimate standard errors by bootstrapping the entire joint estimation procedure, resampling routes with replacement. We include 28 days before the price change (before which there was a temporary supply shock) and 42 days following the second price change (which coincides with December 18), as travel demand drops off around Christmas (December 25).

Results of the two specifications are shown in corresponding columns of Table S4. In both specifications, we see that trips adjust quickly in response to the price change: the price adjustment in later periods is similar to that in the first 14 day period, and if anything lower. Based on this, we move forward with 14 day windows, which allows us to use variation from more price changes.

TABLE S1. Response to a Price Change in Public System: Dynamic

	(1)	(2)
Price Impact ≤14 days (₦: ζ_1)	91.0832***	91.0832***
	(4.925)	(5.5768)
Price Impact 15-28 days (₦: ζ_2)	89.6402***	89.6402***
	(5.1617)	(5.6865)
Price Impact 29-42 days (₦: ζ_3)	88.9993***	88.9993***
	(5.2662)	(5.7557)
Log Trip Impact ≤14 days (α_1)	-0.2327***	-0.2569***
	(0.0394)	(0.0549)
Log Trip Impact 15-28 days (α_2)	-0.2115***	-0.2534***
	(0.0367)	(0.0714)
Log Trip Impact 29-42 days (α_3)	-0.1632***	-0.223***
	(0.0317)	(0.0853)
Price Sensitivity ≤14 days (log trips/₦: $\frac{\alpha_1}{\zeta_1}$)	-0.0026***	-0.0028***
	(0.0005)	(0.0007)
Price Sensitivity 15-28 days (log trips/₦: $\frac{\alpha_2}{\zeta_2}$)	-0.0024***	-0.0028***
	(0.0005)	(0.0009)
Price Sensitivity 29-42 days (log trips/₦: $\frac{\alpha_3}{\zeta_3}$)	-0.0018***	-0.0025**
	(0.0004)	(0.001)
Trips detrended		X
N	13466	13466
System R^2	0.9402	0.9402

Notes: Fare and log trips effects estimated jointly in a seemingly unrelated regression around the 7 November 2023 price change, including route and day of week fixed effects. Ratio of effects computed from these individual estimates. Specifications also include an indicator for 6 November 2023 (the single day where the subsidy was entirely removed). In the detrended specification, a linear time trend in the trips measure is estimated on the pre-period; this trend is then removed from all periods. Standard errors in parentheses estimated via bootstrapping the entire procedure, resampling routes with replacement. * p<0.1; ** p<0.05; *** p<0.01.

Pooled estimates. We produce our main estimates with an instrumental variables specification. We estimate price sensitivity with a specification of the form

$$logN_{rt} = \eta p_{rt} + \mu_r + \boldsymbol{\lambda} AroundDiscontinuity_t + \epsilon_{rt}$$

We instrument for price using the first stage specification

$$p_{rt} = \boldsymbol{\zeta} AfterDiscontinuity_t + \phi_r + \tilde{\boldsymbol{\lambda}} AroundDiscontinuity_t + \nu_{rt}$$

where $AfterDiscontinuity_t$ is a vector of indicator variables for which the k'th is 1 after the k'th price change and zero otherwise, and $AroundDiscontinuity_t$ is a vector of indicator variables for which the k'th is 1 within 14 days of the k'th price change and zero otherwise. We include only observations within 14 days of a price change.[44]

Estimated price sensitivities are shown in Table S5. The first column shows the estimate pooled over all price changes. The second column shows the estimate pooled over all but the first price change, since that change coincides with a slight supply increase and the announced change on minibus prices. The last 4 columns report the estimates from each price change individually. Estimated sensitivities are fairly similar regardless of which price change is used, which grants confidence that the shifts in ridership are not driven by extraneous factors. We use the estimate from column (2) as our value of $\frac{\partial \ln N_{rt}}{\partial p_{rt}} = -\theta\gamma\mathbb{E}[(1 - s_{ijP})]$.

As a robustness check, we verify that our estimate is not arising from a supply shift, in Appendix Table S21. We estimate the same specifications but with the outcome set to the log number of buses. The estimated effects are an order of magnitude smaller, have mixed signs, and the estimate on the 'All but first' specification is not statistically significantly different from zero. This suggests our procedure is not simply capturing shifts in supply.

Appendix S2. Wait Time Experiment

This section provides more details on the wait time experiment described in Section 6.2.

S2.1. Implementation

Enumerators had bright yellow hats, and waited near bus stops. Figure S5 shows a participant checking in with one of our enumerators.

The design of the experiment had several features to improve performance under poor network connectivity, and to minimize the chance of fraud. The sequence of random numbers was drawn in advance and so only needed to be loaded once on the enumerator's phone (it did not require an active internet connection). Numbers were different from day to day so one could not text the previous day's code. The sequence was saved in a separate file and designed to be difficult to parse even if one viewed the source code. The website required logging in with a valid enumerator phone number, and all usage was logged to detect suspicious usage or sharing. We did not find evidence of suspicious usage.

All participants responded to a baseline survey during onboarding. We cross randomized several aspects of the design:

- Bus stops were randomly selected to have the game play for either 3 or 5 weeks
- Each participant received a random checkin offer $s_n^{checkin}$ which was then held constant throughout the experiment

[44] We also include an indicator for the date 2023-11-6 (the single day where the subsidy was entirely removed) in both stages, for regressions that span that date.

- Upon checking in at the bus stop, each participant received a wait offer draw $(s_{nt}, \Delta t_{nt})$ which differed by day:
  - Participants were randomly allocated to one of two onboarding experiences:
    * For one group, on the first checkin at the bus stop, participants received a reward of $s_{nt} =$₦2000 for zero wait ($\Delta t_{nt} = 0$). On their next two checkins, participants received a random draw $(s_{nt}, \Delta t_{nt})$ which was generous (high payment per wait).
    * For the other group, on the first *two* checkins at the bus stop, participants received a reward for zero wait ($\Delta t_{nt} = 0$; $s_{nt} =$₦2000 on the first checkin and ₦500 on the second). On their following checkin, participants received a random draw $(s_{nt}, \Delta t_{nt})$ which was generous (high payment per wait).
  - On each checkin after their third, all participants received their own random draw $(s_{nt}, \Delta t_{nt})$ from the stable distribution.
- Starting July 24, 2023, bus stops were randomly selected to either (1) transition to a different set of 'scheduled' wait time offers which was announced by text message, (2) be sent a reminder message about the game (to act as a placebo) and then continue as normal, or (3) continue as normal with no reminder message. We omit the scheduled user-days from the analysis in this paper.

Near the end of the game, we followed up with an endline survey. For some participants this took place during the final week of the game; for some it took place after the game had concluded.

S2.2. Deviations from Pre-Analysis Plan

This section describes deviations from our pre-analysis plan (PAP).

Compliance rates were lower than we expected, so we revised our design to (1) use a selection correction in our estimation, (2) record intentions to travel as well as actual check ins, and (3) randomize the checkin offer $s_n^{checkin}$ to act as an instrument for checkins that is excluded from the wait decision. We treated initial data as pilot data, and revised the PAP accordingly. When implementing the theory in the paper, we corrected a mistake in the error terms in the selection correction, and also simplified the model so that ν_{nt}^{wait} is unknown at the point of checking in.

We refined a few aspects of the experiment while it was under way. Our main specifications include only users exposed to the final design. Table S24 column (4) shows that results are similar if we include earlier observations while the design was changing.[45]

The experiment was occasionally affected by network downtime. If the network prevented the sending of text messages, we informed participants to resend the messages in the same sequence when network became available (which would result in them being paid out as normal, since our system

[45]On June 9, 2023, to increase takeup we increased the payment upon registration from ₦500 to ₦1000 and increased the first day offer amount from ₦500 to ₦2000. We also began randomly allocating participants to either receive one or two days of zero wait offers to measure anticipation. Early recruits were given the information about the distribution of offers (as described in footnote 32) via text message on June 16; recruits after then were provided this on a handout upon intake. Prior to June 18 we varied the distribution of offers as we were learning the range that attained variation in acceptance; from June 19 onward, we used a single stable distribution for our main treatment. Our main sample includes only participants who began on or after June 19.

validates waits based on the random codes, not on when they are sent). When systematic downtime affected many users, we followed a protocol to send apology text messages and transfer airtime once the network was up.

S2.3. Likelihood

Let F^x indicate the marginal CDF along error x. Then the average log likelihood is given by

$$
\begin{aligned}
&\bar{l}(\gamma, \eta, \sigma^{checkin}, \rho | \mathbf{C}, \mathbf{D}, \mathbf{s}^{checkin}, \mathbf{s}, \Delta\mathbf{t}) = \\
&\quad \frac{1}{N} \sum_{nt} \Big[C_{nt} D_{nt} \log \Big(1 - F^{\nu^{wait}}(-\underline{D}_{nt}) - F^{\nu^{checkin}}(-\underline{C}_{nt}) + F(-\underline{D}_{nt}, -\underline{C}_{nt}) \Big) + \\
&\qquad C_{nt}(1 - D_{nt}) \log \Big(F^{\nu^{wait}}(-\underline{D}_{nt}) - F(-\underline{D}_{nt}, -\underline{C}_{nt}) \Big) + \\
&\qquad (1 - C_{nt}) \log F^{\nu^{checkin}}(-\underline{C}_{nt}) \Big]
\end{aligned}
\tag{S1}
$$

where participation thresholds are given by $\underline{D}_{nt}(\gamma, \eta) = \gamma s_{nt} - \eta \Delta t_{nt}$ and $\underline{C}_{nt}(\gamma, \eta, s_n^{checkin}) = \gamma s_n^{checkin} - \eta t^{checkin} + \mathbb{E}[\gamma s_{nt} - \eta \Delta t_{nt} + \nu_{nt}^{wait} | \gamma s_{nt} - \eta \Delta t_{nt} + \nu_{nt}^{wait} > 0] \cdot \Pr(\gamma s_{nt} - \eta \Delta t_{nt} + \nu_{nt}^{wait} > 0)$, the number of total observations is N.

S2.4. Additional Results

We present descriptives from our participants in Appendix Table S22. The rows are divided into three panels. The first panel presents characteristics measured in the baseline survey. The second panel shows settings and behavior in the game itself. The final panel shows responses in the endline.

Table S22 columns (1-6) report summary statistics of these measures across each individual to provide a description of our sample. The remaining columns (7-11) assess the success of our randomization. They report the correlation between the variables listed in the column and row, at the individual level. The correlation of randomly selected variables with baseline characteristics are all close to zero. Some of these variables are correlated with game outcomes downstream of treatment (for example, the checkin offer, $s_n^{checkin}$, is correlated with the proportion of days checking in, $\overline{C}_n$).

In the endline we asked about the wait time and offer they expected to obtain in the study.[46] The expected wait time (mean 10.61 minutes; median 10) lines up closely with the distribution we drew from (mean 10), as well as the empirical average (mean 10.08; median 9.92). However, participants appeared to struggle with answering the monetary offer; there were many outliers in these responses, and the mean participants reported is roughly 10 times the empirical mean, suggesting the question was not understood. (Participants may have answered how much they would have liked to be paid, rather than what they expected the system's offer would be.)

[46] We asked, 'How long did you think we would ask you to wait at the bus stop before taking the bus?' and 'How much did you think we would offer you to wait that long?', respectively.

S2.5. Robustness

S2.5.1. Sample Definitions

We assess robustness to alternate sample definitions in Table S24. In column (2) we use survey data to remove observations for days in the first week that participants told us they did not plan to travel (based on the baseline), and days in the last week that participants told us they did not travel (based on the endline). Column (3) excludes the high offers from the first days of checking in. Column (4) includes observations during the a pilot portion of the experiment where some design features were changing.[47] Estimates are similar in all cases.

S2.5.2. Arrival Time Adjustment

Another possible concern is that participants may anticipate a return to waiting, and so arrive at the bus stop early. If there were consistent evidence of this, our model could be adjusted to account for the scheduling cost. We assess the degree to which arrival times change in response to wait offers in Table S25 by regressing check in times at the bus stop (in minutes since midnight) on covariates. We perform three types of comparisons. Column (1) compares the time of the first checkin (omitted category) to later checkins, broken down by offer type, over the entire sample. Offer types include the no-wait second checkin (randomly assigned), the generous offers in the third and second checkin (for those not assigned a no-wait second checkin), and the stable distribution which was offered from the fourth checkin onward. For all of these offers, estimates are similar: participants check in on average 10.3 to 11.7 minutes earlier for the first checkin. This effect is the opposite one would expect if they solely factored in the wait time: they may have arrived earlier on the first check in to have enough time to resolve uncertainty about the experimental setup. Column (2) adds to this specification a control for days elapsed. If it takes time for participants to adjust their schedules to arrive earlier, this coefficient would be negative. However, it is a small and noisy zero. Column (3) restricts the sample to only the second checkin, for which participants were told that they would receive a payment either with or without a wait (randomly assigned). Here we see some evidence of adjustment: those assigned the no-wait offer arrive on average 6 minutes later; however the estimate is extremely noisy: despite having 535 observations we fail to reject a difference with zero (p-value: 0.50). Altogether, we do not see consistent evidence of schedule adjustment in response to the wait time experiment, and so have currently left that out of the model.

S2.5.3. Arrival Dependent Waiting

We asked our enumerators to stand away from bus stops, not in direct line of sight. However, it is possible that participants monitored bus arrivals, and decided whether to accept our wait offer depending on whether a bus arrived in the waiting time interval. As a robustness check we estimate a likelihood for which waiting depends on arrivals, using data we gathered on the frequency of minibus departures.

[47] Described in Section S2.2.

Let $\Pr(A)$ be the probability that a bus arrives within a timespan of Δt_{nt} minutes. We assume that the number of buses within that period, X, follows a Poisson arrival process, so that the probability of at least one arrival is given by $\Pr(A) = \Pr(X \geq 1) = 1 - e^{-\Delta t_{nt}\lambda}$ where λ is the average rate at which buses arrive.

Now let's refine the effect of the wait offer on travel time, building on equations (1) and (4). Let t_m be the status quo departure time and $t_m(\Delta t_{nt})$ be the departure time if the person accepts a wait offer of Δt_{nt} minutes. Conditional on checking in, the utility of accepting the offer has two cases. If no bus arrives within the interval Δt_{nt} (case $N = 1 - A$), then the offer entails no additional wait and the person will check out as long as

$$\alpha_m - \gamma s_{nt} - \eta t_m + \epsilon_{mnt+\Delta t_{nt}} > \alpha_m - \gamma p_m - \eta t_m + \epsilon_{mnt}.$$

On the other hand, if a bus arrives in that interval (case A) then the person will skip the bus to accept the offer only if they value the payment more than the wait. How long is the additional wait? Let's assume that the person makes the decision at the beginning based on the expected wait. Since the Poisson arrival process is memoryless, the arrival of a bus within the interval does not affect the probability of a bus after, and $\mathbb{E}[t_m(\Delta t_{nt}) - t_m] = \Delta t_{nt}$. This leads to the original condition,

$$\alpha_m - \gamma(p_m - s_{nt}) - \eta(t_m + \Delta t_{nt}) + \epsilon_{mnt+\Delta t_{nt}} > \alpha_m - \gamma p_m - \eta t_m + \epsilon_{mnt}.$$

Now, decompose the idiosyncratic error into a component that is stable across short waits and one that may vary, $\epsilon_{mnt} = \nu_{mn} + \nu_{nt}$. Then the consumer will wait in the two cases if

$$D_{nt}^{*N} = \gamma s_{nt} + \nu_{nt}^{wait} > 0$$
$$D_{nt}^{*A} = \gamma s_{nt} - \eta \Delta t_{nt} + \nu_{nt}^{wait} > 0.$$

where we define $\nu_{nt}^{wait} = \nu_{nt+\Delta t_{nt}} - \nu_{nt}$.

Perfect Compliance. For now, assume that compliance is perfect so participants always check in. Then, if there is no arrival then the probability of waiting is given by $F^{\nu^{wait}}(-\underline{D}_{nt}^N)$ for threshold $\underline{D}_{nt}^N(\gamma) = \gamma s_{nt}$. If there is an arrival, the probability of waiting is given by $F^{\nu^{wait}}(-\underline{D}_{nt}^A)$, for $\underline{D}_{nt}^A(\gamma, \eta) = \gamma s_{nt} - \eta \Delta t_{nt}$. Combining these and the probability of arrival yields the average log likelihood

$$\begin{aligned} \bar{l}(\gamma, \eta, \sigma^{wait}, \rho | \mathbf{D}, \mathbf{s}, \Delta \mathbf{t}) = \frac{1}{N} \\ \sum_{nt} D_{nt} \log\Big(1 - \Pr(1-A) F^{\nu^{wait}}(-\underline{D}_{nt}^N) - \Pr(A) F^{\nu^{wait}}(-\underline{D}_{nt}^A)\Big) + \\ (1 - D_{nt}) \log\Big(\Pr(1-A) F^{\nu^{wait}}(-\underline{D}_{nt}^N) + \Pr(A) F^{\nu^{wait}}(-\underline{D}_{nt}^A)\Big) \end{aligned} \tag{S2}$$

Note that when $A = 1$ this corresponds to the main model with perfect compliance. As A decreases, that increases the likelihood of accepting the offer ($D_{nt} = 1$) since the threshold for accepting the offer is lower since it involves no wait ($\underline{D}_{nt}^A \leq \underline{D}_{nt}^N$ so $F^{\nu^{wait}}(-\underline{D}_{nt}^A) \geq F^{\nu^{wait}}(-\underline{D}_{nt}^N)$).

Imperfect Compliance. Now, let's consider compliance. The utility of checking in is given by

$$C^*_{nt} = \gamma s_n^{checkin} - \eta t^{checkin} \qquad + \Pr(1-A)\mathbb{E}[D^{*N}_{nt} | D^{*N}_{nt} > 0] \Pr(D^{*N}_{nt} > 0)$$
$$+ \Pr(A)\mathbb{E}[D^{*A}_{nt} | D^{*A}_{nt} > 0] \Pr(D^{*A}_{nt} > 0)$$
$$+ \nu^{checkin}_{nt}$$

The average log likelihood is given by

$$\begin{aligned}
\bar{l}(\gamma, \eta, \sigma^{wait}, \sigma^{checkin}, \rho | \mathbf{C}, \mathbf{D}, \mathbf{s}^{checkin}, \mathbf{s}, \Delta\mathbf{t}) = \frac{1}{N} \\
\sum_{nt} C_{nt} D_{nt} \log \Big(1 - F^{\nu^{checkin}}(-\underline{C}_{nt}) + \Pr(1-A)\Big[-F^{\nu^{wait}}(-\underline{D}^N_{nt}) + F(-\underline{D}^N_{nt}, -\underline{C}_{nt})\Big] \\
+ \Pr(A)\Big[-F^{\nu^{wait}}(-\underline{D}^A_{nt}) + F(-\underline{D}^A_{nt}, -\underline{C}_{nt})\Big]\Big) + \\
C_{nt}(1 - D_{nt}) \log \Big(\Pr(1-A)\Big[F^{\nu^{wait}}(-\underline{D}^N_{nt}) - F(-\underline{D}^N_{nt}, -\underline{C}_{nt})\Big] \\
+ \Pr(A)\Big[F^{\nu^{wait}}(-\underline{D}^A_{nt}) - F(-\underline{D}^A_{nt}, -\underline{C}_{nt})\Big]\Big) + \\
(1 - C_{nt}) \log F^{\nu^{checkin}}(-\underline{C}_{nt})
\end{aligned} \tag{S3}$$

where participation thresholds are given by $\underline{D}^N_{nt}(\gamma, \eta) = \gamma s_{nt}$, $\underline{D}^A_{nt}(\gamma, \eta) = \gamma s_{nt} - \eta \Delta t_{nt}$ and $\underline{C}_{nt}(\gamma, \eta, s_n^{checkin}) = \gamma s_n^{checkin} - \eta t^{checkin} + \Pr(1-A)\mathbb{E}[\gamma s_{nt} + \nu^{wait}_{nt} | \gamma s_{nt} + \nu^{wait}_{nt} > 0] \cdot \Pr(\gamma s_{nt} + \nu^{wait}_{nt} > 0) + \Pr(A)\mathbb{E}[\gamma s_{nt} - \eta \Delta t_{nt} + \nu^{wait}_{nt} | \gamma s_{nt} - \eta \Delta t_{nt} + \nu^{wait}_{nt} > 0] \cdot \Pr(\gamma s_{nt} - \eta \Delta t_{nt} + \nu^{wait}_{nt} > 0)$, the number of total observations is N, and bold symbols represent vectors. Note that when $A = 1$ this corresponds to the main model. We estimate parameters using maximum likelihood, and cluster standard errors at the commuter level.

Results are shown in Table S26 for different bus arrival rates λ. Estimates are very similar even under extreme arrival rates. We trace out estimates that result under the arrival rates corresponding to various quantiles of realized headway between individual minibuses observed in departure observations. Note that these are observations of headways between individual minibuses, not average headways, so will have a more extreme distribution than any average λ commuters would expect. When buses are very frequent, the estimates coincide with the main estimate; they remain very similar up to the 95th percentile of observed individual headways which corresponds to 1.5 arrivals per half hour. At the 99th percentile of headway (entailing 0.8 buses per half hour), this model would expect commuters to accept almost all wait offers; the fact that they reject some would then suggest a high value of time ($\frac{\eta}{\gamma} = 48$ ₦/min). The implied value of time only begins to differ dramatically for very extreme values of λ (0.1 buses per half hour, corresponding to a departure every 5 hours, leads to a more extreme estimate of $\frac{\eta}{\gamma} = 373$ ₦/min). Since average headways are not this extreme, we interpret the results to suggest that arrival dependent waiting would not meaningfully affect our estimates of the value of time.

Appendix S3. Theory Appendix

S3.1. Complete Model Details

Model Overview. Given the queuing structure we document in these markets, the supply side consists of an M/M/1 queuing model with bulk service (Kendall 1953; Kleinrock 1975). Having chosen a route to work on, drivers queue, load passengers, complete their trip, and return to the origin, taking prices and the number of entrants as given. Daily profits depend on both the number of trips they expect to make and the profit per trip. The number of trips they can make in a workday depends on the time each trip takes plus the time spent queuing. The queuing time is shorter when demand is higher (as buses fill and depart faster) and when fewer buses are in the queue (since buses reach the front more quickly). Prices in the market are set by an association acting as a monopolist seeking to maximize its profits (akin to a rideshare platform).

Government entry introduces a new variety of travel mode that commuters value. As commuters adopt the new public mode, the arrival rate of passengers into the private market falls, creating a shock to its equilibrium.

S3.1.1. Commuters

Setup. Time is discrete and the horizon is infinite. Agents do not discount the future, but expect to exit the model after some period of time. There are I locations, $i \in \{1, \ldots, I\}$. Each period, commuters arrive at i intending to travel to j according to a Poisson process with parameter μ_{ij}. We call the pair ij a route.

Mode Choice. Commuters, indexed by n, select a mode $m \in \mathcal{M}$ to travel the route. Prior to government entry, $\mathcal{M} = \{M, 0\}$ includes minibus (M) and an outside option (0) capturing other modes such as walking or automobile. After government entry, public buses (P) are added to treated routes ($m \in \mathcal{M}' = \{M, P, 0\}$). The individual utility provided by mode m is given by $u_{ijmn} = u_{ijm} + \epsilon_{ijmn}$ where ϵ_{ijmn} is an additive type 1 extreme value preference distributed with scale parameter $1/\theta$ and location parameter $-\alpha_m/\theta \ \forall \, m \in \mathcal{M}$.

The fraction of commuters who choose minibuses is therefore

$$s_{ijm} = \frac{\exp(\theta u_{ijm})}{\sum_{m' \in \mathcal{M}} \exp(\theta u_{ijm'})} \tag{S4}$$

Overall consumer surplus on route ij is

$$\bar{U}_{ij} = \frac{1}{\gamma\theta} \ln\left(\sum_{m' \in \mathcal{M}} \exp(\theta u_{ijm'})\right). \tag{S5}$$

We are agnostic about the utility provided by public buses u_{ijP}, and normalize the mean utility of the outside option $u_{ij0} = 0$. To account for the potential changing utility provided by minibuses following government entry, we next model u_{ijM} explicitly.

Value Function for Minibus Travelers. Conditional on having chosen to travel via minibus, a commuter arrives at a queue for route ij. Passengers arrive at rate $\mu_{ij}s_{ijM}$, where s_{ijM} is the fraction of commuters who choose to travel via minibus. In what follows, we drop the explicit dependence of minibus market-specific objects on M where it does not introduce confusion.

With probability β_{ij} there is a bus waiting at the top of the queue. The commuter boards the bus, and pays a per period wait cost η as they wait to depart. Buses depart once they are full to their $\bar{n}$ passenger capacity. With probability $1-\beta_{ij}$ there is no bus waiting on the queue, so the commuter waits until one arrives and boards the bus. In steady state, it will turn out there are sufficient passengers for this bus to immediately depart, so we assume this from the outset and verify the conjecture below.

Buses arrive to the queue at Poisson rate λ_{ij}. The departure rate $\mu_{ij}s_{ijM}/\bar{n}$ depends on how fast passengers arrive and bus capacity, since each waits to fill before leaving. Once a bus departs, it arrives at its destination at Poisson rate δ^A_{ij}. Traveling passengers continue to pay the time cost η, but upon arrival at the destination receive a payoff $y - p_{ijM}$ consisting of their earnings for the day net of the fare, which they value with parameter γ.

We show in Appendix Section S3.2.1 that the expected value function for a commuter who chooses to travel via minibus is

$$
\begin{aligned}
u_{ijM} &= \gamma y - \gamma p_{ijM} - \eta t_{ijM} \\
\text{where} \quad t_{ijM} &= t^T_{ijM} + \underbrace{(1-\beta_{ij})t^W_{ijM} + \beta_{ij}t^F_{ijM}}_{\bar{t}^W_{ijM}} \\
t^W_{ijM} &= 1/\lambda_{ij} && \text{(S6)} \\
t^F_{ijM} &= \frac{1}{\mu_{ij}s_{ijM}}\left(\frac{\bar{n}}{2} - 1\right). && \text{(S7)}
\end{aligned}
$$

Total travel time t_{ijM} consists of both expected travel time $t^T_{ijM} = 1/\delta^A_{ij}$ and expected wait time $\bar{t}^W_{ijM}$. With probability β_{ij} there is a bus in the queue, and wait time depends on the time it takes for the bus to fill t^F_{ijM}. Since each bus is half full in expectation, this is given by the time it takes for $\bar{n}/2 - 1$ more passengers to arrive. With probability $1-\beta_{ij}$ there is no bus in the queue, and wait time depends on the arrival rate of buses to the queue $t^W_{ijM} = 1/\lambda_{ij}$.

S3.1.2. Supply

We begin by characterizing minibus behavior and profits conditional on having chosen a route, and then consider driver route choice.

Value Functions for Minibus Drivers. Each route follows a queuing model as follows. At terminal i, drivers may join a queue for route ij, and wait for buses ahead of them to fill up and depart on a first-in-first-out basis. A driver joining a queue with N^Q_{ij} buses in it expects to wait

$$
t^Q_{ij} = \frac{\bar{n}}{\mu_{ij}s_{ijM}}(N^Q_{ij} + 1) \tag{S8}
$$

minutes in the queue. This is the time it takes for these N_{ij}^{Q} buses, along with the driver arriving in the queue, to fill and depart. Once the driver reaches the top of the queue and fills up, it departs and receives net income per trip of $p_{ijM}\bar{n} - c_{ij}$. This depends on the revenues from passenger fares, as well as a lump sum cost of making the trip c_{ij}.

Buses arrive probabilistically at the destination, and at the end of each trip, drivers exit the model with a probability δ_{ij}^{E} proportional to the total length of a trip (micro-founded in Appendix Section S3.2.5). If they do not exit, they return to the end of the queue at i immediately. For tractability we abstract from the return leg of trips, and take the decision to leave when full as exogenous.[48]

Appendix Section S3.2.2 shows that the value function of a driver who enters a route ij (specifically, their value from joining the queue) is given by

$$V_{ij}^{Q} = \underbrace{\frac{T}{t_{ij}^{Q} + t_{ij}^{T}}}_{N_{ij}^{\text{Trips}}} \times \underbrace{[p_{ijM}\bar{n} - c_{ij}]}_{\pi_{ij}}$$

Intuitively, the value from entering a route depends on the number of trips a driver expects to make per day on that route and the profit per trip. Business stealing operates through queue lengths: more entrants on a route will, all else equal, increase time spent in queues through equation (S8) and reduce the number of trips the driver can complete in a day.

Route Choice. As explained in Section 3, drivers face high costs by the association to register to operate from a terminal. We therefore treat as separate the decisions of which terminal i to enter and which route ij to enter conditional on having chosen a terminal.

The value to entering a route ij is given by V_{ij}^{Q}. Drivers, indexed by φ, who have already entered terminal i solve the route choice problem $\max_j\{V_{ij}^{Q}\nu_{ij\varphi}\}$, where $\nu_{ij\varphi}$ is an idiosyncratic profit shock for each route. We assume these shocks are drawn from a Fréchet or type 2 extreme value distribution with shape parameter σ, so that the fraction of drivers at terminal i choosing route ij is given by

$$\rho_{ij} = \frac{\left(V_{ij}^{Q}\right)^{\sigma}}{\sum_k \left(V_{ik}^{Q}\right)^{\sigma}} = \frac{\left(N_{ij}^{trips} \times [p_{ijM}\bar{n} - c_{ij}]\right)^{\sigma}}{\sum_k \left(N_{ik}^{trips} \times [p_{ikM}\bar{n} - c_{ik}]\right)^{\sigma}}. \tag{S9}$$

Each period B_i drivers enter terminal i, so that $B_{ij} = B_i\rho_{ij}$ join the queue for route ij. We discuss how total entry B_i is determined below.

Due to properties of the Fréchet distribution, average profits for entrants at terminal i are the same regardless of the route they choose. These are related to the denominator of the choice probabilities through

$$\Pi_i = \underbrace{\Gamma\left(\frac{\sigma - 1}{\sigma}\right)\left[\sum_k \left(N_{ik}^{trips} \times [p_{ikM}\bar{n} - c_{ik}]\right)^{\sigma}\right]^{1/\sigma}}_{\Pi_i^{V}} - F_i \tag{S10}$$

[48]In the data we find that 96% of minibuses leave when full.

where Π_i^V are average variable profits, $\Gamma(\cdot)$ is the gamma function, and F_i are registration costs charged by the minibus association to operate at terminal i.

S3.1.3. Minibus Association

We will allow our model to accommodate free or fixed entry of drivers. We solve the association's problem under free entry, and then state how the results change under fixed entry.

The minibus association sets prices and registration fees to maximize its revenues at each terminal. Under free entry of minibus drivers, these are equal to (per-period) variable profits $B_i \Pi_i^V$. We formulate the problem in terms of choosing optimal prices p_{ijM} and the number of entrants B_i, where the latter can then be inverted to solve for optimal registration fees using the free entry condition.[49]

The association maximizes this objective subject to several constraints. First, it cannot directly control drivers choice of which route to enter after entry into a terminal. Instead, it understands that as it shifts overall entry into the terminal and prices on each route, it affects the number of buses on each route B_{ij} via drivers' "route choice" constraint[50]

$$\frac{B_{ij}}{B_i} = \left(\frac{T}{t_{ij}^Q + t_{ij}^T} \frac{p_{ijM}\bar{n} - c_{ij}}{\Pi_i^V} \right)^{\sigma}. \tag{S11}$$

Second, the association understands that by changing prices and entry it affects queue times faced by drivers

$$t_{ij}^Q = \frac{\bar{n}}{\mu_{ij} s_{ijM}(p_{ij}, B_{ij})} (1 + N_{ij}^Q(p_{ij}, B_{ij})). \tag{S12}$$

Third, it faces an adding up constraint

$$B_i = \sum_j B_{ij}. \tag{S13}$$

The association's problem is therefore represented by the lagrangian

$$\begin{aligned}
\mathcal{L} = {} & B_i \Pi_i^V \\
& + \sum_j \kappa_{ij} \left[\frac{T}{t_{ij}^Q + t_{ij}^T} \left[p_{ijM}\bar{n} - c_{ij} \right] \left(\frac{B_{ij}}{B_i} \right)^{-1/\sigma} - \Pi_i^V \right] \\
& + \sum_j \lambda_{ij} \left[t_{ij}^Q - \frac{\bar{n}}{\mu_{ij} s_{ijM}(p_{ij}, B_{ij})} (1 + N_{ij}^Q(p_{ij}, B_{ij})) \right]
\end{aligned}$$

[49] In a quantitative implementation we could follow the literature on ridesharing platforms (e.g. Rosaia (2024)) and assume the association maximizes a combination of profits and consumer surplus. This would capture that the government may pressurize the association towards benefiting commuters in exchange for the right to oversee transit provision and for the land given to it for terminals. However since we do not use the association side of the model in the sufficient statistics approach, we omit this for brevity.

[50] We drop the dependence of profits on the constant $\Gamma(\frac{\sigma-1}{\sigma})$ to economize on notation. We also note that choice probabilities s_{ijM} and queue lengths N_{ij}^Q depend on entry through its effects on the arrival rate of buses into the queue λ_{ij} and the probability of finding a bus on the queue β_{ij}, so denote this dependence implicitly.

$$+\mu_i\left[\sum_j B_{ij}-B_i\right]$$

where $\kappa_{ij}, \lambda_{ij}, \mu_i$ are the multipliers on the driver route choice constraint, the queue time constraint, and the adding up constraint respectively. The necessary first order at an optimum are

$$\kappa_{ij}\frac{T}{t_{ij}^Q+t_{ij}^T}\bar{n}-\lambda_{ij}t_{ij}^Q\frac{\partial \ln t_{ij}^Q}{\partial p_{ij}}=0 \tag{p_{ijM}}$$

$$\Pi_i^V+\frac{1}{\sigma}\frac{\Pi_i^V}{B_i}\sum_j \kappa_{ij}-\mu_i=0 \tag{B_i}$$

$$-\kappa_{ij}\frac{1}{\sigma}\frac{\Pi_i^V}{B_{ij}}-\lambda_{ij}t_{ij}^Q\frac{\partial \ln t_{ij}^Q}{\partial B_{ij}}+\mu_i=0 \tag{B_{ij}}$$

$$B_i=\sum_j \kappa_{ij} \tag{Π_i^V}$$

$$\lambda_{ij}-\kappa_{ij}\frac{\Pi_i^V}{t_{ij}^Q+t_{ij}^T}=0 \tag{t_{ij}^Q}$$

Optimal Prices. Combining first order conditions (p_{ijM}) and (t_{ij}^Q) yields

$$\frac{T}{t_{ij}^Q+t_{ij}^T}\bar{n}-\frac{t_{ij}^Q}{t_{ij}^Q+t_{ij}^T}\Pi_i^V\underbrace{\left[\left|\frac{\partial \ln s_{ijM}}{\partial p_{ij}}\right|+\frac{N_{ij}^Q}{1+N_{ij}^Q}\frac{\partial \ln N_{ij}^Q}{\partial p_{ij}}\right]}_{\frac{\partial \ln t_{ij}^Q}{\partial p_{ij}}}=0$$

When the association raises prices on route ij, it increases profits for each driver by the number of tickets it expects to sell on a day (captured by the first term). But it also increases the time each bus spends in the queue as the arrival rate of passenger falls (captured by the second term). This happens both because higher prices cause fewer passengers to arrive each period thus lowering the departure rate of buses from the queue, as well as having effects on the equilibrium queue length. The optimal price equates these costs and benefits, leading to a markup

$$p_{ijM}-c_{ij}/\bar{n}=\frac{1}{\frac{t_{ij}^Q}{t_{ij}^Q+t_{ij}^T}\left(\frac{B_{ij}}{B_i}\right)^{-1/\sigma}\frac{\partial \ln t_{ij}^Q}{\partial p_{ij}}} \tag{S14}$$

Prices will therefore be lower whenever queue times are more sensitive to prices, since the association loses more revenues as a result of higher prices, adjusted for the productivity of drivers on the route $(B_{ij}/B_i)^{-1/\sigma}$.

Optimal Entry. Combining first order conditions (B_i) and (B_{ij}), multiplying by ρ_{ij} and summing across routes yields

$$\Pi_i^V - \sum_j \rho_{ij}\lambda_{ij}\frac{\partial t_{ij}^Q}{\partial B_{ij}} = 0$$

When the association adds an entrant, it gains its variable profits (captured by the first term). But the entrant steals business from incumbents by increasing the time they spend queuing. Since the cost to the association of raising queue times in route ij is captured by the multiplier λ_{ij}, the term $\lambda_{ij}\frac{\partial t_{ij}^Q}{\partial B_{ij}}$ is the cost of increasing adding an entrant to route ij. The second term is therefore the expected cost of adding a driver to the terminal, where the expectation is taken over the probability the entrant chooses the various available routes ρ_{ij}. Rearranging this condition to solve for κ_{ij} and combining this with the first order condition (Π_i^V) yields

$$B_i = \frac{\sigma+1}{\sigma}\sum_j \frac{1}{\frac{1}{\sigma B_{ij}} + \frac{t_{ij}^Q}{t_{ij}^Q + t_{ij}^T}\frac{\partial \ln t_{ij}^Q}{\partial B_{ij}}}.$$

The optimal number of entrants is lower when queue times are more sensitive to the number of entrants on each route, since entrants steal more business from incumbents.

Association Behavior Under Fixed Entry. When the overall number of entrants is fixed, the association takes B_i as given and chooses F_i, p_{ijM} to maximize $B_i F_i$ subject to the same set of constraints as above, plus one additional constraint that $\Pi_i^V \geq F_i$, i.e. that drivers earn non-negative profits. Solving this problem yields exactly the same price setting condition (S14). The association also again captures driver surplus since the non-negative profit constraint binds.

S3.1.4. Steady State Equilibrium

Queue Length. Letting B_{ij}^T denote the number of traveling buses on route ij in steady state, the arrival rate of buses into the queue is

$$\lambda_{ij} = \chi_{ij} \times \left[(1-\delta_{ij}^E)B_{ij}^T + B_{ij}\right]. \tag{S15}$$

Each period, $1-\delta_{ij}^E$ of the traveling buses arrive at their destination and re-join the queue while B_{ij} entering buses also join. $\chi_{ij} \in (0,1]$ is a parameter that reflects a possible delay in buses arriving in the queue.[51] The exit rate from the queue is $\mu_{ij}s_{ijM}/\bar{n}$, i.e. the arrival rate of $\bar{n}$ passengers. We show in Appendix Section S3.2.4 that in steady state, the average number of buses in the queue is given by

$$N_{ij}^Q = \left[\frac{\mu_{ij}s_{ijM}}{\chi_{ij}\lambda_{ij}\bar{n}} - 1\right]^{-1}. \tag{S16}$$

This shows how greater entry from minibus drivers will tend to increase queue lengths (and queue times) through λ_{ij}. While greater demand through $\mu_{ij}s_{ijM}$ will tend to reduce queue lengths by increasing

[51] This is introduced to ensure a finite queue length in equation (S16).

the departure rate from the queue, it will also have an effect on arrival rates λ_{ij} through the number of entrants.

Entry. Our assumption for long-run equilibrium in the market is that the number of entrants B_i is determined by free entry. Under free entry, B_i adjusts to affect queue times until

$$\Pi_i^V - F_i = 0 \; \forall i \tag{S17}$$

We assume this determines the initial equilibrium prior to public entry, and impose this in the equilibrium definition below.

The model can also accommodate a fixed number of entrants, and we impose this assumption to evaluate the changes in surplus from the policy given we do not observe driver exit (Table 4). We view this as a medium-run response with exit potentially following in the long-run (in which case we would impose the free entry condition in the post-entry equilibrium once more).

Traveling Buses. In steady state, the number of traveling buses leaving the state $B_{ij}^T \delta_{ij}^A$ must equal the inflows $\mu_{ij} s_{ijM}/\bar{n}$, so that[52]

$$B_{ij}^T = \frac{\mu_{ij} s_{ijM}}{\bar{n}\delta_{ij}^A}. \tag{S18}$$

Equilibrium Definition. *Given model parameters* $\{\gamma, \eta, \alpha_m, \theta; \bar{n}, c^d, \chi, \sigma, T\}$ *and data* $\{\mu_{ij}, t_{ij}^T, d_{ij}\}$*, an equilibrium is a vector* $\{s_{ijm}, \bar{U}_{ij}, \rho_{ij}, \Pi_i, t_{ij}^W, t_{ij}^F, t_{ij}^Q, p_{ij}, N_{ij}^Q, \lambda_{ij}, B_i, B_{ij}^T\}$ *such that i) commuter surplus and mode choices satisfy (S4), (S5) ; ii) driver surplus and route choices satisfy (S9), (S10); iii) equilibrium waiting and queue times satisfy (S6), (S7), and (S8); iv) prices satisfy association optimality* (S14) *and v) equilibrium queue lengths, arrival rates of buses into the queue, the entry rate and number of traveling buses satisfy steady state conditions (S15), (S16),* (S17) *and (S18).*

S3.2. Additional Results and Derivations

S3.2.1. Derivation of Commuter Value Functions

We derive the value function on a single route, and so omit dependency of variables on route ij. We begin by solving for utility of a traveler who has chosen to travel via minibus. When this traveler arrives at the origin there is either a bus waiting or not. If there is a waiting bus, the passenger boards and waits for it to depart. If not, the passenger waits for one to arrive, enters it, and waits for it to depart.

Value Function for Waiting Passengers. With probability β there is a bus waiting. As shown in Appendix Section S3.2.3, the expected number of passengers waiting in the bus is $\bar{n}/2$. We want to solve for the value of joining a bus with this number of passengers already on board.

[52]This last term is the probability a bus in the queue has $\bar{n} - 1$ passengers $1/\bar{n}$ times the probability an additional passenger shows up $\mu_{ij} s_{ijM}$

Let $U^B(n)$ be the value of arriving at a bus with $n < \bar{n}$ passengers in it. A commuter waiting at a bus stop incurs a per-period wait cost of $-\eta$. Since the bus leaves when it has $\bar{n}$ passengers, if there are $\bar{n}-2$ passengers on the bus she boards, the commuter waits until one additional passenger arrives. The value function is therefore

$$\begin{aligned} U^B(\bar{n}-2) &= -\eta + \mu s_M U^T + (1-\mu s_M)U^B(\bar{n}-1) \\ &= -\eta \frac{1}{\mu s_M} + U^T, \end{aligned}$$

where U^T is the value of being on a traveling bus, and $1/\mu s_M$ is the expected time for an additional passenger to join the waiting bus.

The value of arriving at a bus with $\bar{n}-3$ passengers on it is therefore

$$\begin{aligned} U^B(\bar{n}-3) &= -\eta \frac{1}{\mu s_M} + U^B(\bar{n}-2) \\ &= -\eta \frac{2}{\mu s_M} + U^T \end{aligned}$$

Continuing, the expected value of arriving when there is a waiting bus (which has $\bar{n}/2 = \bar{n} - \bar{n}/2$ passengers on it) is

$$\begin{aligned} U^B &= -\eta t^F + U^T \\ \text{where } t^F &= \frac{1}{\mu s_M}\left(\frac{\bar{n}}{2} - 1\right) \end{aligned}$$

is the expected time it takes for the bus to fill $\bar{n}/2 - 1$ passengers under passenger arrival rate μs_M.

With probability $1-\beta$ there is no bus waiting when they arrive. One arrives at Poisson rate λ. The value of arriving when there is no bus waiting is therefore

$$\begin{aligned} U^{NB} &= -\eta + \lambda \tilde{U}^B + (1-\lambda)U^{NB} \\ &= -\eta t^W + \tilde{U}^B \end{aligned}$$

where $t^W \equiv 1/\lambda$ is the expected time to wait for a bus to arrive, and $\tilde{U}^B$ is the value of the passenger being able to load the bus after waiting t^W periods, at which point there are $\mu_m t^W$ passengers waiting. We know that if $\mu_m t^W > \bar{n}$, then the bus departs immediately. We will show later this is satisfied in steady state, so $\tilde{U}^B = U^T$. Therefore

$$U^{NB} = -\eta t^W + U^T.$$

Value Function for Traveling Passengers. A traveling bus arrives according to a Poisson process with parameter δ^A. While traveling, passengers pay the time cost $-\eta$. If they arrive, they receive a payoff $y-p$ consisting of their earnings for the day net of the price of the fare, which they value with parameter γ. Their value function is therefore

$$U^T = -\eta + \delta^A(\gamma(y-p)) + (1-\delta^A)U^T$$

$$= -\eta t^T + \gamma(y - p)$$

where $t^T = 1/\delta^A$ is expected travel time on the route.

Expected Value Function. Using these results to compute the expected value from traveling by minibus $U_m = (1-\beta)U^{NB} + \beta U^B$, and adding back the dependency of variables on route, we find that

$$\begin{aligned} U_{ijM} &= \gamma y - \gamma p_{ijM} - \eta t_{ijM} \\ \text{where } \ t_{ijM} &= t^T_{ijM} + \underbrace{(1-\beta_{ij})t^W_{ijM} + \beta_{ij} t^F_{ijM}}_{\bar{t}^W_{ijM}} \end{aligned}$$

where $t^T_{ijM} = 1/\delta^A_{ij}$ is expected travel time, and $\bar{t}^W_{ijM}$ is the expected time the passenger waits at the bus queue until they depart. This consists of $t^W_{ijM} = 1/\lambda_{ij}$, the expected wait time when no bus is on queue when the passenger arrives, and $t^F_{ijM} = \frac{1}{\mu_{ij} s_{ijM}} \left(\frac{\bar{n}}{2} - 1\right)$, the expected time for the bus to fill and depart if there is one on the queue when the passenger arrives. Note that the endogenous probability $\beta_{ij} = \lambda_{ij}\bar{n}/\mu_{ij}s_{ijM}$ is derived in Appendix Section S3.2.4.

S3.2.2. Derivation of Minibus Driver Value Functions

We derive the value function on a single route, and so omit dependency of variables on route ij.

Value Functions, Traveling Buses. When traveling, a bus arrives at its destination with probability δ^A. If it arrives, it exits the model with probability δ^E. With probability $1-\delta^E$ it returns to the start of the queue at the route origin. We also allow for drivers to have a time cost c when traveling or queuing. The value function of a traveling minibus is therefore

$$\begin{aligned} V^T &= -c + \delta^A(1-\delta^E)V^Q + (1-\delta^A)V^T \\ &= -ct^T + (1-\delta^E)V^Q. \end{aligned}$$

Value Functions, Queuing Buses. Consider a bus joining a queue with N buses. Departures from the queue occur at rate $\mu s_M/\bar{n}$ since each bus waits to fill to capacity $\bar{n}$ before departing. Using the recursion

$$\begin{aligned} V^Q(N) &= -c + \frac{\mu s_M}{\bar{n}} V^Q(N-1) + (1 - \frac{\mu s_M}{\bar{n}})V^Q(N) \\ &= -\frac{c\bar{n}}{\mu s_M} + V^Q(N-1) \end{aligned}$$

allows us to solve for the value of joining a queue with N buses as a function of being at the front of the queue $V^Q(0)$ as

$$V^Q(N) = -c\frac{N\bar{n}}{\mu s_M} + V^Q(0) \tag{S19}$$

This is intuitive, as $\frac{N\bar{n}}{\mu s_M}$ is the expected time it takes to for the queue of length N to clear.

Once at the top of the queue, the bus starts from zero waiting passengers. Let $V^Q(0,n)$ be the value of being at the top of the queue with n waiting passengers in the vehicle. Then $V^Q(0) = V^Q(0,0)$ which satisfies the recursion

$$\begin{aligned} V^Q(0,0) &= -c + \mu s_M V^Q(0,1) + (1-\mu s_M)V^Q(0,0) \\ &= -\frac{c}{\mu s_M} + V^Q(0,1) \\ V^Q(0,1) &= -\frac{c}{\mu s_M} + V^Q(0,2) \\ &\vdots \\ V^Q(0,\bar{n}-1) &= -\frac{c}{\mu s_M} + p\bar{n} - c_M + V^T \end{aligned}$$

The last line says that once the bus has one vacant seat left, it pays the cost to wait the expected amount of time $1/\mu s_M$ for one more passenger to arrive, gets the fares from passengers $p\bar{n}$, pays the lump sum monetary cost of travel c_M, and gains the value from becoming a traveling bus.

Solving this recursion yields $V^Q(0) = p\bar{n} - c_M - \frac{c}{\mu s_M} + V^T$. Substituting this, and the expression for V^T into (S19) allows us to express the value of joining a queue on ij as

$$V^Q_{ij} = \frac{1}{\delta^E_{ij}} \times \left[p_{ij}\bar{n} - c_{ij} - c(t^Q_{ij} + t^T_{ij})\right] \qquad \text{where} \qquad t^Q_{ij} = \frac{\bar{n}}{\mu_{ij} s_{ijM}}(N^Q_{ij}+1)$$

Note that queue time t^Q_{ij} is an endogenous object which depends on the length of the queue in steady state N^Q_{ij}, and we replace c_M with c_{ij} to match the notation in the text.

Note that $1/\delta^E_{ij}$ is the expected number of trips the driver expects to make in a day. Appendix Section S3.2.5 shows that if we assume a finite workday length without driver exit, we get exactly the expression above for the value of entry into a route, with $T/(t^Q + t^T)$ instead of $1/\delta^E_{ij}$ premultiplying the per-trip profit function. This is because in a workday of length T, since each trip takes $t^Q + t^T$, drivers make exactly $T/(t^Q + t^T)$ trips in a day. We therefore parameterize $\delta^E_{ij} = (t^Q_{ij} + t^T_{ij})/T$ to deliver this same expression. The overall value of joining a queue is then

$$V^Q_{ij} = \underbrace{\frac{T}{t^Q_{ij} + t^T_{ij}}}_{N^{\text{Trips}}_{ij}} \times \underbrace{\left[p_{ij}\bar{n} - c_{ij} - c\left(t^Q_{ij} + t^T_{ij}\right)\right]}_{\pi_{ij}}$$

which depends on the number of trips drivers expect to make in a day, times the profits per trip.

Finally, since the time cost of queuing is already captured through its effect on the number of trips, we assume $c = 0$ to deliver the final expression for the value function used in the text.

S3.2.3. Distribution of Passengers Waiting on a Bus

The probability distribution p_n of the number people n waiting evolves according to

$$p^{pass}_{n,t+dt} = p^{pass}_{n,t}(1 - \mu_{ij}s_{ijM}dt) + p^{pass}_{n-1}\mu_{ij}s_{ijM}dt.$$

In steady state this becomes $p^{pass}_n = p^{pass}_{n-1}$,which implies a uniform distribution, so

$$p^{pass}_n = \begin{cases} \frac{1}{\bar{n}} & \text{if } n \leq \bar{n} \\ 0 & \text{otherwise.} \end{cases}$$

Therefore the expected number of passengers waiting on a bus if there is one in the queue is $\bar{n}/2$.

S3.2.4. Derivation of Steady State Queue Length

This section characterizes equilibrium queue lengths. We again suppress dependence on route ij. The arrival rate of buses into the queue is

$$\lambda = \chi \times \left[(1 - \delta^E)B^T + B\right]$$

where B^T, B are the number of traveling and entering buses in steady state and $\chi \in (0, 1]$ is a parameter that reflects a potential delay in buses arriving into the queue. The exit rate from the queue is $\mu s_M/\bar{n}$. The Kolgomorov Forward Equation describing the distribution β_n of the number of buses n is then

$$\begin{aligned} \beta_{0,t+dt} &= \beta_{0,t}\,(1 - \lambda dt) + \beta_{1,t}\frac{\mu s_M}{\bar{n}}dt \\ \beta_{n,t+dt} &= \beta_{n+1,t}\frac{\mu s_M}{\bar{n}}dt + \beta_{n-1,t}\lambda dt + \beta_{n,t}\left(1 - \lambda dt - \frac{\mu s_M}{\bar{n}}dt\right) \quad \forall\, n > 0 \end{aligned}$$

Letting $dt \to 0$ we get

$$\begin{aligned} \beta_1 &= \frac{\lambda \bar{n}}{\mu s_M}\beta_0 \\ 0 &= (\beta_{n+1} - \beta_n)\,\frac{\mu s_M}{\bar{n}} + (\beta_{n-1} - \beta_n)\,\lambda \end{aligned}$$

Solving this recursively, we find

$$\beta_n = \xi^n \beta_0 \quad \text{where } \xi \equiv \frac{\lambda \bar{n}}{\mu s_M}$$

Since this is a probability distribution, we find β_0 from the normalization

$$\beta_0 \sum_{n=0}^{\infty} \xi^n = 1 \quad \Rightarrow \quad \beta_0 = 1 - \xi$$

Note β_0 also provides the probability of commuters finding zero buses on the queue needed to compute expected wait times for passengers, where we define in the paper the probability of finding a bus in the queue as $\beta_{ij} \equiv 1 - \beta_{0,ij}$.

The average number of buses in the queue ij is then

$$N_{ij}^Q = \sum_{n=0}^{\infty} n(1-\xi_{ij})\xi_{ij}^n = \frac{\xi_{ij}}{1-\xi_{ij}} = \left[\frac{\mu_{ij}s_{ijM}}{\lambda_{ij}\bar{n}} - 1\right]^{-1}$$

where we have used $\sum_{n=0}^{\infty} n\xi^n = \xi\frac{\partial}{\partial\xi}\sum_{n=0}^{\infty}\xi^n$ in the second equality. Note these results require $\lambda_{ij}\bar{n} < \mu_{ij}s_{ijM}$, which is why we include the delay parameter $\chi_{ij} \in (0,1]$.

S3.2.5. Alternative Value Function in Finite Time

This section solves driver value functions under a finite work day length. The aim is to microfound the exit probability (which governs the average work day length, and number of trips each driver expects to make, in the main model).

A workday has a finite length T. We first characterize the value functions of traveling buses. In a small period of length dt, traveling buses pay a time cost cdt, and arrive with probability $\delta^A dt$ (in which case they immediately return to the start of the queue, otherwise they continue traveling). The value function is then

$$V^T(t) = -cdt + (1-\delta^A dt)V^T(t+dt) + \delta^A dt V^Q(t+dt).$$

Subtracting $V^T(t)$ from both sides, dividing by dt and letting $dt \to 0$ yields

$$V^T(t) = -t^T\left[c - \dot{V}^T(t)\right] + V^Q(t)$$

where $t^T = 1/\delta^A$ is expected travel time, and $\dot{V}^T(t) \equiv \partial V^T(t)/\partial t$. In words, the value of traveling is the time cost (both the length of the trip itself, plus the reduction in work time), plus the value of rejoining the queue after the trip is complete. We again consider a single route and drop the notational dependence of variables on ij.

In equilibrium, a queue has length N^Q. In the main text, the expected time to leave the queue is $t^Q(N^Q) = \frac{\bar{n}}{\mu s_M}(N^Q+1)$. We therefore consider a simplified process where the bus departs the queue with probability $\delta^Q = \mu s_M/(\bar{n}(N^Q+1))$ giving the same expected time in the queue. The value of joining the queue is therefore

$$V^Q(t) = -cdt + \delta^Q dt\left[p\bar{n} - c_M + V^T(t+dt)\right] + (1-\delta^Q dt)V^Q(t+dt),$$

where c_M is again the lump sum monetary cost of the trip. Subtracting $V^Q(t)$ from both sides, dividing by dt and letting $dt \to 0$ yields

$$V^Q(t) = p\bar{n} - c_M - t^Q\left[c - \dot{V}^Q(t)\right] + V^T(t)$$

At the end of the period, the value of joining the queue is zero so $V^Q(T) = 0$. The system of equations is then

$$V^T(t) = -t^T\left[c - \dot{V}^T(t)\right] + V^Q(t)$$

$$V^Q(t) = p\bar{n} - c_M - t^Q \left[c - \dot{V}^Q(t)\right] + V^T(t)$$
$$V^Q(T) = 0$$

Guess and Verify. We guess the value functions take the form

$$V^Q(t) = \alpha^Q + \beta^Q(T - t)$$
$$V^T(t) = \alpha^T + \beta^T(T - t)$$

where the dependence of V^Q on N, which is constant in equilibrium, is absorbed in the coefficients. Then $\dot{V}^T(t) = -\beta^T$ and $\dot{V}^Q(t) = -\beta^Q$. Plugging this into these two equations gives

$$\alpha^T + \beta^T(T - t) = -t^T \left[c + \beta^T\right] + \alpha^Q + \beta^Q(T - t)$$
$$\alpha^Q + \beta^Q(T - t) = p\bar{n} - c_M - t^Q \left[c + \beta^Q\right] + \alpha^T + \beta^T(T - t)$$

Equating coefficients we get $\beta^T = \beta^Q = \beta$, and substituting this in and doing the same for the α shifters yields

$$\alpha^T = -t^T [c + \beta] + \alpha^Q$$
$$\alpha^Q = p\bar{n} - c_M - t^Q [c + \beta] + \alpha^T$$

Substituting the second into the first yields

$$0 = p\bar{n} - c_M - t^T [c + \beta] - t^Q [c + \beta]$$
$$\beta = \frac{p\bar{n} - c_M - ct^T - ct^Q}{t^T + t^Q}$$

The boundary condition implies $\alpha^Q = 0$, which delivers a final expression for

$$\alpha^T = -t^T [c + \beta]$$

These conditions collectively verify the guess. Putting these together delivers the functional form for the value of joining a queue at time $t = 0$ as

$$V^Q(0) = \underbrace{\frac{T}{t^T + t^Q}}_{N^{\text{Trips}}} \times \underbrace{\left[p\bar{n} - c_M - c(t^T + t^Q)\right]}_{\pi^{\text{PerTrip}}}$$

where $N^{Trips} \equiv \frac{T}{t^T + t^Q}$ is the number of trips the driver can make in a period of length T. As in Section S3.2.2, we simplify by assuming $c = 0$.

S3.2.6. Derivation of Change in Consumer Surplus

We first compute the change in welfare on a single route, dropping the dependence on ij. Consumer surplus is given by

$$\bar{U} = \frac{1}{\gamma\theta} \ln \left(1 + \sum_{m \in \mathcal{M}} \exp \left(\alpha_m - \theta\eta t_m - \theta\gamma p_m \right) \right)$$

where we impose the normalization of the utility of the outside option We want to know how this changes after mode P is added to the set of available modes which become $\mathcal{M}' = \mathcal{M} \cup \{P\}$.

The change in consumer surplus is given by

$$\begin{aligned}
\Delta CS &= \frac{1}{\gamma\theta} \ln \left(\frac{1 + \exp\left(\alpha_M - \theta\eta t'_M - \theta\gamma p'_M\right) + \exp\left(\theta u_P\right)}{1 + \exp\left(\alpha_M - \theta\eta t_M - \theta\gamma p_M\right)} \right) \\
&= \frac{1}{\gamma\theta} \ln \left(\frac{1 + \exp\left(\alpha_M - \theta\eta t'_M - \theta\gamma p'_M\right)}{1 + \exp\left(\alpha_M - \theta\eta t_M - \theta\gamma p_M\right)} + \frac{\exp\left(\theta u_P\right)}{1 + \exp\left(\alpha_M - \theta\eta t_M - \theta\gamma p_M\right)} \right) \\
&= \frac{1}{\gamma\theta} \ln \left(\frac{1 + \exp\left(\alpha_M - \theta\eta t'_M - \theta\gamma p'_M\right)}{1 + \exp\left(\alpha_M - \theta\eta t_M - \theta\gamma p_M\right)} + \frac{\exp\left(\theta u_P\right)}{\sum_{n \in \mathcal{M}'} \exp\left(u'_n\right)} \frac{\sum_{n \in \mathcal{M}'} \exp\left(\theta u'_n\right)}{1 + \exp\left(\alpha_M - \theta\eta t_M - \theta\gamma p_M\right)} \right) \\
&= \frac{1}{\gamma\theta} \ln \left(\frac{1 + \exp\left(\alpha_M - \theta\eta t'_M - \theta\gamma p'_M\right)}{1 + \exp\left(\alpha_M - \theta\eta t_M - \theta\gamma p_M\right)} + s'_P \exp\left(\gamma\theta\left(CS' - CS\right)\right) \right) \\
&= \frac{1}{\gamma\theta} \ln \left(s_0 + \frac{\exp\left(\alpha_M - \theta\eta t_M - \theta\gamma p_M\right)}{1 + \exp\left(\alpha_M - \theta\eta t_M - \theta\gamma p_M\right)} \frac{\exp\left(\alpha_M - \theta\eta t'_M - \theta\gamma p'_M\right)}{\exp\left(\alpha_M - \theta\eta t_M - \theta\gamma p_M\right)} + s'_P \exp\left(\gamma\theta\Delta CS\right) \right) \\
&= \frac{1}{\gamma\theta} \ln \left(s_0 + s_M \exp\left(-\theta\eta\Delta t_M - \theta\gamma\Delta p_M\right) + s'_P \exp\left(\gamma\theta\Delta CS\right) \right) \\
\exp\left(\gamma\theta\Delta CS\right) &= s_0 + s_M \exp\left(-\theta\eta\Delta t_M - \theta\gamma\Delta p_M\right) + s'_P \exp\left(\gamma\theta\Delta CS\right) \\
\exp\left(\gamma\theta\Delta CS\right) &= \frac{1}{1 - s'_P} \left[s_0 + \exp\left(-\theta\eta\Delta t_M - \theta\gamma\Delta p_M\right) \right] \\
\Rightarrow \Delta CS &= \frac{1}{\gamma\theta} \ln \left[\frac{1}{1 - s'_P} \times \left[s_0 + \exp\left(-\theta\eta\Delta t_M - \theta\gamma\Delta p_M\right) \right] \right]
\end{aligned}$$

Summing across all routes gives the change in aggregate surplus

$$\Delta CS = \sum_{ij} \mu_{ij} \left[\frac{1}{\gamma\theta} \ln \left(\frac{1}{1 - s'_{ijP}} \right) + \frac{1}{\gamma\theta} \ln \left(s_{ij0} + \exp\left(-\theta\eta\Delta t_{ijM} - \theta\gamma\Delta p_{ijM}\right) \right) \right].$$

S3.2.7. Computing General Equilibrium Counterfactuals

We begin by showing the system of equations that characterize equilibrium. In the initial equilibrium we impose the free entry condition, but in the system of equations governing the change in equilibrium variables in response to public entry we will take the number of entrants to be held fixed as explained in Section S3.1.4.

Equilibrium Definition. Given model parameters $\{\gamma, \eta, \alpha_m, \theta; \bar{n}, c_{ij}, \chi_{ij}, \sigma, T\}$ and data $\{\mu_{ij}, t^T_{ij}, F_i\}$, an equilibrium is a vector $\{s_{ijM}, t^W_{ij}, t^F_{ij}, \lambda_{ij}, t^Q_{ij}, p_{ij}, N^Q_{ij}, B^T_{ij}, B_{ij}, B_i, \bar{U}_{ij}\}$ such that

$$
\begin{aligned}
s_{ijM} &= \frac{\exp\left(\alpha_M - \theta\eta t_{ijM} - \theta\gamma p_{ijM}\right)}{\sum_{n\in\mathcal{M}} \exp\left(\alpha_n - \theta\eta t_{ijn} - \theta\gamma p_{ijn}\right)} \\
t_{ij}^W &= 1/\lambda_{ij} \\
t_{ij}^F &= \frac{1}{\mu_{ij} s_{ijM}} \left(\frac{\bar{n}}{2} - 1\right) \\
\lambda_{ij} &= \chi_{ij}\left[(1-\delta_{ij}^E)B_{ij}^T + B_{ij}^E\right] \\
t_{ij}^Q &= \frac{\bar{n}}{\mu_{ij} s_{ijM}}(N_{ij}^Q + 1) \\
N_{ij}^Q &= \left[\frac{\mu_{ij} s_{ijM}}{\chi_{ij}\lambda_{ij}\bar{n}} - 1\right]^{-1} \\
p_{ijM} - c_{ij}/\bar{n} &= \frac{1}{\frac{t_{ij}^Q}{t_{ij}^Q + t_{ij}^T}\left(\frac{B_{ij}}{B_i}\right)^{-\frac{1}{\sigma}}\left[\gamma(1-s_{ijM}) + \frac{N_{ij}^Q}{1+N_{ij}^Q}\frac{\partial \ln N_{ij}^Q}{\partial p_{ij}}\right]} \\
B_{ij}^T &= \frac{\mu_{ij} s_{ijM} t_{ij}^T}{\bar{n}} \\
B_{ij} &= B_i \times \frac{\left(N_{ij}^{trips} \times [p_{ijM}\bar{n} - c_{ij}]\right)^{\sigma}}{\sum_k \left(N_{ik}^{trips} \times [p_{ikM}\bar{n} - c_{ik}]\right)^{\sigma}} \\
0 &= \Gamma\left(\frac{\sigma-1}{\sigma}\right)\left[\sum_k \left(N_{ik}^{trips} \times [p_{ikM}\bar{n} - c_{ik}]\right)^{\sigma}\right]^{1/\sigma} - F_i \\
\bar{U}_{ij} &= \frac{1}{\theta}\ln\left(1 + \sum_{m\in\mathcal{M}} \exp\left(\alpha_m - \theta\eta t_{ijm} - \theta\gamma p_{ijm}\right)\right)
\end{aligned}
$$

where $t_{ijm}, \delta_{ij}^E, \beta_{ij}, N_{ij}^{trips}$ are auxiliary variables

$$
\begin{aligned}
t_{ijM} &= t_{ijM}^T + (1-\beta_{ij})t_{ij}^W + \beta_{ij} t_{ij}^F \\
\delta_{ij}^E &= \frac{t_{ij}^Q + t_{ij}^W}{T} \\
\beta_{ij} &= \frac{\chi_{ij}\lambda_{ij}\bar{n}}{\mu_{ij} s_{ijM}} \\
N_{ij}^{trips} &= \frac{T}{t_{ij}^Q + t_{ij}^T}
\end{aligned}
$$

The partial elasticity $\frac{\partial \ln N_{ij}^Q}{\partial p_{ij}}$ in the optimal price formula is also a function of equilibrium objects and parameters

$$
\frac{\partial \ln N_{ij}^Q}{\partial p_{ij}} = \left(N_{ij}^Q + 1\right)\gamma(1-s_{ijM})\left[1 - \frac{(1-\delta_{ij}^E)\frac{\mu_{ij}s_{ijM}t_{ij}^T}{\bar{n}}}{(1-\delta_{ij}^E)\frac{\mu_{ij}s_{ijM}t_{ij}^T}{\bar{n}} + B_{ij}} - \frac{1}{\chi_{ij}\left[(1-\delta_{ij}^E)\frac{\mu_{ij}s_{ijM}t_{ij}^T}{\bar{n}} + B_{ij}\right]}\frac{\sigma B_{ij}(1-B_{ij})}{\gamma(1-s_{ijM})}\frac{\partial B_{ij}}{\partial p_{ijM}}\right]
$$

where $\frac{\partial B_{ij}}{\partial p_{ijM}} = \sigma B_{ij}(1 - B_{ij}) \left[\frac{\bar{n}}{p_{ij}\bar{n} - c_{ij}} - \frac{1}{t_{ij}^Q + t_{ij}^T} \frac{\frac{(t_{ij}^Q)^2}{\bar{n}} \mu_{ij} \left(1 - \chi_{ij}(1 - \delta_{ij}^E) t_{ij}^T\right)}{1 + \frac{(t_{ij}^Q)^2}{\bar{n}} \sigma B_{ij}(1 - B_{ij}) \frac{1}{t_{ij}^Q + t_{ij}^T}} \gamma (1 - s_{ijM}) s_{ijM} \right]$

General Equilibrium Counterfactuals. We now show how the equilibrium system of equations can be used to compute the impacts of government entry. The shock to this system is the market share of the government entrant s'_{ij} in the post-entry period.

Letting $\hat{x} \equiv x'/x$ denote the relative change in a variable x between the pre- and post-entry period, the system of equilibrium equations (assuming the number of entrants at each terminal is fixed) can be rewritten as

$$\begin{aligned}
\hat{s}_{ijM} &= \frac{\exp\left(-\theta\eta\Delta t_{ijm} - \theta\gamma\Delta p_{ijm}\right)}{(1 - s_{ijm}) + s_{ijm}\exp\left(-\theta\eta\Delta t_{ijm} - \theta\gamma\Delta p_{ijm}\right)} \times \left[1 - s'_{ijP}\right] \\
\hat{t}_{ij}^W &= \hat{\lambda}_{ij}^{-1} \\
\hat{t}_{ij}^F &= \frac{1}{\hat{s}_{ijM}} \\
\hat{\lambda}_{ij} &= \pi_{ij}^\lambda \widehat{(1 - \delta_{ij}^E)} \hat{B}_{ij}^T + (1 - \pi_{ij}^\lambda) \hat{B}_{ij} \\
\hat{B}_{ij}^T &= \hat{s}_{ijM} \\
\hat{t}_{ij}^Q &= \frac{\widehat{N_{ij}^Q + 1}}{\hat{s}_{ijM}} \\
\widehat{N_{ij}^Q + 1} &= \frac{1 - \xi_{ij}}{1 - \xi_{ij}\hat{\xi}ij} \\
\hat{\xi}_{ij} &= \frac{\hat{\lambda}_{ij}}{\hat{s}_{ijM}} \\
\hat{B}_{ij} &= \frac{\left(\hat{N}_{ij}^{trips}\right)^\sigma \left[\hat{p}_{ijM}\pi_{ij}^{rev} + \pi_{ij}^{rev} - 1\right]^\sigma}{\sum_k \rho_{ik} \left(\hat{N}_{ik}^{trips}\right)^\sigma \left[\hat{p}_{ikM}\pi_{ik}^{rev} + \pi_{ik}^{rev} - 1\right]^\sigma} \\
\Delta p_{ijM} &= p_{ijM}\left(\hat{p}_{ijM} - 1\right)
\end{aligned}$$

where

$$\begin{aligned}
\pi_{ij}^\lambda &= \frac{(1 - \delta_{ij}^E) B_{ij}^T}{(1 - \delta_{ij}^E) B_{ij}^T + B_{ij}} \\
\Delta t_{ijm} &= \pi_{ij}^T + (1 - \pi_{ij}^T)\left[\pi_{ij}^W \widehat{(1 - \beta_{ij})} \hat{t}_{ij}^W + \pi_{ij}^F \hat{\beta}_{ij} \hat{t}^F\right] \\
\pi_{ij}^T &= \frac{t_{ijM}^T}{t_{ijM}} \\
\pi_{ij}^W &= \frac{(1 - \beta_{ij}) t_{ij}^W}{(1 - \beta_{ij}) t_{ij}^W + \beta_{ij} t_{ij}^F} \\
\pi_{ij}^F &= \frac{\beta_{ij} t_{ij}^F}{(1 - \beta_{ij}) t_{ij}^W + \beta_{ij} t_{ij}^F}
\end{aligned}$$

$$\hat{\beta}_{ij} = \frac{\hat{\lambda}_{ij}}{\hat{s}_{ijM}}$$

$$\widehat{(1-\beta_{ij})} = \frac{1-\beta_{ij}\hat{\beta}_{ij}}{1-\beta_{ij}}$$

$$\hat{\delta}^{E}_{ij} = \frac{t^Q_{ij}}{t^Q_{ij}+t^W_{ij}}\hat{t}^Q_{ij} + \frac{t^W_{ij}}{t^Q_{ij}+t^W_{ij}}\hat{t}^W_{ij}$$

$$\hat{N}^{trips}_{ij} = \left[\frac{t^Q_{ij}}{t^Q_{ij}+t^T_{ij}}\hat{t}^Q_{ij} + \frac{t^T_{ij}}{t^Q_{ij}+t^T_{ij}}\right]$$

$$\rho_{ij} = \frac{\left(N^{trips}_{ij} \times [p_{ijM}\bar{n} - c_{ij}]\right)^{\sigma}}{\sum_k \left(N^{trips}_{ik} \times [p_{ikM}\bar{n} - c_{ik}]\right)^{\sigma}}$$

$$\hat{p}_{ijM} = \frac{p_{ijM} - c_{ij}/\bar{n}}{p_{ijM}}\widehat{p_{ijM} - c_{ij}}/\bar{n} + \frac{c_{ij}/\bar{n}}{p_{ijM}}$$

$$\widehat{p_{ijM} - c_{ij}}/\bar{n} = \frac{1}{\frac{\hat{t}^Q_{ij}}{\widehat{t^Q_{ij}+t^T_{ij}}}\left(\frac{\hat{B}_{ij}}{\hat{B}_i}\right)^{-\frac{1}{\sigma}}\left[\frac{\gamma(1-s_{ijM})}{\gamma(1-s_{ijM}) + \frac{N^Q_{ij}}{1+N^Q_{ij}}\frac{\partial \ln N^Q_{ij}}{\partial p_{ij}}}\widehat{1-s_{ijM}} + \frac{\frac{N^Q_{ij}}{1+N^Q_{ij}}\frac{\partial \ln N^Q_{ij}}{\partial p_{ij}}}{\gamma(1-s_{ijM}) + \frac{N^Q_{ij}}{1+N^Q_{ij}}\frac{\partial \ln N^Q_{ij}}{\partial p_{ij}}}\widehat{\frac{N^Q_{ij}}{1+N^Q_{ij}}}\widehat{\frac{\partial \ln N^Q_{ij}}{\partial p_{ij}}}\right]}$$

This system of equations would allow us to use the model to compute full general equilibrium counterfactuals. However they also elucidate why the model's many interactions restrict its ability to deliver clear comparative statics.

S3.2.8. Testing Profit Equalization Across Treated and Connected Routes

Our empirical results show queue lengths and prices change on treated and connected routes. We use results from the driver survey to argue this is due to route substitution by drivers. This section uses the model to test whether the empirical results on treated and connected routes are consistent with average profit equalization across routes.[53]

Taking logs of equation (5) and substituting in its components, we have

$$\log(V^Q_{ij}) = \log(T) - \log(t^T_{ij} + t^Q_{ij}) + \log(p_{ijM}\bar{n} - c_{ijM})$$

We next take differences and simplify using first order approximations to get

$$\begin{aligned} d\ln(V^Q_{ij}) &\approx -\frac{t^Q_{ij}}{t^Q_{ij}+t^T_{ij}}d\ln(t^Q_{ij}) + \pi^r_{ijM}d\ln(p_{ijM}) \\ &\approx -\frac{t^Q_{ij}}{t^Q_{ij}+t^T_{ij}}\left[\frac{N^Q_{ij}}{N^Q_{ij}+1}d\ln(N^Q_{ij}) - d\ln(\mu_{ij}s_{ijM})\right] + \pi^r_{ijM}d\ln(p_{ijM}). \end{aligned}$$

Here we use that $d\ln(T) = d\ln(\bar{n}) = d\ln(t^T_{ij}) = 0$ given that none of minibus workdays, minibus

[53] We thank Gabriel Kreindler for this suggestion. We also note we are abstracting from the Fréchet adjustment for the idiosyncratic term, and are thus looking at the change in the common commponent of profits.

occupancy or road speeds respond to the policy. In the first line we use the approximation $\log(t_{ij}^T + t_{ij}^Q) \approx \frac{t_{ij}^Q}{t_{ij}^Q + t_{ij}^T} d\ln(t_{ij}^Q)$ since $d\ln(t_{ij}^T) = 0$. In the second line, we take a first order expansion of queue times $t_{ij}^Q = \frac{\bar{n}}{\mu_{ij} s_{ijM}}(N_{ij}^Q + 1)$ from equation (S8) to deliver the substitution in the second line. Recall also that π_{ijM}^r is the ratio of gross to net driver revenue defined in the text.

From Appendix Table S2 we can approximate the baseline time spent in queues $\frac{t_{ij}^Q}{t_{ij}^T + t_{ij}^Q} = 0.424$, and the inverse profit margin $\pi_{ijM}^r = 3.36$ based on reported income and expenses broken down by day. The mean queue length of 4.75 yields $\frac{N_{ij}^Q}{N_{ij}^Q + 1} = 0.83$. This yields a model-implied (first order) change in profit of

$$d\log(V_{ij}^Q) \approx -0.42\left(0.83 \cdot d\log(N_{ij}^Q) - d\log(\mu_{ij} s_{ijM})\right) + 3.36 \cdot d\log(p_{ijM}). \tag{S20}$$

We compute this object for both treated and spillover routes using the specifications in even columns of Table 5 via seemingly unrelated regression. Appendix Table S27 shows the results. The change in profits are remarkably similar, with a reduction of 0.376 log points on treated routes and 0.334 log points on connected routes. Despite the relative precision with which these objects are estimated, we fail to reject their equality (p-value 0.78). This supports the model mechanism of driver sorting across routes until profits are equalized.

S3.3. Additional Details on Quantification

Implementing the sufficient statistics approach for the welfare change of commuters and minibus drivers in (10) and (11) requires measuring three sets of objects.

S3.3.1. Descriptive Statistics

First, we require a collection of descriptive statistics $(s_{ijM}, \pi_{ij}^{rev}, B_i, \rho_{ij}, \mu_{ij}, s'_{ijP})$. We estimate the pre-entry minibus market share using the 2009 Lagos Travel Survey which yields a minibus share of trips at $s_{ijM} = 0.56$.[54] Driver profit margins π_{ij}^{rev} are measured directly in our driver surveys, yielding an average value of 3.3.

Our welfare decomposition in (11) requires data only from terminals where the public system operates, as we argue there are no effects on routes where public transit is unavailable at either endpoint. We construct our measures of B_i, ρ_{ij} in two steps: first, by estimating key inputs within our baseline sample of observed routes, and then by extending these inputs to all routes at treated terminals to determine total entrants and driver share distributions.

Total Entrants B_i. Using baseline driver survey data, we regress log daily trips on log trip distance to estimate daily trips per driver per route $N_{ij}^{\text{TripsPerDriverPerDay}} = \exp\left(\hat{\alpha} + \hat{\beta}\ln Dist_{ij}\right)$ as a function of its distance, where hats denote estimated values. We then estimate total minibus daily trips per route by

[54] This statistic considers all modes, while the 62% mentioned elsewhere excludes walking. In the driver survey, we ask total revenue collected on the last working day as well as the income the driver earned after paying all fees and expenses. π_{ij}^{rev} is the ratio of the two.

summing bus departures within our three observation windows and applying two adjustments. First, since these windows capture only part of the day, we scale up based on e-ticketing data, which indicates that 40% of weekday trips occur during the observation windows. We assume the same distribution across times of day applies to minibus trips. Second, we account for "sole" trips—those not originating from terminals—estimated at 21% of driver trips based on survey data. Total daily trips by drivers are thus computed as $\text{TotalDriverTrips}_{ij} = \frac{1}{0.4\times0.79} \times \text{ObservedTrips}_{ij}$. Since TotalTrips_{ij} is the product of the number of drivers on ij and their expected daily trips, we recover the number of drivers on a route ij at baseline from

$$N_{ij}^{\text{Drivers}} = \frac{\text{TotalDriverTrips}_{ij}}{N_{ij}^{\text{TripsPerDriverPerDay}}}. \tag{S21}$$

This measure includes only routes covered in our route observation survey, which may not capture all routes at a terminal. For terminals with public service which are in our observation survey sample, we use our network census to measure the number of treated routes $N_{i,\text{Treat}}$ and the number of connected routes $N_{i,\text{Connected}}$. We use the measure of N_{ij}^{Drivers} from above to compute the average number of drivers on treated routes $\bar{N}_{i,\text{Treat}}^{\text{Drivers}}$ and connected routes $\bar{N}_{i,\text{Connected}}^{\text{Drivers}}$, allowing us to compute total entrants as:

$$B_i = N_{i,\text{Treat}} \times \bar{N}_{i,\text{Treat}}^{\text{Drivers}} + N_{i,\text{Connected}} \times \bar{N}_{i,\text{Connected}}^{\text{Drivers}}.$$

For terminals with public service not covered in our survey sample, we use an observation we conducted for all routes in the network census immediately following the route mapping to compute the total number of drivers using (S21). For these terminals, $B_i = \sum_j N_{ij}^{\text{Drivers}}$. Ideally, we would measure total entrants for these routes at baseline rather than relying on 2022 network census data. However, the two measures are highly correlated (correlation coefficient 0.96) for terminals included in both datasets, suggesting this approach is reliable.

Distribution of drivers ρ_{ij}. Since treatment effects are constant across treated and connected routes, we only need to measure the fraction of drivers at terminals with public entry who operate on treated routes; the remainder operate on connected routes. For terminals with public service included in our observation survey sample, we compute this directly as $s_{i,\text{Treat}}^{\text{Driver}} = N_{i,\text{Treat}} \times \bar{N}_{i,\text{Treat}}^{\text{Drivers}}/B_i$. We then regress the share of treated drivers on the share of treated routes for these terminals ($R^2 = 0.71$) and use the fitted values to predict the treated driver share at terminals with public service that are not in our survey sample, based on the share of their routes that are treated (which we observe in the network census). Altogether, this delivers $\rho_{i,\text{Treat}}^{\text{Driver}} = \sum_{j\in\text{Treated}_i} \rho_{ij}$ and $\rho_{i,\text{Connected}}^{\text{Driver}} = 1 - \rho_{i,\text{Treat}}^{\text{Driver}}$. These are the terms we need to estimate the change in driver surplus.[55]

Post-entry public share s'_{ijP}. A fraction $1 - s_{ij0}$ of travelers use public transit. In the pre-entry period, we measure $s_{ijM} = 1 - s_{ij0}$ directly from the Lagos Travel Survey. For the post-entry period, we know

[55] Since treatment effects are constant on treated and connected routes, the change in surplus at treated terminals is

$$\hat{\Pi}_i^V = \left[\rho_{i,\text{Treat}}^{\text{Driver}} \left(\hat{N}_{\text{Treat}}^{\text{Trips}}\right)^{\sigma} \left[\hat{p}_{\text{Treat}}\pi_{ij}^{rev} + 1 - \pi_{ij}^{rev}\right]^{\sigma} + \rho_{i,\text{Connected}}^{\text{Driver}} \left(\hat{N}_{\text{Connected},i}^{\text{Trips}}\right)^{\sigma} \left[\hat{p}_{\text{Connected},i}\pi_{ij}^{rev} + 1 - \pi_{ij}^{rev}\right]^{\sigma}\right]^{1/\sigma}$$

where changes on connected routes can differ by terminal due to the number of open public routes at that terminal.

that

$$s'_{ijP} = 1 - s_{ijM}\hat{s}_{ijM} - s_{ij0}\hat{s}_{ij0} \tag{S22}$$

where hats denote relative changes. This equation highlights how the post-entry public market share depends on shifts in the share of the outside option—i.e., whether trips on the new public system substitute for minibus trips or come from other sources.

To estimate $\hat{s}_{ij0}$, we differentiate the expression for total trip,s $N_{ijt} = N^0_{ijt} + N^{Transit}_{ijt}$, which says that total trips are comprised of those on transit (private and public) and the outside option. Assuming that the total number of trips is unchanged (i.e. the new public system does not generate entirely new trips), differentiating this expression yields

$$\hat{s}_{ij0} = \exp\left(-\frac{1-s_{ij0}}{s_{ij0}}\frac{d\ln N^{Transit}_{ijt}}{d\text{Open}_{ij}}\right)$$

Estimating the change in the share of users choosing the outside option therefore requires knowing the elasticity of the total number of transit passengers to public entry. Table S28 shows that total transit trips (minibus and public transit combined) increase by 0.149 log points (standard error 0.088) after public transit opens on a route. Using this, we compute $\hat{s}_{ij0}$ from the equation above.

Finally, we estimate $\hat{s}_{ijM} = \exp\left(\frac{d\ln Pass_{ijM}}{d\text{Open}_{ij}}\right)$ using our main specification but with log passengers as the outcome and find an elasticity of -0.298 (standard error 0.153). Substituting these values into (S22), we obtain a post-entry public share of $s'_{ijP} = 0.193$.

Traveler arrival rates μ_{ij}. The total number of trips μ_{ij} is the sum of trips on public transit $\mu_{ij}s'_{ijP}$ and private transit $\mu_{ij}s'_{ijM}$, adjusted for the outside option, from the identity

$$\mu_{ij}(1 - s'_{ij0}) = \mu_{ij}s'_{ijP} + \mu_{ij}s'_{ijM}$$
$$\Rightarrow \mu_{ij} = \frac{\mu_{ij}s'_{ijP} + \mu_{ij}s'_{ijM}}{1 - s'_{ij0}} \tag{S23}$$

We measure daily public transit trips $\mu_{ij}s_{ijP'}$ as the average number of daily trips from the e-ticketing data for each route. To estimate daily trips on the private system, $\mu_{ij}s_{ijM'}$, we first sum total private trips on each route as recorded in our network census observation survey, conducted immediately after the 2022 network mapping. We then apply three adjustments to scale these numbers to daily totals. First, we account for the fact that only 40% of public trips occur during our observation windows. We assume the same distribution across times of day applies to minibus trips. Second, we adjust for the 21% of trips that are "sole" and do not originate from terminals. Third, we correct for passenger boardings along the route rather than at the origin, based on GPS tracking data collected by enumerators during network mapping, which indicates that 92% of passengers along a route board at the origin terminal.

We therefore compute total minibus passenger trips as

$$\mu_{ij}s'_{ijM} = \frac{1}{0.4 \times 0.79 \times 0.92} \times \text{ObservedPassTrips}_{ij}$$

Plugging in $\mu_{ij}s'_{ijM}$, $\mu_{ij}s'_{ijP}$ and our estimate of $1 - s'_{ij0}$ outlined in the previous section allows us to compute passenger arrival rates μ_{ij} using (S23).

S3.3.2. Policy Elasticities

We require estimates of the changes in minibus prices (Δp_{ijM}, $\hat{p}_{ijM}$), commuter wait times (Δt_{ijM}) and driver daily trips ($\hat{N}_{ij}^{\text{Trips}}$) in response to public entry. These come from our reduced form results.

We find no effects on minibus departures on connected routes, and so define a change in commuter wait times only on treated routes equal to $\Delta t_{ijM} = \bar{t}_{ijM} \times 0.16$, where $\bar{t}_{ijM}$ is the average initial wait time on treated routes and $0.16 = -\frac{\partial \ln Dep_{ij}}{\partial \text{Open}_{ij}}$ is minus one times the elasticity of departures to public entry from column (7) of Table 5. Under Poisson departures, this corresponds to minus one times the elasticity of wait times to public entry.

We set price changes on treated and connected routes based on the spillover specification results from column (4) of Table 5. On treated routes, $\hat{p}_{ij} = -0.108$, while on connected routes, $\hat{p}_{ij} = -0.016 \times$ NumConnectedRoutes$_i$, where NumConnectedRoutes$_i$ is the number of connected routes at terminal i. The change in prices is then $\Delta p_{ijM} = \bar{p}_{ijM}\hat{p}_{ij}$, where $\bar{p}_{ijM}$ is the average initial fare, measured separately for treated and connected routes.

We set the relative change in the number of trips per driver to $\hat{N}_{ij}^{\text{Trips}} = 0.84$, based on column (1) of Table 4 ($0.84 = 1 - 1.55/9.58$). For connected routes, the coefficient in the continuous spillover specification in Table 6 is highly imprecise, while the dummy spillover specification in Table S20 is more precise and larger in magnitude. Observation surveys indicate no change in departures but an increase in queue lengths on connected routes, suggesting a decline in trips per driver. Given this collective evidence, we allow trips per driver on connected routes to decrease and set the change to 24.6% of the decline on treated routes, based on the ratio of coefficients on treated and connected routes in Panel B of Table S20 ($0.246 = -1.45/-0.36$).

S3.3.3. Commuter and Driver Preference Parameters

Estimation of commuter preference parameters θ, η, γ is described in the main text.

We estimate the driver route choice elasticity σ using the responsiveness of route choice to the profit shock represented by public entry. The fraction of drivers choosing route ij in terminal i depends on its profits relative to other routes from the terminal:

$$\rho_{ij} = \left(V_{ij}^{Q}/\Pi_i^{V}\right)^{\sigma}$$

We know that

$$\sigma = \frac{1}{1-\rho_{ij}} \frac{\partial \ln \rho_{ij}}{\partial \ln V_{ij}^{Q}} = \frac{1}{1-\rho_{ij}} \frac{\partial \ln \rho_{ij}/\partial \text{Open}_{ij}}{\partial \ln V_{ij}^{Q}/\partial \text{Open}_{ij}},$$

and therefore estimate σ by combining our reduce form elasticities that tell us how public entry changed profits and entry decisions on different routes.

To compute the expression in the numerator, we pool routes in each treated terminal into two groups: those which receive public service by the end of the driver survey and those which do not. We do this to increase the number of drivers in each cell. We then look, within each terminal, at the change in drivers choosing routes which receive public service through the regression

$$\ln \rho_{ict} = \gamma_{ic} + \delta_{it} + \beta \text{Open}_{ict} + \epsilon_{ict}$$

where i is a terminal, c is a category (those which receive public service by the end of the survey for which $\text{Open}_{ict} = 1$ in the endline survey), and $t = 0, 1$ indicates the baseline and endline surveys respectively. This elasticity is therefore identified from the increase in route switching for drivers who drive treated routes at baseline, between the baseline and endline surveys (to try and capture the long-run response). We find an estimate of $\beta = \partial \ln \rho_{ij} / \partial \text{Open}_{ij}$ of -0.377 (0.131) when estimating in logs and -0.277 (0.082) when estimating using PPML.

To compute the expression in the denominator, we differentiate equation (5) to get

$$\frac{\partial \ln V_{ij}^{Q}}{\partial \text{Open}_{ij}} = \frac{\partial \ln N_{ij}^{Trips}}{\partial \text{Open}_{ij}} + \pi_{ij}^{rev} \frac{\partial \ln p_{ij}}{\partial \text{Open}_{ij}}$$

As in the prior step, we use our within-terminal results from Table 4 to measure these elasticities, using $\frac{\partial \ln N_{ij}^{Trips}}{\partial \text{Open}_{ij}} = \ln((9.58 - 1.55)/9.58) = -0.1765$ and set $\frac{\partial \ln p_{ij}}{\partial \text{Open}_{ij}} \approx 0$ from that table. We also measure that $E\left[\frac{1}{1-\rho_{ij}}\right] = 1.29$.

Putting these results together, we arrive at

$$\sigma = E\left[\frac{1}{1-\rho_{ij}}\right] \frac{\partial \ln \rho_{ij} / \partial \text{Open}_{ij}}{\partial \ln V_{ij}^{Q} / \partial \text{Open}_{ij}} = 1.27 \times \frac{-0.377}{-0.177} = 2.77.$$

using our OLS estimate of $\partial \ln \rho_{ij} / \partial \text{Open}_{ij}$, and $\sigma = 2.04$ when using the PPML estimate.

Appendix S4. Additional Empirical Results

S4.1. Testing for the Presence of Higher-Order Spillovers

The spillover specifications in the paper remain valid only if our measure of connections capture all spillovers from treated to untreated routes. In other words, there should be no "higher-order" spillovers beyond interactions at origin or destination terminals.

To test this, we run an augmented version of our spillover regression

$$\begin{aligned} Y_{rt\tau} = {} & \beta \mathbb{I}\{\text{Open}_{rt}\} + \alpha \text{ Connections to public transit}_{rt} \\ & + \gamma \text{Unconnected overlap with public transit}_{rt} + \gamma_{m(r\tau)} + \boldsymbol{\eta}_t{}' X_{rt} + \epsilon_{rt\tau}. \end{aligned}$$

This specification includes a term that measures the fraction of each control route ("unconnected" with public transit at both endpoints) that overlaps with a public transit route at each survey date. To construct this measure, we intersect the shapefile of each minibus route with a 50-meter buffer around each public transit route that opens during our sample period. We then use the opening dates of each public transit route to calculate the fraction of each minibus route that overlaps a public route at each survey date. We construct this measure only for routes that are in the control group of the spillover specification, i.e. those which do not share any connection with public transit at either endpoint; for treated and connected routes it is set to zero.

Our goal is to test whether minibus routes in the control group are affected by the treatment. We do this in two ways. First, we test whether impacts on control routes are the same regardless of their overlap with the public system ($\gamma = 0$). Second, we examine whether the treatment effect estimate (β) changes when this overlap measure is included. If treatment affects control routes through the overlap measure we construct, and this overlap influences outcomes in the control group, this SUTVA violation would introduce an omitted variable bias that would cause the estimate of β to change.

The results are presented in Appendix Table S29. Column (1) repeats the main spillover specification, column (2) adds controls for the fraction of each route overlapping with different road types (motorway, main, secondary) since new public routes are more likely to enter on busier roads, and column (3) includes the overlap variable for unconnected routes.

First, we fail to reject $\gamma = 0$ for each of the three outcomes. However, the estimates are relatively noisy, and for two outcomes—fares and queues—the point estimates are non-negligible compared to the main treatment effect. To further investigate, we turn to the second test: examining whether the coefficient on the treatment variable (Open_{rt}) changes when the overlap variable is included. We find that the coefficients are statistically indistinguishable between these specifications, and the point estimates are remarkably consistent across outcomes.

Taken together, we interpret this evidence to suggest that the primary effects from new public transit openings occur at endpoints. This supports the validity of our spillover specifications and suggests that their estimates do not seem influenced by possible violations of SUTVA.

Appendix S5. Additional Figures

FIGURE S3. Google Mobility Data: Visits to Transit Stations

exhibits/fig/google_mob_transit_ppt.png

FIGURE S4. Oyingbo Public Terminal: Fire and Aftermath

exhibits/photos/Oyingbo_Fire.jpg

A. Fire

exhibits/photos/Oyingbo_After.jpg

B. Aftermath

FIGURE S5. Participant Checking in for Wait Experiment

exhibits/photos/waittime/20230803_091039_rot.jpg

FIGURE S6. Event Study of Public Transit Entry

A. Minibus Departures

exhibits/for_paper/fig/event_plots_logMPD.png

B. Minibus Fares

exhibits/for_paper/fig/event_plots_logFare.png

C. Minibus Driver Queues

exhibits/for_paper/fig/event_plots_logQueue.png

Note: Each panel reports coefficient estimates from a regression which replicates the main specification (column (7) of Table 2) but replaces the singular Open_{rt} with a set of quarter-to-treatment dummies which reflect the quarter of observation relative to the quarter of opening. Blue points report coefficients and 95% confidence intervals from a TWFE regression, while red points represent those from the Sun and Abraham (2021) estimator.

Appendix S6. Additional Tables

TABLE S2. Minibus Drivers

	Mean	SD	N
Demographics			
Age (years)	43.40	0.31	849
Male	0.993	0.00	849
Has secondary education	0.611	0.02	849
Driving experience (years)	12.65	0.34	847
Operations			
Own bus	0.509	0.02	847
Choose own route	0.846	0.01	849
Number of routes plied	1.185	0.02	849
Proportion of trips skipping terminal start ('sole')	0.209	0.01	849
Number of days worked last week	5.622	0.04	849
Number of trips on last day worked	9.201	0.21	849
Hours between start and end of work on last day worked	12.13	0.12	849
Proportion of work time spent driving	0.576	0.01	847
Proportion of work time spent queuing	0.424	0.01	847
Income and Costs			
Last day worked			
Total revenue from all trips (₦)	17269.4	403.71	811
Net income (₦)	5140.1	103.88	818
Cost of fuel (₦)	3766.1	54.91	846
Fees paid to the association (₦)	691.0	52.29	849
Employed conductor	0.306	0.02	843
If employed conductor, amount paid (₦)	2531.4	69.49	237
If do not own vehicle, amount paid to the minibus owner (₦)	5972.8	148.27	410
Last month			
Had a repair	0.919	0.01	844
If had a repair, cost of last repair (₦)	11538.8	944.63	769
Had a fine	0.830	0.02	480
If had a fine, cost of last fine (₦)	6505.6	732.02	376
One-time			
Average terminal registration fee (₦)*	15494.13	7486.50	67

Notes: Survey of minibus drivers, sampled in queues and outside terminals. All statistics are weighted to account for differential ease of sampling those waiting in queues, as described in Section S1.1. Proportion of work time spent driving and queuing is based on responses to trip diary, based on the first 8 trips on the last day worked. Number of trips and total revenue are winsorized at 99th percentile due to the presence of large outliers. *Average terminal registration fee is the current registration fee reported using a terminal survey, for terminals where drivers in the sample are registered, hence the smaller sample since this is recorded at the terminal-level.

TABLE S3. Effect of Public Transit on Private Transit: Dynamic

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A: log(Departures)							
Open < 3 months	-0.079**	-0.119***	-0.113**	-0.115**	-0.117**	-0.161**	-0.084
	(0.038)	(0.034)	(0.045)	(0.047)	(0.056)	(0.071)	(0.076)
Open 3-6 months	-0.133*	-0.241***	-0.237**	-0.259***	-0.252**	-0.253**	-0.287**
	(0.068)	(0.079)	(0.098)	(0.093)	(0.099)	(0.098)	(0.121)
Open >6 months	-0.152	-0.217**	-0.218*	-0.226*	-0.225**	-0.257*	-0.355***
	(0.132)	(0.105)	(0.114)	(0.119)	(0.109)	(0.145)	(0.112)
Panel B: log(Fare)							
Open < 3 months	-0.045	-0.064	-0.047	-0.055	-0.053	-0.063	-0.017
	(0.043)	(0.054)	(0.054)	(0.053)	(0.055)	(0.056)	(0.044)
Open 3-6 months	-0.019	-0.028	-0.016	-0.040	-0.049	-0.049	-0.014
	(0.041)	(0.046)	(0.050)	(0.046)	(0.046)	(0.030)	(0.031)
Open >6 months	-0.022	-0.056	-0.047	-0.074	-0.082	-0.090	-0.047
	(0.093)	(0.091)	(0.093)	(0.092)	(0.088)	(0.071)	(0.074)
Panel C: log(Queues)							
Open < 3 months	-0.064	-0.080	-0.063	-0.048	-0.042	-0.057	-0.001
	(0.119)	(0.143)	(0.120)	(0.120)	(0.124)	(0.115)	(0.090)
Open 3-6 months	-0.442***	-0.486***	-0.459***	-0.473***	-0.459***	-0.494***	-0.514***
	(0.067)	(0.088)	(0.057)	(0.061)	(0.073)	(0.065)	(0.087)
Open >6 months	-0.240	-0.374**	-0.364**	-0.393***	-0.371**	-0.375**	-0.475***
	(0.191)	(0.148)	(0.150)	(0.144)	(0.147)	(0.167)	(0.160)
Route X Period FE	X	X	X	X	X	X	X
Day of Week X Survey Round FE	X	X	X	X	X	X	X
Hour of Dep X Survey Round FE	X	X	X	X	X	X	X
Terminal X Survey Round FE		X	X	X	X	X	X
Trip Dist Controls X Survey Round FE			X	X	X	X	X
Dep. Plan X Survey Round FE				X	X	X	X
CBD Controls					X		
O & D Lat-Lon Poly X Survey Round FE						X	
O & D LGA X Survey Round FE							X

Notes: Standard errors clustered by route and terminal reported in parentheses. N and R^2 rows omitted for brevity. * p<0.1; ** p<0.05; *** p<0.01.

TABLE S4. Response to a Price Change in Public System: Dynamic

	(1)	(2)
Price Impact ≤14 days (₦: ζ_1)	91.0832***	91.0832***
	(4.925)	(5.5768)
Price Impact 15-28 days (₦: ζ_2)	89.6402***	89.6402***
	(5.1617)	(5.6865)
Price Impact 29-42 days (₦: ζ_3)	88.9993***	88.9993***
	(5.2662)	(5.7557)
Log Trip Impact ≤14 days (α_1)	-0.2327***	-0.2569***
	(0.0394)	(0.0549)
Log Trip Impact 15-28 days (α_2)	-0.2115***	-0.2534***
	(0.0367)	(0.0714)
Log Trip Impact 29-42 days (α_3)	-0.1632***	-0.223***
	(0.0317)	(0.0853)
Price Sensitivity ≤14 days (log trips/₦: $\frac{\alpha_1}{\zeta_1}$)	-0.0026***	-0.0028***
	(0.0005)	(0.0007)
Price Sensitivity 15-28 days (log trips/₦: $\frac{\alpha_2}{\zeta_2}$)	-0.0024***	-0.0028***
	(0.0005)	(0.0009)
Price Sensitivity 29-42 days (log trips/₦: $\frac{\alpha_3}{\zeta_3}$)	-0.0018***	-0.0025**
	(0.0004)	(0.001)
Trips detrended		X
N	13466	13466
System R^2	0.9402	0.9402

Notes: Fare and log trips effects estimated jointly in a seemingly unrelated regression around the 7 November 2023 price change, including route and day of week fixed effects. Ratio of effects computed from these individual estimates. Specifications also include an indicator for 6 November 2023 (the single day where the subsidy was entirely removed). In the detrended specification, a linear time trend in the trips measure is estimated on the pre-period; this trend is then removed from all periods. Standard errors in parentheses estimated via bootstrapping the entire procedure, resampling routes with replacement. * p<0.1; ** p<0.05; *** p<0.01.

TABLE S5. Trips Price Sensitivity in Public System

	(1) All changes	(2) All but first	(3) 2023-08-02	(4) 2023-11-07	(5) 2024-01-29	(6) 2024-02-26
Fare	-0.0022***	-0.0017***	-0.0032***	-0.0025***	-0.0018***	-0.0004
	(0.0003)	(0.0003)	(0.0005)	(0.0004)	(0.0004)	(0.0004)
N	10199	7942	2257	2637	2677	2628
N_{routes}	158	148	120	129	132	130
Window (days)	14	14	14	14	14	14
First stage F stat	2501.9	2146.0	7100.1	2714.8	3781.9	3998.5
R^2	0.79	0.801	0.839	0.82	0.847	0.846

Notes: Instrumental variables estimates of effect of fare on log trips based on price changes on designated dates. Instruments are indicator variables for the periods between price changes, with sample restricted to 14 days from the nearest price change, plus an indicator for 6 November 2023 (the single day where the subsidy was removed). Regressions include fixed effects by route, day of week, and for being within the window of each price change. Bootstrapped standard errors in parentheses, resampling routes with replacement. * p<0.1; ** p<0.05; *** p<0.01.

TABLE S6. Wait Experiment: Alternate Estimation Strategies

	(1) Main	(2) Perfect Compliance	(3) Stated Preference
γ (utils/₦)	0.0025***	0.0031***	0.0002**
	(0.0002)	(0.0002)	(0.0001)
η (utils/min)	0.0464***	0.0254***	0.0109***
	(0.0031)	(0.0035)	(0.0013)
$\frac{\eta}{\gamma}$ (₦/min)	18.9357***	8.3295***	46.4624**
	(1.7123)	(0.983)	(20.4845)
$\sigma^{checkin}$	14.3662***		
	(3.901)		
ρ	0.5163***		
	(0.0588)		
N	8640	4722	4398
Avg. Log Likelihood	-8720.18	-2843.73	-2641.69

Notes: Left column reports the selection corrected estimates. The middle column reports estimates from equation (S1) assuming compliance is perfect ($C_{nt} \equiv 1$ and $F^{\nu^{checkin}}(-\underline{C}) = F(-\underline{D}, -\underline{C}) = 0$). The right column estimates the perfect compliance specification using stated preferences from the baseline survey. Standard errors clustered at the user level. Estimation fixes $\sigma^{wait} = 1$. * p<0.1; ** p<0.05; *** p<0.01.

TABLE S7. Minibus Drivers: Comparison of Weighted and Unweighted Statistics

	Weighted			Unweighted		
	Mean	SD	N	Mean	SD	N
Demographics						
Age (years)	43.40	0.31	849	43.69	0.30	849
Male	0.993	0.00	849	0.994	0.00	849
Has secondary education	0.611	0.02	849	0.603	0.02	849
Driving experience (years)	12.65	0.34	847	12.75	0.33	847
Operations						
Own bus	0.509	0.02	847	0.514	0.02	847
Choose own route	0.846	0.01	849	0.848	0.01	849
Number of routes plied	1.185	0.02	849	1.173	0.02	849
Proportion of trips skipping terminal start ('sole')	0.209	0.01	849	0.170	0.01	849
Number of days worked last week	5.622	0.04	849	5.631	0.03	849
Number of trips	9.201	0.21	849	9.092	0.20	849
Total hours between start and stop on last day worked	12.13	0.12	849	12.16	0.12	849
Proportion of work time spent driving	0.576	0.01	847	0.567	0.01	847
Proportion of work time spent queuing	0.424	0.01	847	0.433	0.01	847
Income and Costs						
Last day worked						
Total revenue from all trips (₦)	17269.4	403.71	811	17144.6	379.90	811
Net income (₦)	5140.1	103.88	818	5167.6	103.20	818
Cost of fuel (₦)	3766.1	54.91	846	3740.1	55.23	846
Fees paid to the association (₦)	691.0	52.29	849	705.9	53.45	849
Employed conductor	0.306	0.02	843	0.295	0.02	843
If employed conductor, amount paid (₦)	2531.4	69.49	237	2551.5	66.83	237
If do not own vehicle, amount paid to the minibus owner (₦)	5972.8	148.27	410	6021.2	146.00	410
Monthly (last month)						
Had a repair	0.919	0.01	844	0.923	0.01	844
If had a repair, cost of last repair (₦)	11538.8	944.63	769	11497.3	866.27	769
Had a fine	0.830	0.02	480	0.827	0.02	480
If had a fine, cost of last fine (₦)	6803.3	1011.60	376	6463.2	738.46	376
Disputes						
Proportion of drivers in weekly passenger dispute	0.477	0.02	849	0.484	0.02	849
Proportion of drivers in weekly driver dispute	0.366	0.02	849	0.367	0.02	849

Notes: Survey of minibus drivers, sampled in queues and outside terminals. Except for expectations panel, statistics in the weighted panel are weighted to account for differential ease of sampling those waiting in queues, as described in Section S1.1. $\hat{8}$1% of the drivers report being registered at a terminal. Missing registration fees are imputed using a dataset of union registration fees by terminal.

TABLE S8. Minibus Drivers: Awareness of Public Transit

	Mean	SD	N
Expectations			
Have heard of public transit rollout (by 2020)	0.572	(0.50)	849
If heard, correctly predicted if public transit will open on surveyed route*	0.794	(0.41)	243
If heard, expect public transit will not affect them	0.476	(0.50)	246
If heard, expect public transit to reduce their passengers	0.362	(0.48)	246

Notes: Survey of minibus drivers, sampled in queues and outside terminals. Statistics are not weighted to account for differential ease of sampling those waiting in queues. *Calculated only for those drivers who answered and whose main route had not yet seen the introduction of public transit. Of the 486 drivers who were aware of the public transit rollout, 34% had already seen public transit services introduced along their route by the time of the survey. The last two questions were asked to a random 50% of the respondents who had heard of the public transit rollout.

TABLE S9. Minibus Driver Survey Observations

	Number of Respondents
Baseline	854
Follow up 1	564
Follow up 2	528
Follow up 3	514
Follow up 4	423

Notes: Number of respondents for each round of the minibus driver survey.

TABLE S10. Minibus Driver Survey Attrition

	Proportion of Sample
5 Surveys	0.342
4 or more Surveys	0.550
3 or more Surveys	0.663
2 or more Surveys	0.821
1 or more Surveys	1.000

Notes: Proportion of sampled minibus drivers who respond to at least given number of survey rounds, in minibus driver survey.

TABLE S11. Minibus Driver Survey Attrition Correlates

	By driver No follow ups			By driver-survey-round Completed		
	(1)	(2)	(3)	(4)	(5)	(6)
Log(Age)	-0.143**		-0.149**	0.121**		0.119**
	(0.065)		(0.065)	(0.053)		(0.053)
Own Vehicle	-0.006		-0.001	0.030		0.029
	(0.028)		(0.028)	(0.023)		(0.023)
Log(Income)	0.000		-0.005	-0.026		-0.026
	(0.022)		(0.023)	(0.019)		(0.019)
Main Route Treated		-0.034	-0.043		-0.005	0.006
		(0.031)	(0.031)		(0.025)	(0.026)
N	808	847	806	4,040	4,235	4,030
R^2	0.01	0.00	0.01	0.01	0.00	0.00
Mean of Dependent Variable	.175	.179	.174	.68	.676	.68

Notes: In columns 1 to 3, outcome is a dummy for whether the driver does not appear in any follow up survey. Only data from the baseline is used. In columns 4 to 6, data is at the driver-survey level and the outcome is a dummy for whether a driver completed a survey. Right hand side variables are log of driver age, a dummy for whether they own their vehicle, log revenue on last day driving (all from the baseline), and a dummy for whether the driver's main route in the baseline is treated at any point in the data. Regressions are weighted by the sampling weights discussed in Section 3.1. Standard errors clustered by driver reported in parentheses. * p<0.1; ** p<0.05; *** p<0.01.

TABLE S12. Baseline Average Characteristics of Private Transit Routes

	Treated Receives public transit	Connected Will share endpoint with public transit	Control No public transit	Difference T-Ctd	Difference T-Ctr
Departures per 30 mins	4.11	3.60	3.38	0.51	0.74
	(1.11)	(0.27)	(0.24)	(0.91)	(0.87)
Passengers at Departure	13.49	10.15	13.10	3.34	0.39
	(1.69)	(0.50)	(0.62)	(1.67)	(2.20)
Fare (₦)	246.15	203.75	239.03	42.41	7.13
	(30.62)	(14.78)	(11.49)	(46.46)	(39.12)
Distance (km)	8.61	7.50	7.91	1.11	0.70
	(1.75)	(0.86)	(0.54)	(2.71)	(1.85)
Driver Queue Length	4.90	5.30	4.56	-0.40	0.34
	(0.75)	(0.36)	(0.30)	(1.14)	(1.02)
Driver Queue Length > 0	0.88	0.88	0.84	-0.00	0.04
	(0.08)	(0.02)	(0.02)	(0.07)	(0.08)
Number of Routes	13	123	142		
F-Stat				1.26	0.41

Notes: Table reports means and standard errors of baseline characteristics for routes which received public service in our sample (Treated), those which share a node with a route which received public service (Connected) and those which did not (Control). Fares and passenger counts are reported for routes where buses are observed in our sample. Distance is computed on the straight line between start and end point of the route. Driver queue length is the number of buses waiting in the queue for a given route at the beginning of each time period.

TABLE S13. Baseline Average Characteristics of Terminals

	Treated Receives public transit	Control No public transit	Difference T-C
Total Departures	314.60	135.96	178.63
	(110.77)	(17.82)	(61.51)
Total Passengers across all Departures	3983.40	1292.16	2691.25
	(1474.30)	(178.43)	(731.62)
Number of Private Transit Routes Operational	10.86	8.05	2.80
	(2.51)	(0.84)	(2.21)
Number of Terminals	7	38	
F-stat			5.26***

Notes: Table reports means and standard errors of baseline characteristics of terminals which received any public service in our sample (Treated) and those which did not (Control).

TABLE S14. Effect of Public Transit on Private Transit: TWFE Robustness

	log(Departures)		log(Fare)		log(Queues)	
	(1)	(2)	(3)	(4)	(5)	(6)
Open	-0.221***	-0.203***	-0.024	-0.023**	-0.289***	-0.283***
	(0.075)	(0.054)	(0.035)	(0.011)	(0.072)	(0.038)
N	21,284	21,284	23,067	23,067	22,290	22,290
R^2	0.66	0.64	0.95	0.94	0.59	0.55
TWFE	X		X		X	
Sun and Abraham		X		X		X

Notes: Specification is the same as column 7 of Table 2. Even columns use Sun and Abraham (2021) estimator. Standard errors clustered by route and terminal reported in parentheses. * p<0.1; ** p<0.05; *** p<0.01.

TABLE S15. Effect of Public Transit on Private Transit (Linear Outcomes)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A: Departures							
Open	-0.383**	-0.461***	-0.461***	-0.426***	-0.426***	-0.426***	-0.649*
	(0.169)	(0.103)	(0.103)	(0.118)	(0.118)	(0.118)	(0.365)
N	24,597	24,597	24,597	24,597	24,597	24,597	24,597
R^2	0.57	0.62	0.62	0.62	0.62	0.62	0.64
Mean Outcome	3.45	3.45	3.45	3.45	3.45	3.45	3.45
Panel B: Fare							
Open	-4.007	-5.693	-5.693	-10.085	-10.085	-10.085	-2.518
	(10.977)	(13.238)	(13.238)	(11.965)	(11.965)	(11.965)	(7.454)
N	23,067	23,067	23,067	23,067	23,067	23,067	23,067
R^2	0.93	0.94	0.94	0.94	0.94	0.94	0.95
Mean Outcome	209.51	209.51	209.51	209.51	209.51	209.51	209.51
Panel C: Queues							
Open	-0.812**	-1.022*	-1.022*	-0.940*	-0.940*	-0.940*	-1.194*
	(0.365)	(0.519)	(0.519)	(0.544)	(0.544)	(0.544)	(0.696)
N	24,587	24,587	24,587	24,587	24,587	24,587	24,587
R^2	0.53	0.59	0.59	0.60	0.60	0.60	0.62
Mean Outcome	4.75	4.75	4.75	4.75	4.75	4.75	4.75
Route X Period FE	X	X	X	X	X	X	X
Day of Week X Survey Round FE	X	X	X	X	X	X	X
Hour of Dep X Survey Round FE	X	X	X	X	X	X	X
Terminal X Survey Round FE		X	X	X	X	X	X
Trip Dist Controls X Survey Round FE			X	X	X	X	X
Dep. Plan X Survey Round FE				X	X	X	X
CBD Controls					X		
O & D Lat-Lon Poly X Survey Round FE						X	
O & D LGA X Survey Round FE							X

Notes: Standard errors clustered by route and terminal reported in parentheses. * p<0.1; ** p<0.05; *** p<0.01.

TABLE S16. Effect of Public Transit on Private Transit: Inference Robustness

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A: log(Departures)							
Open	-0.114	-0.182	-0.180	-0.189	-0.186	-0.219	-0.221
p-val (clustered)	0.008	0.000	0.002	0.002	0.003	0.008	0.005
p-val (wild)	0.144	0.040	0.076	0.062	0.058	0.078	0.060
Panel B: log(Fare)							
Open	-0.031	-0.051	-0.037	-0.055	-0.059	-0.060	-0.024
p-val (clustered)	0.512	0.324	0.473	0.273	0.221	0.144	0.501
p-val (wild)	0.563	0.368	0.531	0.351	0.299	0.229	0.585
Panel C: log(Queue)							
Open	-0.228	-0.282	-0.266	-0.270	-0.254	-0.275	-0.289
p-val (clustered)	0.000	0.005	0.001	0.001	0.005	0.001	0.000
p-val (wild)	0.047	0.132	0.074	0.070	0.084	0.049	0.033
Route X Period FE	X	X	X	X	X	X	X
Day of Week X Survey Round FE	X	X	X	X	X	X	X
Hour of Dep X Survey Round FE	X	X	X	X	X	X	X
Terminal X Survey Round FE		X	X	X	X	X	X
Trip Dist Controls X Survey Round FE			X	X	X	X	X
Dep. Plan X Survey Round FE				X	X	X	X
CBD Controls					X		
O & D Lat-Lon Poly X Survey Round FE						X	
O & D LGA X Survey Round FE							X

Notes: Wild p-values computed using Cameron, Gelbach, and Miller (2008).

TABLE S17. Effect of Public Transit on Traffic Congestion

	log(Speed)		log(Time)	
	(1)	(2)	(3)	(4)
Open	0.000		0.007	
	(0.023)		(0.026)	
Open $<$ 3 months		-0.002		0.004
		(0.021)		(0.024)
Open 3-6 months		-0.005		0.012
		(0.026)		(0.027)
Open $>$6 months		0.008		0.005
		(0.027)		(0.029)
N	7,362,322	7,362,322	7,362,322	7,362,322
R^2	0.63	0.63	0.86	0.86

Notes: Outcome is either log speed or log trip time. Data is from Google Maps, standard errors clustered at the route-level (288 routes). Controls include route fixed effects, and week-year, hour-month-year and trip distance quartile-month-year fixed effects. * p<0.1; ** p<0.05; *** p<0.01.

TABLE S18. Placebo Tests: Spillover Specification

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A: log(Departures)							
Open	-0.221***	-0.221***	-0.172**	-0.161*	-0.208***	-0.166**	-0.158*
	(0.075)	(0.075)	(0.067)	(0.090)	(0.078)	(0.066)	(0.091)
Open ENDSARS		-0.012	0.109	0.112			
		(0.149)	(0.146)	(0.151)			
Number of open routes at terminal				0.002			0.002
				(0.013)			(0.013)
Open cancelled					0.088	0.056	0.055
					(0.078)	(0.072)	(0.070)
N	21,284	21,284	21,284	21,284	21,284	21,284	21,284
R^2	0.66	0.66	0.63	0.63	0.66	0.63	0.63
Panel B: log(Fare)							
Open	-0.024	-0.024	-0.030	-0.108**	-0.029	-0.034	-0.111**
	(0.035)	(0.035)	(0.037)	(0.052)	(0.035)	(0.038)	(0.052)
Open ENDSARS		0.185*	0.068	0.050			
		(0.104)	(0.075)	(0.073)			
Number of open routes at terminal				-0.016***			-0.016***
				(0.006)			(0.006)
Open cancelled					-0.036	-0.032	-0.025
					(0.022)	(0.020)	(0.020)
N	23,067	23,067	23,067	23,067	23,067	23,067	23,067
R^2	0.95	0.95	0.93	0.94	0.95	0.93	0.94
Panel C: log(Queues)							
Open	-0.289***	-0.289***	-0.296***	-0.160*	-0.282***	-0.296***	-0.164
	(0.072)	(0.072)	(0.054)	(0.094)	(0.075)	(0.058)	(0.098)
Open ENDSARS		0.087	0.148	0.178			
		(0.164)	(0.171)	(0.181)			
Number of open routes at terminal				0.029*			0.029*
				(0.017)			(0.017)
Open cancelled					0.044	0.010	-0.002
					(0.100)	(0.100)	(0.105)
N	22,290	22,290	22,290	22,290	22,290	22,290	22,290
R^2	0.59	0.59	0.55	0.55	0.59	0.55	0.55
Terminal X Survey Round FE	X	X			X		

Notes: Columns (1), (2) and (5) replicate each column from Table 3. Columns (3) and (6) run the same placebo specifications for the ENDSARS and Cancelled placebos, in the spillover specification without terminal-by-survey round fixed effects. Columns (4) and (7) then add to this the measure of public transit connections. Standard errors clustered by route and terminal reported in parentheses. * p<0.1; ** p<0.05; *** p<0.01.

TABLE S19. Comparison of Connectedness and Fixed Effect Specifications

	(1)	(2)	(3)	(4)
Panel A: log(Departures)				
Open	-0.163*	-0.197**	-0.232***	-0.221***
	(0.090)	(0.082)	(0.069)	(0.075)
Number of open routes at terminal	0.002			
	(0.013)			
1-4 routes at terminal open		-0.101**		
		(0.040)		
5+ routes at terminal open		-0.048		
		(0.069)		
Any routes at terminal open			-0.099**	
			(0.041)	
N	21,284	21,284	21,284	21,284
R^2	0.63	0.63	0.63	0.66
p-val: Same estimate on Open	0.40	0.67	0.76	
Panel B: log(Fare)				
Open	-0.108**	-0.082	-0.041	-0.024
	(0.052)	(0.050)	(0.041)	(0.035)
Number of open routes at terminal	-0.016***			
	(0.006)			
1-4 routes at terminal open		-0.016		
		(0.028)		
5+ routes at terminal open		-0.079**		
		(0.031)		
Any routes at terminal open			-0.019	
			(0.027)	
N	23,067	23,067	23,067	23,067
R^2	0.94	0.93	0.93	0.95
p-val: Same estimate on Open	0.01	0.02	0.48	
Panel C: log(Queues)				
Open	-0.163*	-0.181**	-0.291***	-0.289***
	(0.093)	(0.076)	(0.057)	(0.072)
Number of open routes at terminal	0.029*			
	(0.017)			
1-4 routes at terminal open		0.003		
		(0.065)		
5+ routes at terminal open		0.176*		
		(0.097)		
Any routes at terminal open			0.011	
			(0.064)	
N	22,290	22,290	22,290	22,290
R^2	0.55	0.55	0.55	0.59
p-val: Same estimate on Open	0.21	0.16	0.97	
Terminal FE				X

Notes: Column 1 repeats the baseline spillover specification from odd columns in Table 5. Column 2 replaces the public transit connection measure with two dummies that bin the number of open routes at a terminal variable from column 1 into two groups above and below 5 open routes. Column 3 does the same with a single dummy for whether a route has any public transit connection (i.e. whether Number of open routes at terminal is greater than zero). Column 4 repeats the main specification with terminal by survey round fixed effects (from column 7 of Table 2). The last row of each panel reports p-value from a hypothesis test of equality between the coefficient on Open in each spillover specification with the specification with terminal by survey round fixed effects in column (4). Standard errors clustered by route and terminal reported in parentheses. * $p<0.1$; ** $p<0.05$; *** $p<0.01$.

TABLE S20. Driver Robustness

	N Trips	log(AvgFare)	Log(Trip Fee)	log(Rev)	log(DaysWork)	Change Route Any	Change Route Same Terminal
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A: Unweighted Spillover Specification							
Open	-1.052*	-0.072**	-0.024	-0.130**	-0.006	0.075*	0.152***
	(0.558)	(0.036)	(0.064)	(0.054)	(0.029)	(0.043)	(0.051)
Number of routes open at terminal	-0.053	-0.004	0.000	-0.017*	-0.006	0.006	0.021**
	(0.074)	(0.004)	(0.008)	(0.010)	(0.004)	(0.007)	(0.008)
N	2,173	2,011	2,026	1,966	2,178	1,405	1,405
R^2	0.71	0.84	0.73	0.70	0.40	0.79	0.75
Panel B: Spillover Dummy Specification							
Open	-1.451***	-0.045	0.005	-0.138**	-0.014	0.094**	0.147***
	(0.526)	(0.033)	(0.055)	(0.059)	(0.039)	(0.038)	(0.052)
Any routes at recruitment terminal open	-0.357	0.007	0.042	-0.054	-0.035	0.032	0.056*
	(0.325)	(0.025)	(0.056)	(0.035)	(0.031)	(0.025)	(0.030)
N	2,177	2,015	2,030	1,970	2,182	1,411	1,411
R^2	0.71	0.84	0.73	0.69	0.41	0.80	0.75

Notes: Panel A replicates the main spillover Table 6 without sampling weights. Panel B replicates it using a dummy for whether the route has any public transit connections as the connection measure. Standard errors clustered by driver and recruitment terminal reported in parentheses. * p<0.1; ** p<0.05; *** p<0.01.

TABLE S21. Does Supply Respond to Price Changes in Public System?

	(1)	(2)	(3)	(4)	(5)	(6)
	All changes	All but first	2023-08-02	2023-11-07	2024-01-29	2024-02-26
Fare	-0.0002***	-0.0001	-0.0005***	-0.0006***	-0.0002	0.0009***
	(0.0001)	(0.0001)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
N	10199	7942	2257	2637	2677	2628
N_{routes}	158	148	120	129	132	130
Window (days)	14	14	14	14	14	14
First stage F stat	2501.9	2146.0	7100.1	2714.8	3781.9	3998.5
R^2	0.869	0.881	0.919	0.918	0.927	0.917

Notes: Instrumental variables estimates of effect of fare on log buses based on price changes on designated dates. Instruments are indicator variables for the periods between price changes, with sample restricted to 14 days from the nearest price change, plus an indicator for 2023-11-6 (the single day where the subsidy was removed). Regressions include fixed effects by route, day of week, and for being within the window of each price change. Bootstrapped standard errors in parentheses, resampling routes with replacement. * p<0.1; ** p<0.05; *** p<0.01.

TABLE S22. Wait Time Game Descriptives

	(1) min	(2) mean	(3) std	(4) median	(5) max	(6) count	(7) corr(gameLength)	(8) corr(zeroWaitDays)	(9) corr(sCheckin)	(10) corr(sWaitMean)	(11) corr(tWaitMean)
Baseline											
Gender	0.0	0.47	0.5	0.0	1.0	640.0	-0.01	0.04	-0.06	0.03	-0.06
Age	18.0	36.88	12.75	35.0	78.0	640.0	0.01	-0.02	-0.02	0.04	-0.06
Education Category	1.0	5.12	0.94	5.0	7.0	640.0	0.01	-0.01	-0.07	-0.0	-0.01
Monthly Income (₦)	12500.0	61289.43	79331.78	37500.5	750000.0	640.0	0.06	-0.05	0.04	-0.02	0.01
Game											
Game Length (weeks)	3.0	3.46	0.67	3.0	5.0	640.0	1.0	0.01	-0.01	-0.28	0.16
Number of Initial Zero Wait Days	1.0	1.48	0.5	1.0	2.0	640.0	0.01	1.0	-0.06	0.06	-0.1
$s_n^{checkin}$ (₦)	200.0	550.94	290.05	400.0	1000.0	640.0	-0.01	-0.06	1.0	-0.04	-0.01
$\overline{s}_n$ (₦)	69.12	285.75	80.14	285.98	640.0	640.0	-0.28	0.06	-0.04	1.0	-0.11
$\overline{\Delta t}_n$ (min)	4.4	8.72	1.59	8.65	13.85	640.0	0.16	-0.1	-0.01	-0.11	1.0
$\overline{C}_n$	0.0	0.59	0.34	0.69	1.0	640.0	-0.13	-0.03	0.1	0.41	-0.23
$\overline{D}_n$	0.0	0.41	0.28	0.39	1.0	640.0	-0.21	-0.05	0.01	0.43	-0.23
Endline											
Expected $\overline{s}_n$ (₦)	10.0	1411.06	4959.46	1000.0	100000.0	575.0	-0.01	-0.08	-0.06	-0.1	0.05
Expected $\overline{\Delta t}_n$ (min)	1.0	10.63	7.85	10.0	59.0	575.0	-0.05	-0.08	-0.02	-0.03	0.03

Notes: Individuals selected an income category; we designate an individual's monthly income as the median income for the category chosen. 'corr' reports the correlation between the designated column and row variables. Individuals were assigned to possibly different game lengths (weeks) and initial days with zero wait (zeroWaitDays). Variables include check in offer $s_n^{checkin}$=sCheckin, average wait offer payment $\overline{s}_n$=sWaitMean, average wait offer duration $\overline{\Delta t}_n$=tWaitMean (in minutes), proportion of days checked in $\overline{C}_n$, and proportion of wait offers accepted $\overline{D}_n$. Endline asks about participants' expectations about wait offers (both payment $\overline{s}_n$ and duration $\overline{\Delta t}_n$).

TABLE S23. Wait Experiment: Alternate Utility Specifications

	(1) Main	(2) Income Heterogeneity	(3) Curvature in Wait Time
γ (utils/₦)	0.0025***	0.0025***	0.0022***
	(0.0002)	(0.0002)	(0.0002)
η (utils/min)	0.0464***		0.0723***
	(0.0031)		(0.0086)
η^H (utils/min)		0.0507***	
		(0.0028)	
η^L (utils/min)		0.0447***	
		(0.0038)	
$\eta^{SquaredWait}$			-0.0012***
			(0.0004)
$\frac{\eta}{\gamma}$ (₦/min)	18.9357***		
	(1.7123)		
$\frac{\eta^H}{\gamma}$ (₦/min)		20.6187***	
		(1.6831)	
$\frac{\eta^L}{\gamma}$ (₦/min)		18.1737***	
		(1.9662)	
$\sigma^{checkin}$	14.3662***	14.35***	12.3846***
	(3.901)	(3.9145)	(3.5069)
ρ	0.5163***	0.5168***	0.68***
	(0.0588)	(0.0591)	(0.0705)
N	8640	8640	8640
Avg. Log Likelihood	-8720.18	-8718.71	-8715.92

Notes: η^H represents the coefficient for above median income; η^L for below. Standard errors clustered at the user level. Estimation fixes $\sigma^{wait} = 1$. * p<0.1; ** p<0.05; *** p<0.01.

TABLE S24. Wait Experiment Robustness

	(1) Main	(2) Omit Nontravel Days†	(3) Exclude First Checkins	(4) Include Early User-Days
γ (utils/₦)	0.0025***	0.0024***	0.0026***	0.0025***
	(0.0002)	(0.0002)	(0.0002)	(0.0002)
η (utils/min)	0.0464***	0.0465***	0.0426***	0.0389***
	(0.0031)	(0.0031)	(0.0036)	(0.0022)
$\frac{\eta}{\gamma}$ (₦/min)	18.9357***	19.4297***	16.4055***	15.7436***
	(1.7123)	(1.7821)	(1.6209)	(1.224)
$\sigma^{checkin}$	14.3662***	10.3003***	36.0153	46.3072
	(3.901)	(2.1381)	(26.3611)	(34.0152)
ρ	0.5163***	0.5551***	0.3839***	0.5234***
	(0.0588)	(0.0608)	(0.0644)	(0.0419)
N	8640	7886	7880	17291
Avg. Log Likelihood	-8720.18	-8024.04	-7955.94	-16700.48

Notes: The second column (†) omits days in the first week that participants told us they did not plan to travel (based on the baseline survey), and days in the last week that participants told us they did not travel (based on the endline). These are likely to represent a subset of the days that participants did not travel. The third column excludes the first checkins which had an optimistic offer. The fourth column includes even users who faced an early version of the design, as described in Section S2.2. Standard errors clustered at the user level. Estimation fixes $\sigma^{wait} = 1$. * p<0.1; ** p<0.05; *** p<0.01.

TABLE S25. Wait Experiment Robustness: Check in Time

	(1)	(2)	(3)
Offer: Second checkin no wait	10.424*	10.286*	6.149
	(5.732)	(5.758)	(9.046)
Offer: Second/third checkin generous	11.712***	11.489***	
	(4.175)	(4.266)	
Offer: Stable distribution	10.305***	9.330*	
	(3.920)	(4.786)	
Day		0.120	
		(0.343)	
Sample	All checkins	All checkins	Second checkin
N	5494	5494	535
R^2	0.609	0.609	0.038
Day of Week FE	X	X	X
Individual FE	X	X	
Start Date FE			X

Notes: The outcome is check in time, in minutes since midnight. In the first two columns, the omitted category is the first day offer with no wait. In the third column, the omitted category is the generous offer. The third column omits 11 cases who received the stable distribution rather than the generous distribution on their second day. * p<0.1; ** p<0.05; *** p<0.01.

TABLE S26. Wait Experiment: Arrival Dependent Waiting

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Main	λ=150.0 dep/30 min (Headway Q1)	λ=23.7 dep/30 min (Headway Q10)	λ=6.7 dep/30 min (Headway Q50)	λ=2.1 dep/30 min (Headway Q90)	λ=1.5 dep/30 min (Headway Q95)	λ=0.8 dep/30 min (Headway Q99)	λ=0.1 dep/30 min
γ (utils/₦)	0.0025***	0.0025***	0.0025***	0.0026***	0.0028***	0.003***	0.005	0.0037***
	(0.0002)	(0.0007)	(0.0007)	(0.0006)	(0.0006)	(0.0007)	(0.0042)	(0.001)
η (utils/min)	0.0464***	0.0464***	0.0462***	0.0444***	0.0559***	0.0702***	0.2401	1.3901
	(0.0031)	(0.0032)	(0.0032)	(0.0034)	(0.0064)	(0.0126)	(0.2719)	(1.1064)
$\frac{\eta}{\gamma}$ (₦/min)	18.9357***	18.9357***	18.7826***	17.3052***	20.0311***	23.6811***	47.8999***	373.1481*
	(1.7123)	(4.8738)	(4.7944)	(3.8734)	(3.1467)	(3.0303)	(14.8144)	(202.1312)
$\sigma^{checkin}$	14.3662***	14.3662	14.4355	15.4013	17.0815	18.0341	28.6195	12.4344
	(3.901)	(37.0444)	(37.3864)	(41.0838)	(44.2656)	(49.8159)	(162.9444)	(15.6073)
ρ	0.5163***	0.5163**	0.5082**	0.4078**	0.279*	0.2547*	0.0766	-0.1498
	(0.0588)	(0.2162)	(0.2151)	(0.1953)	(0.1537)	(0.1507)	(0.4023)	(0.1376)
N	8640	8640	8640	8640	8640	8640	8640	8640
Avg. Log Likelihood	-8720.18	-8720.18	-8719.66	-8722.11	-8725.67	-8722.87	-8688.93	-8769.74

Notes: In columns after the first, participants also accept the wait offer if no bus arrives during the wait time. We simulate bus departures following a Poisson process with average rate λ departures per half hour Standard errors clustered at the user level. Estimation fixes $\sigma^{wait} = 1$. * p<0.1; ** p<0.05; *** p<0.01.

TABLE S27. Testing Equality of the Change in Profits on Treated and Connected Routes

	Treated	Connected
$\Delta \ln(V_{ij}^Q)$	-0.376**	-0.334***
	(0.177)	(0.090)
P-value T==C	0.777	

Notes: Table reports values for change in profits on treated and connected routes using equation (S20) via seemingly unrelated regression with standard errors clustered by terminal. The last row reports a p-value for the test of equality. See Appendix Section S3.2.8 for details.

TABLE S28. Total Passenger Elasticity

	(1)
Open	0.149*
	(0.088)
N	6,041
R^2	0.65

Notes: Outcome is log total number of passengers (summed across minibus and public bus) per hour on each route in each of our 3 time periods across multiple year-months. Specification includes fixed effects for each unit of observation (route by time period), as well as year-month fixed effects, and year-month fixed effects interacted with fixed effects for terminals, trip distance quartiles, LGA of origin, and LGA of destination. Standard errors clustered by route and terminal reported in parentheses.

TABLE S29. Testing Higher-Order Spillovers through Public Transit Overlap on Control Routes

	(1)	(2)	(3)
Panel A: log(Departures)			
Open	-0.163*	-0.170	-0.168
	(0.090)	(0.102)	(0.106)
Number of connected routes	0.002	0.007	0.007
	(0.013)	(0.012)	(0.013)
Unconnected overlap with public bus route			0.034
			(0.311)
N	21,284	21,189	21,189
R^2	0.63	0.63	0.63
p-val Overlap==0			0.914
p-val Open (2)==(3)			0.912
Panel B: log(Fare)			
Open	-0.108**	-0.091*	-0.094**
	(0.052)	(0.048)	(0.047)
Number of connected routes	-0.016***	-0.013**	-0.014**
	(0.006)	(0.005)	(0.006)
Unconnected overlap with public bus route			-0.058
			(0.107)
N	23,067	22,959	22,959
R^2	0.94	0.94	0.94
p-val Overlap==0			0.591
p-val Open (2)==(3)			0.610
Panel C: log(Queues)			
Open	-0.163*	-0.198*	-0.202*
	(0.093)	(0.109)	(0.112)
Number of connected routes	0.029*	0.037**	0.036*
	(0.017)	(0.018)	(0.018)
Unconnected overlap with public bus route			-0.068
			(0.383)
N	22,290	22,182	22,182
R^2	0.55	0.56	0.56
p-val Overlap==0			0.859
p-val Open (2)==(3)			0.861
Road Type Intersections X Survey Round FE		X	X

Notes: Table reports regression from Appendix Section S4.1. Road Type Intersections measure the fraction of each minibus road that overlap different road types (motorway, main, secondary). Column (3) adds the fraction of each control route that overlaps the public system at each survey round. P-val Overlap==0 tests whether the coefficient on this overlap variable is zero. P-val Open (2)==(3) tests whether the coefficient on Open is the same in columns 2 and 3.

TABLE S30. Welfare Effects of Introducing Public Transit (Wild Inference)

		Individuals ($/individual/day)		**Aggregate** ($mn/month)
		Treated	Connected	
Panel A: Commuters	*Number:*	**252,004**	**919,579**	**1,171,583**
Baseline surplus from private transit		0.86	0.86	24.01
		[0.67,1.19]	[0.67,1.19]	[18.76,33.13]
Effect of introducing public transit		+0.20	+0.01	+1.47
		[0.13,0.30]	[-0.00,0.03]	[0.78,2.30]
Direct benefit of public transit		+0.22	0	+1.33
		[0.17,0.31]		[1.04,1.83]
Additional impact from private Δdepartures		-0.04	0	-0.26
		[-0.08,-0.00]		[-0.50,-0.02]
Additional impact from private Δprices		+0.02	+0.01	+0.41
		[-0.01,0.05]	[-0.00,0.03]	[0.58,0.90]
Panel B: Minibus Drivers	*Number:*	**1,800**	**10,040**	**11,840**
Baseline surplus from private transit		11.87	11.87	2.97
		[9.01,13.36]	[9.01,13.36]	[2.25,3.34]
Effect of introducing public transit		-2.98	-2.98	-0.75
		[-4.38,-0.31]	[-4.38,-0.31]	[-1.10,-0.08]
Accounting for private Δdepartures, ignoring route switching		-2.35	0	-0.09
		[-3.90,-0.17]		[-0.15,-0.01]
Accounting for private Δdepartures and Δprices, ignoring route switching		-4.76	0	-0.18
		[-7.53,-0.90]		[-0.29,-0.03]
Additional impact of allowing route switching		+1.78	-2.98	-0.57
		[-0.01,3.12]	[-1.10,-0.08]	[-0.83,-0.05]
Panel C: Public Bus Drivers	*Number:*	**1,640**	**0**	**1,640**
Wages		-	-	+0.21
Panel D: Costs				
Operating costs (buses)		-	-	+2.15
Operating costs (terminals)		-	-	+0.11

Notes: Confidence intervals are reported using the same bootstrap procedure as Table 8, but using standard deviations for the changes in times and fares that equal the wild bootstrapped standard errors from the corresponding regressions (Table S16, column (7)).

TABLE S31. Welfare Effects of Introducing Public Transit: Robustness

	(1) Baseline	(2) σ PPML	(3) 25% Lower θ	(4) 25% Higher θ	(5) 25% Higher η
Panel A: Commuters, Individual ($/day)					
Treated Routes					
Effect of introducing public transit	0.20	0.20	0.27	0.15	0.19
Direct benefit of public transit	0.22	0.22	0.29	0.18	0.22
Additional impact from private Δdepartures	-0.04	-0.04	-0.04	-0.04	-0.05
Additional impact from private Δprices	0.02	0.02	0.02	0.02	0.02
Connected Routes					
Direct benefit of public transit	0	0	0	0	0
Impact from private Δprices	0.01	0.01	0.01	0.01	0.01
Panel B: Commuters, Aggregate ($mn/month)					
Effect of introducing public transit	1.47	1.47	1.91	1.21	1.41
Direct benefit of public transit	1.33	1.33	1.77	1.06	1.33
Additional impact from private Δdepartures	-0.26	-0.26	-0.26	-0.26	-0.33
Additional impact from private Δprices	0.41	0.41	0.41	0.41	0.41
Panel C: Minibus Drivers, Individual ($/day)					
Effect of introducing public transit	-2.98	-3.00	-2.98	-2.98	-2.98
Panel D: Minibus Drivers, Aggregate ($mn/month)					
Effect of introducing public transit	-0.75	-0.75	-0.75	-0.75	-0.75

Notes: Robustness exercises of the results in Table 8, under alternative assumptions for parameters in the column headings.