Public and Private Transit: Evidence from Lagos

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Many of the world's fastest growing cities rely on private transit, commonly networks of minibuses. As these cities become wealthier they have been investing in centralized public transit. But if private incumbents respond, public investment will indirectly affect even those who do not use the new system. This paper studies how providing public transit affects minibus service in Lagos, Africa's largest city. We collect new panel data on the minibus network to measure how it responds to the rollout of public buses on 14 routes in the city's Bus Reform Initiative. Following government entry, minibus departures fall by around 26%, and prices fall on routes where the new option has relatively lower prices. To measure the impacts on consumer welfare, we develop a custom app to measure commuter valuations for price and wait time in an RCT. We find the welfare benefits from expanding public transit are muted by the reactions of the private system.

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1. Introduction

Much of what we know about transit is on centralized public systems, such as public buses or rail (Gibbons and Machin 2005; Glaeser, Kahn, and Rappaport 2008; Tsivanidis 2023). But that does not match how much of the world travels. Large populations in developing country cities travel by decentralized transit, commonly networks of privately operated minibuses. Decentralization tends to lead to low quality and coordination problems: drivers try to steal business from each other, which can lead to dangerous driving and excess entry.

As these cities grow, policymakers have proposed building centralized public transit systems. But given the cost of building these systems, they are typically incomplete. In many cities, after public sector entry, private and public networks will coexist. 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.[1] Introducing public service may induce private providers to respond, and thus have indirect effects on those who do not use the new option. A response from private incumbents also complicates measuring the return to public investment in new transit: typical approaches that focus on the new infrastructure alone, such as the travel time saved by riders, may not reveal the full impact on commuters.

This paper measures the impacts of providing government transit in a market dominated by private provision. Doing so necessitates confronting three key challenges.

First, it is rare to observe a large scale rollout of a public transit system. We address this by turning to the context of Lagos, a city of 22 million that is currently the largest city in Africa, and by 2100 is projected to become the largest in the world. At baseline, travel is dominated by private minibuses, which accounted for 72% of all motorized trips in 2015 (Taiwo 2015), and the existing public system is miniscule: accounting for only 5% of motorized trips.[2] We study Lagos' Bus Reform Initiative (BRI): an expansion of the public transit system in late 2020 and 2021. The city expanded public transit by 40 routes and 840 vehicles, building a bus system of a scale equivalent to that of San Francisco's within a few short years.

The second challenge is that even if a new public transit system is rolled out, there is little data on private transit networks. These decentralized networks do not naturally make themselves legible (Williams et al. 2015). In this project, we proceed with an extensive data collection strategy. We hired enumerators to document the locations of minibus routes by discovering and riding 759 routes throughout the city, traveling nearly 30,000 km. As the public system is rolled out, we stationed enumerators at terminals and roadside stops to count buses and passengers, and record fares, covering 278 routes and 79 bus stops over 13 rounds. We also survey over 800 minibus drivers at terminals, and follow up with repeated phone surveys. We complement this

[1] And private transit emerges in the fringes of cities like New York City, where private 'dollar vans' feed remote passengers into the public system.

[2] There is sparse data on these initial travel patterns, but this is the most recent estimate used by the transit authority. An earlier travel study reports a similarly small share of trips via public transit (ALG 2013).

with digital ridership data from the public system–which is sufficiently centralized to gather it.

A third challenge is that it is hard to measure how much consumers value any impacts on the price and wait time of transit. We address this through a new field experiment, detailed below.

We use the panel data we collected to measure how minibuses respond to entry from the new government service through a staggered difference-in-difference design. Our baseline strategy compares changes in outcomes—mainly departure frequencies and fares—on routes that experienced public transit entry with similar routes that did not.

The main difficulty with this design is that the choice of which routes to provide the new service was non-random, and the routes where the government chose to enter may have been experiencing differential trends in outcomes absent the policy. We pursue three approaches to build a body of evidence that the effects we document were indeed caused by the public transit entry. First, our sampling strategy was to collect data only on routes that had been chosen by the government for their long-term transit network plan for the city. Our control group therefore contains routes which the government had chosen to be part of their eventual network, so are comparable in nature though still differ in some respects. Second, we use frequent changes in opening plans across 22 rollout plans we digitized over our sample period to create a finer control group of routes which slated to have new service during the rollout phase we study but for operational reasons were cancelled or delayed outside out sample. Third, we use a natural experiment provided by the burning down of a bus terminal during the EndSARS protests in October 2020 (a protest movement against police brutality).[3] Following a fatal police shooting at Lekki Tollgate, groups of protesters burned a television station and the Oyingbo BRI bus terminal. This terminal had been slated to receive 8 new routes at the end of October and late November, but these were subsequently cancelled. They provide a comparison group of 'phantom' routes which we use in falsification tests.

Our findings suggest that both minibus frequencies and fares respond to the new public provision of transit. Minibus departure frequencies fall by 26% when public transit buses enter the same route. This translates to an increase in wait times.[4] On average, minibus fares do not change significantly but on routes where the new system is priced lower than minibus—that is, where it is competitive on fares—minibus prices fall compared with other routes.

These results suggest that the two key attributes of private transit providers valued by commuters—wait time (i.e. departure frequencies) and price—are affected by government entry. Typical approaches to measure the changes in welfare from new transit, such as looking at the value of time saved by its passengers or the change in accessibility due to the new option, would miss these changes. Building public transit affects even those users who continue to use the private system.

We develop a simple model of travel demand that decomposes the welfare change from

[3] See https://en.wikipedia.org/wiki/End_SARS.

[4] Public and private buses tend to use different stops so one must decide which to wait for.

government entry into (i) how much commuters value the new mode and (ii) how users of the existing modes are affected through the changes in wait times and prices.[5] The model delivers a set of sufficient statistics to measure this welfare change using the data on mode choices, the impact of public transit entry on minibus prices and wait times, and parameters for commuter valuations of these attributes and the substitution elasticity between different modes.

We design a field experiment to estimate how commuters value wait time and price. Recent approaches have used 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 low-income countries. Data from smartphones can thus yield biased estimates of population parameters in low income settings (Milusheva, Bjorkegren, and Viotti 2021). The choice of when to request a rideshare may also be endogenous: if users are more likely to request rideshare when they are in a hurry, then they will interact with these apps only when their value of time is high, resulting in biased estimates of the value of time.

We instead design a custom application to measure commuter valuations of price and time in a randomized experiment. We enroll commuters in a repeated interaction, where when they arrive to their bus stop they are provided random monetary offers to wait. We implement this by hiring enumerators to stand at bus stops during commuting hours, and provide them a custom designed app that displays a different cryptographic code each minute. Participants check in by texting the current code, and then receive a check in payment, as well as an random offer of a monetary amount to wait a certain 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 doing such an exercise with recruitment at a bus stop would likely cause people with high value of time to ignore enumerators.

Our design faces a challenge that commuters may participate in our game only on days when they are not rushed and so have a low value of time. This is the same issue as selecting when to open a rideshare app based on the urgency of travel, in our case causing an opposite bias. Our experimental design confronts this by directly modeling the selection into playing the game on each day. In addition to the randomized wait time offer on each day, participants receive a fixed 'check-in' offer they are paid each time they play regardless of whether they accept the offer or not. We randomize this offer across participants, providing an instrument for participation in this selection equation. By tracking which offers are accepted, we obtain an estimate of the disutility of waiting of ₦18.94 per minute ($1.42 per hour). We show that a naïve estimation strategy that does not account for imperfect compliance undervalues the hassle of waiting by 56%. We additionally asked participants to make hypothetical choices between

[5]The model delivers that the change in total travel time (waiting plus in-vehicle times) is what matters for welfare. Empirically we find no change in congestion and the new buses use the same roads as minibuses, so that only changes in wait times matter in our context.

travel options with different fares and waits, to mimic a stated preference procedure commonly used in the transportation literature. Stated preferences overvalue the hassle of waiting by 145% relative to our main estimates.

Our quantitative results suggest that the private sector response to public transit entry plays an important role in determining the overall return of public transit. Ignoring the response of private transit, commuters on the average route where the government entered experience a rise in welfare of 14% as revealed through their adoption of the new mode. When we allow prices of minibuses to adjust, the benefits increase even further to around 17%, since prices fall in response to entry. But when we allow minibus wait times to also rise (as we document in the reduced form), the net welfare gain falls to 6%. This suggests that 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 on focuses primarily on centralized public transit (Tsivanidis 2023; Kreindler et al. 2023), 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 despite their dominance in developing country cities, there are 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, and a randomized experiment to measure how commuters value the change in the choice and attributes of available options in the transit market.[6]

Our paper is one of few that causally estimates the value of time while traveling in a low-income 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

[6]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), suggesting that smaller vehicles can be desirable because they afford higher service frequency but may not be feasible in settings where driver wages are high.

uses experiments to measure value of time for rideshare apps in the US measures value of time. Our contribution is to develop a methodology suitable for low-income settings with non-smart phones to measure of 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.[7] Recent work focuses on settings in education, showing that 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. Transit in Lagos

Like many other developing country cities, transit in Lagos is dominated by private minibuses, which are locally called danfo (similar to matatus, or dala dalas). In 2015, private minibuses were used for 72% of passenger trips; only 5% were on public transit (Taiwo 2015). However, the government developed a plan to build a centralized public system.

2.1. Private Transit in Lagos

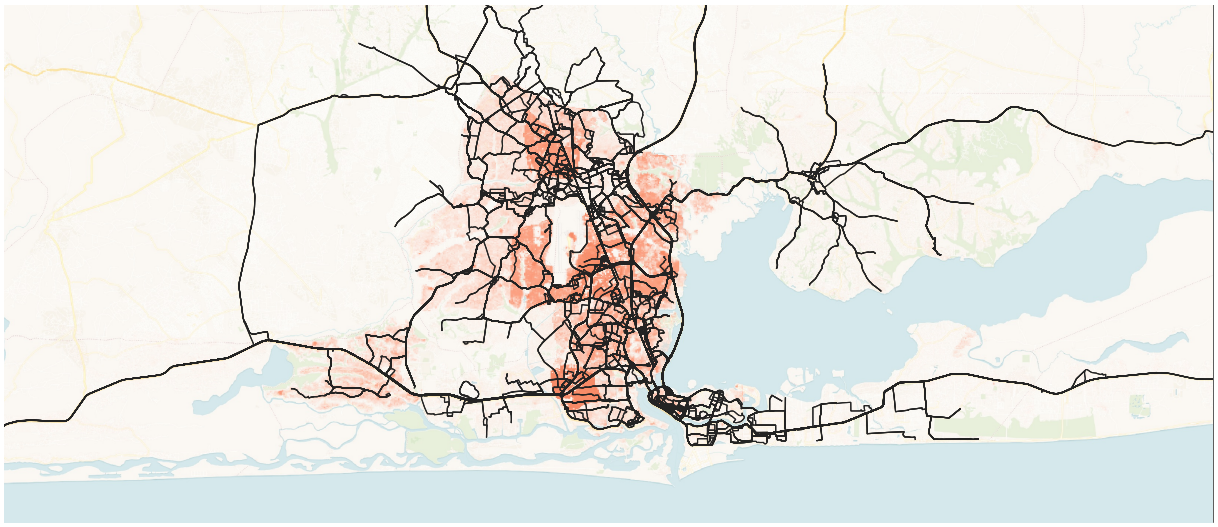
The minibus network is extensive, as shown in Figure 1A, which maps the routes we discovered in our data collection. The network is organized around major terminals (motorparks). Most drivers begin a journey by queueing at a terminal, to depart along a particular route. Once the vehicles in the front of the queue have departed and a driver is next in line, it may load passengers until full, at which point it may depart. Some drivers skip terminals and the queue to start driving along a route with an empty bus (locally this is called driving 'sole'), but our survey suggests this constitutes a minority (26%) of driver trips. Our survey also suggests that most drivers drive a single route in a day. The most common size of minibus holds 14 passengers, although this can range from 7 to 22 passengers.

The industry is overseen by a bus drivers' association called the National Union of Road Transport Workers (NURTW). The NURTW controls terminals, managing the shared infrastructure and enforcing the rule of law. It also sets the fares for trips beginning at terminals, and charges drivers fees for registering at a terminal and a particular route. The NURTW contributes some of these funds to the government, so that the private system raises public funds. At bus stops outside terminals, NURTW has less oversight, and drivers have more leeway on setting prices in response to factors such as demand or weather.

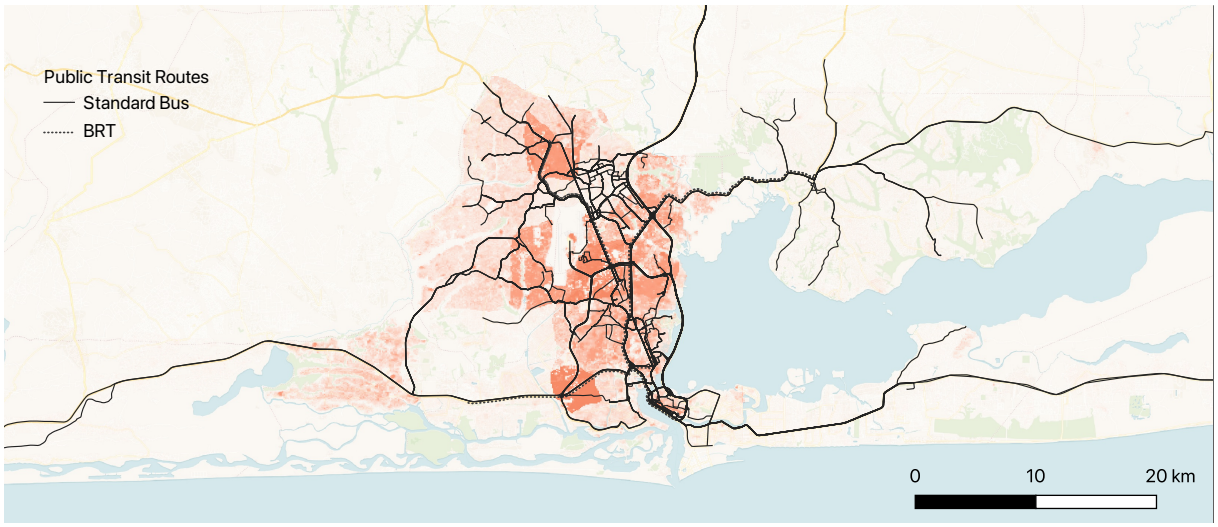
[7] There is a long tradition of similar work in developed countries, such as Brown and Finkelstein (2008) in health insurance.

FIGURE 1. Transit in Lagos

A. Private Transit Network



B. New Public Transit Network



Note: The first panel shows the existing private transit routes, as discovered in our network mapping exercise. The second panel shows the new public transit routes. Base layer color shows population density.

2.2. Lagos Bus Reform Initiative

As part of several modernization plans, the Lagos state government developed a Bus Reform Initiative (BRI) to introduce a new public bus network consisting of 820 larger city buses serving 40 routes, shown in Figure 1B. This was a large expansion relative to the previous public transit system, which included only a single Bus Rapid Transit (BRT) route and a handful of regular routes that phased in and out of existence. New buses are larger than the minibuses (most had 70 seats but some have 30, plus standing room) and more modern, offering 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, did not have dedicated lanes. Public buses travel alongside minibuses, and as a result have similar travel times.

A handful of routes opened in 2019, but the majority of routes opened in late 2020 and 2021. We analyze openings between October 2020 and December 2021.[8] We selected 14 routes to collect baseline data on. The plans for route openings changed frequently, primarily due to operational considerations. Overall, 33 routes opened during our sample period.[9] To track these changes in plans, we collected a series of 22 opening plans from LAMATA at regular dates between March 2020 and December 2021. This includes some shocks; for example, one of the terminals was burned down during the protests against police brutality (EndSARS) in October 2020; this resulted in 8 routes which had been slated to open at the end of the month being cancelled. Using the data we describe fully in Section 3, Figure 2 shows the timing of openings within our sample.

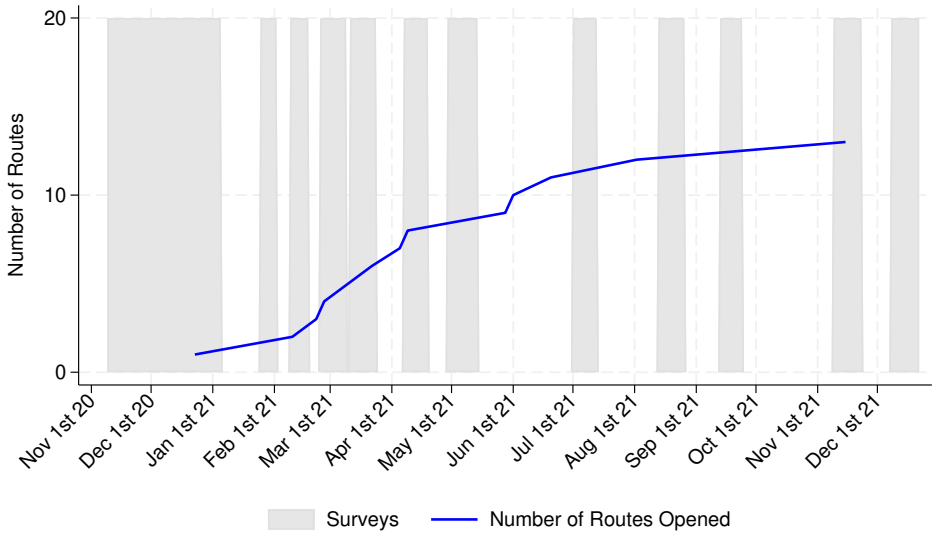
The bus expansion we study was followed by two other expansions. One was a series of 'First and Last Mile' routes operated by smaller 7-seater vehicles to connect nearby neighborhoods to these terminals (some via narrow and muddy roads). These were on lower demand routes than we study. A second was two rail lines connecting Lagos Island to the west and north. The rail lines and most of the smaller routes opened after our data was collected.[10]

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

[9] We consider routes as opened if they served passengers for at least 3 months.

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

FIGURE 2. Sampled Routes Served by Public Transit Over Time



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.

Comparison of Public and Private Service. Table 1 compares public and private supply on routes where public transit entered. Specifically, it compares characteristics of public transit to private transit, before and after public transit entered on given routes. Statistics are reported for journeys beginning at the terminal. 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 only 0.8-1.3 public buses passed per hour.[11] Overall, the public buses posed meaningful competition in the number of buses operating, with departures constituting 21-28% of the number of baseline minibus departures.

Minibuses tend to fill up to near capacity before departure. In contrast, the public buses were not always full to capacity, especially during the midday offpeak times.

On public buses, for most routes the fare is flat regardless of distance; a handful of routes use a zonal fare structure so passengers get a discount if they tap off before the last stop. On private buses, the fare is lower if you get off at an earlier stop. We compares fare for traversing the entire route: on average the public system set prices lower than the incumbent private fares, though on a minority of routes fares were higher. 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 is relatively more attractive 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.

Public buses were introduced on routes that were already served by minibuses; however,

[11] In the e-ticketing data, some stops are mislabeled so we report the number of unique public buses operational on the route each hour and multiply by two.

they serve different physical stops, so that one must make a choice about which system to wait for (an important distinction noted by Bly and Oldfield 1986). By our measurement, the public and private stops serving the same location are separated by an average distance of 180m.[12] While this is close enough to transfer, it is far enough that commuters must decide which type of bus to wait for–it would be difficult to monitor arrivals and hop on the first departing bus. Commuters seldom queue to board the minibus system; however, during the morning peak there may be queues to board public buses.

[12]This is computed on a subset of 36 public and private stops that we could match.

TABLE 1. Comparison of Private and Public Service on the Same Route

	Before Rollout		After Rollout	
	Private transit	Public transit	Private transit	Public transit
Departures per 30 min				
Peak	4.47	-	3.78	1.25
	(2.46)		(2.70)	(0.38)
Off peak	3.79	-	3.66	0.80
	(1.93)		(2.35)	(0.32)
Passengers at Departure				
Peak	13.63	-	12.94	19.24
	(4.44)		(5.61)	(5.59)
Off peak	13.88	-	13.60	8.13
	(4.74)		(6.03)	(3.37)
Fare (₦)				
Peak	202.13	-	223.50	200.50
	(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 period for routes that are eventually served by public transit, before and after public transit commences on the route. Standard deviations reported in parentheses. Computed for the 8 (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, departures are computed as the average number of buses operational during each hour of the relevant time period, divided by two, and the passenger count is the number of swipes per operational bus. Relative fares are computed by dividing the average fare on the specified route by the monthly average fare across all private transit routes in our data.

3. Data

We rely on multiple sources of data to measure the public and private networks.

3.1. Public transit

For the public network, we rely on administrative data.

Electronic ticketing data. Public buses use electronic payment cards. We observe every tap in to the system, so we see origins, fares, and timestamps (though not destinations). From this data we derive passenger volumes and fares. Similar data is collected in many cities and has been increasingly used in studies of public transit (Kreindler et al. 2023).

3.2. Private transit

In contrast, there are no preexisting data collection systems measuring even the routes served by private buses, not to mention their prices or ridership. We collected those through a series of efforts.

Network map. We commissioned a network mapping, which identified and georeferenced every usual transit route in the Lagos Metropolitan area. It was conducted by a specialized firm, WhereIsMyTransport, during the winter 2022 by sending enumerators to enumerate and identify routes and ride private transit while using a GPS tracker to map it.[13] A total of 759 routes, and almost 30,000 km, were mapped over the metropolitan area. The mapping covered mostly standard minibuses (danfo), but also included larger size buses (locally called molue) and smaller size vehicles (locally called korope). For simplicity we refer to all of these vehicles as minibuses.

Bus stop observations. We hired observers to count bus departures and passengers throughout the network as the public system was rolled out. Our data comes from observations our team conducted from October 2020 until December 2021. Our team collected 13 rounds of data, spaced approximately every month. The majority of data was collected at terminals where enumerators collected data on driver queues, fares, and departures, on 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. This constituted the bus network they would like to develop in the future, with the BRI constituting the first portions. A subset of routes were planned to open in 2020 and 2021 and these were shared with our team in deployment plans that were updated over time as their plans evolved. 55 of our routes appeared in any deployment plans, and 41 appeared in the March 2020 deployment plan close to opening (before the COVID-19 pandemic delayed rollout).

[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.

Driver surveys. We additionally assemble a panel survey of 1,040 minibus drivers who we attempt to survey over 4 rounds. We sampled drivers in queues at terminals and outside terminals. Because this sampling procedure 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 drive sole, and use that to reweight the sample, as described in Appendix B.1. This reweighted sample contains 1,009 drivers.

Wait Time Experiment. We additionally ran an experiment on sensitivity to wait time 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 7.1.

4. Descriptives

We next use our data to describe minibus drivers, and patterns of ridership during the rollout.

4.1. Minibus Drivers

The baseline survey of drivers was sampled on treated, spillover and control routes. We report baseline descriptives in Table 2, which is weighted to correct for the likelihood of sampling drivers who skip terminals, as described in Appendix B.1. A comparison to unweighted results is presented in Appendix Table S1.

Most minibus drivers we surveyed in Lagos are middle-aged men and about half have completed secondary education. 51% of drivers own their buses; the remainder either rent or pay for their vehicle on installments (rent to own).

Drivers have incentives to adapt, as most are the residual claimants on fare payments on their route. On the last day worked, the average net income was ₦4,263, net of fuel, payments to conductors, fees paid at terminals, and any side payments. Fuel is a substantial component of expenses, ₦3,151 in that day. 27% of drivers hire a conductor to collect fares and help passengers board. Drivers pay the association an average one time fee of ₦6849 to register to pick up at each terminal, and ₦624 per day in terminal fees. Minibuses frequently break down, with 78% of drivers reporting a repair in the last month. Also in the last month, 72% 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. Drivers drove 7.8 trips on average on the last working day. 41% of drivers' working time is spent waiting in queues.

Drivers have a few margins on which they can adjust. Formally, prices for each route are to be set by the driver's association, but in practice drivers sometimes charge different prices, particularly outside the terminal. Drivers can also change routes: 76% of drivers report that they choose the routes they operate. Drivers on average ply 1.1 routes. Drivers typically register at

the terminal they use as their main base; in order to join the queue to pick up passengers at the arrival terminal, they must also register at that terminal. Changing a route requires paying a fee to the association, and possibly obtaining permission if their vehicle is rented and the owner assigns the route. Alternately, drivers may elect to skip the queue and informally pick up passengers along the road without starting at a terminal, known as driving sole. Drivers report doing this on 26% of trips.

The work entails conflict: 42% of drivers report having disputes with passengers weekly, and 33% report having disputes with other drivers weekly, reported in Appendix Table S1.

We additionally asked drivers about their expectations about the public transit rollout, reported in Online Appendix Table S2. As of 2020, only 57% of drivers had heard about the 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). 36% expected public transit would reduce their passengers.

We followed up with these drivers over several rounds over the phone; however, they are a difficult group to track down. The response rate dropped to about 50% for follow-up 4.

TABLE 2. Minibus Drivers

	Mean	SD	N
Demographics			
Age (years)	37.59	(14.50)	823
Male	0.852	(0.33)	823
Has secondary education	0.508	(0.34)	823
Driving experience (years)	10.58	(6.73)	821
Operations			
Own bus	0.436	(0.32)	821
Choose own route	0.755	(0.35)	823
Number of routes plied	1.114	(0.59)	823
Proportion of trips skipping terminal start ('sole')	0.257	(0.20)	823
Number of days worked last week	4.857	(1.96)	823
Number of trips on last day worked	7.830	(4.82)	823
Hours between start and end of work on last day worked	10.32	(4.43)	823
Proportion of work time spent driving	0.594	(0.08)	823
Proportion of work time spent queuing	0.406	(0.08)	823
Income and Costs			
Last day worked			
Net income (₦)	4263.7	(2326.29)	794
Cost of fuel (₦)	3151.4	(1571.03)	820
Fees paid to the association (₦)	623.8	(819.50)	823
Employed conductor	0.270	(0.30)	817
If employed conductor, amount paid (₦)	2227.2	(1106.28)	217
Last month			
If do not own vehicle, amount paid to the minibus owner (₦)	5105.2	(2690.25)	399
Had a repair	0.780	(0.34)	818
If had a repair, cost of last repair (₦)	9802.5	(14859.49)	745
Had a fine	0.715	(0.36)	463
If had a fine, cost of last fine (₦)	6256.0	(6690.25)	364
One-time			
Average motorpark registration fee (₦)	6849.3	(4052.69)	541

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 B.1. Proportion of work time spend driving and queuing is based on responses to trip diary, based on the first 8 trips on the last day worked. Motorpark registration fee reported for drivers who registered at at least one motorpark and knew the fee.

5. Theory

This section provides a simple framework to think about the welfare gains from public transit in a context where transit services are already provided by the private sector. The model highlights the terms we need to estimate in the empirical analysis, and will decompose the welfare change into a direct component which comes from the provision of new public transit buses, and an indirect component, from the adjustment of minibuses.

A commuter ω has already chosen their commute from o to d, and chooses which mode of transport to use $m \in \mathcal{M}_t$, where $\mathcal{M}_t$ is the set of available modes at time t. We consider two periods, $t = 0$ before government entry where only minibus transit is available and $t = 1$ after government entry with both minibus and public transit services.[14]

Commuter ω's utility from choosing mode m on their commute from o to d at time t is

$$U_{modt}(\omega) = \alpha_m - \gamma p_{modt} - \eta t_{modt} + \epsilon_{modt}(\omega). \tag{1}$$

Here α_m is an amenity from the bus, γ is the disutility from paying fares, and η is the value of time. p_{modt} is the bus fare, and $t_{modt} = t^V_{modt} + t^W_{modt}$ is total travel time (wait time plus in-vehicle time). The outside option is normalized to zero. If $\epsilon_{modt}(\omega)$ is drawn from a T1EV with shape $1/\theta$, then the probability of choosing mode m is given by

$$\pi_{modt} = \frac{\exp\left(\theta(\alpha_m - \gamma p_{modt} - \eta t_{modt})\right)}{1 + \sum_{n \in \mathcal{M}_t} \exp\left(\theta(\alpha_n - \gamma p_{nodt} - \eta t_{nodt})\right)} \tag{2}$$

Sufficient Statistics for Welfare Evaluation. We now consider the change in welfare between periods t and $t+1$ that arises from government entry, which can be written as

$$\begin{aligned} \Delta \bar{U}_{mod} = & \frac{1}{\theta} \ln\left(\frac{1}{1 - \pi_{Fodt+1}}\right) \\ & + \frac{1}{\theta} \ln\left(\pi_{0odt} + \sum_{m \in \mathcal{M}_t} \pi_{modt} \exp\left(-\theta\left(\eta \Delta t_{mod} - \gamma \Delta p_{mod}\right)\right)\right) \end{aligned} \tag{3}$$

The change in welfare depends on both the adoption of the new transit mode (line 1) and the change in attributes of incumbent options (line 2).[15] Consider the first effect. If public entry has

[14] We allow the outside option to capture journeys by car, as do not find evidence that the rollout of transit changed road speeds for cars nor expect to find substitution from car owners to BRI in our price subsidy experiment based on pilot results. For that reason we consider choices in a collective nest (so that consumers choose between transit modes and an outside option).

[15] This relates to work in trade measuring changes in price indices incorporating the value of new varieties, e.g. Feenstra (1994).

no effect on the attributes of existing private service, the second line drops out, and the change in welfare is simply determined by the fraction of commuters who choose the new public mode π_{Fodt+1} on routes where it enters, scaled by θ which governs the ease with which commuters substitute between different modes. The second line shows the impact due to the response of incumbent modes.

Travel time here is composed of both wait time and travel time. We do not find evidence that congestion changes in response to BRI entry (presumably because the shock is small relative to the number of vehicles on the road). The change in total travel time is therefore given by the change in wait time.

If wait times and fares for minibuses respond to government entry, commuters will be indirectly affected. The extent to which they value these changes will depend on their valuation of prices (γ) relative to wait times (η).

This decomposition suggests that four measures are sufficient to estimate the welfare gains from public transit provision in our setting

1. Choice shares
2. Substitution elasticity between modes
3. Preferences for wait time and fares
4. Reduced form elasticities of changes in price and wait time to public entry

The first statistics we have collected in our baseline and endline data. The second statistic is the longer-run substitution elasticity we will estimate in our price subsidy experiment. The third set of statistics are the (dis)utilities of wait time and fares which we estimate in our wait time experiment. The final set of statistics are the reduced form elasticities of prices and wait times to public entry, which now turn to now.

6. 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 interested in whether and how much minibuses adjust prices and departure frequencies, which determine wait times.

Our main specifications conduct simple difference-in-difference specifications to measure how prices and departure frequencies responded to the new competition from the public system. We compare routes that received new public service to control routes that were included in the government's long-term plan for the new network but on which public service had not yet commenced.

6.1. Which Routes Received Public Transit

First, Table 3 compares baseline characteristics for routes which received public transit with those which did not (which we will treat as 'control' routes). The routes chosen were slightly higher demand routes (they had more frequent minibus departures), but had similar fares and trip distances to control routes. Recall our sampling strategy sampled from the set of routes in the government's long-term plan for the new network, potentially explaining these muted differences. In some analyses we will additionally assess the impact of public transit on spillover routes, which did not receive service themselves but share an endpoint with a route upon which public transit launches. At baseline, spillover routes tend to have slightly lower fares than control routes, and buses tend to leave with slightly fewer passengers, as shown in Table S3.

TABLE 3. Baseline Average Characteristics of Private Transit Routes

	Treated	Control	Difference T-C
	Receives public transit	No public transit	
Departures per 30 min	4.11	3.48	0.63
	(1.11)	(0.18)	(1.09)
Passengers at Departure	13.49	11.74	1.75
	(1.69)	(0.42)	(1.68)
Fare (₦)	246.15	222.72	23.43
	(30.62)	(9.26)	(30.95)
Distance (km)	8.61	7.72	0.89
	(1.75)	(0.49)	(1.76)
Number of Routes	13	265	
Test of Joint Signifiance (F-stat)			0.79

Notes: Table reports means and standard errors of baseline characteristics for routes which received public service in our sample (Treated) and those which did not (Control). Departures computed by summing total departures across our observation time windows (5 hours total) and dividing by the number of half hours. Fares and passenger counts are reported for routes where at least one departure is observed in our sample. Distance is computed on the straight line between start and end point of the route.

6.2. Baseline Specification

We consider outcomes by route r and time period (morning peak, afternoon off peak, afternoon peak), which accounts for different conditions. Our data is collected by route r, 30 minute time interval τ and survey round t. Letting $m(rt)$ denote one of our 3 route-by-time-period cells (or

'markets') for each route, our main estimating equation is

$$Y_{r\tau t} = \beta_1 \mathbb{I}\{\text{Public buses running}_{rt} \text{ for 0-2 months}\} + \beta_2 \mathbb{I}\{\text{Public buses running}_{rt} \text{ for 3-6 months}\} + \beta_3 \mathbb{I}\{\text{Public buses running}_{rt} > 6 \text{ months}\} + \gamma_{m(r\tau)} + \boldsymbol{\eta}_t{}' X_{rt} + \epsilon_{r\tau t}.$$

This regresses outcome $Y_{r\tau t}$ on indicator variables representing treatment, which are equal to one if 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. These represent our coefficients of interest. We include a set of route-by-time-period fixed effects to account for baseline differences, and a vector of control variables X_{rt} to account for other time varying shifts. We also include additional controls. In practice, our control variables will always include day of week and hour of departure fixed effects interacted with survey round fixed effects so we always flexibly control for time trends.[16]

Identification comes from comparing changes in outcomes within routes that receive public service to those which do not, conditional on controls. The assumption is therefore that these sets of routes would be on parallel trends absent the entry of public buses. Since our variation is at the route-level but our sampling was done by terminal, we cluster standard errors two ways, by route and terminal.

Table 4 shows the results. Introducing public buses decreases the departures of minibuses, as shown in Panel A. In the simplest specification in column (1), departures fall by 0.646 per 30 minute interval 6 months after public entry. Column (2) adds fixed effects for the terminal of observation, allowing for aggregate shocks to locations, which sharpens up these effects. Column (3) adds an exogenous trip characteristics (distance from the origin and destination to the CBD, and trip distance) interacted with survey round fixed effects (to allow for differential trends by these characteristics). Column (4) adds a dummy for whether the route was ever included in one of the government's opening plans for this phase of the system interacted with a time dummy to allow these routes to have differential trends over time. Column (5) adds flexible controls for origin and destination characteristics through a 3rd order polynomial in their longitude and latitude. Column (6) includes controls for baseline departure frequencies and fares. Finally, column (7) adds origin LGA (local government area) and destination LGA fixed effects interacted with time dummies. LGAs are 20 broad administrative units partitioning the city of Lagos, so that this specification controls for origin and destination region time trends.

Given a mean departure frequency of 3.45 minibuses per half hour, these results represent

[16]The vast majority of our origin-destination pairs are not treated (14 routes 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)). Later versions of this paper will augment this specification to allow for heterogeneity in treatment effects between routes or over time. Standard errors are clustered by route and terminal since treatment is at the route level but our sampling was at the terminal level. Due to the small number of treated routes, future versions of the paper will conduct robustness exercises using randomization inference and the wild bootstrap to compute standard errors.

a 29-41% reduction in departure frequencies, with the largest figure coming from our most restrictive specification in column (7). We treat column (7) as the preferred specification going forward since it includes the richest set of controls.

This finding that the entry of the new public provider led to a drop in minibus departures may seem somewhat mechanical. However, public transport works by pooling passengers. Less frequent departures means 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. Minibus stops are typically at some distance from public bus stops, so passengers do not benefit from pooling across the two types of buses. We turn to estimating the welfare effects of these indirect impacts in Section 7.

TABLE 4. Effect of Public Transit on Minibus Departures and Fares

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A: Minibus Departures							
Open $<$ 3 months	0.052	0.143	-0.015	0.029	-0.048	-0.037	-0.044
	(0.199)	(0.109)	(0.152)	(0.146)	(0.140)	(0.269)	(0.245)
Open 3-6 months	-0.262	-0.696***	-1.002***	-1.055***	-1.020***	-1.068**	-1.509**
	(0.250)	(0.208)	(0.356)	(0.323)	(0.350)	(0.414)	(0.614)
Open $>$6 months	-0.646*	-0.830***	-0.986**	-0.945***	-0.958***	-0.848***	-1.431**
	(0.366)	(0.294)	(0.376)	(0.317)	(0.300)	(0.300)	(0.612)
N	24,567	24,567	24,567	24,567	24,567	23,655	24,567
R^2	0.57	0.62	0.63	0.63	0.63	0.65	0.64
Panel B: Minibus Fares							
Open $<$ 3 months	-0.753	-1.114	-1.834	-4.070	-7.379	2.143	-3.170
	(4.082)	(6.308)	(5.594)	(5.895)	(8.427)	(7.471)	(9.026)
Open 3-6 months	2.444	2.664	2.742	-5.381	-9.458	1.082	-4.360
	(10.591)	(11.925)	(11.296)	(10.434)	(6.364)	(11.932)	(7.847)
Open $>$6 months	8.165	6.578	6.567	-4.272	-10.313	-3.637	-4.257
	(19.903)	(21.684)	(21.015)	(20.499)	(15.298)	(18.067)	(15.929)
N	23,069	23,069	23,069	23,069	23,069	22,571	23,069
R^2	0.93	0.94	0.94	0.94	0.95	0.95	0.95
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
MP 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
Lat-Lon Poly X Survey Round FE					X		
Trip Init. Char Controls X Survey Round FE						X	
Orig LGA FE X Survey Round FE							X
Dest LGA FE X Survey Round FE							X

Notes: Outcome is departures and fares. Distances in control variables are logged. Trip initial characteristics are dummies for each quartile of baseline departure frequencies and fares. Lat-lon poly is a 3rd order polynomial in origin and destination longitude and latitude. Standard errors clustered by route and terminal reported in parentheses. * p<0.1; ** p<0.05; *** p<0.01.

We find that the *average* effect of introducing public transit on minibus fares is economically small and not statistically significantly different from zero, as shown in Panel B of Table 4. However, there was heterogeneity across routes in the relative price of the new public service: on some routes, the new option was cheaper than the incumbents, on others it was more expensive. We might expect the incumbent response on fares to be greater on routes where the new service was priced comparatively lower.

We find evidence of different effects on fares depending on the relative pricing of public transit. Table 5 repeats the main specification with fares as the outcome, but interacts the opening dummies with an indicator variable equal to one if public bus service along the route was cheaper than incumbent minibuses (measured 30 days prior to public transit entry). It documents a reduction in minibus fares along routes where the new public competitor introduced service *and* prices were lower than the incumbent competitors. This result becomes increasingly precise as more controls are added with a reduction in fares of around ₦24 (11.5% of the sample mean fare of ₦210) relative to the change where public buses were priced higher.

The main concern with these results is that fares were endogenously chosen. This heterogeneity may therefore reflect different underlying trends on routes where the public service was priced above or below minibuses. Discussions with the government suggest that fares were set largely on a cost basis, reflecting distance and congestion along a route. Our main evidence for the causal nature of these effects therefore come in the placebo analysis below, where for the subset of routes cancelled due to the Oyingbo terminal fire we know the planned fares since the routes were cancelled so close to opening.

TABLE 5. Effect of Public Transit on Minibus Fares: Heterogeneity by Fare

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Open $<$ 3 months	-1.277	-3.077	-3.456	-7.400	-13.356	-1.063	-8.975
	(5.142)	(11.251)	(9.883)	(9.926)	(11.087)	(10.031)	(11.002)
Open 3-6 months	11.974	13.386	13.877	6.131	-1.670	12.995	3.761
	(13.249)	(14.973)	(13.879)	(13.361)	(9.591)	(14.428)	(10.720)
Open $>$6 months	19.933	19.984	19.999	11.066	1.719	15.391	6.002
	(24.155)	(26.168)	(24.836)	(24.606)	(16.989)	(24.346)	(15.241)
Open $<$ 3 months X Cheaper	-1.891	0.426	-0.371	2.685	8.719	1.704	9.324
	(7.933)	(11.401)	(10.205)	(10.634)	(9.728)	(10.107)	(9.506)
Open 3-6 months X Cheaper	-21.434*	-23.480**	-24.320**	-25.230**	-16.564*	-26.902**	-17.976*
	(10.858)	(11.298)	(10.780)	(10.975)	(8.544)	(12.390)	(9.752)
Open $>$6 months X Cheaper	-20.463	-23.668*	-23.589*	-26.645*	-19.661**	-35.585	-17.294*
	(13.966)	(12.955)	(12.012)	(13.824)	(7.729)	(22.938)	(9.021)
N	23,062	23,062	23,062	23,062	23,062	22,571	23,062
R^2	0.93	0.94	0.94	0.94	0.95	0.95	0.95
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
MP 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
Lat-Lon Poly X Survey Round FE					X		
Trip Init. Char Controls X Survey Round FE						X	
Orig LGA FE X Survey Round FE							X
Dest LGA FE X Survey Round FE							X

Notes: Outcome is fares. Cheaper is a dummy for whether public service on route r was cheaper than minibus fares 30 days prior to public entry. Specifications otherwise the same as Table 4

6.3. Placebo Tests

The EndSARS Protests and Fire at Oyingbo Terminal. In October 2020, a protest against police brutality swept Lagos and the rest of the country, 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 BRI bus terminal (see Figure A1). The Oyingbo bus terminal had been slated to host 8 new BRI routes opening at the end of October and early November. We use these routes as an additional placebo check to see if outcomes trended differentially amongst these routes that were almost opened but ended up cancelled due to these unexpected events. Importantly, since these routes were cancelled abruptly we know the fares the government was going to set on those routes, and so can conduct the same heterogeneity analysis as in the main results.

Evolving Opening Plans. While our entire sample is composed primarily of routes in Lagos State Government's planned future bus system, a subset of these routes were included in their deployment plans for the phase of route openings during our sample period. 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. 55 of our routes appeared in any deployment plans, and 41 appeared in the March 2020 deployment plan close to opening (before the COVID-19 pandemic delayed rollout). These evolving plans allow us to construct finer and finer control groups to address potential endogenous route selection.

Results. Table 6 shows the results for departures. Column 1 repeats the baseline specification (column 7 in Table 4). Column 2 adds event-time dummies for whether a route from Oyingbo would have opened but was cancelled after the fire. Column 3 does the same for planned openings that were cancelled due to changes in government deployment plans. Column 4 varies the comparison group by including dummies for whether a route was included in March 2020 deployment plan (routes which were close to opening prior to COVID), interacted with time fixed effects. Overall we see no reduction in minibus departures after planned but cancelled public transit entry, in particular in our preferred specification of column (2) where the cancellation of entry was plausibly exogenous. This supports the notion that our treatment effects are due to entry itself, and not other pre-existing trends on routes the government decided to enter.

Table 7 provides the analogous table using fares as the outcome and shows the same implications. Importantly in column (2) we can run exactly the same regression as we do in Table 5 as the government shared the the fares these routes were going to be assigned on opening.[17] While

[17] In other cases, such as changes in government plans for other reasons, these planned fares are not available as the fares were only set right before route opening and these planned but cancelled routes never got to this very late stage.

TABLE 6. Placebo: Minibus Departures

	(1)	(2)	(3)	(4)
Open $<$ 3 months	-0.044	-0.042	0.022	-0.163
	(0.245)	(0.249)	(0.358)	(0.255)
Open 3-6 months	-1.509**	-1.498**	-1.557*	-1.630***
	(0.614)	(0.614)	(0.923)	(0.581)
Open $>$6 months	-1.431**	-1.409**	-1.446	-1.492**
	(0.612)	(0.612)	(0.870)	(0.584)
Cancelled, Planned Open $<$ 3 months		0.274	1.152*	
		(0.868)	(0.593)	
Cancelled, Planned Open 3-6 months		-0.275	0.887	
		(0.860)	(0.664)	
Cancelled, Planned Open $>$6 months		0.572	0.581	
		(0.968)	(0.857)	
N	24,567	24,567	24,567	24,567
R^2	0.64	0.64	0.65	0.65
Cancelled Measure		ENDSARS	Plan Change	
March 2020 Dep Plan X Period FE				X

Note: Outcome is departures. Specification includes controls from column (7) of main table. Standard errors clustered by route and terminal reported in parentheses. * p<0.1; ** p<0.05; *** p<0.01.

minibus fares fall after 3 months following government entry on routes where the public option is cheaper (column 1), the estimate is noisy (and in the opposite direction) on routes where the government planned to enter with cheaper service but was cancelled due to the Oyingbo fire. Column 3 then shows no significant change in fares on routes the government planned to enter but did not due to changes in its deployment plans, while column 4 again shows the main coefficients are robust to comparing with routes initially planned to be included in the first phase of the BRI network.

TABLE 7. Placebo: Minibus Fares

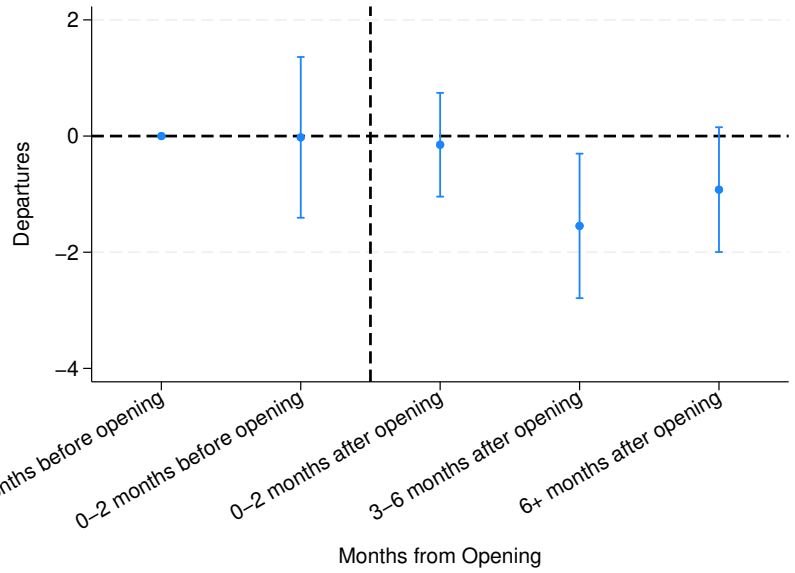
	(1)	(2)	(3)	(4)
Open $<$ 3 months	-8.975	-9.337	-5.287	-7.677
	(11.002)	(10.923)	(12.342)	(10.272)
Open 3-6 months	3.761	3.360	6.550	3.499
	(10.720)	(10.871)	(10.425)	(10.340)
Open $>$6 months	6.002	5.568	8.612	4.212
	(15.241)	(15.547)	(14.373)	(14.880)
Open $<$ 3 months X Cheaper	9.324	9.742	9.587	10.534
	(9.506)	(9.579)	(9.885)	(8.508)
Open 3-6 months X Cheaper	-17.976*	-18.170*	-17.185*	-17.365*
	(9.752)	(9.745)	(9.924)	(9.518)
Open $>$6 months X Cheaper	-17.294*	-17.799**	-16.332*	-16.384*
	(9.021)	(8.820)	(8.888)	(9.237)
EndSARS, Planned Open $<$ 3 months		47.582		
		(40.187)		
EndSARS, Planned Open 3-6 months		50.612*		
		(25.665)		
EndSARS, Planned Open $>$6 months		18.820		
		(27.778)		
EndSARS, Planned Open $<$ 3 months X Cheaper		28.395		
		(40.503)		
EndSARS, Planned Open 3-6 months X Cheaper		-0.876		
		(25.242)		
EndSARS, Planned Open $>$6 months X Cheaper		36.662*		
		(21.514)		
Cancelled, Planned Open $<$ 3 months			-10.386**	
			(4.353)	
Cancelled, Planned Open 3-6 months			7.840	
			(7.446)	
Cancelled, Planned Open $>$6 months			2.605	
			(7.862)	
N	23,062	23,062	23,062	23,062
R^2	0.95	0.95	0.95	0.95
Cancelled Measure		ENDSARS	Plan Change	
March 2020 Dep Plan X Period FE				X

Note: Outcome is fares. Specification includes controls from column (7) of main table. Standard errors clustered by route and terminal reported in parentheses. * p<0.1; ** p<0.05; *** p<0.01.

6.4. Event Studies

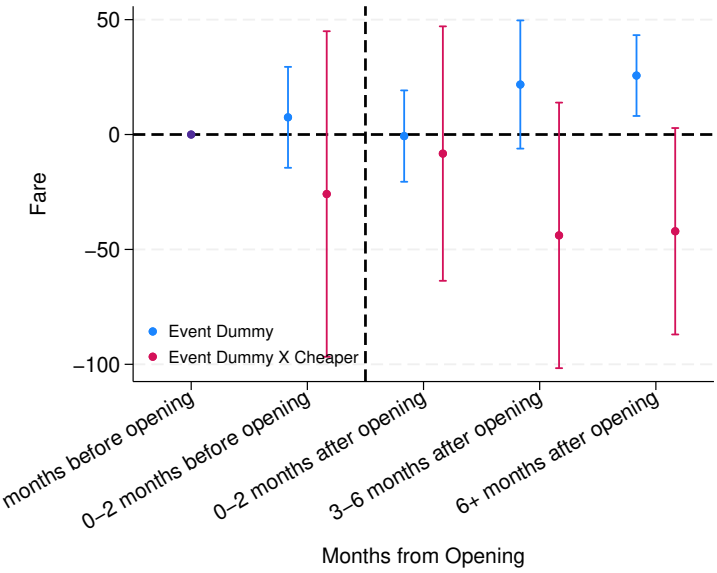
Figures 3 and 4 plot event studies for our two main results which includes dummies for a period before the route opens to test for pre-trends. Given the timing of the route openings in our sample (Figure 2), we do not have a lot of data across finer periods prior to route openings. These figure therefore add a dummy for whether a route is 0-2 months from having public transit service, so that the omitted category is when they are 3 months or earlier from entry. For departures there is no clear pre-trend (although the confidence interval is fairly wide), and for fares the confidence intervals are predictably wider in the pre-period since we are estimating two sets of coefficients. While these figures do not show strong pre-trends, we are relatively underpowered to identify them given the rollout timing and our sampling plan. We therefore prefer to focus on the placebo checks in the previous section as evidence that the effects are driven by the public sector entry.

FIGURE 3. Event Study: Departures



Note: Plots show the baseline specification including an additional dummy for being 0-2 months before opening. The omitted category is a route that is 3 months or earlier from opening.

FIGURE 4. Event Study: Fares



Note: Plots show the baseline specification including an additional dummy for being 0-2 months before opening. The omitted category is a route that is 3 months or earlier from opening.

7. Welfare Effects

Next we estimate the welfare effects of the rollout of public transit, using our RCT to estimate how commuters value the changes in minibus prices and wait times documented in the previous section. This experiment was preregistered in the AEA RCT registry (AEARCTR-0010283).[18]

7.1. 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 bus.

Implementation. Our team developed an SMS-based app which allows us to estimate commuters' value of time at bus 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.[19] We informed them that on weekdays morning that they commute over the next 3-5 weeks, they will find an enumerator waiting at their registered bus stop. The enumerator holds a phone or tablet, which displays a random code which changes every minute. The participant texts this code to our SMS-service (see Figure A2 for a photo of this interaction). The service sends an immediate airtime reward of $s_i^{checkin}$ for checking in, as well as a randomized offer to

[18]Deviations are detailed in Online Appendix S1.1.

[19]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.

wait Δt_{it} minutes for a payment of s_{it} Naira. To accept the offer, a participant will wait at the bus stop and then send back the new code that the enumerator's tablet displays after at least Δt_{it} minutes, 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 $s_i^{checkin}$ were randomized between individuals (₦200, 400, 700, or 1000) and then held fixed over the experiment. Wait offers $(\Delta t_{it}, s_{it})$ were randomized for each individual-day. Individuals were told summary statistics about the distribution of wait offers.[20] Under the first three days checking in, participants were given shorter (or no) waits and higher offers, to get them accustomed to checking in.[21]

Theory. Because engaging with our experiment represents a slight hassle, we model that decision explicitly. Suppose a commuter has arrived at a bus stop, having already chosen a travel mode (bus). First, she decides whether to check in with us. If she checks in, we will pay her an immediate amount $s_i^{checkin}$, but checking in incurs a slight hassle, with a wait of $t^{checkin}$. If she checks in, we send a wait offer, to pay s_{it} to wait for Δt_{it} minutes. Second, the commuter decides whether to accept or reject the offer.

Let's work backwards, based on utility defined in equation (1). Conditional on checking in, she will accept the offer if

$$\alpha_m - \gamma(p_m - s_{it}) - \eta(t_m + \Delta t_{it}) + \epsilon_{mit+\Delta t_{it}} > \alpha_m - \gamma p_m - \eta t_m + \epsilon_{mit}$$

Now, decompose the idiosyncratic error into a component that is stable across short waits and one that may vary, $\epsilon_{mit} = \nu_{mi} + \nu_{it}$. Then the consumer will wait if

$$\begin{aligned} \alpha_m - \gamma(p_m - s) - \eta(t_m + \Delta t_{it}) + \nu_{mi} + \nu_{it+\Delta t_{it}} &> \alpha_m - \gamma p_m - \eta t_m + \nu_{mi} + \nu_{it} \\ D_{it}^* = \gamma s_{it} - \eta \Delta t_{it} + \nu_{it}^{wait} &> 0. \end{aligned}$$

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

The utility of checking in is given by

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

so that a commuter will not check in the value of their time is high relative to the known checkin offer and expected wait offers, or due to idiosyncratic reasons captured in $\nu_{it}^{checkin}$.

[20] 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."

[21] Participants were randomly assigned to either have one or two initial days with zero wait, and then optimistic offers for the rest of this initial period; see Appendix B.3

Estimation Procedure. We assume that the idiosyncratic errors are jointly distributed according to CDF F,

$$\begin{bmatrix} \nu_{it}^{wait} \\ \nu_{it}^{checkin} \end{bmatrix} \sim F(C, D|\sigma^{wait}, \sigma^{checkin}, \rho).$$

where we assume the distribution has parameters that control the spread of the two primitive errors (σ^{wait} and $\sigma^{checkin}$), and a parameter that controls the correlation between them (ρ). Let F^x indicate the marginal CDF along error x. Then in our data we will observe the decision to check in $C_{it} = \mathbb{I}\{C_{it}^* > 0\}$ and, only if the person checks in ($C_{it} = 1$), the decision to accept $D_{it} = \mathbb{I}\{D_{it}^* > 0\}$. We will assume that the distribution F is normal. Because the check in offer $s_i^{checkin}$ is excluded from the waiting decision, we can use it as an instrument for the decision to check in.

The average log likelihood is given by

$$\begin{aligned} \bar{l}(\gamma, \eta, \sigma^{wait}, \sigma^{checkin}, \rho|\mathbf{C}, \mathbf{D}, \mathbf{s}^{checkin}, \mathbf{s}, \Delta\mathbf{t}) = \frac{1}{N} \\ \sum_{it} C_{it} D_{it} \log\left(1 - F^{\nu^{wait}}(-\underline{D}_{it}) - F^{\nu^{checkin}}(-\underline{C}_{it}) + F(-\underline{D}_{it}, -\underline{C}_{it})\right) + \\ C_{it}(1 - D_{it}) \log\left(F^{\nu^{wait}}(-\underline{D}_{it}) - F(-\underline{D}_{it}, -\underline{C}_{it})\right) + \\ (1 - C_{it}) \log F^{\nu^{checkin}}(-\underline{C}_{it}) \end{aligned} \tag{4}$$

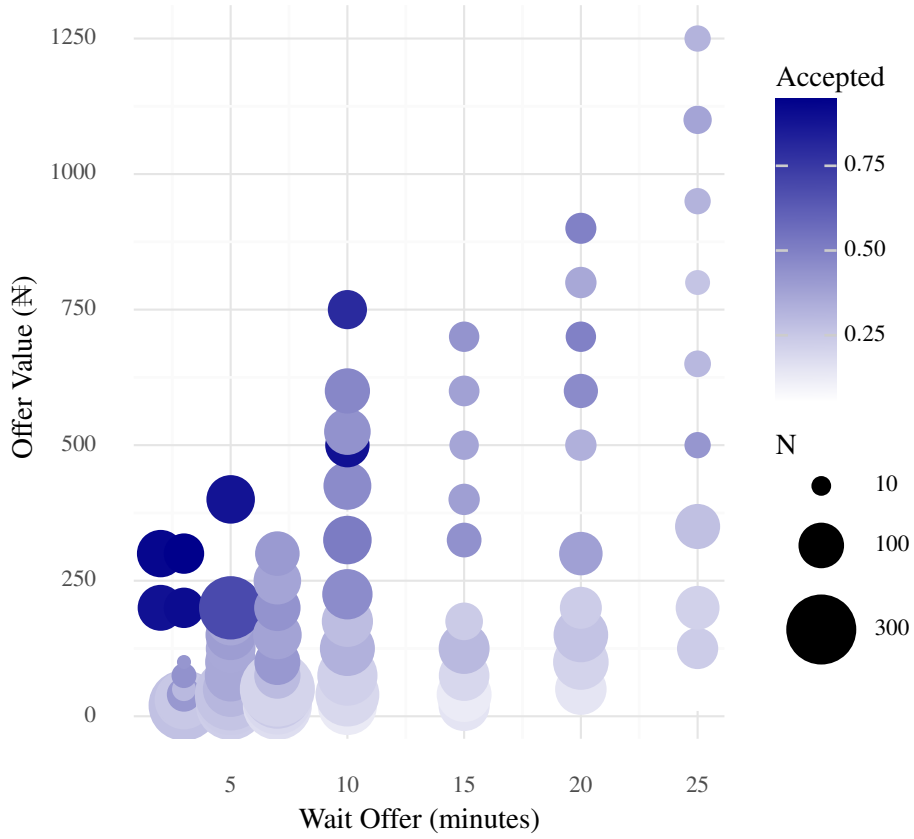
where participation thresholds are given by $\underline{D}_{it}(\gamma, \eta) = \gamma s_{it} - \eta \Delta t_{it}$ and $\underline{C}_{it}(\gamma, \eta, s_i^{checkin}) = \gamma s_i^{checkin} - \eta t^{checkin} + \mathbb{E}[\gamma s_{it} - \eta \Delta t_{it} + \nu_{it}^{wait} | \gamma s_{it} - \eta \Delta t_{it} + \nu_{it}^{wait} > 0] \cdot \Pr(\gamma s_{it} - \eta \Delta t_{it} + \nu_{it}^{wait} > 0)$, the number of total observations is N, and bold symbols represent vectors. We fix $\sigma^{wait} = 1$ and 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.[22] The remaining parameters are estimated using maximum likelihood. Standard errors are clustered at the commuter level.

Results. We show the distribution of offers and acceptances in Figure 5. We drew offers from a distribution under which shorter times are more likely, with offer values tend 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 variation, which depends on the individual and day.

Estimated parameters are shown in Table 8. We obtain $\hat{\eta} = 0.0464$ and $\hat{\gamma} = 0.0025$; combined these suggest a disutility of waiting of ₦18.94 per minute.

[22] 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 by bus stop; we took the average.

FIGURE 5. Wait Offer Acceptances



Note: Plots the proportion of acceptances for given offers (₦: y-axis) to wait (minutes: x-axis). 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, but still included some weight on more extreme values.

Comparison to other estimation procedures Selection into participating is important for estimation. Estimates of $\sigma^{checkin}$ are substantially larger than those of σ^{wait}, suggesting the decision to commute and check in is more idiosyncratic than that to accept waits. We also estimate a positive ρ, suggest a positive correlation of wait and checkin shocks, which is consistent with people being more rushed on some days, and being less likely to both accept and check in. We show this latter fact descriptively in Appendix Table A3, which shows that people who were randomly given higher payments to check in are less likely to accept the offers they receive, suggesting the payments induce them to check in on days they are rushed. In Appendix Table A4 column (2), we show that a model that assumes perfect compliance estimates a value of time of ₦8.34 per minute: undervaluing the hassle of waiting by 56% relative to using a method to correct for selection into engaging in the experiment.

In transportation studies it is common to infer the value of time from hypothetical choices or stated preference. In the baseline survey we asked participants to consider the last motorized trip they took, and make hypothetical choices between options with varying costs and wait times.[23] In Appendix Table A4 column (3) we show that stated preferences yield a value of time of ₦46.45 per minute–overstating our main estimate by a factor of 2.5. This coincides with other work finding stated preferences can greatly overstate valuations relative to revealed preferences (Kremer et al. 2011).

Robustness We assess several notions of robustness in Online Appendix S1.2.2.

We assess alternate specifications in Online Appendix Table S6. 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 Online Appendix Table S7.

Estimates are also similar under a model that accounts for the possibility that participants accepted wait offers only if a bus did not arrive. 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 accepted our wait offer if no bus had arrived in the waiting time interval. As a robustness check, in Online Appendix S1.2.2 we estimate 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.

[23] We asked about 5 pairs of offers.

7.1.1. 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 B.2.

TABLE 8. 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.

7.2. Welfare Results

To implement the welfare decomposition in (3), we require values for choice shares π_{odmt}, reduced form elasticities $\Delta p, \Delta t^w$ measuring the response of minibus prices and wait times to public transit entry, and preference parameters θ, γ, η.

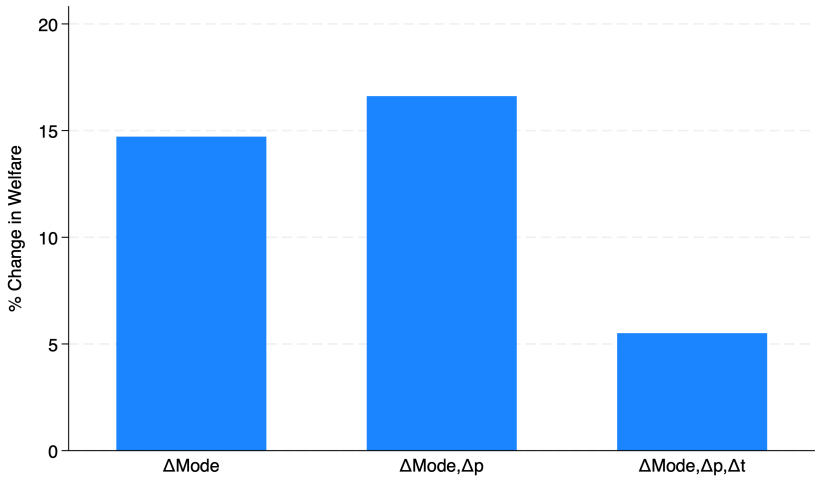
For a preliminary analysis, we consider welfare on an average route. Using travel survey data, the mean share of minibus trips π_{Iodt} is 0.57. On routes where public transit enters, it takes about 55% of transit trips giving it an overall share of $\pi_{Fodt} = 0.31$. The elasticities $\Delta p, \Delta t^w$ we retrieve from the reduced form results, and γ, η are reported in the previous section. We take the substitution elasticity of $\theta = 1.88$ from Tsivanidis (2023).[24]

Figure 6 reports the results. The first column shows a 14% increase in welfare on the average route with public sector entry, considering only the gains that come from the new mode (the first

[24]In that paper, the semi-elasticity of mode choice to time across public modes of transit is $\lambda/\kappa = 0.087$. In our model, this semi-elasticity is $\theta\eta$, so dividing by our estimate of $\eta = 0.0463$ yields the result.

line of equation (3)). This comes from the relatively large use of public service where available. The second column allows the price of the minibus service to change. This boosts the benefits from the new public service to 17%, as customers who do not use the public service benefit from the lower prices it induces for competing minibus services. The last column reports the full welfare impacts, allowing both prices and wait times to respond. Since wait times rise by around 6 minutes for minibus service, our estimate of $\eta = 0.0464$ implies a sizeable utility drop for those continuing to use the service, resulting reducing the total welfare gain to around 6%.

FIGURE 6. Welfare Decomposition



This suggests that indirect effects play an important role in determining the total return to public transit, in cities where the private sector continues to provide transportation services.

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 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, and suggestive evidence of an effect on fares. 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.

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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Appendix A. Additional Figures

FIGURE A1. Oyingbo Public Terminal: Fire and Aftermath



A. Fire

B. Aftermath

FIGURE A2. Participant checking in for wait time experiment



Appendix B. Additional Details

B.1. Driver Sampling Correction

Here we describe a procedure to reweight our sample to account for differential ease of surveying different types of drivers.[25]

We seek to estimate the number of individuals of a given type i in the population, α_i. However, individuals may be either in different states, and we only sample individuals in state 1. The true likelihood that i is in state 1 is π_i. In a single period, we draw all individuals that are in state 1, and ask them their overall likelihood of being in state 1 (which yields an estimate of π_i: p_i). Let a_i be the number of individuals of type i in our state 1 sample. Then an estimator for the number of individuals of type i in the population is given by

$$\hat{\alpha}_i = \frac{a_i}{p_i}.$$

Note that if i is always in state 1 ($p_i = 1$), then there is no correction: $\hat{\alpha}_i = a_i$. Alternately, note that if i is *never* observed in state 1 ($p_i = 0$), then this correction cannot help us: $\hat{\alpha}_i$ is undefined.

In our setting, we sampled drivers who were waiting, either in queues in terminals or outside the parks. However, drivers who are younger, who rent their vehicles, and who drive sole are likely to spend less time waiting in these places. Thus, we estimate the proportion of each type using this correction based on the fraction of time spent driving sole. Our main estimates from the driver survey use those weights. Table S1 extends Table 2 to compare the weighted statistics to their unweighted counterparts.

B.2. Price Sensitivity

We use the response to price changes on public buses to infer the substitution parameter.

B.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 announced a 50% subsidy on public transit, and said it had arranged with minibus operators to reduce prices by 25%. On November 7 the public transit subsidy was reduced to 25%.[26] On January 29, 2024, the public transit subsidy was eliminated, and on February 26, 2024, it was reinstated at 25%.

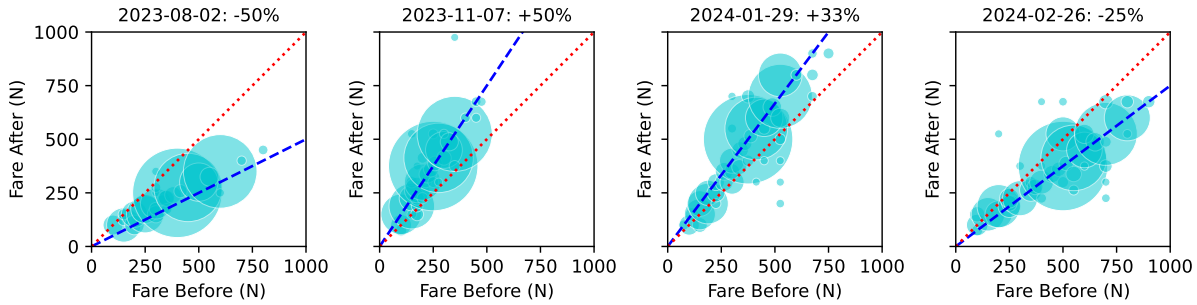
We illustrate the price changes by route in Figure A3. Each panel shows a different price change date, plotting the price two weeks prior (x-axis) and and two weeks after (y-axis), with

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

[26] 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.

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.

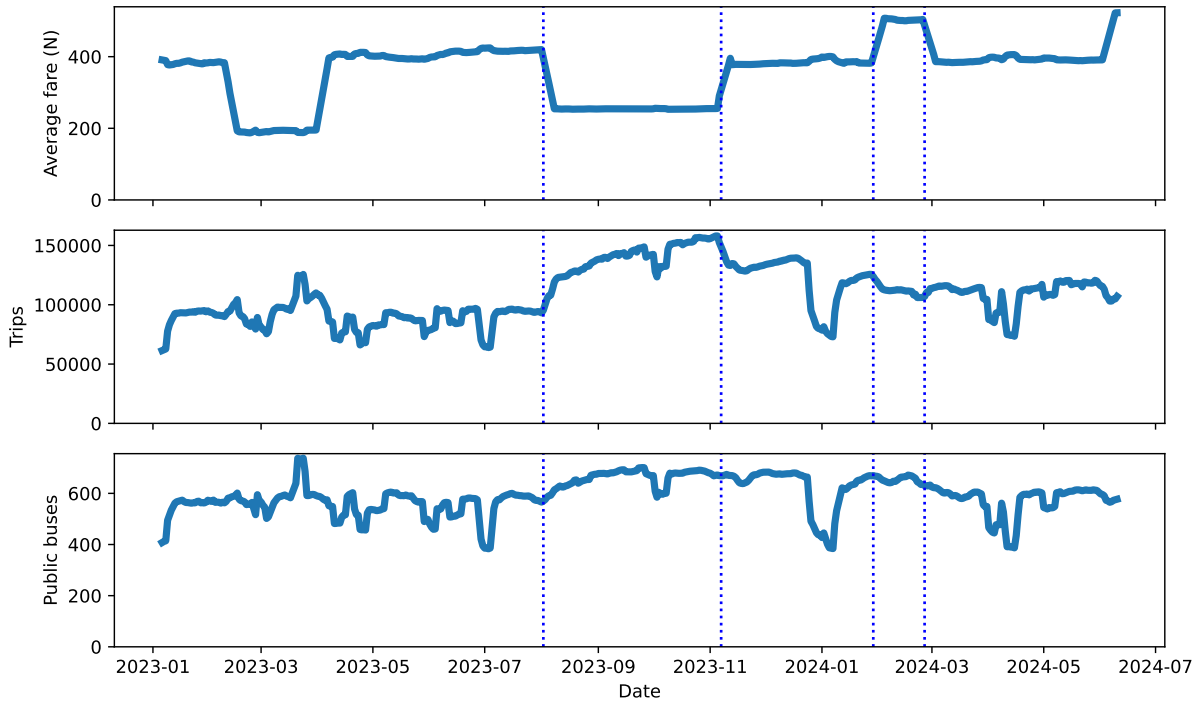
FIGURE A3. Public Bus Price Changes



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 A4. The dates of the price changes are designated with dashed blue lines. The sharp changes in average fair 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. 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 A4. Public Transit Bus Trends 2023-2024



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.

B.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 level, and include only observations within a designated number of days of a price change.[27]

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

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

[27]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.

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

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 (r) and day of week ($DoW(t)$). The price sensitivity is then given by $\eta = \frac{\alpha}{\zeta}$ (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 include the detrended equation in our 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 A1. 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 A1. 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 j'th is 1 after the j'th price change and zero otherwise, and $AroundDiscontinuity_t$ is a vector of indicator variables for which the j'th is 1 within 14 days of the j'th price change and zero otherwise. We include only observations within 14 days of a price change.[28]

Estimated price sensitivities are shown in Table A2. 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.

As a robustness check, we verify that our estimate is not arising from a supply shift, in Online Appendix Table S4. 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.

TABLE A2. Trips Price Sensitivity 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	-0.0022***	-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.

[28]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.

B.3. Wait Time Experiment

Implementation details. Enumerators had bright yellow hats, and waited near bus stops. Figure A2 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 $s_i^{checkin}$ which was then held constant throughout the experiment
- Upon checking in at the bus stop, each participant received a wait offer draw $(s_{it}, \Delta t_{it})$ 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 an reward of $s_{it} =$₦2000 for zero wait ($\Delta t_{it} = 0$). On their next two checkins, participants received a random draw $(s_{it}, \Delta t_{it})$ which was generous (high payment per wait).
    - For the other group, on the first *two* checkins at the bus stop, participants received an reward of $s_{it} =$₦2000 for zero wait ($\Delta t_{it} = 0$). On their next one checkin, participants received a random draw $(s_{it}, \Delta t_{it})$ which was generous (high payment per wait).
  - On each checkin after their third, all participants received their own random draw $(s_{it}, \Delta t_{it})$ 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.

Descriptives. We present descriptives from our participants in Online Appendix Table S5. 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 S5 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, $s_i^{checkin}$, is correlated with the proportion of days checking in, $\overline{C}_i$).

In the endline we asked about the wait time and offer they expected to obtain in the study.[29] 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.)

Additional results. We show rates of check in and acceptance by the check in offer in Table A3. Higher offers to check in (column (1)) induce people to check in more frequently (column (2)), but they are less likely to accept those offers (column (3)). This pattern could be rationalized if the higher check in offers induce them to check in on days they don't have time to wait. This pattern suggests that simply looking at the decision to accept offers (column (3)) is not sufficient to value wait time, because people will only take the time to get an offer on days they are not rushed.

[29] 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.

TABLE A3. Wait Experiment: Decisions by Checkin Offer

	(1)	(2)	(3)	(4)	(5)	(6)
Check-in Offer (₦) $s_i^{checkin}$	Planned travel Baseline, first week	Actual travel Endline, last week	Prop. days checked in Mean of C_{it}	Prop. checkin offers accepted Mean of $D_{it}\|C_{it}=1$	Users	N
200	0.89	0.79	0.49	0.68	165	2278
400	0.93	0.78	0.54	0.66	170	2221
700	0.90	0.81	0.57	0.63	178	2397
1000	0.91	0.84	0.59	0.57	127	1744

TABLE A4. Wait Experiment: Alternate Estimation Strategies

	(1)	(2)	(3)
	Main	Perfect Compliance	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 (4) assuming compliance is perfect ($C_{it} \equiv 1$ 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.

Online Appendix: Public and Private Transit

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Appendix S1. Wait Experiment

S1.1. 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 $s_i^{checkin}$ 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_{it}^{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 S7 column (4) shows that results are similar if we include earlier observations while the design was changing.[30]

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 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.

[30]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 20) 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.

S1.2. Robustness

S1.2.1. Sample definitions

We assess robustness to alternate sample definitions in Table S7. 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 optimistic 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.[31] Estimates are similar in all cases.

S1.2.2. 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.

Let $\Pr(A)$ be the probability that a bus arrives within a timespan of Δt_{it} 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 $\Pr(A) = \Pr(X \geq 1) = 1 - e^{-\Delta t_{it}\lambda}$ 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 equation (1). Let t_m be the status quo departure time and $t_m^{\Delta t_{it}}$ be the departure time if the person accepts a wait offer of Δt_{it} minutes.

Conditional on checking in, the utility of accepting the offer has two cases. If no bus arrives within the interval Δt_{it} (case $N = 1 - A$), then the offer entails no additional wait and the person will check out as long as

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

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 $\mathbb{E}[t_m^{\Delta t_{it}} - t_m] = \Delta t_{it}$. This leads to the original condition,

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

[31] Described in Section S1.1.

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

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

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

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 $F^{\nu^{wait}}(-\underline{D}_{it}^{N})$ for threshold $\underline{D}_{it}^{N}(\gamma) = \gamma s_{it}$. If there is an arrival, the probability of waiting is given by $F^{\nu^{wait}}(-\underline{D}_{it}^{A})$, for $\underline{D}_{it}^{A}(\gamma, \eta) = \gamma s_{it} - \eta \Delta t_{it}$. Combining these and the probability of arrival yields the average log likelihood

$$\begin{aligned} \bar{l}(\gamma, \eta, \sigma^{wait}, \rho | \mathbf{D}, \mathbf{s}, \Delta \mathbf{t}) = & \frac{1}{N} \\ & \sum_{it} D_{it} \log \left(1 - \Pr(1-A) F^{\nu^{wait}}(-\underline{D}_{it}^{N}) - \Pr(A) F^{\nu^{wait}}(-\underline{D}_{it}^{A}) \right) + \\ & (1 - D_{it}) \log \left(\Pr(1-A) F^{\nu^{wait}}(-\underline{D}_{it}^{N}) + \Pr(A) F^{\nu^{wait}}(-\underline{D}_{it}^{A}) \right) \end{aligned} \tag{S1}$$

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 ($D_{it} = 1$) since the threshold for accepting the offer is lower since it involves no wait ($\underline{D}_{it}^{A} \leq \underline{D}_{it}^{N}$ so $F^{\nu^{wait}}(-\underline{D}_{it}^{A}) \geq F^{\nu^{wait}}(-\underline{D}_{it}^{N})$).

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

$$\begin{aligned} C_{it}^{*} = \gamma s_{i}^{checkin} - \eta t^{checkin} & + \Pr(1-A) \mathbb{E}[D_{it}^{*N} | D_{it}^{*N} > 0] \Pr(D_{it}^{*N} > 0) \\ & + \Pr(A) \mathbb{E}[D_{it}^{*A} | D_{it}^{*A} > 0] \Pr(D_{it}^{*A} > 0) \\ & + \nu_{it}^{checkin} \end{aligned}$$

The average log likelihood is given by

(S2)

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

where participation thresholds are given by $\underline{D}^N_{it}(\gamma, \eta) = \gamma s_{it}$, $\underline{D}^A_{it}(\gamma, \eta) = \gamma s_{it} - \eta \Delta t_{it}$ and $\underline{C}_{it}(\gamma, \eta, s^{checkin}_i) = \gamma s^{checkin}_i - \eta t^{checkin} + \Pr(1-A)\mathbb{E}[\gamma s_{it} + \nu^{wait}_{it} | \gamma s_{it} + \nu^{wait}_{it} > 0] \cdot \Pr(\gamma s_{it} + \nu^{wait}_{it} > 0) + \Pr(A)\mathbb{E}[\gamma s_{it} - \eta \Delta t_{it} + \nu^{wait}_{it} | \gamma s_{it} - \eta \Delta t_{it} + \nu^{wait}_{it} > 0] \cdot \Pr(\gamma s_{it} - \eta \Delta t_{it} + \nu^{wait}_{it} > 0)$, 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 S8 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 S2. Additional Exhibits

TABLE S1. Minibus Drivers: Comparison of Weighted and Unweighted Statistics

	Weighted			Unweighted		
	Mean	SD	N	Mean	SD	N
Demographics						
Age (years)	37.59	(14.50)	823	43.69	(8.82)	849
Male	0.852	(0.33)	823	0.994	(0.08)	849
Has secondary education	0.508	(0.34)	823	0.603	(0.49)	849
Driving experience (years)	10.58	(6.73)	821	12.75	(9.71)	847
Operations						
Own bus	0.436	(0.32)	821	0.514	(0.50)	847
Choose own route	0.755	(0.35)	823	0.848	(0.36)	849
Number of routes plied	1.114	(0.59)	823	1.173	(0.52)	849
Proportion of trips skipping terminal start ('sole')	0.257	(0.20)	823	0.170	(0.25)	849
Number of days worked last week	4.857	(1.96)	823	5.631	(0.89)	849
Number of trips	7.830	(4.82)	823	9.170	(6.10)	849
Total hours between start and stop on last day worked	10.32	(4.43)	823	12.16	(3.39)	849
Proportion of work time spent driving	0.594	(0.08)	823	0.567	(0.16)	847
Proportion of work time spent queuing	0.406	(0.08)	823	0.433	(0.16)	847
Income and Costs						
Last day worked						
Net income (₦)	4263.7	(2326.29)	794	5167.6	(2951.67)	818
Cost of fuel (₦)	3151.4	(1571.03)	820	3740.1	(1606.35)	846
Fees paid to the association (₦)	623.8	(819.50)	823	705.9	(1557.55)	849
Employed conductor	0.270	(0.30)	817	0.295	(0.46)	843
If employed conductor, amount paid (₦)	2227.2	(1106.28)	217	2551.5	(1028.85)	237
Monthly (last month)						
If do not own vehicle, amount paid to the minibus owner (₦)	5105.2	(2690.25)	399	6021.2	(2956.19)	410
Had a repair	0.780	(0.34)	818	0.923	(0.27)	844
If had a repair, cost of last repair (₦)	9802.5	(14859.49)	745	11497.3	(24022.27)	769
Had a fine	0.715	(0.36)	463	0.827	(0.38)	480
If had a fine, cost of last fine (₦)	6256.0	(6690.25)	364	6463.2	(14319.23)	376
One-time						
Number of motor parks registered at	0.979	(0.59)	823	1.247	(0.80)	849
If paid, average motorpark registration fee	6849.3	(4052.69)	541	7759.5	(5192.14)	550
Disputes						
Proportion of drivers in weekly passenger dispute	0.419	(0.32)	823	0.484	(0.50)	849
Proportion of drivers in weekly driver dispute	0.326	(0.30)	823	0.367	(0.48)	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 B.1. ̂81% of the drivers report being registered at a motorpark. Missing registration fees are imputed using a dataset of union registration fees by motorpark.*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.

TABLE S2. Minibus Drivers: Awareness of Public Transit

	Weighted		
	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 S3. Baseline Average Characteristics of Private Transit Routes

	Treated	Spillover	Control	Difference T-C	Difference S-C
	Receives public transit	Will share end point with public transit	No public transit		
Departures per 30 mins	4.11	3.60	3.38	0.74	0.22
	(1.11)	(0.27)	(0.24)	(1.10)	(0.37)
Passengers at Departure	13.49	10.15	13.10	0.39	-2.95
	(1.69)	(0.50)	(0.62)	(1.74)	(0.80)
Fare (₦)	246.15	203.75	239.03	7.13	-35.28
	(30.62)	(14.78)	(11.49)	(31.78)	(18.72)
Distance (km)	8.61	7.50	7.91	0.70	-0.41
	(1.75)	(0.86)	(0.54)	(1.77)	(1.01)
Number of Routes	13	123	142		
Test of Joint Signifiance (F-Stat)				0.60	4.58***

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 (Spillover) 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.

TABLE S4. 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 S5. Wait Time Game Descriptives

	(1) min	(2) mean	(3) std	(4) median	(5) max	(6) count	(7) cor(gameLength)	(8) cor(zeroWaitDays)	(9) cor(sCheckin)	(10) cor(sWaitMean)	(11) cor(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
$s_i^{checkin}$ (₦)	200.0	550.94	290.05	400.0	1000.0	640.0	-0.01	-0.06	1.0	-0.04	-0.01
$\overline{s}_i$ (₦)	69.12	285.75	80.14	285.98	640.0	640.0	-0.28	0.06	-0.04	1.0	-0.11
$\overline{\Delta t}_i$ (min)	4.4	8.72	1.59	8.65	13.85	640.0	0.16	-0.1	-0.01	-0.11	1.0
$\overline{C}_i$	0.0	0.59	0.34	0.69	1.0	640.0	-0.13	-0.03	0.1	0.41	-0.23
$\overline{D}_i$	0.0	0.41	0.28	0.39	1.0	640.0	-0.21	-0.05	0.01	0.43	-0.23
Endline											
Expected $\overline{s}_i$ (₦)	10.0	1411.06	4959.46	1000.0	100000.0	575.0	-0.01	-0.08	-0.06	-0.1	0.05
Expected $\overline{\Delta t}_i$ (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.

TABLE S6. Wait Experiment: Alternate Utility Specifications

	(1)	(2)	(3)
	Main	Income Heterogeneity	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 S7. Wait Experiment Robustness

	(1)	(2)	(3)	(4)
	Main	Omit Nontravel Days†	Exclude First Checkins	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 S1.1. Standard errors clustered at the user level. Estimation fixes $\sigma^{wait} = 1$. * p<0.1; ** p<0.05; *** p<0.01.

TABLE S8. 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.