Improving Mobility in Developing Country Cities: Evaluating Bus Rapid Transit and Other Policies in Jakarta*

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November 2017

Abstract

In many developing countries, urbanization is proceeding at an astonishing pace, but transport policy decisions have often not anticipated the pace of growth, leading to congestion. This paper uses reduced form and structural techniques to evaluate different transport policy options for reducing congestion in the city of Jakarta. We first study the TransJakarta Bus Rapid Transit (BRT) system, a public transport initiative designed to reduce congestion and improve mobility for the greater Jakarta metropolitan area. To evaluate the system, we compare changes in outcomes for neighborhoods close to BRT stations to neighborhoods close to planned but unbuilt stations. Contrary to anecdotal evidence from other city experiences with BRT systems, we find that the BRT system did not greatly increase transit ridership or reduce motor vehicle ownership. Instead, motorcycle vehicle ownership increased substantially, while ridership in the traditional public bus system fell. Moreover, by taking up scarce road space, the BRT system exacerbated congestion on the routes it served, leading to increased travel times for other modes. To better predict the impacts of counterfactual transport policies, we estimate an equilibrium model of commuting choices with endogenous commuting times. Our findings suggest that improvements to the BRT system would only modestly impact public transit ridership. Instead, implementing congestion pricing or reducing gasoline price subsidies would have a much larger impact on mode and departure time choices.

*Acknowledgement: We thank Bryan Graham, Edward Miguel, Paul J. Gertler, Sylvia J. Radford and seminar participants at the DC Urban Economics Day 2017 for for helpful suggestions. This project was partially funded by financial support from RAND's Center for Asia and Pacific Policy. Cole Sutera provided excellent research assistance. All errors remain our own.

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1 Introduction

In many developing countries, urbanization is proceeding at an astonishing pace. In Asia in particular, from 1980 to 2010, more than one billion people were added to urban populations, and population growth in cities is expected to continue (ADB, 2012). The process of urbanization is often associated with a structural transformation of the economy, as a large share of employment that had been previously been working in agriculture moves into more productive, higher wage sectors like manufacturing and services (Herrendorf et al., 2014). Firms in these industries tend to cluster in cities and benefit from external economies of scale (Marshall, 1890).

Although urbanization has been a key feature of economic growth and poverty reduction experienced by many transitioning economies, in many cities, transport policies have not anticipated this economic growth. Consumer income gains that are associated with urbanization often result in increased vehicle ownership, and in the absence of efficient public transit options, this has lead to significant traffic congestion. By increasing commuting and other urban transport costs, traffic congestion can widen the spatial separation of firms, workers, and other productive inputs, and this can exacerbate many market frictions. Chin (2011) argues that heavy traffic has cost cities in Asia between 3 to 6 percent of their GDP per year, due to the combined effects of time lost in traffic, added fuel costs, increased business operating expenses, and productivity losses. Moreover, because high commuting costs may create barriers to employment and education, they may be most harmful for the poor and vulnerable, exacerbating socio-economic disparities. Apart from the economic consequences of traffic congestion, traffic related air pollution is also a major public health concern.[1]

Investments in public transportation are often proposed as a way to facilitate the movement of people within cities in an environmentally friendly, efficient, and affordable manner. However, most public transport systems, such as subways or light rail, require large capital investments. With limited funding, many cities in developing countries have turned to Bus Rapid Transit (BRT) systems.[2] BRT systems, which provide dedicated right-of-way lanes for city buses and use a network of strategically located stations instead of more frequent bus stops, provide transport services that are comparable to subways or light rail but are far less expensive to develop and operate (Wright and Hook, 2007).

In this paper, we begin by providing new evidence from Jakarta, Indonesia on how the development of the TransJakarta BRT system impacted vehicle ownership, commuting patterns, and travel times. Together with the greater Jabodetabek metropolitan region, Jakarta is one of the world's largest urban agglomerations, with a total population of more than 31 million. The city also has some of the worst traffic in the world (Castrol, 2015). After decades of severe under-investment in public transportation, the DKI Jakarta government developed a BRT system, known as TransJakarta, which opened in early 2004. This system was the first BRT in Southeast Asia, and it is now the world's longest system, with 12 primary routes and more than 200 stations.

[1] Motor vehicles contribute greatly to urban air pollution, anthropogenic carbon dioxide, and other greenhouse gases (Institute, 2010). As a result of traffic congestion, air quality in Jakarta is abysmal, with dangerously high concentrations of particulate matter and carbon monoxide (Best et al., 2013).

[2] There are now BRT systems in several Latin American cities (São Paulo and Curitiba, Brazil; Bogotá and Pereira, Columbia; Santiago, Chile; León and Mexico City, Mexico; Quito and Guayaquil, Ecuador). China now has more BRT systems in 20 cities (including Beijing, Hangzhou, and Kunming), with more planned for development, while in India, there are currently BRTs operating in 8 cities (including Ahmedabad, Delhi, and Jaipur), and in Pakistan, BRT systems are located in Lahore, Karachi, and Multan, among others (Deng and Nelson, 2011)

To study the impacts of TransJakarta, we use high quality data from two unique cross-sectional surveys: the 2002 Household Travel Survey, which was fielded before the BRT opened, and the 2010 Commuter Travel Survey, fielded 6 years afterward. Both surveys were designed and implemented by the Japanese International Cooperation Agency (JICA) to assess commuting patters in the Jabodetabek metropolitan region. The surveys were designed as 3 percent samples of the urban population, and over 160,000 households were interviewed in each wave. The data contain responses from nearly all communities (*kelurahan*) in Jabodetabek, with a median of 300 observations per community per wave. The survey timing and representative nature of the data at local levels enable us to accurately assess how the BRT has impacted local outcomes. These surveys are also highly detailed, providing information on the demographic composition of households, incomes, and data on regular commuting behavior. We combine these surveys with community level aggregates of the household census in 2000 and 2010, as well as detailed maps of transport infrastructure changes that took place over the same periods.

The TransJakarta BRT represents an interesting and challenging case for program evaluation. First, because the BRT system is potentially used by all city residents, it is challenging to find an adequate comparison group. Second, there were major city-level trends that impacted commuting outcomes and vehicle ownership between 2000 and 2010. For instance, during the same time that the public transit system was developed, incomes in the city rose dramatically, and private vehicle ownership increased rapidly, especially for motorcycles. Finally, because the BRT system occupies road space on major intra-urban arteries, it takes road lanes away from other vehicles. If fewer people drive as a result of the BRT system, this could create positive spillovers (Anderson, 2014), but if the BRT system creates more congestion along the routes it serves, it could have negative externalities.

We first use semi-parametric regression techniques to assess how changes in a neighborhood's vehicle ownership or commuting mode shares are related to the distance to the closest BRT station. Although these associations control for predetermined site selection variables that influenced the placement of stations, the regression relationships are primarily descriptive. Overall, in 2010, only 4.3 percent of commuters in Jabodetabek chose the BRT to be their main transit mode. While the mode share is positive throughout the city, it is highest in areas closest to the stations, as expected. However, despite the positive mode share, TransJakarta ridership is not very large compared with other BRT systems; for instance, in Bogotá, Colombia, the TransMilenio BRT system had attained a 26 percent mode share after 7 years of operation.

Instead, we find that throughout Jakarta, there was a substantial increase in motorcycle ownership and car ownership, and a similarly large decrease in the percentage of commuters who used the traditional public bus system. This suggests that over the analysis period, the major changes in commuting choices came from people substituting away from public transportation and into private vehicles, trends that are precisely what a well-designed public transport system would hopefully negate or counteract. The lack of strong ridership cannot be explained by changes in the fare costs of riding the BRT, which have remained low and flat in nominal terms over the period. Instead, the results are consistent with excess ridership capacity and under-utilization, trends that are apparent in aggregate ridership statistics data.

Next, we provide estimates of the average treatment effect on the treated (ATT) of being a community within close proximity (1 km) to a BRT station. In estimating the impact of place-based policies like the TransJakarta BRT program, a central concern is that there are omitted variables correlated with station location that both influenced selection into the program and also affect outcomes. We document that communities in close proximity to BRT stations were closer to the city center, more densely populated, and were populated with more highly educated residents at baseline. Because these features may affect the choices of vehicle ownership and transport modes, the endogenous placement of BRT stations could create bias in a naive treated vs. non-treated comparison, leading to inconsistent estimation of program impacts.

To improve identification, for a comparison group, we rely on communities located close a set of planned stations that were selected for an expansion to the BRT system but have yet to be constructed. These BRT expansion plans were part of Jakarta's spatial plans for 2010, but have been mired in delays due to disagreements between the DKI Jakarta government and the governments of surrounding municipalities. Further, we use an inverse probability weighting (IPW) approach that explicitly adjusts for potential *ex ante* differences between close proximity communities and communities in our comparison group. This approach reweighs the contribution of non-treated communities to the counterfactual in accordance with their odds of treatment. These odds are constructed from a propensity score estimation, where station placement depends on observable, pre-determined characteristics, measured in baseline surveys.

Our ATT results of station proximity suggest that neighborhoods treated with BRT stations had no differences in motor vehicle ownership. Although they experienced statistically significant increases in BRT ridership and significant reductions in car use, the point estimates are small and not economically meaningful. These muted effects of the BRT system are robust to controlling for changes in neighborhood composition that could explain some of the low ridership impacts, including changes in population density, education shares, and income shares.

Next, we evaluate the impact of the BRT system on travel times. We find that overall, between 2002 and 2010, travel times fell on average by 11.6 percent, which represents roughly 4 minutes saved on the median commute time of 31.5 minutes in 2002. However, after accounting for a variety of trip characteristics, including trip purposes, mode choices, departure times, distances travelled, and origin-by-destination fixed effects, we find that travel times only fell by 3.2 percent from 2002 to 2010. Although this impact is statistically significant, it represents a very small time savings of roughly a minute for the median commute. This also suggests that between 2002 and 2010, individuals made important changes in their travel patterns, either by switching destinations, departing earlier, or using new modes, possibly to offset expected changes in travel times.

Next, we demonstrate that instead of reducing congestion along peak corridors, the BRT system actually had negative externalities, increasing travel times for other sharing the same routes. To do so, we use trip-level travel time regressions to assess estimate the differential changes in travel times for trips that originated and terminated within 1 km of a BRT station. Overall, instead of reducing congestion, we find that trips along BRT corridors had longer durations, and these effects are found for most modes of transit, including the traditional public bus system, cars, and motorcycles. However, the effects are insignificant, precisely estimated zeros for train times, which makes sense given that the BRT system did not compete with trains for space. We also find that the entire negative spillover effect comes from peak travel times, exactly when a public transport system like the BRT would hopefully be reducing congestion. These effects are also robust to controlling for changes in demand for trips along BRT routes. Like many other BRT systems, the TransJakarta BRT operates on a dedicated lane in major intra-urban arteries, and this bus lane is separated from use by other vehicles. The increase in travel times along BRT corridors for other modes suggests that these lanes increased congestion because they occupied crucial space that could have otherwise be used by other vehicles.

Our paper represents the first complete quantitative evaluation of Jakarta's experience with the TransJakarta BRT system. It benefits from comprehensive data on commuting mode choices, vehicle ownership, and ridership patterns available at a high spatial resolution. Considerable previous research has evaluated BRT systems by focusing on performance metrics that are easily observable, such as the difference in speed between a BRT bus and traditional buses, or the number of riders who use the system on a daily basis (e.g. Levinson et al., 2003; Cain et al., 2007; Hidalgo and Graftieaux, 2008; Deng and Nelson, 2011). Because we focus on multimodal choices made by riders, vehicle ownership outcomes, travel times, and because we estimate the congestion externalities associated with the BRT system, our work is more comprehensive.

Our findings raise an important question: given that the TransJakarta BRT system did not significantly impact commuting outcomes, what can be done to alleviate congestion? Could the BRT system be improved in order to attract more commuters? What about other transport policies, such as proposed congestion pricing or reducing gasoline price subsidies (which were in effect as of 2010)? In order to evaluate the effects of different transport policies, we build a simple equilibrium model of mode choice and departure times, estimate its parameters, and use it to conduct policy simulations.

In the model, individuals make choices over transport modes, and when to take them, for commuting purposes. When making these choices, drivers have preferences over many different choice attributes, some of which may be unobserved. To model preferences, we use a simple aggregate nested logit model, which we transform into a linear estimating equation that relates market shares to choice characteristics (Berry, 1994; Verboven, 1996). Some key attributes of commuting choices, like the speed of travel along a particular route, are determined in equilibrium, and this necessitates the use of instrumental variables. We describe a novel instrumental variables strategy for estimating demand, relying on cost shifters driven from traffic generated by drivers on overlapping routes. This instrument has a strong first stage and generates much larger estimates of the impact of travel times on mode and departure time choice than naive OLS estimates.

On the supply side, traffic routes are congestible, and as more people drive simultaneously along the same routes, travel times increase. Following Couture et al. (2016) and Akbar and Duranton (2017), we specify and estimate Cobb-Douglas cost of travel functions that capture this supply curve relationship, mapping the total number of vehicles along roads to travel times for different transport modes. We also describe an instrumental variables strategy that relies on time-of-day demand shifters to identify supply curve parameters. Echoing Akbar and Duranton (2017), we find that supply elasticities are not large over much of the range of traffic volumes, suggesting that the presence of many alternative routes provides flexibility for traffic patterns to adjust.

After estimating parameters on both the demand and supply sides, we use the model to simulate the impact of counterfactual transport policies. We first map those policies into changes in mode-by-departure time choice characteristics. Then, we use estimated demand parameters to predict how changing those attributes results in changes in demand. Consider, for example, a policy that makes the BRT more attractive. This increases demand for the BRT, meaning that fewer vehicles will be on the roads. Now, based on the supply curve relationship, travel times along those roads should fall slightly, and that could encourage even greater private transport ridership. We iterate between changes in demand and supply until we converge at a new counterfactual equilibrium.

Our findings from policy simulations suggest that modifying the BRT by improving its speed, comfort, or convenience would do little to increase demand for the system. Instead, if policymakers want to reduce congestion and increase the use of public transportation, they will have more success by turning to the pricing mechanism. Increasing the price of gasoline will have substantial effects on mode choices, and congestion pricing should encourage fewer private vehicles at peak times. Fortunately, the DKI Jakarta government is currently actively pursuing congestion pricing strategies, and Indonesia has already abandoned gasoline price subsidies, and the results of these simulations provide more rationale to support those policies.

Our work contributes to several strands of literature on estimating urban travel supply and demand. In surveying the literature on travel demand, Small and Verhoef (2007) focuses on travel mode choices, but we extend that to incorporate choices of departure times in order to evaluate the impact of more flexible transport policies, like congestion pricing. On the supply side, several attempts have been made to estimate the relationship between vehicle speeds and traffic volumes (the speed-density curve), although most work uses traffic simulation models instead of observational data (e.g. Dewees, 1979). An important exception is (Geroliminis and Daganzo, 2008), which uses high frequency vehicle counts data from road censors in Yokohama, Japan. This work is closest in spirit to Akbar and Duranton (2017), which attempts to separately identify supply from demand, but instead of estimating the deadweight loss of congestion, our focus is on evaluating the mode choice and departure time impacts of different transport policies.

The rest of this paper is organized as follows. Section 2 presents background information on commuting in Jakarta and the development of the BRT system. Section 3 describes the different datasets we analyze. Section 4 uses these data to present descriptive statistics about changes in commuting patterns, mode choices, and vehicle ownership for the city of Jakarta. Section 5 presents semiparametric estimates of the relationship between distance to stations and a variety of commuting outcomes, while Section 6 discusses our reduced form results of the impact of station proximity on vehicle ownership, commuting choices, and travel times. Section 7 presents a model of equilibrium commuting choices and describes how we use our data to identify parameters, estimate them, and conduct policy simulations. Section 8 presents results of estimating the model and simulating counterfactual policies. Section 9 concludes.

2 Congestion in Jabodetabek and the BRT System

Jakarta is the economic and political center of Indonesia. Located on the northwest coast of Java, the special capital region of Jakarta (*Daerah Khusus Ibu Kota Jakarta*, or DKI Jakarta) is surrounded by a greater metropolitan area which includes the districts and municipalities of Bogor, Bekasi, Depok, and Tangerang. Together, this metropolitan area is known as *Jabodetabek* and is home to over 31 million people, making it one of the world's largest agglomerations.[3] Navigating the city of Jakarta can be frustrating and unpredictable because of congestion, particularly during peak times. As a result, several independent assessments have determined that Jakarta has some of the world's worst traffic.[4]

Since independence, planners and policymakers in Indonesia have enacted policies that favor motorization and private vehicle ownership. Combined with weak urban planning, this has helped to create chronic congestion in many cities.[5] The government has consistently subsidized fossil fuel consumption, often at great fiscal expense (Savatic, 2016), and it has promoted road construction programs over the development of mass transit. Hook and Replogle (1996) argues that because the rapid road construction programs of the 1980s and 1990s were not accompanied with corresponding increases in vehicle user fees, this amounted to a significant subsidy for road users. Various agencies responsible for managing land use and urban planning have generally been ineffective in dealing with rising vehicle ownership, and this has led to sprawl and exacerbated congestion problems (Susantono, 1998; Goldblum and Wong, 2000).

Jakarta's decision to develop a BRT system came after several failed attempts to address the city's endemic traffic congestion. These attempts included establishing a curbside bus-only lane (which was poorly enforced), a monorail line (which was started but never completed), and a metro rail line, which has been planned and, as of November 2017, is currently under construction (Ernst, 2005). In May 2003, Bogotá's former mayor, Enrique Peñalosa, visited Jakarta and gave a presentation to the Governor at the time, Sutiyoso, about his city's BRT system, TransMilenio. This presentation convinced Sutiyoso to adopt the BRT as a public transport model, and the project was rapidly implemented. TransJakarta began operations in January 2004 as the first BRT system in Southeast Asia.

At the time of the development of TransJakarta, a number of municipalities in Latin America—particularly, Bogotá (Colombia) and Curitiba (Brazil)—had successfully implemented BRT systems, increasing public transit ridership and reducing congestion (Deng and Nelson, 2011). One important factor favoring the development of BRT systems was that they are cheap to develop and can be expanded more easily than alternative systems of mass transit, such as a subway system or light rail. Constructing a BRT system typically costs 4-20 times less than an LRT system and 10-100 times less than a subway system (Wright and Hook, 2007). Because BRT systems have lower fixed costs, they are more likely to be more quickly profitable than other mass-rapid transit modes. Interestingly, TransJakarta was particularly inexpensive to develop, with a total capital cost of less than $1.4 million per km, compared to $8.2 million per km in Bogotá (Hidalgo and Graftieaux, 2008).

In 2004, the TransJakarta BRT system began with an initial, 13.6 km north-south corridor, but it

[3] Jabodetabek is an acronym combining the first 2 to 3 letters from the names of each municipality and district of which it is comprised. Demographia (2014) lists Jabodetabek as the second most populous agglomeration in the world after the greater Tokyo area, while Brinkhoff (2017) lists Jakarta as the fourth most populous agglomeration (after Guangzhou, China, Tokyo, and Shanghai).

[4] From data on vehicle starts, stops, and idling times, Castrol (2015) constructed an index to measure traffic congestion in 78 cities worldwide, and they found that Jakarta had the worst traffic in the world. However, in 2016, the INRIX Global Traffic Scorecard ranked Jakarta 22nd out of 1064 cities in terms of the peak hours spent in congestion, with 22 percent of overall driving time spent in congestion (INRIX, 2016). Note that Jakarta does not appear on other international traffic monitoring surveys, such as the Tom Tom Traffic Congestion Index, and the methodologies between international comparisons differ.

[5] Hook and Replogle (1996) discusses how some policies to encourage private, motorized transport use may stem from crony capitalism under the Suharto regime. They argue that the banning of non-motorized *becak* (cycle-rickshaws) in 1989-1990 throughout Indonesian cities directly benefited two corporations specializing in producing motorized tuk-tuk vehicles. These corporations were managed by members of the President's family.

expanded services throughout DKI Jakarta over time. Currently, TransJakarta has 12 operating corridors and more than 200 stations, with a total system length of nearly 200 km. A map of the system's corridors appears in Figure 1; the locations of lines and stations were digitized using Open Street Map data, and the timing of station openings was obtained from TransJakarta. Although the system is currently one of the largest BRT systems in operation worldwide, it operates on less than 3 percent of DKI Jakarta's total road length, and it mostly serves the DKI Jakarta area. In 2002, Jakarta's spatial plan for 2010 contained a series of lines and stations that were expected to be completed by 2010. These planned lines, which extend beyond the DKI Jakarta boundary, appear in red in Figure 1, but have yet to be developed, largely due to jurisdictional issues between the DKI Jakarta government and the surrounding municipalities.

3 Data

To study how Jakarta's BRT system impacted commuting outcomes for residents, and to examine other policy options for alleviating congestion in the city, we analyze data from a unique source: two rounds of commuter travel surveys conducted by the Japan International Cooperation Agency (JICA). JICA researchers designed and fielded commuter surveys as part of a Study on Integrated Transportation Master Plan (SITRAMP), a technical assistance project that was designed to increase public transport use and promote policies to encourage greater mobility in the city of Jakarta. The first survey round, known as the Household Travel Survey (HTS), was conducted in 2002 and recorded detailed information on the regular travel patterns, vehicle ownership, and demographic characteristics of more than 160,000 households.[6] The survey was designed to be a 3 percent sample of households in the city and contains observations on households in almost all of the 1,622 communities (*kelurahan*) in Jabodetabek, our spatial unit of analysis.

A second round of the survey, the 2010 Commuter Travel Survey (CTS), was a follow-up to the first survey and contained similar information on nearly 179,000 households. Although these two surveys are repeated cross sections of the Jabodetabek population, in some analyses, we use survey weights to aggregate the data by community, obtaining a panel of neighborhoods. Importantly, the 2002 and 2010 commuter surveys were designed to be representative at the community level. In 2002, the median community had over 200 individual-level observations, while in 2010, the median community had over 300 individual-level observations. The spatial coverage and representativeness allow us to calculate neighborhood-level means with relative accuracy, which is unique for survey data in an urban developing country setting.

Another remarkable feature of the dataset is its trip-level information. The surveys collect data on regularly made trips, asked about a typical workday, for all respondents who regularly travel in each household. In 2002, the HTS asked respondents about trips made on a weekday (Tuesday-Thursday) for all purposes, including work-related trips, school trips, and trips for leisure or shopping. Data collected on each trip include origin and destination information by community, trip purpose, modes used for all links on the trip chain, transfers, departure times, arrival times, and costs or fees incurred during

[6] According to background reports, this 2002 survey was a massive undertaking, with 2,418 enumerators each making approximately 70 home visits over a 3 month period (July-September) (PCIAC, 2004). In 2010, the survey team employed 1,800 enumerators, each of whom surveyed approximately 100 households over a 6 month period (March-August). The 2010 field team also consisted of 65 supervisors, 13 field coordinators, and 4 region chiefs to administer the survey work (OCAC, 2011).

travel. The 2010 CTS trip data is similar to the 2002 data, collecting most of the same variables, but unlike the 2002 data, the 2010 data only asks only about outbound and return trips made for school or work purposes. To make the two samples consistent, we only consider trips that either work or school related trips in our analysis.

The entire pooled trip-level dataset contains information on 1,387,079 trips (727,754 from 2002 and 659,325 from 2010) that are either work or school-related trips (including outbound and return trips). However, for a number of trip-level observations, certain variables are missing, and after dropping trips with either missing mode, travel time, or origin and destination information, we are left with a sample of 1,195,444 trips (653,814 from 2002 and 541,630 from 2010).[7] We denote these trips as the set of "well-defined trips", borrowing terminology from Akbar and Duranton (2017).

Demographic and Economic Characteristics Our analysis combines this unique commuter survey data with community-level aggregates of the 2000 and 2010 population censuses. These censuses, designed to be complete enumerations of the entire Indonesian population, were collected by Indonesia's national statistical agency, *Badan Pusat Statistik* (BPS). Census data contain multiple measures of demographic characteristics, including the size of the local population, levels of educational attainment, and migration status. In the year 2000, the median community in Jabodetabek had an area of 3.2 square kilometers and was home to nearly 9,000 residents.

Geospatial Data: Roads, Railroads, and BRT Lines and Stations We also rely on measures derived from detailed maps of the locations of Jakarta's roads, railroads, and BRT lines. Some of these maps were produced digitally by JICA for their field work and policy reports. Others were derived from Open Street Map and produced by the authors using GIS software. Note that data on the locations of planned but not completed stations area also from JICA, which developed an expansion plan for the BRT system for the DKI Jakarta government and TransJakarta during the initial feasibility studies. These plans were eventually incorporated into Jakarta's Master Spatial Plan for 2010 (PCIAC, 2004).

4 Characterizing Jakarta's Urban Form

Using these datasets, we first provide some descriptive statistics characterizing Jakarta's spatial structure, and how it has evolved over time. First, we describe the economic and demographic characteristics of the metropolitan area. We then provide an overview of different modes of transportation, including private and public transport options, focusing on vehicle ownership and mode choice. Finally, we describe in detail the characteristics of commuting trips in our sample.

4.1 Residential and Workplace Locations

From 2000 to 2010, the Jabodetabek metropolitan region experienced rapid growth, adding 7 million more people to its total population. This amounts to an annual population growth rate of 3.6 percent

[7] Note that when distance is not recorded in the data, we use centroid distance (as the crow flies) between kelurahan to measure trip distance. For trips that take place within a kelurahan, we calculated missing distances using GIS software. To do so, we randomly sampled 100 points in each kelurahan and calculated the average distance between those points.

per year. In Figure 2, Panel A, we depict the population growth across communities, with darker areas corresponding to faster growth. This figure shows that population growth in the city has tended to be more pronounced in the peripheral regions of the city, outside of DKI Jakarta borders (depicted in thick black) and symptomatic of urban sprawl. As sprawl grows, this has increased the spatial separation of residential and workplace locations, increasing the demand for travel and potentially exacerbating congestion and commuting costs (Turner, 2012).

Employment in Jakarta is largely service-sector oriented, and most employers tend to locate in DKI Jakarta. In Figure 2, Panel B, we present a map of employer locations, showing the probability that an individual works in a kelurahan, using the 2010 CTS data. This figure shows that the greatest employment probabilities in Jabodetabek are found in the center of the city, although significant employment centers are also located in other areas throughout the metropolitan region.

4.2 Vehicle Ownership and Commuting Mode Choice

Vehicle ownership is related to household income. As incomes rise, households in Jabodetabek often first begin to purchase motorcycles, then cars.[8] Over the 2002-2010 period, the JICA data suggest that Jakarta experienced a dramatic increase in vehicle ownership, especially motorcycles. The grey bars in Figure 3 show that the share of households owning at least one motorcycle more than doubled, increasing from 37.0 percent in 2002 to a staggering 75.8 percent in 2010.[9] Although some of the expansion in motorcycle ownership could be explained by per-capita income gains that accrued to city residents over the period, another explanation may be new loan schemes and expanded consumer credit, which enabled even the lowest income households to own motorcycles (Yagi et al., 2012). In 2010, nearly one third of the lowest-income households surveyed owned a motorcycle.

Car ownership also increased from 2002 to 2010, but not as significantly as motorcycle ownership. The blue bars in Figure 3 show that the share of households owning at least one car increased from 18.9 percent in 2002 to 28.9 percent in 2010. Figure 4 shows how the increases in motor vehicle ownership resulted in significant changes to mode choice over the 2002-2010 period. Throughout the paper, to measure mode choice, we rely on a question in both surveys that asks the respondent to name the mode they most commonly use for intra-city travel purposes. Other measures, such as those constructed from trip data to calculate the mode consuming the most distance or the most time during an individual's trips, yield similar results.

In 2002, the most frequent transport mode for commuting (with a share of 52.3 percent) was the traditional public bus system. Most traditional buses are relatively small, mini-buses that are not air-conditioned. Some, like the *angkot* minivans, seat 8-10 people, while others, operated by *Metromini* or *Kopaja* cooperatives, are larger, seating roughly 20-30 people. These vehicles tend to be older, are sometimes poorly maintained, and may, on net, worsen the city's traffic-related air pollution. Moreover, although they tend to follow set routes in Jakarta, traditional public buses do not keep a fixed schedule,

[8] Senbil et al. (2007) shows that the share of motorcycle and car ownership in *Jabodetabek* increases with income. However, unlike the case of cars, the share of motorcycle ownership actually declines for the top 3 income groups in the JICA data.

[9] Yagi et al. (2012) also document this trend but use a different data source: the number of registered vehicles in DKI Jakarta. From 2000 to 2010, the number of registered cars doubled, while the number of registered motorcycles more than quadrupled. Note also that by 2010, according to the JICA data, over 20 percent of households owned more than one motorcycle.

making it difficult for commuters to plan their arrival and departure times (Radford, 2016).[10] By 2010, the share of public bus riders fell to 23.4 percent.

In 2010, the most frequent mode of transportation in Jakarta was private motorcycles. During the sample period, private motorcycle's mode share more than doubled, rising from 21.5 percent in 2002 to 50.8 percent in 2010. In a congested traffic environment, motorcycles offer commuters a way to weave through traffic that can allow them to reduce travel times. In 2010, the large share of motorcycles substantially dwarfs the small portion of commuters who mainly ride the TransJakarta BRT system (4.3 percent).

4.3 Commuting Characteristics

Table 1 contains summary statistics for all well defined trips. Panel A shows that overall, the average trip in 2002 had a distance of 4 km, with an average travel time of over 30 minutes, and a slow speed of just over 8 km per hour. By 2010, trip distances had increased slightly, to an average of 4.7 km, travel times fell slightly to an average of 29 minutes, and average speeds increased to nearly 12 km per hour. Interestingly, in 2002, 50 percent of trips in the data took place within a single community, but this share increased to 51 percent in 2010.

In Panels B and C, we examine work trips and school trips separately. Overall, people travelled farther for work than for school in both 2002 and 2010, and both work and school-related trip distances increased. School related trips were also considerably more likely to take place within a single community, and to be much slower than work related trips.[11]

5 BRT Proximity, Mode Choice, and Vehicle Ownership

To evaluate the impact of the TransJakarta BRT system on vehicle ownership and commuting choice outcomes, we begin by estimating a partially linear regression function that relates changes in outcomes at the community (kelurahan) level to the community's distance to the closest BRT station in 2009. The model we estimate is the following:

$$\Delta y_c = \alpha + f\left(d_c\right) + \mathbf{x}_c'\beta + \varepsilon_c \ , \tag{1}$$

where c indexes communities (*kelurahan*), $\Delta y_c \equiv y_{c,2010} - y_{c,2002}$ denotes community c's change in y over the span of the surveys, d_c is the distance to the closest BRT station, measured in 2010, and $\mathbf{x}_c$ is a vector of controls, measured before the construction of the BRT, that impact the location decisions of stations but could also affect outcomes.[12] The distance function, $f(\cdot)$ is allowed to be flexible, and we estimate

[10] One reason for the haphazard nature of the public bus system is that drivers are not paid a fixed salary, but are instead compensated on a per-fare basis, and hence must compete for riders. They make stops anywhere they want to pick up and drop off customers, instead of using designated bus stops, which the city has not provided (Radford, 2016).

[11] Interestingly, although trips appear to be faster and farther in 2010, school and work trips began slightly earlier in 2010 than in 2002. The average school or work trip began at 7 AM in 2002, but this figure became 6:47 AM by 2010, earlier by approximately 15 minutes. However, most of the changes in departure time comes from school trips; work trips were only about 5 minutes earlier in 2010.

[12] Our distance measure, d_c, is defined as the minimum distance from community c to the closest station, where the minimum is taken by comparing the distance between all points in kelurahan d_c and all stations.

(1) semi-parametrically, following Robinson (1988). The control variables in $\mathbf{x}_c$ include several measures from the 2000 census, including population density, the percent of the neighborhood's population with different levels of educational attainment, and the share of recent migrants (from another district) in the neighborhood. From the 2002 JICA data, we also include baseline motorcycle ownership and shares of the population with different income levels. Finally, we also control for log distance to *Kota Tua*, the original center of the city.

Although we control for many characteristics that influenced the selection of BRT stations, we view these regressions as primarily descriptive. As a first difference, this comparison does little to control for other neighborhood-level changes in treated areas that took place simultaneously with the program. One possibly important policy change was the hours extension to the 3-in-1 policy that took place in December 2003. In March, 1992, the Jakarta government instituted a 3-in-1 HOV policy on major streets in the city center, including Jl. M.H. Thamrin, Jl. Sudirman, and Jl. Gatot Subroto. During peak hours, cars driven along these routes are required to have at least 3 passengers. Initially, the policy applied only in the morning from 6-10 AM, Monday through Friday, but in December 2003, the Jakarta government changed the regulation to include evening peak hours (4-7 PM) and reduced the morning hours to 7-10 AM (Hanna et al., 2017). We explore the interactions of this policy, which remained largely unchanged until it was abandoned in May 2016, and the TransJakarta BRT system in robustness checks.

5.1 Mode Choice and Vehicle Ownership

Overall, across Jabodetabek, only 4.3 percent of commuters chose the BRT to be their main mode of transit. Figure 5 shows that this BRT mode share is positive everywhere, throughout the distribution of station distance, but it is highest for communities that are closest to the stations. However, in level terms, it only peaks out at just over 6 percent at areas very close to the station, and it dips below 4 percent in intermediate distances.

Despite this positive mode share, ridership on TransJakarta's BRT system is not large compared to other BRT systems. For example, in Bogotá, Columbia, the TransMilenio BRT system opened in 2000, and by 2007, it had attained a mode share for commuters of approximately 26% (Cain et al., 2007). By 2007, total public transit usage in Columbia (including the BRT and non-BRT bus ridership) was approximately 70%. Although Bogotá is a much smaller city than Jakarta (9.8 million vs. 31 million), like Jakarta it is also very dense (210 people per hectare). Moreover, both BRT systems operate with an exclusive right-of-way and were developed to use the medians and center lanes of major roads, making TransMilenio a good benchmark for the TransJakarta BRT system (Deng and Nelson, 2011).

In Figure 6, we use the same partially linear regression model, (1), to estimate how distance to the BRT impacted mode choices for all modes. Panel A replicates Figure 5 but rescales the graph so that it is identical with all other mode choice graphs. From this figure, we see several important trends. First, the increase in motorcycle share (Panel F) is huge and significant across the entire distance distribution. The decline in other public transit share (Panel C) is also just as huge. Although we do not have individual-level panel data, the magnitudes suggest that between 2002 and 2010, the major changes in mode shares involved people substituting away from the traditional public bus system and into motorcycles, instead of using the BRT system. Interestingly, non-motorized transit actually even fell in areas close to BRT stations (Panel H), suggesting that the BRT system did not seem to increase walking or the use of bicycles.

Note that in Panel B, we created an indicator variable for whether commuters chose the BRT as their main or alternative mode, and while the level effects are higher than in Panel A, they are still quite low.[13] Throughout the city, only 8.0 percent of commuters chose the BRT as either their main or alternative mode.

Figure 7 repeats this same analysis but looks for the effects of distance on changes to vehicle ownership. Panel A shows that positive increases in car ownership are significant across the distribution of distance to a BRT station, but they are highest beyond 25 km. This suggests that to a certain extent, the BRT system could be reducing the growth of car ownership. However, Panel B shows substantial increases in motorcycle ownership throughout the distribution of distances to the nearest BRT station. Growth in motorcycle ownership seems slightly slower at areas very close to BRT stations, and after 10 km, increases in distance do not change motorcycle ownership growth noticeably. Overall, these findings suggest that the BRT system may not have meaningfully curbed growth in vehicle ownership.

5.2 Ridership Statistics

Is the low utilization of the BRT system explained by capacity constraints? If only 4.3 percent of commuters in Jabodetabek use the BRT regularly, one explanation is that the system is full and can support no more passengers. To examine this further, Figure 8, Panel A, shows how ridership of TransJakarta evolved over time, during the city's first decade of experience with the BRT system. This figure plots the average total number of weekday riders on the BRT, annually from 2004-2014, using data from Sayeg (2015). After the first corridor opened in 2004, on average, 52,400 riders used TransJakarta each weekday. By 2014, this figure had increased to 368,000, an increase of a factor of 6. In Panel B, we plot the total number of kilometers of busway that comprises the extent of the TransJakarta system. Over the 2004-2014 period, busway length increased by a factor of nearly 13. As a result, the total number of weekday riders per km of busway fell substantially (Figure 8, Panel C). From a peak of over 5 thousand weekday riders per km in 2005, by 2014, the system had less than 2 thousand riders per km in 2014.

Compared to Bogota's Transmilenio BRT system, which had attained a ridership figure of 9.5 thousand weekday riders per km in 2013, TransJakarta's performance has been relatively poor, and Sayeg (2015) argues that there is ample excess capacity in the system. The underwhelming ridership figures are also probably not explained by pricing. TransJakarta charges a flat fare for riding anywhere on the system, and the cost of Rp 3,500 (or USD 0.26 in 2017 dollars) has been stable for the entirety of the system's existence. In real terms, the price of riding the BRT has fallen substantially.[14]

5.3 Neighborhood Composition and BRT Proximity

Another explanation for relatively low BRT ridership is that the system may not have been well targeted, to the extent that public transport is used more intensively by lower-income riders without the means to make use of alternative transport options.[15] To examine this, in Appendix Figure A.1, we estimate

[13] Alternative mode share is coded as a response to a separate question in the survey data.

[14] Note that although the flat fare of IDR 3,500 per trip is quite small, in order to ride the system, individuals now need to purchase an e-money/tap card of IDR 20,000. Some observers have suggested that when TransJakarta moved to the e-money/tap card system, ridership among poorer individuals fell substantially (Witoelar et al., 2017).

[15] Appendix Table A.1 examines correlates of individual BRT choice using a linear probability model. Overall, middle income individuals are more likely to ride the BRT system, and people with no primary schooling are less likely to ride the BRT

(1) on several different demographic measures from the 2000 and 2010 census data. Panel A shows that population density increases throughout the city, but the increases are highest at intermediate levels of distance to the station, suggestive of sprawl. However, Panels B and C show that increases in recent migrant shares are highest in areas closest to the stations. This indicates that areas near the BRT stations experienced a significant influx of migrants. Panels D-J examine changes in educational attainment by BRT distance, generally finding that areas at a moderate distance from stations (10-20 km) experienced more rapid educational improvements than areas very close to BRT stations. Although this is suggestive that compositional changes cannot entirely explain the low BRT ridership effects, the increases in migrant shares are quite strong, and we explore this possibility in robustness checks below.[16]

6 Reduced Form Results: Evaluating the TransJakarta BRT System

So far, we have investigated the relationship between distance to the BRT and outcomes using variation from across the city, but the analysis has mostly been descriptive. We now study the causal effects of a community being treated with close BRT station proximity. To do so, we compare communities treated with a BRT station to communities that were planned to be treated, but were not because of delays in system expansion. This analysis draws on techniques from the econometrics of program evaluation to estimate the average treatment effects on treated (ATT) communities (Imbens and Wooldridge, 2009). We first present neighborhood summary statistics to motivate the comparison between treated and almost treated communities. Next, we present ATT estimates of close station proximity on vehicle ownership and mode choice. Finally, we investigate the impact of the BRT system on travel times, both for the city as a whole and for the corridors directly served by the BRT system.

6.1 Neighborhood Comparisons

To motivate this comparison, Table 2 presents summary statistics across neighborhoods of several different variables, each measured before the TransJakarta BRT system was operational in 2004. The first set of columns reports the means, standard deviations, and sample sizes of variables for the 192 communities that are less than 1 km from the nearest BRT station, our baseline definition of communities that are "treated" with proximity to BRT stations.[17] The second set of columns reports the difference in means between these "treated" communities and the other 1472 communities in Jabodetabek that are located more than 1 km away from a BRT station. Finally, in the third set of columns, we report the difference in means between "treated" communities and the 92 communities that are greater than 1 km from a BRT station but less than 1 km from the planned but unbuilt "placebo" stations.

system. However, these effects are not robust to including neighborhood-level fixed effects.

[16] To better understand heterogeneity in the effects of BRT station distance, Appendix Table A.2 examines the relationship between log station distance and outcome variables, where the neighborhood-level changes in outcome variables are averaged over different subsamples. Columns 2 and 3 show that station distance effects are fairly consistent across gender, while columns 5 and 6 show that the effects are also similar across education groups. However, from columns 8 and 9, it seems that lower income individuals in neighborhoods farther away from a BRT station had greater increases in motorcycle ownership than higher income individuals.

[17] Note that in constructing distance variables, we coded a kelurahan as "close" to a BRT station if at least some point within the communities polygon was less than 1 km from a BRT station. This differs from the typical centroid distance measure.

Panel A reports summary statistics on demographic variables from the 2000 census. Compared to all other communities, communities in close proximity to BRT stations are denser, closer to the center of the city, and tend to have a relatively more educated population. As discussed above, close proximity communities also have a greater portion of migrants arriving in the last five years ("recent migrants") from both different provinces and different districts. These differences are all significant at the 1 percent level.[18] However, when comparing treated communities to the almost-treated communities, the differences, while sometimes still significant, are much smaller in magnitude. Interestingly, the migration patterns between treated and almost-treated communities look different; relative to the treated communities, almost-treated communities have a greater share of recent migrants, possibly reflecting recent sprawl into these areas.

In Panel B, we use individual-level data from the baseline 2002 HTS to examine pre-treatment differences in commuting behavior and demographic outcomes. The first set of rows repeats the comparison of demographic characteristics, but this time use individual-level data from the survey instead of neighborhood-level aggregates from the census. These lines show similar patterns to those presented in Panel A, namely that individuals living in treated communities tended to be slightly older and more educated than individuals living in non-treated communities. One nice feature of the HTS data is that unlike the census data, they collect income measures, albeit one that is coded on a 7 point scale instead of as a continuous variable. We find that individuals living in treated communities tended to be higher income than individuals in all non-treated communities. Relative to almost-treated communities, individuals in treated areas were also more educated (but less so than relative to all-non treated). However, the income differences between treated, non-treated, and almost-treated communities tend to not be significant. If anything, treated communities tend to have more middle-income households than non-treated communities, but less middle-income households than almost-treated communities.

Panel C examines differences between baseline commuting patterns, using data from the 2002 HTS. At baseline, individuals living in treated communities tended to be more likely to own a motorcycle than individuals living in non-treated communities, but less likely to own a motorcycle than people in almost-treated communities. Presumably because of their vehicle ownership, they were also more likely to select motorcycles as their primary mode of transit, and less likely to select taxis or non-motorized transit. However, when compared to almost-treated communities, individuals living in treated communities were less likely to choose motorcycles, more likely to choose transit, and less likely to choose non-motorized transit as their main transport modes.

Overall, the results presented in Table 2 suggest that treated communities were closer to the city center, and individuals living in those areas tended to be more educated and more affluent. This suggests that BRT stations were constructed in positively selected areas. However, many of these positive-selection differences between treated and non-treated communities become smaller when comparing treated communities to almost-treated communities. Moreover, the migration, income, and vehicle ownership differences between treated and almost-treated communities are very different. If anything, individuals living in almost-treated communities tend to be more likely to be recent migrants, more likely to be middle income, and more likely to own motorcycles than individuals living in treated communities.

[18] In comparing communities based on their pre-treatment characteristics, we use a simple regression, relating the outcome variable to a treatment indicator. Significance levels come from the p-values of these treatment indicators, when we cluster standard errors at the sub-district level. See the notes to Table 2 for more detail.

6.2 ATT Estimates

To obtain estimates of the average treatment effect on treated communities of being within close proximity of a BRT station, we estimate parameters of the following regression equation:

$$\Delta y_c = \alpha + \theta T_c + \mathbf{x}_c'\beta + \varepsilon_c \tag{2}$$

where c again indexes communities (*kelurahan*), Δy_c is the before-after change in outcome y_{ct} for community c, $\mathbf{x}_c$ is a vector of predetermined controls, and ε_{ct} is an error term. The term T_c is an indicator for whether or not community c was within 1 km of a BRT station in 2010; this measures the close-proximity treatment effect.[19] A major concern in assigning a causal interpretation to θ is that T_c is not randomly assigned. To the extent that policymakers targeted BRT stations to these relatively better off areas, we would expect a naive comparison of treated and non-treated communities to result in biased in estimates of θ.

We address these potential biases by implementing a double robust estimator that, in addition to controlling for $\mathbf{x}_c$, reweighs the almost-treated communities according to their odds of treatment. These odds of treatment are estimated based on propensity scores that are a function of predetermined community-level variables that may have influenced criteria. In particular, we implement both the Robins et al. (1995) two-step, double robust estimator for θ and the Oaxaca-Blinder reweighting approach of Kline (2011). Both approaches assign greater counterfactual weight to non-treated communities with similar underlying pre-trends in density, migration, education, and income.[20]

In Table 3, we report results from estimating (2) that compare changes in outcomes for close-proximity communities to changes in outcomes for almost treated communities (recall that planned lines and stations are depicted in red in Figure 1). Standard errors, reported in parentheses, are clustered at the subdistrict (*kecamatan*) level. Several important trends emerge. First, after we condition on variables that influence selection into close proximity (columns 2-4), we find that there were no robust, statistically significant vehicle ownership differences between close-proximity communities and almost-treated communities. These null effects are striking in light of the potential for public transport to reduce the need for drivers to own motor vehicles.

We do find positive effects of close proximity on choosing the BRT as the main mode of transport (row 3) and for the main or alternative transport mode (row 4). Column 4 reports the preferred, Oaxaca-Blinder estimate of a 4.2 percentage point increase in the likelihood of choosing BRT as the main transport mode, and a 6.6 percentage point increase in the likelihood of choosing the BRT as a main or alternative mode. However, these differences, while statistically significant, are not economically meaningful, given the widespread changes in mode shares for motorcycles and other public transit. The final set of rows examine the impact of BRT proximity on other mode shares, finding some small tendencies for close

[19] Note that although we have panel data and could estimate (2) using fixed-effects least squares, we estimate the model in first differences. With two periods and a balanced panel, a fixed effects model will deliver mathematically identical estimates to the first differences model (Wooldridge, 2010).

[20] Appendix Table A.3 reports our estimated propensity scores across all neighborhoods (Column 1) and for the treated vs. placebo comparison (Column 2). Despite using only a parsimonious set of variables in $\mathbf{x}_c$, our model explains a large amount of treatment variation, with the propensity scores having pseudo-R^2's of between 0.5 and 0.6. Appendix Figure A.2 plots a histogram of the propensity score across treated and non-treated communities (Panel A) and across treated and almost-treated communities (Panel B). Overall, this figure showcases that the overlap condition is much better satisfied for the treated and almost-treated communities, motivating the focus on this comparison.

proximity communities to rely more on non-motorized transit. Again, however, these effects are quite small. Moreover, because non-motorized transit use actually fell in treated areas, this effect should be interpreted as suggesting that non-motorized transit use would have fallen even farther without a BRT station.[21]

Because we are identifying effects of the BRT system by comparing outcomes for people close to stations to people who are farther away, one concern is that our estimates could be positively biased because of sorting. If people with strong tastes for public transportation move in to treated areas, this could cause us to overestimate the average impacts of the program in the absence of sorting. The fact that we do not find strong effects of the program suggests that this sort of sorting may not be an issue.

However, sorting for other reasons could potentially explain the muted program impacts. In particular, areas where BRT stations were built attracted migrants, some of whom may have been wealthier, more educated, and less likely to demand public transportation. To examine the extent to which this sorting negatively impacts BRT ridership, Table 4 reproduces the Oaxaca-Blinder specification from Table 3 in column 1, but increasingly adds a series of controls meant to capture shifts in demographic composition. In column 2, we control for changes in density and changes in migration shares, and the point estimates on the BRT impact are largely unchanged as a result. In column 3, we add controls for changes in education shares, and in column 4, we add controls for changes in income shares. Overall, the inclusion of these additional controls do not change our main findings that close-proximity BRT communities had little changes in vehicle ownership and positive, though small, changes in BRT mode shares. This is suggestive evidence that associated changes in neighborhood composition cannot explain the lion's share of TransJakarta's muted impacts.[22]

Taken as a whole, the results from Tables 3 and 4 suggest that BRT station proximity caused no changes in vehicle ownership. Despite positive and statistically significant impacts on BRT ridership, the effects are small and are dwarfed by large increases in motorcycle use and reductions in other public transport use that took place throughout the city. This suggests that the TransJakarta BRT system was largely unsuccessful in reducing vehicle ownership and encouraging transit ridership.[23]

6.3 Travel Times

In evaluating the effects of the TransJakarta BRT system, we have focused on vehicle ownership and mode choice as the key outcome variables. While these play an important role in understanding the impact of the BRT system, the time it takes commuters to get from their home to work is also first order. In traditional models of spatial equilibrium within the city, commuting times determine the shape and structure of the city, and they affect land rents (Alonso, 1964; Mills, 1967; Muth, 1969). Redding and Turner (2015) propose a model where commuters pay iceberg transit costs to get to work; while they commute, their time literally melts away, restricting the amount of time they can use to supply labor or

[21]In Appendix Table A.4, we report an analogous set of results for close proximity communities relative to all non-treated communities (columns 1-4), with columns 5-8 repeating the results found in Table 3. We also remove communities that are greater than 1 km but less than 2 km from the non-treated sample in Appendix Table A.5.

[22]The analogous set of results for treated vs. all non-treated kelurahan can be found in Appendix Table A.6.

[23]In Appendix Table A.7, we report similar results for demographic outcomes. We find that population density is tends to fall in areas closer to BRT stations, but not relative to placebo areas, and we also find that there is no robust evidence on migration patterns. It also looks like relative to all non-treated, BRT kelurahan are becoming relatively lower educated and lower income, but these trends seem to disappear when looking at treated vs. placebo kelurahan.

engage in leisure activities.

To the extent that the BRT system provides a dedicated bus lane, it should reduce travel times for riders, especially relative to traditional buses that have to navigate through traffic (Deng and Nelson, 2011). Had the BRT system encouraged greater public transit use, it may have also directly reduced travel times for other modes. However, by occupying roads space in the median and center lanes of major thoroughfares, the TransJakarta BRT system reduces the amount of road space that might be used for other purposes. As a result, the BRT system could actually exacerbate congestion along BRT corridors by increasing travel times for other modes.[24]

To examine how the BRT system impacted travel times, we use the pooled 2002 and 2010 trip data from the JICA surveys. As discussed in Section 3, these trip data include data on work and school related trips, and they include both outbound and return trips. We first estimate descriptive regressions of self-reported travel times to work on a year indicator and trip characteristics. These regressions take the following form:

$$y_{odt} = \alpha_t + \mathbf{x}'_{odt}\beta + \varepsilon_{odt} \tag{3}$$

where y_{iodt} is the log travel time for individual i between origin community o and destination community d in year t, α_t is an indicator for whether or not the year is 2010, $\mathbf{x}_{odt}$ is a vector of individual i's trip characteristics, and ε_{iodt} is an error term.[25]

Table 5 reports the results, with robust standard errors, clustered at the origin and destination level, in parentheses. In column 1, we include a year indicator and control only for the physical distance between community o and d, and we find that on average, travel times fell by 11.6 percent between 2002 and 2010. In 2002, the average trip took 31.5 minutes, and a 12 percent reduction would reduce this trip by nearly 4 minutes.

Column 2 adds a series of controls for the mode of transit, the purpose of the trip, and a flexible set of departure hour indicators, and this reduces the 2010 effect slightly to 10.7 percent. After conditioning on separate origin and destination fixed effects (column 3), the effect falls substantially to an 8 percent reduction in travel times. However, after comparing trips made between the same origin and destination by conditioning on origin-by-destination fixed effects (column 4), the travel time reduction is only 3.2 percent. Although statistically significant, the effect estimated in column 4 is not economically meaningful; at a median trip duration of 25 minutes, a 3.2 percent reduction shortens this trip just under 1 minute. Overall, while travel times did fall between 2002 and 2010, nearly all of these reductions can be explained by differences in trip characteristics, differences in mode choice, and differences in the origin and destination mix. This suggests that the BRT system probably did not have a large impact on equilibrium commuting times in the city, taken as a whole.

6.4 Commuting Time Externalities

Using data from Los Angeles, Anderson (2014) argues that although overall ridership for mass transit may be quite low, because the transit lines tend to be located on important and frequently used corridors,

[24] Ernst (2005, p.23) also makes this point, noting: "[c]ongestion has increased for mixed traffic on the corridor".

[25] Note that because of a handful implausibly large travel time values, we winsorize the upper 0.5 percent of the t_{odt} observations, to a maximum of approximately 3 hours. In the JICA data, the departure and arrival times were not coded in a standard way between different survey questions, and to a large extent, this explains our need for this procedure.

a small reduction in vehicle use along those corridors actually has substantial time-saving spillovers. These positive externalities are one way to rationalize public expenditures in subsidizing public transport, despite its low ridership. While Jakarta's BRT system could certainly have had positive spillovers on traffic flows, unlike a subway system, it directly takes away lanes from existing road space. As a result, it could crowd out space that could be used by other vehicles, so the spillover effects could actually be negative.

To investigate how the presence of the BRT affects travel times for other modes along the same corridors that the BRT occupies, we estimate parameters of the following regression equation:

$$y_{odt} = \alpha_{od} + \gamma_t + \delta_1 \mathrm{BRT}_{ot} + \delta_2 \mathrm{BRT}_{dt} + \beta \left(\mathrm{BRT}_{dt} \times \mathrm{BRT}_{dt}\right) + \mathbf{x}'_{odt}\theta + \varepsilon_{odt} \tag{4}$$

where the BRT variables are indicators for whether origin o is within 1 km of a BRT station in year t, destination d is within 1 km of a BRT station in year t, and the other variables are defined from (3).

In Table 6, we report the coefficient estimate of the interaction term, β. This measures the differential growth in travel times for routes that originate and terminate within 1 km of a BRT station, above and beyond changes in travel times on other routes between 2002 and 2010. We report these estimates for all travel times (row 1) and separately by modes (rows 2-6). Overall, column 1 shows that travel times along BRT origin-and-destination corridors increased by 12 percent between 2002 and 2010. These effects are large and significant for many modes, including the non-BRT public buses (row 3), private cars (row 4), and motorcycles (row 4). Also, as expected, the impact on private cars is largest, at 20 percent, relative to smaller effects on public buses and private motorcycles. Reassuringly, the impact on travel times for trains, while positive, is not statistically significant. This makes sense because train travel is not congestible; train tracks are elevated in central Jakarta and do not compete with the BRT for road space.

One explanation for these findings is that they could come from differential increases in demand for travel along BRT corridors. In column 2 of Table 6, we add controls for the number of trips taken for each origin-destination pair, while in column 3, we additionally add controls for the kelurahan-level population density at the origin and destination. These time-varying controls should capture much of the variation on the demand side, but when we include these controls, they generally have no effect on the spillover coefficient estimates, or only attenuate point estimates slightly.

In column 4, we estimate spillover effects by restricting attention only to non-peak trips.[26] Interestingly, this specification reveals that during off-peak times, the BRT system has no differential impact on travel times for other modes. This suggest that the negative spillovers occur during peak times, precisely when a public transit system should be reducing traffic congestion, instead of exacerbating it.[27]

Finally, in Figure A.3, we vary the distance width to examine the spatial spillover of the BRT system on travel times. As expected, we find that the negative externality impacts of the BRT system are highly localized, with the effects coming in areas very close to BRT stations, but dissipating at larger distance levels. Overall, these results suggest that instead of improving traffic congestion in Jakarta, the BRT system may have actually had adverse consequences for other modes by occupying crucial space that

[26] In this analysis, a peak trip is defined as an outbound trip departing from 7-9 AM or a return trip departing from 4-7 PM. This definition overlaps with changes to Jakarta's 3-1 HOV policy (Hanna et al., 2017).

[27] Another investigation, ongoing, is to examine the extent to which these peak-time effects are actually part of the changes to the Jakarta 3-1 HOV policy.

could have been used for other purposes. While the possibility for BRT systems to exacerbate traffic along routes has been discussed in anecdotes and by journalists, this is, to our knowledge, the first rigorous demonstration of this negative spillover.[28]

6.5 Discussion

In the analysis presented in this section, we found muted impacts of the TransJakarta BRT system on commuting outcomes, including vehicle ownership and mode choice. We also found that the system did not have large impacts on overall travel times, and that it actually increased travel times along BRT corridors, exacerbating congestion during peak times.

There are many possible reasons for the apparent lack of success of the TransJakarta BRT. One challenge is that in order for mass transit to be successful, cities need to have pedestrian infrastructure that complements transport initiatives. TransJakarta station infrastructure is poorly designed for commuters, sidewalks around the stations are deteriorating, and in the areas around many stations, there is little transit-oriented commercial or residential development. These factors limit the potential complementarities between walking and the BRT system (Cervero, 2013; Cervero and Dai, 2014; Hass-Klau, 1997; Witoelar et al., 2017). Perhaps as a consequence of absent pedestrian amenities, a recent study using walking steps data from smart phones found that Indonesia was last among 46 countries and territories for the number of walking steps its citizens take (Althoff et al., 2017).

Another challenge could be although the stations serve the city center and help individuals reach jobs, they may not be well targeted to residential areas. In a field study of the urban poor in Jakarta, Wentzel (2010) found that one reason for infrequent ridership use was that the locations of BRT corridors were not distributed spatially in a way that made it easy for lower income groups to use the system. Most BRT stations are located in high income neighborhoods, even though most riders of public transportation are typically lower income.

Given the lack of encouraging effects of Jakarta's BRT system, what can be done to reduce congestion, shorten travel times, and improve commuting outcomes for Jakarta's residents? Could attributes of the BRT system, such as its comfort, safety, or speed, be improved to incentivize greater ridership? What would happen if the city's proposals for congestion pricing were implemented? In order to answer these questions, which involve counterfactual choices for what would have happened to equilibrium commuting outcomes if certain features of the transport environment were altered, we need a structural model that explains how individuals make decisions about what modes of transit to take, and when to take them. 'The next section describes a model of the supply and demand for travel, explains how to use the commuting data to estimate parameters of this model, and describes how to use that model, once estimated, to simulate the impact of different policies.'

7 An Equilibrium Model of Jakarta's Morning Commute

In this section, we describe an equilibrium model of travel times and mode choice that can be used to evaluate the impact of different urban transport policies. In the model, individuals make choices about

[28]For an account of how the BRT system worsened traffic along BRT corridors in Delhi, see Misra (2016).

transport modes, and when to take them, for commuting purposes. Our analysis focuses on all to work or to school trips taking place in the morning. When making these choices, drivers have preferences over many different attributes of modes or departure times, and some of these choice characteristics may be unobserved. Individuals choose transport modes and departure times to maximize utility, and to model preferences, we use a simple aggregate nested logit model, which can be transformed into a linear estimating equation that relates market shares to choice characteristics (Berry, 1994; Verboven, 1996). Because key attributes of commuting choices, such as the time it takes to travel along a particular route, are determined in equilibrium, we present a novel instrumental variables strategy that we use to estimate preference parameters.

On the supply side, because traffic routes are congestible, as more people drive on the same routes at the same times of day, travel times along these routes increase. Following Couture et al. (2016) and Akbar and Duranton (2017), we estimate Cobb-Douglas cost of travel functions that capture this supply curve relationship, mapping the total number of vehicles along roads to travel times for different transport modes. We also describe an instrumental variables strategy that relies on demand shifters to identify supply curve parameters.

After estimating parameters on both the demand and supply sides, we use the model to simulate the impact of counterfactual transport policies. We first map those policies into changes in mode-by-departure time choice characteristics. Then, we use estimated demand parameters to predict how changing those attributes results in changes in demand. These demand shifts imply that different types of vehicles will now be on different travel routes at different times of day, and we use the supply curve relationships to estimate how the implied changes in traffic patterns impact travel times. These changed travel times will, in turn, generate demand responses, and we iterate between changes in demand and supply until we converge at a new counterfactual equilibrium.

This section first provides an overview of the setup of the model, and explains how we use our data to calculate the number of vehicles along different routes, which will be important for measurement and for estimating supply and demand relationships. Next, we discuss our strategy for modelling demand and supply, and how to identify key parameters. Finally, we provide an overview for how we use the model to conduct policy simulations.

7.1 Setup: Locations, Routes, and Vehicles

Greater Jakarta (Jabodetabek) consists of a finite set of neighborhood communities (kelurahan), indexed by $o = 1, ..., L$. Each location o houses an exogenous population of workers and students, each of whom commutes to a particular destination location for work or schooling. For simplicity, we also assume that N_{od}, the number of commuters from origin community o who commute each day to destination community d, is exogenous.

Let τ_{od} denote a route (path) from community o to community d, and let $\mathcal{K}(\tau_{od}) = \{o, k_1, k_2, ..., d\}$ denote the set of communities traversed by an individual using path τ_{od}. Our data does not provide any individual-specific route information. Although we know which location a trip originates from, and where it terminates, we do not know the exact roads an individual regularly uses when moving from o to d. To make progress, we assume that individuals choose distance-minimizing routes.

Assumption 7.1. (Distance Minimizing Routes) *For any route τ_{od} from community o to community d, individuals choose a path through a sequence of communities that minimizes the distance between them.*

Although this assumption is restrictive, for many routes, the distance minimizing path will coincide with the actual path taken. Within communities, individuals can take a variety of different roads, but as long as those roads lie along the minimum-distance sequence of communities, our assumption is satisfied. A clear violation of this sort of behavior is toll roads, which are often faster routes but do not necessarily lie along minimum distance paths.[29]

Our data also do not contain any measures on traffic counts, recording the number of vehicles of different types that are present on particular roads at particular times of day. To measure traffic, we combine the regular travel trip information with the route information to count the number of vehicles that come from routes that traverse community k (i.e. τ' such that $k \in \mathcal{K}(\tau')$), and reweigh those vehicle counts to account for the fact that they also spend time on other roads. Doing so requires a further assumption:

Assumption 7.2. (Time Spent in Community k is Proportional to A_k) *Let A_k denote a measure of the physical size of community k. For any route τ_{od} from community o to community d, the amount of time an individual spends in community $k \in \mathcal{K}(\tau_{od})$ is proportional to $A_k / \sum_{l \in \mathcal{K}(\tau_{od})} A_l$.*

In words, this states that while traversing route τ_{od}, the time an individual spends in a particular community $k \in \mathcal{K}(\tau_{od})$ along that route is proportional to the size of that community, weighted by the total size of all other communities that are traversed. In this analysis, our size measure, A_k, is the average distance in that community k. To calculate this average distance measure, we used GIS software to first randomly sample 100 points within that community. Then, we calculate the average distance between those points.

Unlike Assumption 7.1, Assumption 7.2 is actually quite restrictive. It assumes away any bottlenecks or choke points in the network. With better data (e.g. Google Maps directions data), we could incorporate these choke points by measuring how much time an individual is expected to spend in a particular community while on route τ_{od}. Despite this limitation, we proceed by explaining how we use vehicle count information and route data to estimate demand and supply parameters.

7.2 An Aggregate Nested-Logit Model of Demand

When commuting in Jakarta, individuals first choose between one of three different types of transit modes. These mode-types are indexed by h and include: (1) public modes ($h = u$), (2) private modes ($h = p$), and (3) non-motorized transit ($h = 0$). We index modes by m, and within public transport modes, there are three options: (1) the TransJakarta BRT system; (2) the commuter rail train; and (3) other public transit (i.e. the traditional public bus system). There are also three private transport mode options: (1) private taxi (which is mostly a motorcycle-taxi, known as *ojek*); (2) private car; and (3) private

[29] Note that if we had access to historical Google Maps directions data, we could instead use the path information from routes suggested by Google, instead of choosing the distance minimizing route. A prospective validation exercise using Google Maps's distances data could be worth pursuing for future research.

motorcycle.[30] After choosing a transport mode, individuals choose a departure time-window, denoted by $t \in \{t_b, t_p, t_a\}$, where t_b denotes *before peak time* (departing from 1-6 AM), t_p denotes *peak time* (departing from 7-9 AM), and t_a denotes *after peak time* (departing from 10 AM or later). This choice set has a nested structure, depicted in Figure 9. Let $j = (h, m, t)$ denote a typical element of this choice set.

Assume that the indirect utility of consumer i commuting from location o to location d who chooses j is given by the following:

$$V_{iodj} = \underbrace{\alpha_j + \mathbf{x}'_{odj}\beta + \theta C_{odj} + \xi_{odj}}_{\delta_{odj}} + v_{iodj} \equiv \delta_{odj} + v_{iodj} \tag{5}$$

for all choices j and origin/destination markets, od. Here, α_j denotes a product-specific intercept, $\mathbf{x}_{odj}$ is a vector of characteristics specific to choice j in origin-destination market od, C_{odj} is the cost of travel (in minutes per kilometer, or the inverse of speed) for using choice j to get from o to d, ξ_{odj} is an unobserved choice component, and v_{iodj} is an individual-specific error term.

Indirect utility thus consists of a mean-utility portion, δ_{odj}, which is equal for all consumers, and individual-specific deviations from mean utility, given by v_{ij}. Dropping the market-specific subscripts od, we further assume that this individual-specific deviation takes on the following form:

$$v_{ij} = \varepsilon_{ih} + (1 - \sigma_1)\varepsilon_{ihm} + (1 - \sigma_2)\varepsilon_{imt}$$

Here, the error term, ε_{ih}, varies across consumers and types of modes, ε_{ihm} varies across consumers and modes for each type, and ε_{imt} varies across consumers and departure windows for each mode. Following Cardell (1997), we assume that ε_{ih}, ε_{ihm}, and ε_{imt} have the unique distribution such that ε_{ih}, $(1-\sigma 1)\varepsilon_{ihm} + (1-\sigma_2)\varepsilon_{imt}$, and ε_{imt} are all extreme value. The parameters σ_1 and σ_2 measure preference correlation within nests. As σ_1 tends to 1, the within type-correlation of utility levels across modes tends to 1, while as σ_2 tends to 1, the within-mode correlation of utility levels across departure-time windows tends to 1.

As shown by Berry (1994) and Verboven (1996), normalizing the indirect utility of choosing non-motorized transit (during any departure window) to 0 (i.e. $\delta_j = 0$ if $h = 0$ for all t) gives rise to the following linear estimation equations for mode-departure time choices:

$$\ln\left(s_j/s_0\right) = \alpha_j + \mathbf{x}'_j\beta + \theta C_j + \sigma_1 \ln\left(s_{m|h}\right) + \sigma_2 \ln\left(s_{t|hm}\right) + \xi_j \tag{6}$$

where s_j is the market share for choice j, s_0 is the market share for the outside option, $s_{m|h}$ is the market share of mode m conditional on type h, and $s_{t|hm}$ is the market share of departure time t conditional on choosing mode m from type h.[31]

In an ideal experiment for studying transport demand, we would randomly assign choice characteristics, varying travel times, access to public transport infrastructure, and other factors, and we would

[30] Note that as a mode, our taxi option consists mostly of motorcycles. In 2010, of the individuals who chose taxi as their primary mode, 91.3 percent were using *ojek*, 6.4 percent were using *bajaj* (auto-rickshaw), and only 2.3 percent were using car-based taxis. We use these rates of different types of vehicles in counting the supply of vehicles along routes.

[31] More precisely, if $q_j = q(h, m, t)$ is the number of individuals in market od who make choice j, consisting of mode-type h, mode m, and departure window t, $s_j = q_j/N_{od}$, $s_{t|hm} = q(h, m, t)/\sum_{t'} q(h, m, t')$, and $s_{m|h} = \sum_{t'} q(h, m, t')/\sum_{m' \in h}\sum_{t'} q(h, m', t')$.

measure how individuals respond.[32] However, because we work with observational data, and because certain choice characteristics, such as travel times, are determined in equilibrium, this creates identification problems, motivating the use of instrumental variables. A good instrument for demand parameters would isolate changes in travel times that come from supply shifts. Possible supply shifters used in other work include weather shocks, such as rainfall shocks that lead to flooding or road closures, as these would unexpectedly reduce the supply of usable roads (Akbar and Duranton, 2017). Because we work with data on an individual's regular travel patterns, these high frequency weather shocks are unavailable as candidate instruments. Instead, to instrument for travel times, we use time-specific cost shifters driven by variation in the demand for other, overlapping routes.

To illustrate, Figure 10, Panel A depicts a trip from a hypothetical community B to community A during departure-time window t, indicated by the grey arrow. Our instrument for the time costs associated with this trip is the number of different types of vehicles that move along route D to C at the same time t, indicated by the blue arrow. In order for this to be a valid instrument, vehicles on overlapping routes leaving during the same departure time window need to predict travel times from B to A. The exclusion restriction is that the number of vehicles on overlapping routes are not correlated with the unobserved factors influencing mode choice for individuals taking route B to A.

One concern with this instrument is that for routes that share many of the same roads, the unobserved factors that influence mode choice along those routes will be similar. This could lead to a violation of the exclusion restriction. Figure 10, Panel B, illustrates this case, where route F to E (the red dashed arrow) uses almost entirely the same route as the route from B to A. In calculating the overlapping route instruments, we mitigate these concerns by ignoring all routes that originate or terminate in communities adjacent to the origin and destination community we are instrumenting.

7.3 Supply: Cobb-Douglas Cost-of-Travel Functions

On the supply side, roads are congestible by multiple transport modes, and those modes may respond differently to variations in the total volume of traffic. For instance, because motorcycles are more maneuverable, the elasticity of travel costs for motorcycles with respect to increases in traffic volumes may be smaller than the elasticity of travel costs for cars. As above, let C_{odmt} denote the cost of travel, in minutes per km, for using mode m at time t along route od. Following Akbar and Duranton (2017), we assume that for motorcycles, $m = M$, and cars or buses, $m = B$, travel costs are given by:

$$C_{odmt} = N_{odt}^{\theta_m} \exp\left\{\mathbf{w}'_{odt}\beta_m + u_{odtm}\right\} \qquad \text{for } \ m \in \{M, B\} \tag{7}$$

Here, N_{odt} denotes the total number of vehicles on route od at time t, $\mathbf{w}_{odt}$ denotes a vector of characteristics of route od, and u_{odtm} is an error term. The parameter θ_m is a supply elasticity, while β_m maps various route-specific features into travel times. Taking logs yields the following linear equations:

$$\log C_{odtm} = \theta_m \log N_{odt} + \mathbf{w}'_{odt}\beta_m + u_{odtm} \tag{8}$$

[32] Stated choice experiments, which approximate this ideal, have been used for decades in transport research; see Louviere et al. (2000) for an overview.

To identify supply parameters from observations of equilibrium travel costs and travel quantities, we need an exogenous demand shifter: something that influences the number of people taking motorcycles, cars, buses, and BRTs but does not shifting around the supply curve. A natural candidate for demand shifters would be to use within-route information on people traveling at different times of day. Holding the supply curve fixed, shifts in demand due to driving for different purposes across the same day will enable us to trace out the supply curve.

We use a flexible series of departure time indicators to instrument for $\log N_{odt}$ in estimating the supply curve relationship. The exclusion restriction is that departure times are not correlated with unobservable demand factors that also influence the number of vehicles on the road. One concern with this instrument would be that certain roads at certain times of day are closed or more difficult to travel, either because of policy changes (e.g. HOV lanes that are only operating at certain times of day). We explore these concerns in robustness work below.

7.4 Policy Simulations

After obtaining consistent estimates of the supply and demand parameters, we use the model to conduct counterfactual policy simulations, trying to understand how commuting equilibria would be different if different transport policies had been enacted. In this section, we describe three sets of urban transport policies that we use our model to evaluate: (1) improving BRT comfort and convenience; (2) improving BRT speeds; and (3) congestion pricing.

Improving BRT Comfort and Convenience One often cited deterrent to riding public transport is that public transport options are not comfortable or convenient for riders. In January 2014, a UN-sponsored survey of TransJakarta BRT riders found that nearly 30% of riders considered the BRT buses to either be "uncomfortable" or "very uncomfortable" (Sayeg and Lubis, 2014). Convenience is also an important concern; in a recent survey of females in DKI Jakarta, Witoelar et al. (2017) found that many individuals who do not ride the BRT feel that it does not offer convenient, door-to-door service. Because stations are scattered throughout the city, riders are required to walk some distance to stations, or they would have to use other modes to arrive at bus shelters. To model improvements to BRT comfort and convenience, we simply increase the value of the stated comfort and convenience scores for this mode by 5, 10, and 20 percent, and simulate new counterfactual equilibria.

Improving BRT Speeds Apart from improving the comfort and convenience of the BRT system, we also study what would happen if BRT buses were faster. The 2014 UN-sponsored survey of TransJakarta BRT riders also found that 48% considered waiting times to be "very long" or "long", indicating problems with BRT service regularity and reliability (Sayeg and Lubis, 2014). One issue that has plagued TransJakarta is that it has difficulty scheduling BRT buses and managing their departure and arrival to stations. This results in buses that bunch up at stations, and scheduling improvements could reduce these waiting times (Radford, 2016). Although some portion of BRT speeds may be determined in equilibrium (i.e. when motorcycles or cars drive illegally in BRT bus lanes and slow them down), we model an initial 5, 10, or 20 percent increase in BRT speeds and study what happens to commuting outcomes in equilibrium as travelers respond.

Congestion Pricing Another policy that economists, urban planners, and transportation researchers have extolled for decades is congestion pricing (Vickrey, 1963). By charging road user fees for vehicles operating on high-demand corridors during peak times, congestion pricing attempts to ensure that drivers internalize the negative externalities that they impose on other drivers. In Jakarta, policymakers have discussed using electronic road pricing (ERP) to facilitate these charges, but despite limited trials, a program has yet to be fully implemented (Sugiarto et al., 2015). Former Jakarta governor Basuki "Ahok" Purnama made several efforts to advance ERP in Jakarta, but he failed to win reelection, and it is not clear if his successor, Anies Baswedan, will continue to move ahead with congestion pricing. To evaluate the counterfactual impacts of congestion pricing, we increase the monthly transport costs drivers face when they drive during peak periods. We assume that during peak times, all trips using private vehicle modes (taxi, car, or motorcycle) that either originate or terminate in DKI Jakarta will be charged a flat fee. We vary this fee by Rp 5,000 (or USD 0.37), Rp 10,000 (or USD 0.74), and Rp 20,000 (USD 1.48).[33]

Reducing Gasoline Price Subsidies Finally, we examine how commuting outcomes would change if the government reduced gasoline price subsidies. For many decades, Indonesia subsidized oil consumption, and in 2015, the country was ranked by the International Energy Agency as the world's seventh-largest subsidizer of oil use (IEA, 2015; Burke et al., 2017). In 2010, the subsidized pump price for gasoline was 0.79 cents per liter, over 35 percent below the world pump price of $1.22 per liter (GIZ, 2012). To simulate the impact of reducing gasoline subsidies, we increase the per-kilometer cost of driving private cars, private motorcycles, and taxis by 5, 10, and 20 percent. Unlike congestion charges, these fuel price increases are incurred to all residents throughout the entire city. Note that in late December 2014, Indonesia's President Joko Widodo ended the country's gasoline and other fuel subsidies, so this experiment can be thought of as a way of determining what would have happened to commuting patterns if these subsidies had been removed earlier.

Limitations Because our model is used to simulate the impact of different urban transport policies, the assumption that N_{od} is fixed and exogenous is restrictive, to the extent that transport improvements may increase labor supply at the extensive margin, allow workers to find better matches to firms located farther away, or change their residential locations.[34] However, since we expect these labor and housing market outcomes to adjust slowly, the model results should provide guidance for what would happen to commuting outcomes in the short run if different transport initiatives were enacted. Moreover, we also ignore the impact of any policies on vehicle ownership. With better public transportation systems or stronger congestion pricing, some individuals may face different incentives to own motorcycles or cars.[35] Despite these simplifications, our model still provides useful policy lessons for the short run impacts of urban transport policies.

[33]We used the October 2017 nominal exchange rates to convert IDR to USD.

[34]From a recent survey of females in Jakarta, Witoelar et al. (2017) finds that changes to the commuting environment may not have first-order impacts on labor supply, at least not on the extensive-margin. However, most females in the survey choose jobs based on their location, and consequently, these jobs may not suit their interests or be good matches for their skills.

[35]Models that simultaneously address endogenous mode choice and vehicle ownership decisions are not common in the urban economics or transport research literatures (Small and Verhoef, 2007). An exception is Train (1980), who uses a structured logit model to study these decisions jointly.

8 Model Results and Policy Simulations

In Table 7, we present estimates of the demand for different transport choices, relying on the linear regression specification of the aggregate nested logit model, shown in (6). The dependent variable in these regressions is the log of the share of individuals in origin-by-destination market od making choice j minus the log of the share of individuals in market od choosing non-motorized transit.[36] In column 1, the independent variables are choice characteristics, which include choice-specific constants (separate for each mode-by-departure time choice), origin-by-destination sub-district effects, the log of time costs (in minutes per kilometer), the log of monthly transport costs, the share of the neighborhood owning cars (times an indicator for whether or not the choice involves car modes), and the share of the neighborhood owning motorcycles (times an indicator for whether or not the choice involves private motorcycles). Coefficients on correlations in the error structure, σ_1 and σ_2, are captured by the inclusion of $\ln\left(s_{m|h}\right)$ and $\ln\left(s_{t|hm}\right)$ as regressors. In column 2, we add a measure of distance to stations (interacted with whether or not the choice is BRT or train), and in column 3 we include measures of mode comfort, safety, and convenience, asked in the survey for individuals who take these particular modes of transit.

In columns 1-3, all coefficients are statistically significant, but the impact of time costs on demand is not very large. For instance, the coefficients imply that individuals would sacrifice a 0.76 percent increase in time costs (or reductions in speeds) for a 1 percent increase in mode comfort, or they would sacrifice a 2.2 percent increase in monthly travel costs for a 1 percent increase in mode comfort. These relatively high willingness-to-pay estimates are reflective of low slope coefficients on log time costs and monthly travel costs. In turn, these small slope coefficients are potentially explained by endogeneity concerns, the fact that time costs are determined in equilibrium.

In columns 4-6, we instrument time costs using the overlapping routes IV, implemented as the log of total vehicles coming from overlapping routes. Tests of the null hypothesis of weak instruments, such as the Kleibergen-Paap F-stat or the Cragg-Donald Wald F-stat, can be strongly rejected at conventional significance levels. Moreover, the slope coefficients on both time costs and monthly transport costs are now larger and remain significant. They now imply much lower willingness to pay for increases in mode comfort; for example, individuals would now only be willing to sacrifice a 0.085 percent increase in travel times for a 1 percent increase in mode comfort.

Estimates of σ_1 and σ_2 are large, and in all specifications, $0 \leq \sigma_1 \leq \sigma_2 \leq 1$, consistent with random utility maximization (McFadden, 1978). Since both σ_1 and σ_2 are also estimated to be greater than 0, there is positive preference correlation both across departure times for a given mode, and within modes of the same type, rejecting a standard logit model.

Table 8 reports estimates of the supply curve, using the pooled trip-level data in estimation equation (8). Columns 1-3 show fixed-effects least squares estimates of the log-log relationship between time costs (in minutes per km) and total vehicle counts. Robust standard errors, two-way clustered at the origin and destination neighborhood level, are reported in parentheses. To ease interpretation given the non-linear relationship, we also report estimates of the implied average and maximum elasticities

[36] In many markets, not all choices are observed to be chosen, so this dependent variable is missing. When there are no individuals who choose non-motorized transit, we add a small, positive constant to this number to form the dependent variable, so that we do not unnecessarily lose observations. We include a constant in this regression to capture whether or not we have adjusted the outside mode share.

in the table. Interestingly, we find very small supply elasticities from these least squares specifications. The small reported elasticities (on the order of 0.01 in column 2) are similar orders of magnitude to those found in Bogota by Akbar and Duranton (2017), who argue that when cities have many small routes, they may have the ability to absorb traffic, given that cars and motorcycles can use these other routes if one road is badly congested. Note that an important difference between these results and those presented in Akbar and Duranton (2017) is that we estimate total vehicles traveled along specific routes, not the total number of travelers for the entire city.

However, when we instrument log total vehicles with a series of departure hour indicators, the elasticities grow larger, particularly in the cubic specification. Columns 3-6 report coefficient estimates using GMM, and all coefficients of the cubic polynomial in column 6 are strongly significant. Moreover, we can strongly reject weak instruments tests given the large Kleibergen-Paap and Craig-Donald test statistics. Although the average supply elasticity is slightly negative in column 6, the maximum elasticity is over 1.

Columns 7 and 8 report separate estimates of the supply relationship for cars and buses (column 7) and for motorcycle trips (column 8).[37] The results suggest that the estimated elasticities of travel costs with respect to increases in total motor vehicles are slightly smaller for motorcycles than for cars. This would be expected, as motorcycles are more agile and have a greater ability to weave in and out of traffic, so their speeds may be less responsive to increases in total vehicles. Figure 11 illustrates this, plotting separate estimates of the marginal effect of log total vehicles on log travel costs for cars and buses (Panel A) and motorcycles (Panel B), using the results from Table 8. Two features are worth noting. First, both curves are increasing, then level off, presumably as drivers find other alternative routes when faced with increases in traffic. Second, the motorcycle supply curve is clearly flatter than the supply curve for cars and buses when total vehicles increases substantially.

8.1 Counterfactuals

Table 9 shows the results of counterfactual simulations, in which we examine improvements to the BRT system, congestion pricing, and reducing gasoline price subsidies, and study their effects on predictions of mode choice and departure times. In Column 1, we report the baseline mode share and departure time window shares. In the next three columns, we report changes in these choice shares for if we were to increase BRT speeds by 5 percent (Column 2), 10 percent (Column 3), and 20 percent (Column 4). Columns 5-7 report changes in mode and departure-time shares for simulations that increase BRT comfort and convenience by 5, 10, and 20 percent. The next three columns report changes in choice shares for simulations where we introduce fixed congestion charges of Rp 5,000 (Column 8), Rp 10,000 (Column 9), and Rp 20,000 (Column 10) for all private mode trips made within DKI Jakarta during peak times. The last set of columns examines counterfactual simulations for reducing gasoline subsidies, increasing the per-km cost of travel by 5 percent (Column 11), 10 percent (Column 12), and 20 percent (Column 13) for all private transport modes.

In Panel A of Table 9, we begin by showing results for the initial change in mode shares, where we simply alter the choice attributes and study the resulting impact on demand. These results do not

[37]Note that because over 90 percent of taxi-trips use motorcycle taxis, we include taxi trips in column 8.

take into account the fact that these demand responses will alter the equilibrium travel times that all commuters face because of the travel supply curves. For example, suppose we improve attributes of the BRT system, and this encourages a large shift in ridership. Because fewer people are driving cars or motorcycles, traffic improves, and travel times for those modes fall. This may encourage some people on the margins of choosing the BRT to instead choose to drive. The full change in choice shares after the supply adjustments are accounted for is presented in Table 9, Panel B.

Several findings from this table are worth noting. First, from columns 1-6, improvements in BRT speed, comfort, or convenience generate positive increases in BRT mode shares, but the impacts are quite small. Even in Panel A, before we account for adjustment from the supply curve, the highest increase in BRT mode share comes from the 20 percent increase in BRT speed simulation, and this mode share increase is only 0.39 percentage points. After taking into account the supply adjustments in Panel B, this falls to 0.32 percentage points. Both the sign and the magnitude of this effect are expected, given the relatively small supply elasticities as estimated in Table 8.

In Columns 8-10, we examine the impact of congestion pricing on mode and departure time choices. Overall, we find that congestion pricing has a modest impact on mode shares, encouraging some slight reductions in private car and private motorcycle use, and increases in use of the traditional public bus system, trains, and the BRT system. However, turning to time window choices, we see significantly larger effects, with between a 2 and a 2.4 percent decrease in the share of travelers commuting during peak times, and an increase in commuters leaving before peak time and afterward.

In Columns 11-13, we find that reducing gasoline subsidies would have substantial effects on public transport ridership, reducing motorcycle shares by 5.5 to 6.5 percentage points, and generating correspondingly large increases in other public transit use. As expected, because these policy simulations increase the price of driving during all times, the impacts on time window choices are quite small, although there is some indication that this would encourage greater before peak time departures.

Overall, these policy simulations suggest that improvements to different aspects of the BRT system may not greatly encourage greater transit ridership. We predict that increasing the comfort or convenience of the TransJakarta BRT comfort, or increasing its speeds, would not have very large effects on BRT ridership. Instead, if policymakers want to reduce congestion and increase public transport use, they will have more success by using the pricing mechanism. Fortunately, the Indonesian government has already pursued ending oil subsidies, but these results suggest that congestion pricing could have important impacts on reducing congestion.

9 Conclusion

This paper presents estimates of the impact of the TransJakarta BRT system on commuting outcomes, demographic outcomes, and travel times in the greater Jakarta metropolitan region. Using new, high quality datasets, we find that the BRT system had very modest impacts on transit ridership and had little to no impacts on vehicle ownerships. Only 4.3 percent of commuters chose the BRT as their main mode of transportation in 2010, and neighborhoods within 1 km of a BRT station had only modest reductions in car and taxi use, compared with neighborhoods that were planned to be treated with BRT station proximity. On the whole, the biggest changes in the transportation environment in Jakarta seem to have been the rapid increase in motorcycle ownership, with dominant increases in mode shares across all neighborhoods, even those closest to the BRT.

For rapidly growing megacities, our results suggest that the early experience of TransJakarta should be a cautionary tale. In order to evaluate what would happen if different aspects of the BRT system were modified, or if different pricing policies, such as congestion pricing or greater fuel prices, were implemented, we estimate an equilibrium model of travel demand and supply. Policy simulations suggest that improvements to BRT speed or comfort would have little impact on overall transit ridership. Instead, we expect both congestion pricing and raising the price of fuel would do more to increase demand for public transportation, and it may shift travel patterns in a way that reduces traffic during peak times.

Further research could improve upon some of the limitations of the current model. For example, allowing commuters to respond to transport policies by altering their residential and workplace locations would shed some light on the possible longer run impacts of such policies; an example of a modeling approach for this is given by Ahlfeldt et al. (2015) in their study of the economics of density in Berlin. More would would also attempt to shed light upon the equity and efficiency considerations of different transport policies. For example, congestion pricing may benefit the city's commuting equilibrium, but those benefits may be borne by lower income residents who are forced to substitute away from driving during peak times. Stronger characterization of different equity considerations and their possibly tradeoffs with efficiency could help to better inform optimal policy design.

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Table 1: Summary Statistics on Well-Defined Trips

	2002 (N = 653,814)	2010 (N = 541,630)	Δ
Panel A: All Trips	**Mean (sd)**	**Mean (sd)**	p-**Value**
Distance from Origin to Destination (km)	4.00 (5.73)	4.69 (6.87)	0.000
Trip within Kelurahan (0 1)	0.50 (0.50)	0.51 (0.50)	0.000
Travel time (min)	31.56 (27.49)	28.70 (24.49)	0.000
Speed (km / hour)	8.29 (10.13)	11.80 (32.63)	0.000
	2002 (N = 333,818)	**2010 (N = 305,629)**	Δ
Panel B: Work Trips	**Mean (sd)**	**Mean (sd)**	p-**Value**
Distance from Origin to Destination (km)	5.27 (6.91)	6.19 (8.11)	0.000
Trip within Kelurahan (0 1)	0.41 (0.49)	0.43 (0.50)	0.000
Travel time (min)	36.79 (31.25)	34.15 (28.03)	0.000
Speed (km / hour)	9.27 (10.85)	13.59 (38.85)	0.000
	2002 (N = 319,996)	**2010 (N = 236,001)**	Δ
Panel C: School Trips	**Mean (sd)**	**Mean (sd)**	p-**Value**
Distance from Origin to Destination (km)	2.66 (3.70)	2.75 (4.08)	0.000
Trip within Kelurahan (0 1)	0.59 (0.49)	0.61 (0.49)	0.000
Travel time (min)	26.12 (21.60)	21.65 (16.46)	0.000
Speed (km / hour)	7.27 (9.20)	9.49 (21.89)	0.000

Notes: Authors' calculations on well-defined trips, using the 2002 HTS and the 2010 CTS trip data. The sample of well-defined trips consists of all trips that contain information on travel times, origin and destination communities (*kelurahan*), modes, and trip purposes. Each observation is a trip, and means are computed using survey weights. The p-values in this table are computed by conducting a two-sided equality of means t-test between years.

Table 2: Summary Statistics on Communities: Pre-Treatment Characteristics

	$d\,(\mathbf{BRT}) \leq 1$		All Non-Treated		Planned Only	
Panel A: Census 2000	**Mean (sd)**	**N**	**Δ Mean**	**N**	**Δ Mean**	**N**
Log Population Density (2000)	10.21 (1.80)	192	2.08***	1467	0.26	92
Distance to City Center (km)	8.14 (4.14)	192	-26.52***	1472	-9.15***	92
% never completed primary school	13.24 (2.37)	192	-18.07***	1468	-3.35***	92
% w/ primary school or equiv.	20.93 (3.27)	192	-6.21***	1468	0.26	92
% w/ Junior high school or equiv., 2000	17.18 (2.90)	192	4.91***	1468	-0.10	92
% w/ Senior high school or eqiv., 2000	30.37 (4.54)	192	15.45***	1468	2.60**	92
% w/ Diploma I/II	0.93 (0.41)	192	0.36***	1468	0.03	92
% w/ Diploma III/Academy	3.54 (1.89)	192	2.33***	1468	0.81*	92
% w/ Diploma IV/Bachelor's	6.52 (4.38)	192	4.67***	1468	1.81	92
% of recent migrants from a different district	10.77 (4.23)	192	1.61*	1468	-4.34***	92
% of recent migrants from a different province	8.97 (3.97)	192	1.96**	1468	-3.78**	92
	$d\,(\mathbf{BRT}) \leq 1$		All Non-Treated		Planned Only	
Panel B: JICA 2002 (Demographics)	**Mean (sd)**	**N**	**Δ Mean**	**N**	**Δ Mean**	**N**
Age	30.88 (0.05)	126170	2.59***	794183	1.35***	61441
Female (0 1)	0.47 (0.00)	126170	0.01	794183	0.00	61441
Did not complete primary school (0 1)	0.02 (0.00)	123545	-0.02**	779350	-0.00**	60355
Only completed primary school (0 1)	0.22 (0.00)	123545	-0.14	779350	-0.02	60355
Only completed junior high school (0 1)	0.17 (0.00)	123545	-0.01	779350	-0.00	60355
Only completed senior high school (0 1)	0.32 (0.00)	123545	0.09**	779350	0.02**	60355
Monthly income < Rp. 1 mil	0.38 (0.00)	126176	-0.13	794287	0.04	61441
Monthly income Rp. 1-1.5 mil	0.22 (0.00)	126176	0.02	794287	-0.02	61441
Monthly income Rp. 1.5-2 mil	0.13 (0.00)	126176	0.03	794287	-0.00	61441
Monthly income Rp. 2-3 mil	0.12 (0.00)	126176	0.03**	794287	-0.02**	61441
Monthly income Rp. 3-4 mil	0.06 (0.00)	126176	0.02	794287	-0.00	61441
Monthly income Rp. 4-5 mil	0.04 (0.00)	126176	0.02	794287	0.00	61441
Monthly income > Rp. 5 mil	0.05 (0.00)	126176	0.02	794287	0.01	61441
	$d\,(\mathbf{BRT}) \leq 1$		All Non-Treated		Planned Only	
Panel C: JICA 2002 (Commuting)	**Mean (sd)**	**N**	**Δ Mean**	**N**	**Δ Mean**	**N**
Own a car (0 1)?	0.26 (0.00)	126170	0.07	794183	-0.01	61441
Own a Motorcycle (0 1)?	0.40 (0.00)	126170	0.03*	794183	-0.05*	61441
Number of Sedans / Vans Owned	0.32 (0.00)	126170	0.11	794183	-0.00	61441
Number of Motorcycles Owned	0.46 (0.00)	126170	0.05*	794183	-0.06*	61441
Main Mode: Train	0.03 (0.00)	123093	-0.01	771600	0.01	59977
Main Mode: Other Public Transport	0.50 (0.00)	123093	-0.03	771600	0.03	59977
Main Mode: Taxi / Ojek / Bajaj	0.05 (0.00)	123093	-0.03**	771600	0.02**	59977
Main Mode: Car	0.19 (0.00)	123093	0.06	771600	-0.00	59977
Main Mode: Motorcycle	0.23 (0.00)	123093	0.01**	771600	-0.05**	59977
Main Mode: Non-Motorized Transit	0.00 (0.00)	123093	-0.01*	771600	-0.00*	59977

Notes: Authors' calculations. Each observation is a kelurahan. Columns 1 and 2 report the mean, standard deviation (in parentheses), and number of observations of the variable on the left-hand side for communities (*kelurahan*) that are within 1 km of a BRT station in 2010. Columns 3 (4) report the difference in means (number of observations) between the close-proximity kelurahan and all other kelurahan ("non-treated"), and columns 5 (6) report the difference in means (number of observations) between the close-proximity kelurahan and kelurahan within 1 km of a planned BRT station that has yet to be constructed. The signifance stars in this table are computed by regressing the outcome variable on a treatment indicator, restricting the sample in columns 5 (6) to only treated and planned-to-be treated communities. In this regression, we cluster standard errors at the subdistrict (*kecamatan*) level, and significance levels come from the p-values of these treatment indicators. */**/*** denotes significant at the 10% / 5% / 1% levels.

Table 3: Average Treatment Effects on the Treated of BRT Station Proximity

	Treated vs. Planned			
	(1)	(2)	(3)	(4)
Own a car (0 1)?, Delta	-0.001	0.020	-0.125	-0.045
	(0.033)	(0.041)	(0.070)*	(0.052)
Own a Motorcycle (0 1)?, Delta	0.003	-0.024	0.024	-0.037
	(0.021)	(0.022)	(0.053)	(0.029)
Main Mode: BRT, Delta	0.042	0.028	0.026	0.042
	(0.013)***	(0.020)	(0.024)	(0.021)**
Main or Alternative Mode: BRT, Delta	0.088	0.040	0.032	0.066
	(0.019)***	(0.026)	(0.030)	(0.030)**
Main Mode: Car, Delta	0.001	-0.003	-0.104	-0.054
	(0.022)	(0.035)	(0.039)***	(0.026)**
Main Mode: Motorcycle, Delta	-0.051	-0.017	0.113	-0.011
	(0.023)**	(0.030)	(0.090)	(0.048)
Main Mode: Train, Delta	0.015	0.011	-0.020	0.009
	(0.012)	(0.015)	(0.029)	(0.019)
Main Mode: Other Public Transport, Delta	0.004	-0.010	-0.005	0.018
	(0.024)	(0.037)	(0.042)	(0.028)
Main Mode: Taxi / Ojek / Bajaj, Delta	-0.011	-0.012	-0.018	-0.017
	(0.007)	(0.007)	(0.013)	(0.010)*
Main Mode: Non-Motorized Transit, Delta	-0.001	0.003	0.009	0.013
	(0.004)	(0.003)	(0.004)**	(0.006)**
Controls	.	X	X	X
Logistic Reweighting	.	.	X	.
Oaxaca-Blinder	.	.	.	X

Notes: Each cell reports the coefficient from a regression of the given dependent variable (listed in the left-most column) on an indicator for whether or not the kelurahan is within 1 km of a BRT station. Columns 1-4 restrict the non-treated sample to include only kelurahan within 1 km of an unbuilt, placebo station. Column 2 includes pre-treatment controls, and Columns 3 reports a double-robust specification that both includes controls and reweights non-treated districts by $\hat{\kappa} = \hat{P}/(1-\hat{P})$, where $\hat{P}$ is the estimated probability that the kelurahan is within 2 km of a BRT station. Columns 4 reports a control function specification based on a Oaxaca-Blinder decomposition, described in Kline (2011). Robust standard errors, clustered at the sub-district level, are reported in parentheses and are estimated using a bootstrap procedure, with 1000 replications, in column 3 to account for the generated $\hat{\kappa}$ weights. Sample sizes vary across outcomes but include as many 192 "treated" kelurahan and 92 placebo kelurahan. */**/*** denotes significant at the 10% / 5% / 1% levels.

Table 4: Robustness of ATT Estimates to Demographic Controls

	Treated vs. Placebo			
	(1)	(2)	(3)	(4)
Own a car (0 1)?, Delta	-0.045 (0.052)	-0.043 (0.055)	-0.046 (0.052)	-0.013 (0.056)
Own a Motorcycle (0 1)?, Delta	-0.037 (0.029)	-0.039 (0.033)	-0.058 (0.034)*	-0.010 (0.027)
Main Mode: BRT, Delta	0.042 (0.021)**	0.042 (0.020)**	0.033 (0.024)	0.063 (0.021)***
Main or Alternative Mode: BRT, Delta	0.066 (0.030)**	0.066 (0.029)**	0.047 (0.034)	0.090 (0.032)***
Main Mode: Car, Delta	-0.054 (0.026)**	-0.052 (0.028)*	-0.053 (0.028)*	-0.062 (0.030)**
Main Mode: Motorcycle, Delta	-0.011 (0.048)	-0.014 (0.048)	-0.016 (0.055)	-0.026 (0.065)
Main Mode: Train, Delta	0.009 (0.019)	0.009 (0.018)	-0.002 (0.021)	0.014 (0.021)
Main Mode: Other Public Transport, Delta	0.018 (0.028)	0.017 (0.029)	0.037 (0.037)	0.025 (0.051)
Main Mode: Taxi / Ojek / Bajaj, Delta	-0.017 (0.010)*	-0.016 (0.010)*	-0.013 (0.010)	-0.024 (0.010)**
Main Mode: Non-Motorized Transit, Delta	0.013 (0.006)**	0.014 (0.006)**	0.014 (0.006)**	0.010 (0.007)
Oaxaca-Blinder	X	X	X	X
Controls for Δ Density		X	X	X
Controls for Δ Migrant Share		X	X	X
Controls for Δ Education Shares			X	X
Controls for Δ Expenditure Shares				X

Notes: Each cell reports the coefficient from a regression of the given dependent variable (listed in the left-most column) on an indicator for whether or not the kelurahan is within 1 km of a BRT station. Column 1 reproduces Column 4 from Table 3, reporting a control function specification based on a Oaxaca-Blinder decomposition, described in Kline (2011). In Column 2, we add a control for changes in community-level population density and in the share of recent (5-year) province and district migrants. Column 3 adds controls for changes in the educational composition of the community (averages of 7 different indicators for different levels of attainment). Column 4 includes controls for changes in income shares (averages of 7 different indicators for different levels of expenditure). Robust standard errors, clustered at the sub-district level, are reported in parentheses. Sample sizes vary across outcomes but include as many 192 "treated" kelurahan and 92 placebo kelurahan. */**/*** denotes significant at the 10% / 5% / 1% levels.

Table 5: Log Travel Time Regressions

	(1)	(2)	(3)	(4)
Year is 2010 (0 1)	-0.116	-0.107	-0.080	-0.032
	(0.007)***	(0.009)***	(0.009)***	(0.009)***
Distance from Origin to Destination (km)	0.074	0.068	0.063	-0.005
	(0.001)***	(0.001)***	(0.001)***	(0.001)***
Train		-0.058	-0.029	-0.005
		(0.013)***	(0.014)**	(0.013)
Other Public Transport (Bus / Van)		-0.098	-0.038	-0.001
		(0.014)***	(0.015)**	(0.014)
Taxi / Ojek / Bajaj		-0.195	-0.069	-0.012
		(0.018)***	(0.017)***	(0.016)
Private Car		0.095	0.058	0.014
		(0.017)***	(0.016)***	(0.015)
Private Motorcycle		-0.108	-0.089	-0.085
		(0.014)***	(0.015)***	(0.014)***
Non-Motorized Transit		-0.119	-0.089	-0.034
		(0.019)***	(0.021)***	(0.020)*
To School		-0.093	-0.088	-0.003
		(0.005)***	(0.007)***	(0.005)
From Work		0.003	0.040	0.063
		(0.006)	(0.007)***	(0.006)***
From School		-0.044	-0.016	0.073
		(0.007)***	(0.008)*	(0.006)***
N	1137900	1137900	1137900	1137900
Adjusted R^2	0.236	0.268	0.315	0.447
Adjusted R^2 (Within)			0.216	0.032
Departure Hour FE		Yes	Yes	Yes
Origin FE			Yes	
Destination FE			Yes	
Origin × Destination FE				Yes

Notes: This table reports the results of a regression of log travel times on trip characteristics, pooling the HTS/CTS trip data from 2002 and 2010. Column 1 is the unadjusted comparison, including only distance and a 2010 year dummy. Column 2 includes several different trip characteristics (with coefficients reported), while column 3 includes separate origin and destination fixed effects. Column 4 includes fixed effects for origin-by-destination pairs; identification of the distance coefficient comes from variation in trip distances within an origin-destination route. All columns include separate purpose-by-year effects and separate indicators for each possible departure hour. Robust standard errors, two-way clustered by origin and destination community (*kelurahan*), are reported in parentheses. */**/*** denotes significant at the 10% / 5% / 1% levels.

Table 6: Negative Spillovers: Impact of BRT on Travel Times

	(1)	(2)	(3)	(4)
1. All Trips	0.120	0.116	0.110	0.039
	(0.016)***	(0.017)***	(0.017)***	(0.027)
N	1137900	1137900	1119916	686381
Adjusted R^2	0.446	0.446	0.445	0.401
Adjusted R^2 (within)	0.030	0.030	0.029	0.038
2. Train Trips	0.006	0.007	-0.017	-0.010
	(0.161)	(0.162)	(0.165)	(0.361)
N	35900	35900	35379	22121
Adjusted R^2	0.483	0.483	0.481	0.454
Adjusted R^2 (within)	0.059	0.059	0.059	0.080
3. Public Bus Trips	0.123	0.123	0.119	0.065
	(0.035)***	(0.036)***	(0.036)***	(0.042)
N	450485	450485	447243	276806
Adjusted R^2	0.399	0.399	0.398	0.357
Adjusted R^2 (within)	0.027	0.028	0.027	0.034
4. Private Car Trips	0.204	0.190	0.168	0.070
	(0.060)***	(0.060)***	(0.060)***	(0.109)
N	69352	69352	68839	39798
Adjusted R^2	0.499	0.500	0.499	0.454
Adjusted R^2 (within)	0.037	0.038	0.039	0.045
5. Private Motorcycle Trips	0.134	0.132	0.128	0.037
	(0.024)***	(0.024)***	(0.025)***	(0.039)
N	424837	424837	413752	251205
Adjusted R^2	0.421	0.421	0.418	0.374
Adjusted R^2 (within)	0.025	0.025	0.023	0.032
Year FE	Yes	Yes	Yes	Yes
Origin × Destination FE	Yes	Yes	Yes	Yes
Number of Trips		Yes	Yes	Yes
Origin Population Density			Yes	Yes
Destination Population Density			Yes	Yes
Non Peak-Time Trips				Yes

Notes: Each cell in this regression corresponds to a separate estimate of β from the specification (4) to assess the differential impact on travel times for trips originating and terminating within 1 km of a BRT station. The dependent variable is the log travel times, and the parameters are estimated from the pooled 2002 and 2010 HTS/CTS sample. In row 1, we use all trips, while the other rows restrict the sample to train trips (row 2), public bus trips (row 3), private car trips (row 4), and private motorcycle trips (row 5). In column 1, we include separate year fixed effects and origin-by-destination community (*kelurahan*) FE. In column 2, we include a control for changes in total number of trips made for each origin-by-destination pair over time. In column 3, we add controls for origin and destination populations density. Column 4 restricts the sample of column 3 to only include non-peak time trips. All columns include separate purpose-by-year effects and separate departure-hour-by-year indicators. Robust standard errors, two-way clustered by origin and destination community, are reported in parentheses. */**/*** denotes significant at the 10% / 5% / 1% levels.

Table 7: Travel Demand Curves (Aggregate Nested Logit)

	FELS			GMM		
	(1)	(2)	(3)	(4)	(5)	(6)
Log Time Cost (min per km)	-0.077	-0.068	-0.067	-0.883	-0.539	-0.540
	(0.012)***	(0.013)***	(0.013)***	(0.263)***	(0.123)***	(0.123)***
Log Monthly Transport Costs	-0.026	-0.023	-0.023	-0.051	-0.059	-0.059
	(0.006)***	(0.006)***	(0.006)***	(0.011)***	(0.011)***	(0.011)***
(Share owning Cars × Car Mode)	0.136	0.147	0.151	0.066	0.008	0.011
	(0.038)***	(0.038)***	(0.038)***	(0.048)	(0.054)	(0.054)
(Share owning Motorcycle × Motorcycle Mode)	0.874	0.880	0.883	0.848	0.813	0.815
	(0.037)***	(0.038)***	(0.038)***	(0.037)***	(0.038)***	(0.038)***
σ_1	0.815	0.813	0.813	0.705	0.782	0.782
	(0.008)***	(0.008)***	(0.008)***	(0.037)***	(0.011)***	(0.011)***
σ_2	0.863	0.863	0.864	0.786	0.821	0.822
	(0.006)***	(0.006)***	(0.006)***	(0.026)***	(0.013)***	(0.013)***
Distance to Stations		-0.022	-0.021		0.177	0.178
		(0.011)*	(0.011)*		(0.053)***	(0.053)***
Mode Comfort			0.051			0.046
			(0.015)***			(0.015)***
Mode Safety			-0.053			-0.047
			(0.017)***			(0.017)***
Mode Convenience			0.035			0.032
			(0.020)*			(0.020)
N	85926	85926	85926	85926	85926	85926
N Clusters	1494	1494	1494	1494	1494	1494
Adj. R^2	0.799	0.799	0.800	0.728	0.780	0.780
Regression F-Stat	4512.345	3950.340	2972.129	3555.382	3740.539	2786.724
Kleibergen-Paap F-Stat	.	.	.	29.504	104.472	104.461
Cragg-Donald Wald F-Stat	.	.	.	269.933	1120.163	1120.526
Choice-Specific Constants	Yes	Yes	Yes	Yes	Yes	Yes
Origin-by-Destination Sub-District Effects	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table reports estimates of the aggregate nested logit demand curve, using the linear equation specified in (6). Columns 1-3 are estimated using fixed-effects least squares (FELS), while columns 4-6 are estimated using the generalized method of moments (GMM), where the log time cost is instrumented using the overlapping routes IV (log total number of overlapping vehicles). All columns include alternative-specific constants (separate for each mode time × mode × departure window), and origin-by-destination subdistrict (*kecamatan*) effects. The only differences across the columns are the inclusion of different choice characteristics. Robust standard errors, two-way clustered by origin and destination kelurahan, are reported in parentheses. */**/*** denotes significant at the 10% / 5% / 1% levels.

Table 8: Travel Supply Curves (Trip-Level Data)

	All Modes						Cars + Buses	Motorcycles
	FELS (1)	**FELS (2)**	**FELS (3)**	**GMM (4)**	**GMM (5)**	**GMM (6)**	**GMM (7)**	**GMM (8)**
Log Total Vehicles	0.008	0.006	-0.095	0.016	0.116	0.977	1.186	0.936
	(0.002)***	(0.012)	(0.049)*	(0.002)***	(0.021)***	(0.153)***	(0.213)***	(0.208)***
Log Total Vehicles (squared)		0.000	0.016		-0.008	-0.144	-0.181	-0.133
		(0.001)	(0.008)**		(0.002)***	(0.024)***	(0.032)***	(0.032)***
Log Total Vehicles (cubed)			-0.001			0.007	0.009	0.006
			(0.000)*			(0.001)***	(0.002)***	(0.002)***
Distance from Origin to Destination (km)	-0.087	-0.087	-0.087	-0.087	-0.087	-0.087	-0.087	-0.086
	(0.002)***	(0.002)***	(0.002)***	(0.002)***	(0.002)***	(0.002)***	(0.002)***	(0.003)***
N	1124074	1124074	1124074	1124074	1124074	1124074	550813	482562
N Clusters	1528	1528	1528	1528	1528	1528	1517	1526
Adj. R^2	0.446	0.446	0.446	0.446	0.446	0.445	0.438	0.443
Regression F-Stat	961.551	722.045	578.999	1299.081	838.108	644.989	424.612	288.129
Kleibergen-Paap F-Stat	.	.	.	2344.867	210.732	94.868	52.157	80.151
Cragg-Donald Wald F-Stat	.	.	.	1.26e+05	9949.757	3162.318	2009.400	1471.768
Hansen J test p-value	.	.	.	520.741	510.964	494.796	424.607	421.578
Total Vehicles, Mean E	0.008	0.009	-0.112	0.016	0.005	-0.014	-0.019	-0.015
Total Vehicles, Max E	0.008	0.006	0.011	0.016	0.125	1.139	1.390	1.085
Origin × Destination FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

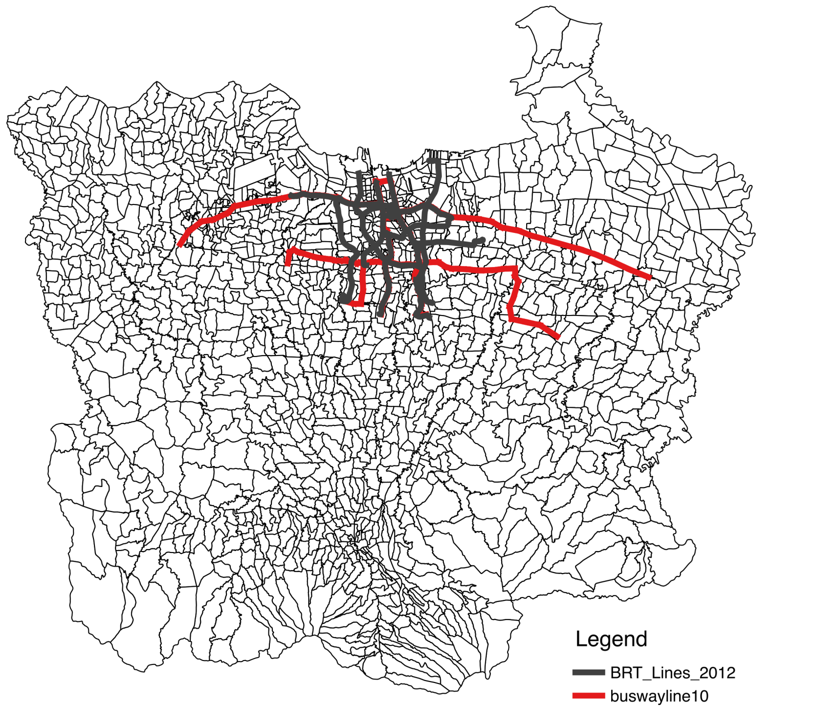
Notes: This table reports the results of a regression of log travel times per kilometer as the dependent variable, pooling the HTS/CTS trip data from 2002 and 2010. Columns 1-3 report fixed-effects least square estimates, while columns 4-8 use GMM and 23 separate departure hour indicators as instruments for log total vehicles (and its square and cubic terms). Columns 1-6 report estimates using all trips. Column 7 restricts the sample to only car and bus trips, while Column 8 restricts the sample to only motorcycle trips. Robust standard errors, clustered at the origin-by-destination pair, are reported in parentheses. */**/*** denotes significant at the 10% / 5% / 1% levels.

Table 9: Policy Simulations: Results for Mode and Departure Time Window Choice

		BRT Speed			**BRT Comfort / Convenience**			**Congestion Pricing (Rp '000)**			**Gasoline Subsidies**		
Panel A: Initial Δ	**Baseline (1)**	**+5% (2)**	**+10% (3)**	**+20% (4)**	**+5% (5)**	**+10% (6)**	**+20% (7)**	**+5 (8)**	**+10 (9)**	**+20 (10)**	**−5% (11)**	**−10% (12)**	**−20% (13)**
TransJakarta BRT	4.12	0.09	0.18	0.39	0.04	0.08	0.17	0.12	0.13	0.14	1.03	1.13	1.24
Train	2.79	-0.00	-0.01	-0.01	-0.00	-0.00	-0.00	0.08	0.09	0.10	0.70	0.77	0.84
Other Public Transit	23.38	-0.02	-0.04	-0.09	-0.01	-0.02	-0.04	0.69	0.75	0.80	5.86	6.42	7.01
Taxi / Ojek / Bajaj	4.08	-0.00	-0.01	-0.02	-0.00	-0.00	-0.01	0.05	0.06	0.06	-0.74	-0.80	-0.86
Private Car	12.19	-0.01	-0.02	-0.05	-0.01	-0.01	-0.02	-0.44	-0.48	-0.53	-1.36	-1.53	-1.72
Private Motorcycle	52.21	-0.05	-0.10	-0.21	-0.02	-0.04	-0.09	-0.55	-0.58	-0.62	-5.80	-6.33	-6.87
Before Peak Time	44.82	-0.00	-0.00	-0.00	0.00	0.00	0.00	1.33	1.44	1.54	0.49	0.52	0.55
Peak Time	31.35	-0.00	-0.00	-0.00	-0.00	-0.00	-0.00	-2.03	-2.20	-2.36	-0.28	-0.33	-0.39
After Peak Time	23.83	0.00	0.00	0.01	0.00	0.00	0.00	0.71	0.76	0.82	-0.20	-0.18	-0.17
		BRT Speed			**BRT Comfort / Convenience**			**Congestion Pricing (Rp '000)**			**Gasoline Subsidies**		
Panel B: Supply Adjustment Δ	**Baseline (1)**	**+5% (2)**	**+10% (3)**	**+20% (4)**	**+5% (5)**	**+10% (6)**	**+20% (7)**	**+5 (8)**	**+10 (9)**	**+20 (10)**	**−5% (11)**	**−10% (12)**	**−20% (13)**
TransJakarta BRT	4.12	0.07	0.15	0.32	0.03	0.07	0.14	0.12	0.13	0.14	0.88	0.97	1.06
Train	2.79	-0.00	-0.00	-0.01	-0.00	-0.00	-0.00	0.06	0.06	0.07	0.43	0.47	0.52
Other Public Transit	23.38	-0.02	-0.04	-0.08	-0.01	-0.02	-0.04	0.67	0.73	0.79	5.66	6.22	6.81
Taxi / Ojek / Bajaj	4.08	-0.00	-0.01	-0.01	-0.00	-0.00	-0.01	0.03	0.03	0.03	-0.67	-0.72	-0.78
Private Car	12.19	-0.01	-0.02	-0.04	-0.00	-0.01	-0.02	-0.31	-0.34	-0.38	-1.01	-1.16	-1.31
Private Motorcycle	52.21	-0.04	-0.08	-0.17	-0.02	-0.04	-0.07	-0.60	-0.64	-0.69	-5.48	-5.99	-6.52
Before Peak Time	44.82	-0.00	0.00	0.00	0.00	0.00	0.00	0.92	1.00	1.07	0.17	0.17	0.17
Peak Time	31.35	-0.00	-0.00	-0.00	-0.00	-0.00	-0.00	-1.41	-1.53	-1.64	-0.12	-0.15	-0.18
After Peak Time	23.83	0.00	0.00	0.00	0.00	0.00	0.00	0.49	0.53	0.57	-0.05	-0.02	0.01

Notes: Simulation results.

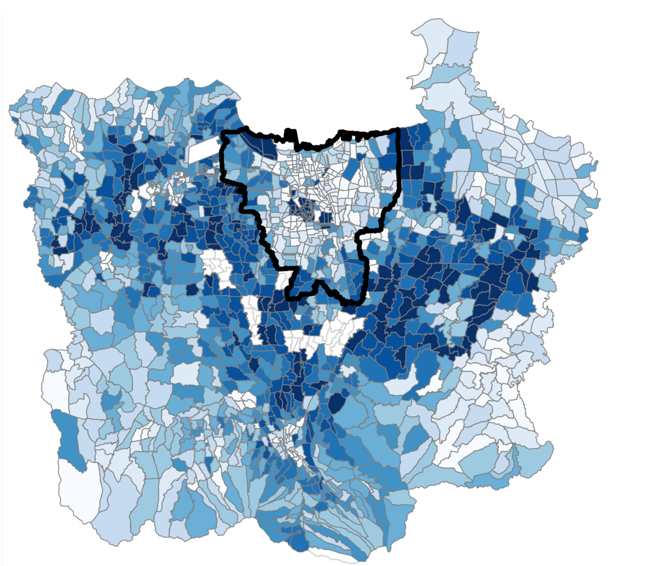
Figure 1: TransJakarta BRT and Planned Lines



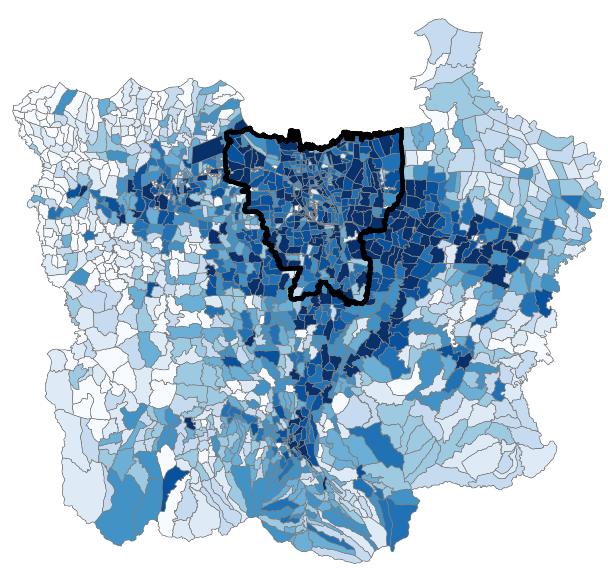
Notes: This figure plots the locations of actual BRT lines (in black) and planned BRT lines (in red). Actual BRT lines were traced from Open Street Map and TransJakarta data. Locations of planned lines are from JICA (2002); the lines are also present in Jakarta's Spatial Plans for 2010.

Figure 2: Population Density and Employment by Kelurahan

(A) GROWTH (2000-2010)

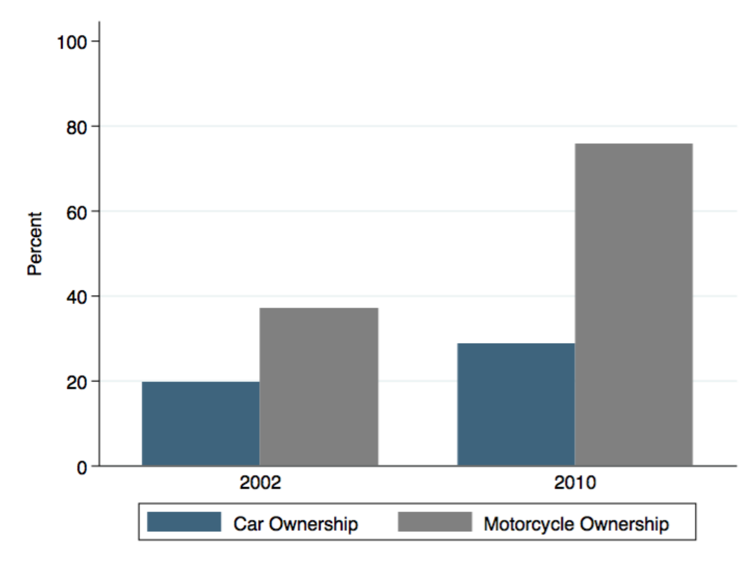


(B) EMPLOYMENT SHARE (2010)



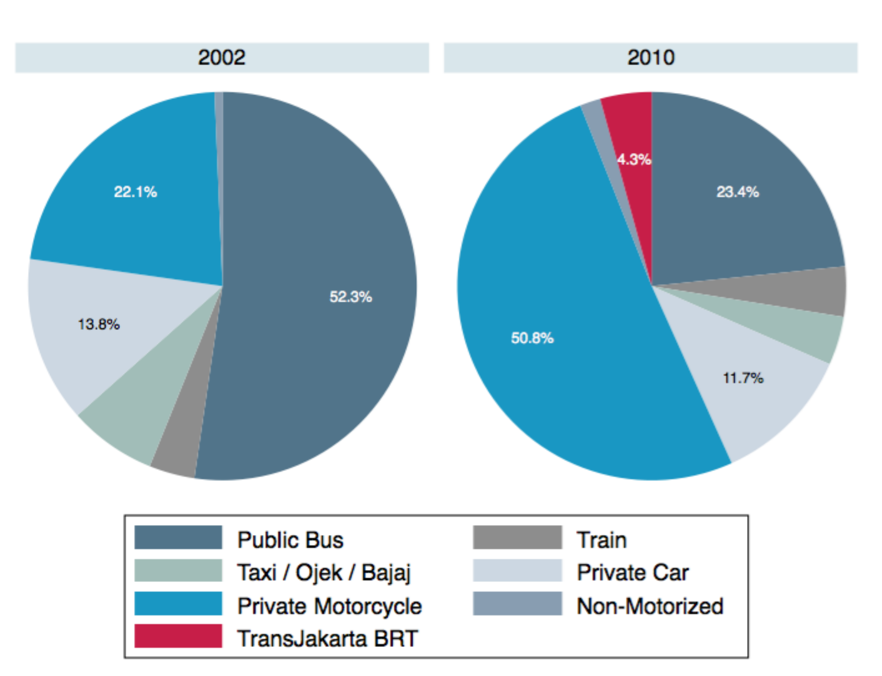
Notes: Authors' calculations, using data from the 2000 and 2010 population censuses in Panel A, and the JICA CTS 2010 data in Panel B. Darker areas correspond to higher population growth (Panel A) and greater employment probabilities (Panel B). The thick dark border denotes the boundaries of DKI Jakarta, the special capital province.

Figure 3: Changes in Vehicle Ownership



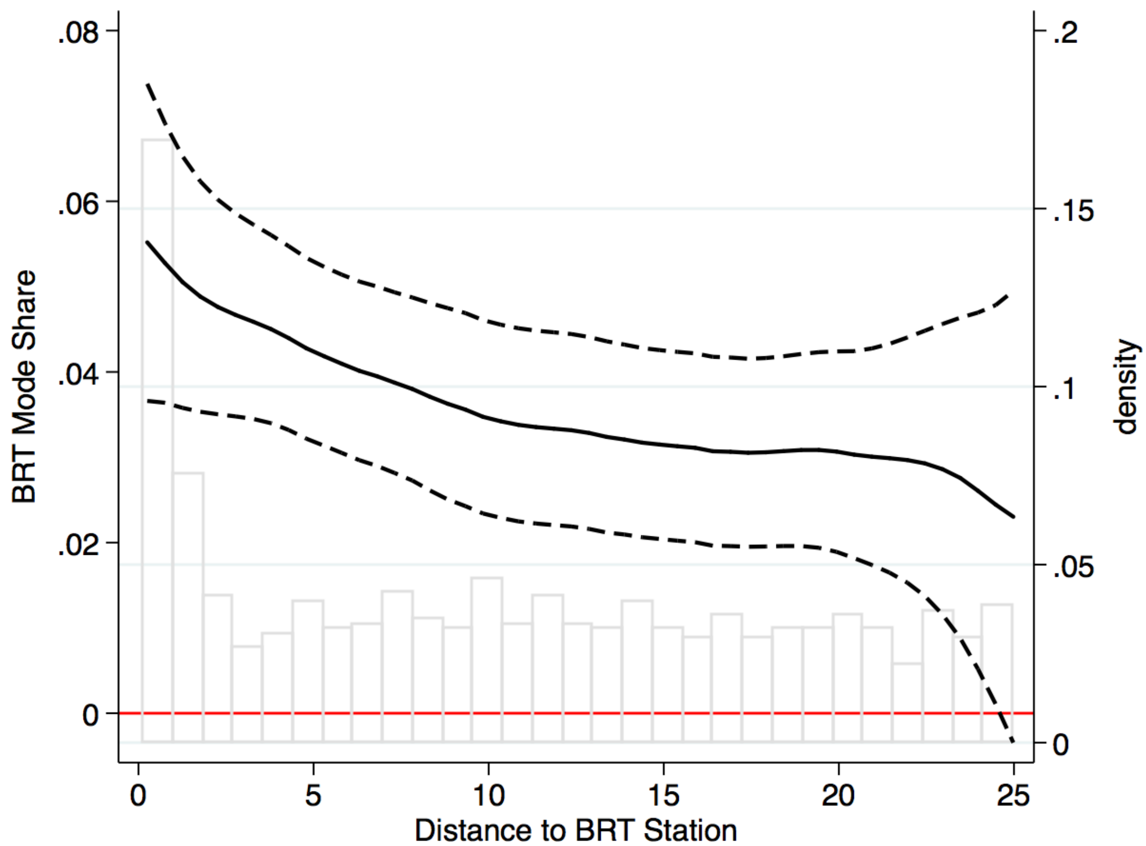
Notes: Authors' calculations, using data from the 2002 and 2010 JICA surveys. All percentages are calculated using survey weights.

Figure 4: Changes in Mode Choice



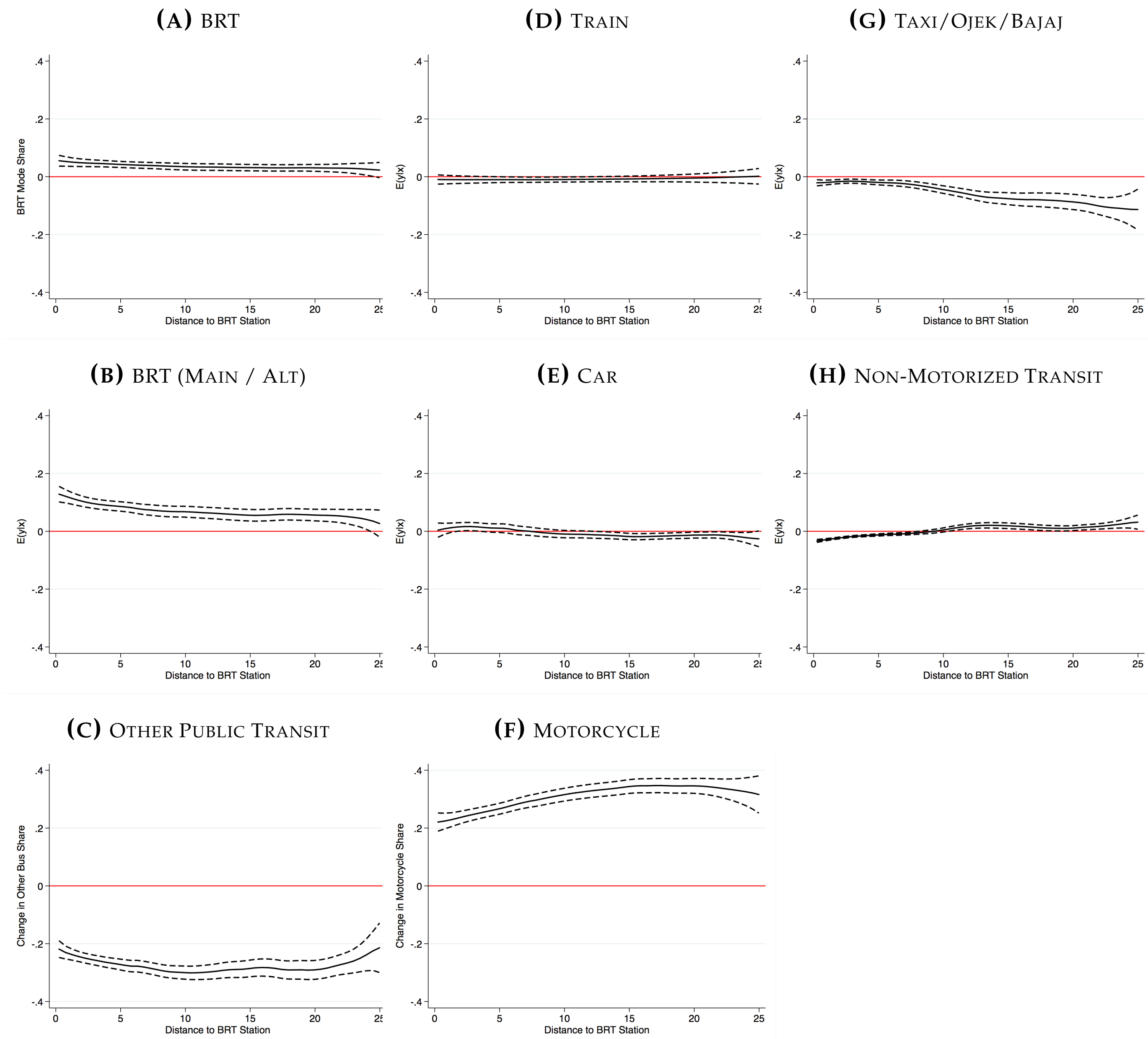
Notes: Authors' calculations, using data from the 2002 and 2010 JICA surveys. All percentages are calculated using survey weights.

Figure 5: Semiparametric Effect: Change in BRT Mode



Notes: This figure reports regressions of the neighborhood change in BRT mode (where BRT mode is defined to be 0 at baseline) on a flexible function of distance and a linear function of control variables. This partially linear regression equation is described in (1) and is estimated following Robinson (1988), using an an Epanechnikov kernel and Fan and Gijbels (1996) rule-of-thumb bandwidth. Control variables include several variables measured in the 2000 census, including the percent of the neighborhood's population with different levels of educational attainment, the share of recent migrants (from another province and another district) in the neighborhood, and population density. From the 2002 JICA data, we also include baseline vehicle ownership shares (motorcycles and cars) and shares of the population with different income levels. Finally, we include levels and a square term of the distance between kelurahan c and the center of the city.

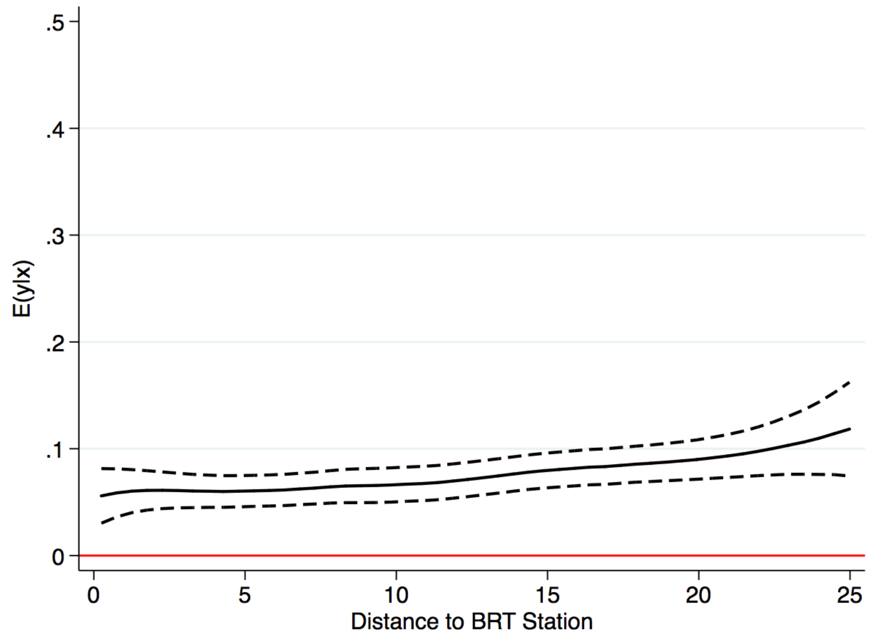
Figure 6: Semiparametric Estimates: Changes in Mode Choice



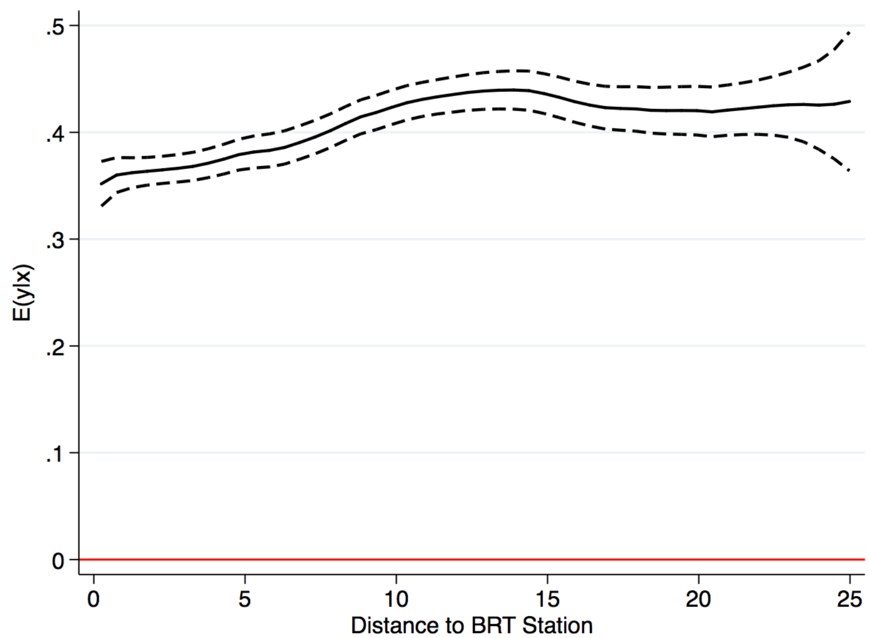
Notes: This figure reports regressions of the neighborhood change in different mode shares (with modes listed in panel subtitles) on a flexible function of distance and a linear function of control variables. These partially linear regression equations are described in (1) and is estimated following Robinson (1988), using an an Epanechnikov kernel and Fan and Gijbels (1996) rule-of-thumb bandwidth. Control variables include several variables measured in the 2000 census, including the percent of the neighborhood's population with different levels of educational attainment, the share of recent migrants (from another province and another district) in the neighborhood, and population density. From the 2002 JICA data, we also include baseline vehicle ownership shares (motorcycles and cars) and shares of the population with different income levels. Finally, we include levels and a square term of the distance between kelurahan c and the center of the city.

Figure 7: Semiparametric Estimates: Changes in Vehicle Ownership

(A) Own Car (0 1)

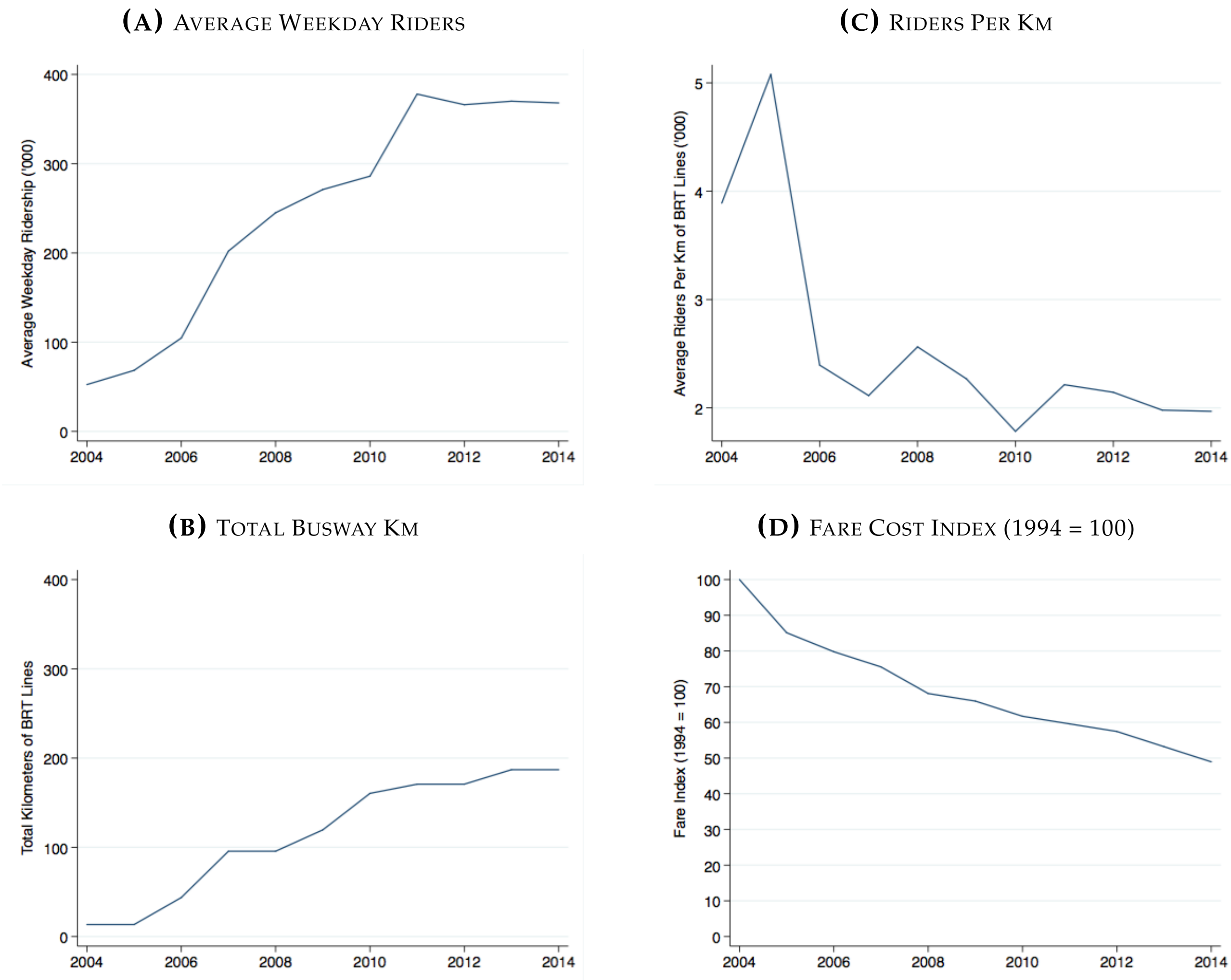


(B) Own Motorcycle (0 1)



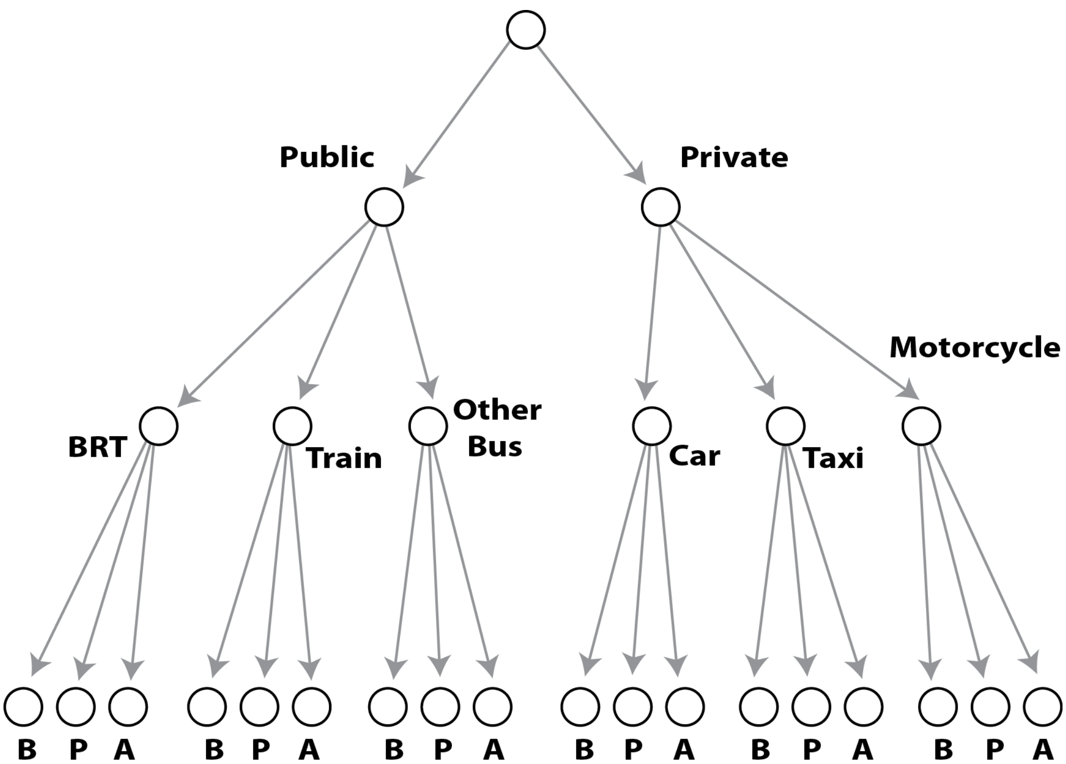
Notes: This figure reports regressions of the neighborhood change in vehicle ownership shares (with different vehicles listed in panel subtitles) on a flexible function of distance and a linear function of control variables. These partially linear regression equations are described in (1) and is estimated following Robinson (1988), using an an Epanechnikov kernel and Fan and Gijbels (1996) rule-of-thumb bandwidth. Control variables include several variables measured in the 2000 census, including the percent of the neighborhood's population with different levels of educational attainment, the share of recent migrants (from another province and another district) in the neighborhood, and population density. From the 2002 JICA data, we also include baseline vehicle ownership shares (motorcycles and cars) and shares of the population with different income levels. Finally, we include levels and a square term of the distance between kelurahan c and the center of the city.

Figure 8: TransJakarta Ridership Statistics



Notes: Data for Panels A and D are from Sayeg (2015). Panel B is derived from the traced BRT lines and calculated using GIS software. Panel C is a ratio of the data plotted in Panel A and Panel B.

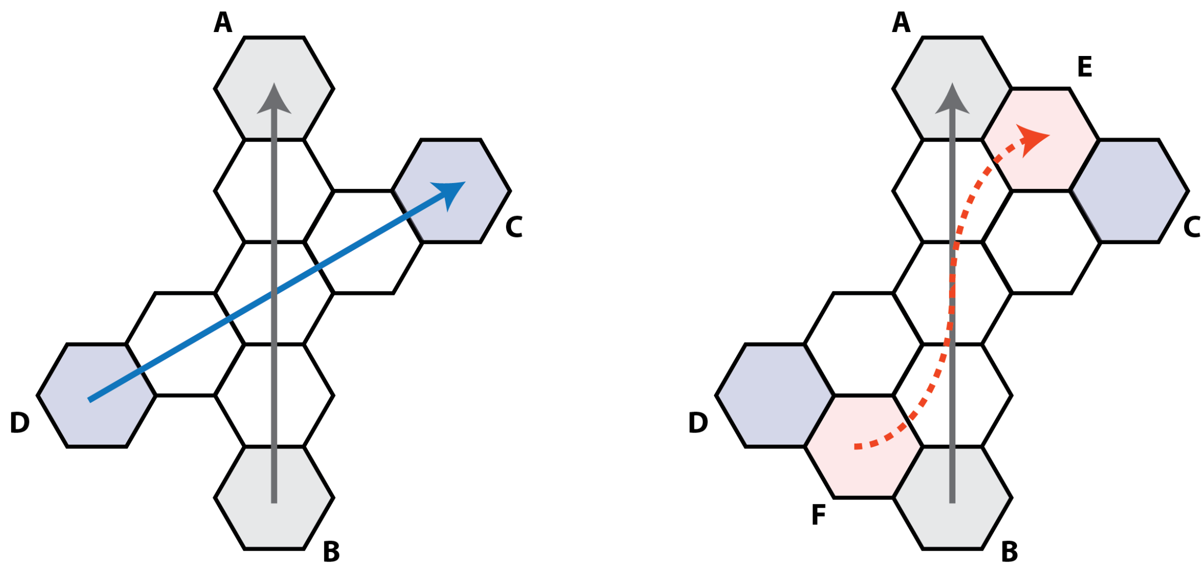
Figure 9: Choice Set: Nested Logit Structure



Notes: This diagram depicts the nested structure of mode choice and departure time windows. The first level is a choice of mode types (public or private). The second level depicts choices of modes within each type. The final level depicts departure time windows: "B" indicates before peak time (1-6 AM), "P" indicates peak time (7-9 AM), and "A" indicates "after peak time" (10-11 AM).

Figure 10: Demand IV: Traffic from Overlapping Routes

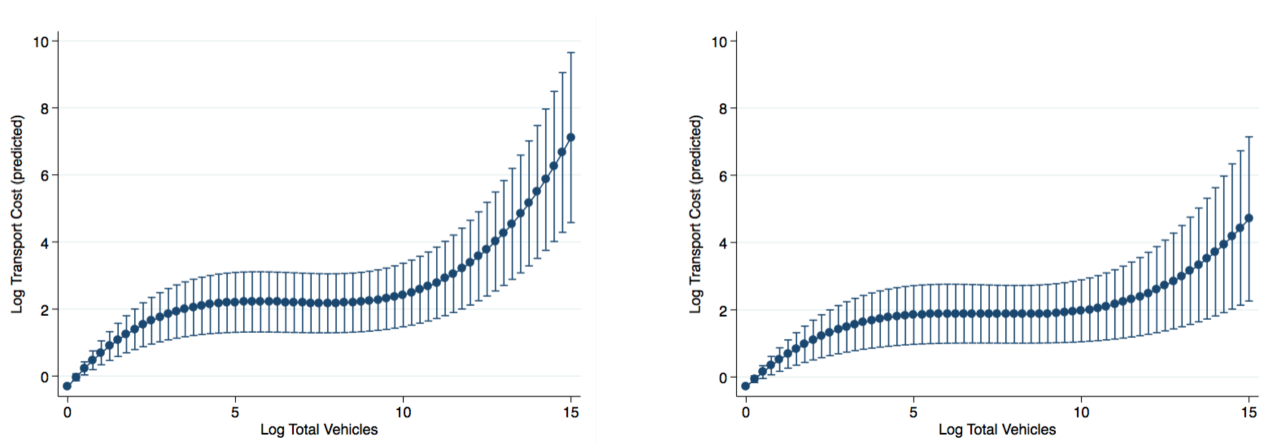
(A) Non-Adjacent Communities **(B)** Adjacent Communities



Notes: This diagram illustrates the instrumental variable we use to study how demand for mode / departure time-windows relates to variation in travel times. Panel A argues that unless the unobserved components that influence mode / departure time choice for a trip from route D to C are correlated with the unobserved components influencing mode / departure time choice from B to A, the number of vehicles on routes that overlap the route taken from B to A will be an instrumental variable with a strong first stage and satisfy the exclusion restriction. Panel B shows how we refine the instrument to excluse trips originating and termining in adjacent communities.

Figure 11: Estimated Supply Curves by Transport Mode

(A) Cars and Buses **(B)** Motorcycles



Notes: This figure plots the marginal effects of increases in log total vehicles on log transport costs for cars and buses (Panel A) and for motorcycles (Panel B), using the specifications from Table 8, Columns 7 and 8. We plot pointwise 95 percent confidence bands, obtained from standard errors that are clustered by origin-by-destination pair.

A Appendix Tables and Figures

Table A.1: Individual BRT: Linear Probability Model

	(1)	(2)
Number of people in household	0.002	0.002
	(0.001)**	(0.001)***
less than Rp. 1,000,000	0.006	0.002
	(0.006)	(0.004)
Rp.1,000,000-Rp.1,499,999	0.015	0.004
	(0.006)**	(0.005)
Rp.1,500,000-Rp.1,999,999	0.014	0.003
	(0.006)**	(0.005)
Rp.2,000,000-Rp.2,999,999	0.015	0.002
	(0.007)**	(0.005)
Rp.3,000,000-Rp.3,999,999	0.013	0.002
	(0.006)**	(0.005)
Rp.4,000,000-Rp.4,999,999	0.006	-0.005
	(0.007)	(0.006)
Female (0 1)	-0.000	0.000
	(0.001)	(0.001)
Did not complete primary school (0 1)	-0.010	-0.004
	(0.005)**	(0.002)*
Only completed primary school (0 1)	-0.002	-0.001
	(0.003)	(0.001)
Only completed junior high school (0 1)	-0.001	0.000
	(0.003)	(0.001)
Only completed senior high school (0 1)	0.002	-0.001
	(0.003)	(0.001)
Age	0.000	-0.000
	(0.000)	(0.000)
N	320687	320686
Adjusted R^2	0.001	0.310
Adjusted R^2 (Within)		0.000
Community FE	No	Yes

Notes: This table reports results of a linear probability model, where the dependent variable is equal to 1 if an individual mainly rides the BRT for his or her regular trips. Column 1 includes no community (*kelurahan*) effects, while column 2 includes community-specific intercepts. */**/*** denotes significant at the 10% / 5% / 1% levels.

Table A.2: Heterogeneous Treatment Effects of Distance to BRT

		Gender			Education			Income		
	All (1)	Male (2)	Female (3)	Δ t-stat (4)	Low (5)	High (6)	Δ t-stat (7)	Low (8)	High (9)	Δ t-stat (10)
Own a car (0 1)?, Delta	0.007	0.005	0.008	-1.029	-0.003	0.009	-1.655	0.016	0.034	-1.139
	(0.013)	(0.013)	(0.013)		(0.014)	(0.014)		(0.011)	(0.019)*	
Own a Motorcycle (0 1)?, Delta	0.035	0.038	0.031	1.527	0.028	0.022	0.725	0.030	-0.004	0.824
	(0.014)**	(0.014)***	(0.014)**		(0.014)**	(0.013)*		(0.014)**	(0.015)	
Main Mode: BRT, Delta	-0.010	-0.010	-0.010	0.529	-0.012	-0.011	-0.465	-0.010	-0.007	0.066
	(0.007)	(0.007)	(0.007)		(0.007)	(0.007)		(0.007)	(0.007)	
Main Mode: Car, Delta	-0.004	-0.004	-0.004	-0.343	-0.013	-0.005	-1.468	0.003	0.030	-1.495
	(0.009)	(0.009)	(0.010)		(0.009)	(0.010)		(0.006)	(0.018)*	
Main Mode: Motorcycle, Delta	0.048	0.049	0.046	0.874	0.040	0.044	-0.520	0.045	-0.014	2.101
	(0.014)***	(0.014)***	(0.014)***		(0.016)**	(0.014)***		(0.015)***	(0.018)	
Main Mode: Train, Delta	-0.006	-0.006	-0.006	0.084	-0.007	-0.006	-0.446	-0.006	-0.004	-0.025
	(0.006)	(0.006)	(0.006)		(0.007)	(0.006)		(0.007)	(0.008)	
Main Mode: Other Public Transport, Delta	-0.019	-0.020	-0.017	-0.582	-0.004	-0.019	1.640	-0.025	-0.025	0.063
	(0.014)	(0.014)	(0.013)		(0.015)	(0.013)		(0.015)	(0.014)*	
Main Mode: Taxi / Ojek / Bajaj, Delta	-0.021	-0.021	-0.021	0.200	-0.020	-0.015	-0.829	-0.021	0.015	-1.778
	(0.009)**	(0.009)**	(0.009)**		(0.009)**	(0.008)*		(0.009)**	(0.008)*	
Main Mode: Non-Motorized Transit, Delta	0.012	0.011	0.013	-1.451	0.016	0.010	2.411	0.014	0.005	0.618
	(0.003)***	(0.003)***	(0.003)***		(0.004)***	(0.003)***		(0.004)***	(0.002)**	

Notes: Columns 1-3, 5-6, and 8-9 report coefficients from separate regressions of the given dependent variable (listed in the left-most column) on the log of distance to the closest BRT station. Column 1 reports estimates for the entire sample, while columns 2 and 3 break out the effects by gender, Columns 5-6 by education, and Columns 8-9 by income. In columns 4 and 5, we coded "low education" to represent individuals that had no formal schooling or had only completed either primary school, while "high education" consisted of everyone else. In columns 6 and 7, we call "low expenditure" individuals those who have a monthly expenditure of less than Rp 1.5 million, while "high expenditure" individuals consist of all others. For these coefficient estimates robust standard errors, clustered by kelurahan, are reported in parentheses. In columns 4, 7, and 10, we report t-statistics for a test of whether the coefficients listed in the previous two columns are significantly different from one other. These tests were computed by estimating the two sample splits in a single regression, using a SUR system, and afterwards, performing a simple test of equality of coefficients. */**/*** denotes significant at the 10% / 5% / 1% levels.

Table A.3: Neighborhood Propensity Score

	(1)	(2)
Population Density (2000)	0.030	0.077
	(0.006)***	(0.026)***
Share of Recent (5-year) District Migrants (2000)	-0.003	-0.008
	(0.002)	(0.007)
Log Distance to City Center	-0.068	-0.350
	(0.012)***	(0.087)***
Motorcycle Ownership (%, 2002)	-0.114	-0.331
	(0.067)*	(0.224)
Monthly Income ¡ Rp 1 mil. (%, 2002)	0.036	0.285
	(0.062)	(0.294)
Monthly Income ¿ Rp 5 mil. (%, 2002)	0.082	0.182
	(0.106)	(0.400)
No Primary School Share (%, 2000)	-0.005	-0.006
	(0.005)	(0.010)
College Completion Share (%, 2000)	0.023	0.044
	(0.008)***	(0.029)
N	1452	197
Pseudo R^2	0.630	0.509
Log Likelihood	-161.9	-62.0
LR χ^2	120.7	31.3

Notes: */**/*** denotes significant at the 10% / 5% / 1% levels.

Table A.4: ATT Estimates of the Effect of BRT on Vehicle Ownership and Mode Choice (Full Results)

	All Kelurahan				Treated vs. Placebo			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Own a car (0 1)?, Delta	-0.010	0.012	-0.007	0.002	-0.001	0.020	-0.125	-0.045
	(0.021)	(0.030)	(0.028)	(0.031)	(0.033)	(0.041)	(0.070)*	(0.052)
Own a Motorcycle (0 1)?, Delta	0.030	-0.081	-0.025	-0.114	0.003	-0.024	0.024	-0.037
	(0.017)*	(0.026)***	(0.017)	(0.035)***	(0.021)	(0.022)	(0.053)	(0.029)
Main Mode: BRT, Delta	0.033	0.022	0.031	0.022	0.042	0.028	0.026	0.042
	(0.010)***	(0.014)	(0.015)**	(0.014)	(0.013)***	(0.020)	(0.024)	(0.021)**
Main or Alternative Mode: BRT, Delta	0.082	0.046	0.059	0.049	0.088	0.040	0.032	0.066
	(0.015)***	(0.018)**	(0.021)***	(0.019)**	(0.019)***	(0.026)	(0.030)	(0.030)**
Main Mode: Car, Delta	-0.052	-0.001	-0.019	-0.005	0.001	-0.003	-0.104	-0.054
	(0.019)***	(0.023)	(0.019)	(0.022)	(0.022)	(0.035)	(0.039)***	(0.026)**
Main Mode: Motorcycle, Delta	-0.036	-0.075	-0.002	-0.103	-0.051	-0.017	0.113	-0.011
	(0.023)	(0.032)**	(0.028)	(0.039)***	(0.023)**	(0.030)	(0.090)	(0.048)
Main Mode: Train, Delta	0.013	0.017	0.019	0.012	0.015	0.011	-0.020	0.009
	(0.009)	(0.012)	(0.016)	(0.012)	(0.012)	(0.015)	(0.029)	(0.019)
Main Mode: Other Public Transport, Delta	0.013	0.027	-0.018	0.052	0.004	-0.010	-0.005	0.018
	(0.025)	(0.030)	(0.024)	(0.034)	(0.024)	(0.037)	(0.042)	(0.028)
Main Mode: Taxi / Ojek / Bajaj, Delta	0.030	0.022	-0.012	0.039	-0.011	-0.012	-0.018	-0.017
	(0.012)**	(0.018)	(0.014)	(0.025)	(0.007)	(0.007)	(0.013)	(0.010)*
Main Mode: Non-Motorized Transit, Delta	0.000	-0.012	0.001	-0.017	-0.001	0.003	0.009	0.013
	(0.004)	(0.007)*	(0.003)	(0.009)*	(0.004)	(0.003)	(0.004)**	(0.006)**
Controls	.	X	X	X	.	X	X	X
Logistic Reweighting	.	.	X	.	.	.	X	.
Oaxaca-Blinder	.	.	.	X	.	.	.	X

Notes: Each cell reports the coefficient from a regression of the given dependent variable (listed in the left-most column) on an indicator for whether or not the kelurahan is within 2 km of a BRT station. Columns 1-4 report a comparson of BRT kelurahan to all other kelurahan, while Columns 5-8 restrict the non-treated sample to include only kelurahan within 2 km of an unbuilt, placebo station. Columns 2 and 6 include pre-treatment controls, and Columns 3 and 7 report a double-robust specification that both includes controls and reweights non-treated districts by $\hat{\kappa} = \hat{P}/(1-\hat{P})$, where $\hat{P}$ is the estimated probability that the kelurahan is within 2 km of a BRT station. Columns 4 and 8 report a control function specification based on a Oaxaca-Blinder decomposition, described in Kline (2011). Robust standard errors are reported in parentheses and are estimated using a bootstrap procedure, with 1000 replications, in column 4 to account for the generated $\hat{\kappa}$ weights. Sample sizes vary across outcomes but include as many 290 "treated" kelurahan, 1370 non-treated kelurahan, and 152 placebo kelurahan. */**/*** denotes significant at the 10% / 5% / 1% levels.

Table A.5: ATT Estimates of the Effect of BRT on Vehicle Ownership and Mode Choice (Dropping Too Close)

	All Kelurahan			
	(1)	(2)	(3)	(4)
Own a car (0 1)?, Delta	-0.011 (0.021)	0.022 (0.031)	-0.039 (0.038)	0.007 (0.032)
Own a Motorcycle (0 1)?, Delta	0.033 (0.017)*	-0.097 (0.036)***	0.042 (0.029)	-0.159 (0.051)***
Main Mode: BRT, Delta	0.034 (0.010)***	0.023 (0.016)	0.015 (0.028)	0.021 (0.018)
Main or Alternative Mode: BRT, Delta	0.084 (0.015)***	0.049 (0.022)**	0.053 (0.028)*	0.053 (0.025)**
Main Mode: Car, Delta	-0.054 (0.019)***	0.010 (0.026)	-0.034 (0.027)	0.006 (0.026)
Main Mode: Motorcycle, Delta	-0.038 (0.024)	-0.113 (0.037)***	0.021 (0.054)	-0.173 (0.047)***
Main Mode: Train, Delta	0.013 (0.009)	0.022 (0.014)	0.032 (0.017)*	0.013 (0.015)
Main Mode: Other Public Transport, Delta	0.013 (0.025)	0.041 (0.034)	-0.014 (0.033)	0.090 (0.039)**
Main Mode: Taxi / Ojek / Bajaj, Delta	0.032 (0.013)**	0.036 (0.025)	-0.014 (0.007)**	0.073 (0.036)**
Main Mode: Non-Motorized Transit, Delta	0.000 (0.004)	-0.019 (0.009)**	-0.005 (0.008)	-0.032 (0.012)***
Controls	.	X	X	X
Logistic Reweighting	.	.	X	.
Oaxaca-Blinder	.	.	.	X

Notes: Each cell reports the coefficient from a regression of the given dependent variable (listed in the left-most column) on an indicator for whether or not the kelurahan is within 2 km of a BRT station. Columns 1-4 report a comparson of BRT kelurahan to all other kelurahan, while Columns 5-8 restrict the non-treated sample to include only kelurahan within 2 km of an unbuilt, placebo station. Columns 2 and 6 include pre-treatment controls, and Columns 3 and 7 report a double-robust specification that both includes controls and reweights non-treated districts by $\hat{\kappa} = \hat{P}/(1-\hat{P})$, where $\hat{P}$ is the estimated probability that the kelurahan is within 2 km of a BRT station. Columns 4 and 8 report a control function specification based on a Oaxaca-Blinder decomposition, described in Kline (2011). Robust standard errors are reported in parentheses and are estimated using a bootstrap procedure, with 1000 replications, in column 4 to account for the generated $\hat{\kappa}$ weights. Sample sizes vary across outcomes but include as many 290 "treated" kelurahan, 1370 non-treated kelurahan, and 152 placebo kelurahan. */**/*** denotes significant at the 10% / 5% / 1% levels.

Table A.6: ATT Estimates of the Effect of BRT on Vehicle Ownership and Mode Choice (Controls)

	All Kelurahan				Treated vs. Placebo			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Own a car (0 1)?, Delta	0.002	0.009	0.005	0.038	-0.045	-0.043	-0.046	-0.013
	(0.031)	(0.031)	(0.032)	(0.024)	(0.052)	(0.055)	(0.052)	(0.056)
Own a Motorcycle (0 1)?, Delta	-0.114	-0.097	-0.088	-0.051	-0.037	-0.039	-0.058	-0.010
	(0.035)***	(0.034)***	(0.030)***	(0.024)**	(0.029)	(0.033)	(0.034)*	(0.027)
Main Mode: BRT, Delta	0.022	0.027	0.023	0.020	0.042	0.042	0.033	0.063
	(0.014)	(0.014)*	(0.015)	(0.015)	(0.021)**	(0.020)**	(0.024)	(0.021)***
Main or Alternative Mode: BRT, Delta	0.049	0.054	0.046	0.042	0.066	0.066	0.047	0.090
	(0.019)**	(0.019)***	(0.020)**	(0.020)**	(0.030)**	(0.029)**	(0.034)	(0.032)***
Main Mode: Car, Delta	-0.005	0.001	-0.001	0.020	-0.054	-0.052	-0.053	-0.062
	(0.022)	(0.022)	(0.022)	(0.018)	(0.026)**	(0.028)*	(0.028)*	(0.030)**
Main Mode: Motorcycle, Delta	-0.103	-0.096	-0.078	-0.059	-0.011	-0.014	-0.016	-0.026
	(0.039)***	(0.038)**	(0.035)**	(0.032)*	(0.048)	(0.048)	(0.055)	(0.065)
Main Mode: Train, Delta	0.012	0.012	0.009	0.008	0.009	0.009	-0.002	0.014
	(0.012)	(0.012)	(0.013)	(0.013)	(0.019)	(0.018)	(0.021)	(0.021)
Main Mode: Other Public Transport, Delta	0.052	0.042	0.036	0.018	0.018	0.017	0.037	0.025
	(0.034)	(0.034)	(0.034)	(0.034)	(0.028)	(0.029)	(0.037)	(0.051)
Main Mode: Taxi / Ojek / Bajaj, Delta	0.039	0.034	0.024	0.009	-0.017	-0.016	-0.013	-0.024
	(0.025)	(0.025)	(0.021)	(0.019)	(0.010)*	(0.010)*	(0.010)	(0.010)**
Main Mode: Non-Motorized Transit, Delta	-0.017	-0.019	-0.013	-0.015	0.013	0.014	0.014	0.010
	(0.009)*	(0.009)**	(0.008)*	(0.008)*	(0.006)**	(0.006)**	(0.006)**	(0.007)
Controls	.	X	X	X	.	X	X	X
Logistic Reweighting	.	.	X	.	.	.	X	.
Oaxaca-Blinder	.	.	.	X	.	.	.	X

Notes: Each cell reports the coefficient from a regression of the given dependent variable (listed in the left-most column) on an indicator for whether or not the kelurahan is within 2 km of a BRT station. Columns 1-4 report a comparson of BRT kelurahan to all other kelurahan, while Columns 5-8 restrict the non-treated sample to include only kelurahan within 2 km of an unbuilt, placebo station. Columns 2 and 6 include pre-treatment controls, and Columns 3 and 7 report a double-robust specification that both includes controls and reweights non-treated districts by $\hat{\kappa} = \hat{P}/(1-\hat{P})$, where $\hat{P}$ is the estimated probability that the kelurahan is within 2 km of a BRT station. Columns 4 and 8 report a control function specification based on a Oaxaca-Blinder decomposition, described in Kline (2011). Robust standard errors are reported in parentheses and are estimated using a bootstrap procedure, with 1000 replications, in column 4 to account for the generated $\hat{\kappa}$ weights. Sample sizes vary across outcomes but include as many 290 "treated" kelurahan, 1370 non-treated kelurahan, and 152 placebo kelurahan. */**/*** denotes significant at the 10% / 5% / 1% levels.

Table A.7: ATT Estimates of the Effect of BRT on Demographic Outcomes

	All Kelurahan				Treated vs. Placebo			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Δ population density	-0.210	-0.128	0.015	-0.122	-0.099	-0.026	0.019	0.015
	(0.025)***	(0.030)***	(0.020)	(0.033)***	(0.062)	(0.029)	(0.022)	(0.064)
Δ % recent migrants from w/in Jakarta	1.041	-0.543	0.920	-0.363	5.506	0.388	-0.429	0.665
	(1.128)	(1.065)	(0.706)	(1.116)	(1.915)***	(0.906)	(1.449)	(1.424)
Δ % recent migrants from outside Jakarta	1.084	0.426	0.765	0.641	4.961	0.569	0.095	0.711
	(0.952)	(0.934)	(0.650)	(0.973)	(1.829)***	(0.885)	(1.297)	(1.269)
Δ % never completed primary school	13.911	1.786	0.896	2.834	2.850	0.794	-0.054	-0.458
	(0.864)***	(0.882)**	(0.305)***	(1.183)**	(0.627)***	(0.465)*	(0.371)	(1.040)
Δ % w/ primary school or equiv.	-3.873	0.840	-0.037	0.525	-0.077	-0.643	-0.611	-0.158
	(0.547)***	(0.610)	(0.264)	(0.742)	(0.638)	(0.488)	(0.467)	(0.912)
Δ % w/ junior high school or equiv.	-4.388	-0.215	-0.755	-0.493	-0.601	-0.626	-1.956	-1.290
	(0.380)***	(0.421)	(0.364)**	(0.542)	(0.540)	(0.504)	(0.761)**	(0.805)
Δ % w/ senior high school or eqiv.	-5.017	-1.673	0.353	-1.742	-1.912	-0.174	1.626	0.712
	(0.655)***	(0.694)**	(0.421)	(0.770)**	(0.958)*	(0.719)	(0.849)*	(1.474)
Δ % w/ Diploma I/II	0.964	0.171	0.228	0.109	-0.541	0.418	0.450	0.678
	(0.190)***	(0.286)	(0.161)	(0.316)	(0.312)*	(0.240)*	(0.281)	(0.416)
Δ % w/ Diploma III/Academy	-2.107	-0.423	-0.174	-0.428	-0.871	-0.106	0.248	0.141
	(0.271)***	(0.137)***	(0.154)	(0.174)**	(0.338)**	(0.190)	(0.235)	(0.224)
Δ % w/ Diploma IV/Bachelor's	-2.531	-1.168	-0.799	-1.223	-1.283	-0.273	0.286	0.743
	(0.536)***	(0.356)***	(0.341)**	(0.384)***	(0.622)**	(0.412)	(0.594)	(0.643)
Monthly income < Rp. 1 mil, Delta	0.065	0.085	0.014	0.112	-0.048	0.010	0.029	0.034
	(0.024)***	(0.026)***	(0.007)**	(0.034)***	(0.024)*	(0.010)	(0.010)***	(0.012)***
Monthly income Rp. 1-1.5 mil, Delta	-0.169	0.008	0.037	0.007	0.033	0.033	0.121	0.067
	(0.018)***	(0.020)	(0.016)**	(0.022)	(0.021)	(0.023)	(0.047)***	(0.034)**
Monthly income Rp. 1.5-2 mil, Delta	-0.056	-0.058	-0.013	-0.067	-0.009	-0.005	0.086	0.021
	(0.015)***	(0.020)***	(0.013)	(0.023)***	(0.021)	(0.025)	(0.049)*	(0.030)
Monthly income Rp. 2-3 mil, Delta	0.008	-0.015	-0.005	-0.017	-0.007	-0.013	-0.195	-0.028
	(0.014)	(0.015)	(0.016)	(0.016)	(0.019)	(0.022)	(0.118)*	(0.061)
Monthly income Rp. 3-4 mil, Delta	0.041	0.006	0.004	0.003	0.004	-0.001	-0.032	-0.012
	(0.009)***	(0.012)	(0.011)	(0.012)	(0.012)	(0.020)	(0.030)	(0.016)
Monthly income Rp. 4-5 mil, Delta	0.029	-0.003	-0.007	-0.001	0.016	0.002	0.021	-0.004
	(0.008)***	(0.009)	(0.012)	(0.009)	(0.010)	(0.013)	(0.013)	(0.015)
Monthly income > Rp. 5 mil, Delta	0.075	-0.018	-0.031	-0.029	0.018	-0.025	-0.013	-0.070
	(0.017)***	(0.020)	(0.019)	(0.021)	(0.025)	(0.035)	(0.058)	(0.042)*
Controls	.	X	X	X	.	X	X	X
Logistic Reweighting	.	.	X	.	.	.	X	.
Oaxaca-Blinder	.	.	.	X	.	.	.	X

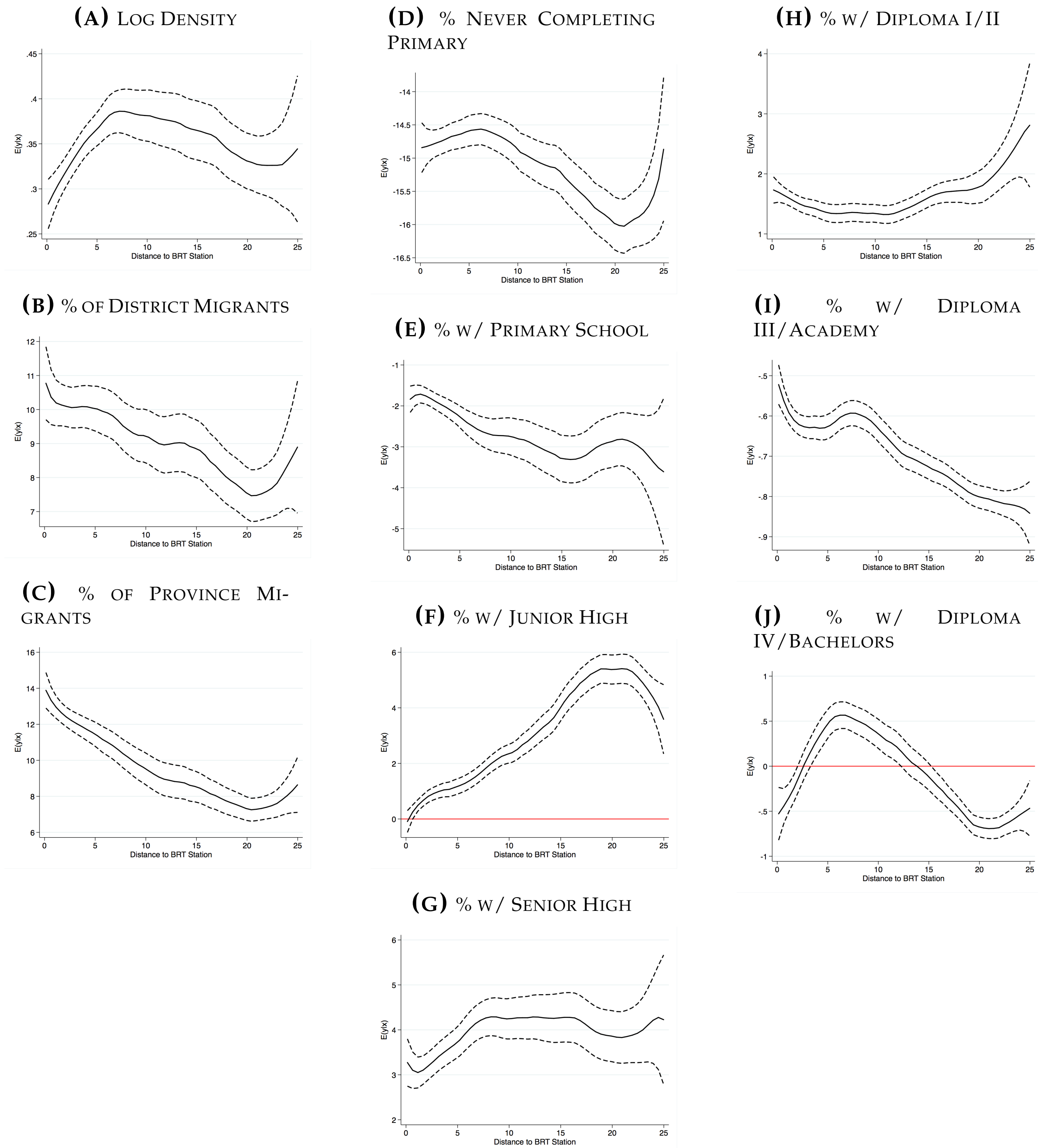
Notes: Each cell reports the coefficient from a regression of the given dependent variable (listed in the left-most column) on an indicator for whether or not the kelurahan is within 2 km of a BRT station. Columns 1-4 report a comparson of BRT kelurahan to all other kelurahan, while Columns 5-8 restrict the non-treated sample to include only kelurahan within 2 km of an unbuilt, placebo station. Columns 2 and 6 include pre-treatment controls, and Columns 3 and 7 report a double-robust specification that both includes controls and reweights non-treated districts by $\hat{\kappa} = \hat{P}/(1-\hat{P})$, where $\hat{P}$ is the estimated probability that the kelurahan is within 2 km of a BRT station. Columns 4 and 8 report a control function specification based on a Oaxaca-Blinder decomposition, described in Kline (2011). Robust standard errors are reported in parentheses and are estimated using a bootstrap procedure, with 1000 replications, in column 4 to account for the generated $\hat{\kappa}$ weights. Sample sizes vary across outcomes but include as many 290 "treated" kelurahan, 1370 non-treated kelurahan, and 152 placebo kelurahan. */**/*** denotes significant at the 10% / 5% / 1% levels.

Table A.8: Negative Spillovers: Impact of BRT on Travel Times (Treated vs. Placebo)

	(1)	(2)	(3)	(4)
1. All Trips	0.114	0.093	0.088	0.046
	(0.026)***	(0.028)***	(0.028)***	(0.035)
N	250824	250824	249467	136451
Adjusted R^2	0.554	0.555	0.553	0.534
Adjusted R^2 (within)	0.032	0.033	0.033	0.040
2. Train Trips	0.030	0.033	0.006	0.221
	(0.183)	(0.182)	(0.191)	(0.190)
N	6427	6427	6395	3565
Adjusted R^2	0.636	0.635	0.632	0.644
Adjusted R^2 (within)	0.031	0.031	0.031	0.051
3. Public Bus Trips	0.120	0.105	0.105	0.088
	(0.055)**	(0.059)*	(0.057)*	(0.065)
N	85306	85306	85066	48684
Adjusted R^2	0.513	0.514	0.512	0.481
Adjusted R^2 (within)	0.029	0.029	0.029	0.039
4. Private Car Trips	0.281	0.233	0.215	0.184
	(0.093)***	(0.096)**	(0.096)**	(0.164)
N	19591	19591	19549	9772
Adjusted R^2	0.580	0.581	0.581	0.578
Adjusted R^2 (within)	0.047	0.049	0.050	0.045
5. Private Motorcycle Trips	0.103	0.087	0.086	0.017
	(0.032)***	(0.034)***	(0.034)**	(0.049)
N	96906	96906	96285	51621
Adjusted R^2	0.521	0.522	0.518	0.482
Adjusted R^2 (within)	0.027	0.028	0.028	0.036
Year FE	Yes	Yes	Yes	Yes
Origin × Destination FE	Yes	Yes	Yes	Yes
Number of Trips		Yes	Yes	Yes
Origin Population Density			Yes	Yes
Destination Population Density			Yes	Yes
Non Peak-Time Trips				Yes

Notes: Each cell in this regression corresponds to a separate estimate of β from the specification (4) to assess the differential impact on travel times for trips originating and terminating within 1 km of a BRT station. The dependent variable is the log travel times, and the parameters are estimated from the pooled 2002 and 2010 HTS/CTS sample. In row 1, we use all trips, while the other rows restrict the sample to train trips (row 2), public bus trips (row 3), private car trips (row 4), and private motorcycle trips (row 5). In column 1, we include separate year fixed effects and origin-by-destination community (*kelurahan*) FE. In column 2, we include a control for changes in total number of trips made for each origin-by-destination pair over time. In column 3, we add controls for origin and destination populations density. Column 4 restricts the sample of column 3 to only include non-peak time trips. All columns include separate purpose-by-year effects and separate departure-hour-by-year indicators. Robust standard errors, two-way clustered by origin and destination community, are reported in parentheses. */**/*** denotes significant at the 10% / 5% / 1% levels.

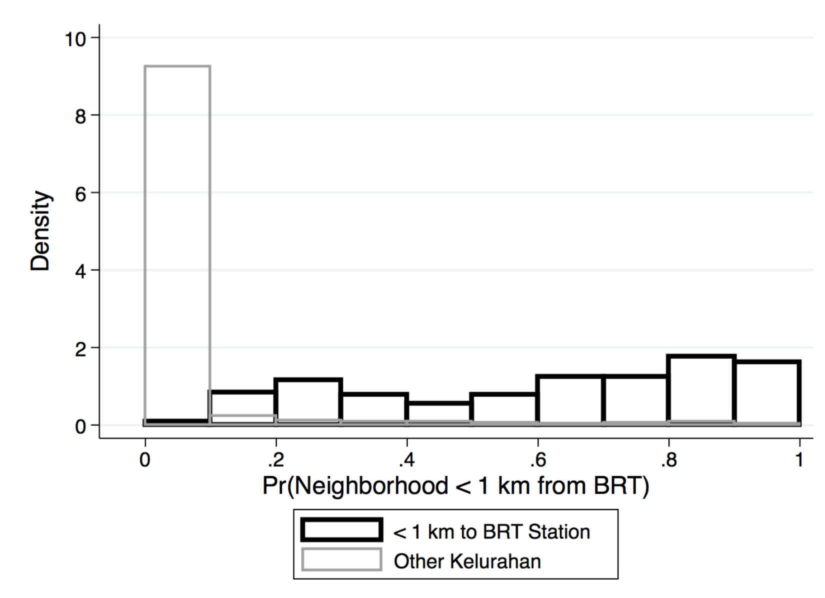
Figure A.1: Semiparametric Estimates: Changes in Census Outcomes



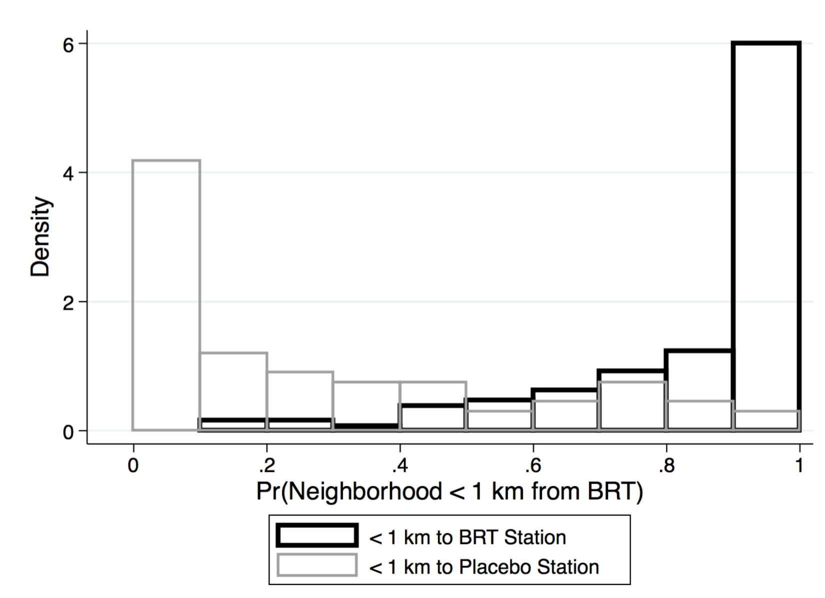
Notes: This figure reports regressions of the neighborhood change in density and the shares of the population with different levels of education on a flexible function of distance and a linear function of control variables. The different variables are listed in panel subtitles. These partially linear regression equations are described in (1) and is estimated following Robinson (1988), using an an Epanechnikov kernel and Fan and Gijbels (1996) rule-of-thumb bandwidth. Control variables include several variables measured in the 2000 census, including the percent of the neighborhood's population with different levels of educational attainment, the share of recent migrants (from another province and another district) in the neighborhood, and population density. From the 2002 JICA data, we also include baseline vehicle ownership shares (motorcycles and cars) and shares of the population with different income levels. Finally, we include levels and a square term of the distance between kelurahan c and the center of the city.

Figure A.2: Neighborhood Propensity Scores

(A) Treated vs. Non-Treated

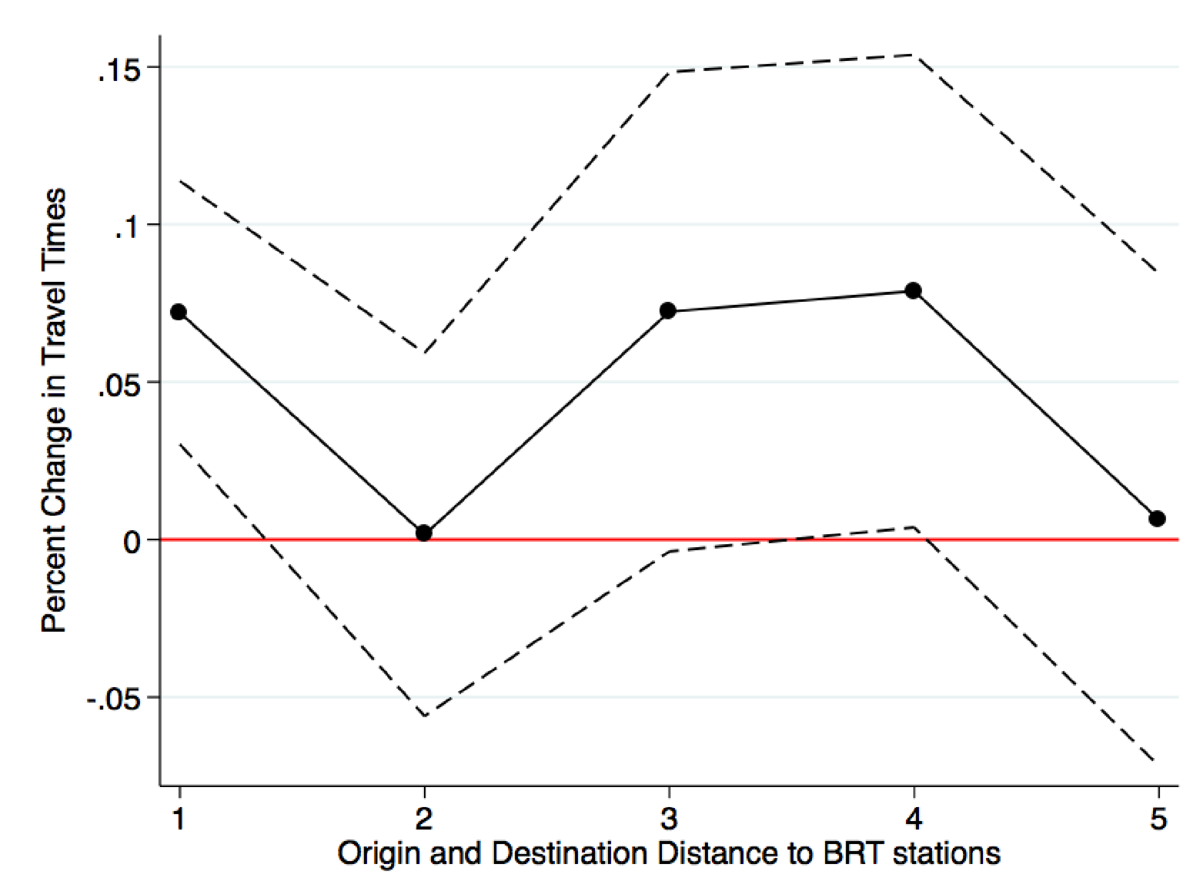


(B) Treated vs. Placebo



Notes: This figure plots the distribution across neighborhoods of the estimated probabilities of being within 1 km of a BRT station, based on the propensity score regressions reported in Appendix Table A.3. Panel A compares propensity scores for close proximity kelurahan to all other kelurahan, while Panel B restricts the comparison to only almost-treated kelurahan.

Figure A.3: Negative Spillovers: Impact of BRT on Travel Times by Distance



Notes: This figure reports estimates of β from the specification (4) to assess the differential impact on travel times for trips originating and terminating within d km of a BRT station. The dependent variable is the log travel times, and the parameters are estimated from the pooled 2002 and 2010 HTS/CTS sample. In this specification, we include several indicators for whether or not a trip originates within d km of a BRT station, terminates within d km of a BRT station, and we plot the separate effects of different interaction terms. The regression includes separate purpose-by-year effects and separate departure-hour-by-year indicators. Robust standard errors, two-way clustered by origin and destination community, are represented by the dashed lines.