# Life in the Slow Lane: Bus Rapid Transit and Commuting Outcomes in Jakarta*

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**Abstract**

This paper studies how TransJakarta, one of the world's largest BRT systems, affected commuting in Jakarta, one of the world's largest megacities. We compare changes in outcomes for neighborhoods close to BRT stations to changes for neighborhoods that were either eventually treated or are close to planned, unbuilt stations. Contrary to evidence on higher quality BRTs, we find that TransJakarta ridership was low and station proximity did not reduce motor vehicle ownership. Instead, motorcycle ownership rose throughout the city while public transit ridership fell. We also find that the BRT reduced road capacity and increased travel times along service corridors, exacerbating congestion. To uncover mechanisms behind these effects, we estimate an equilibrium model of commuting choices with endogenous commuting times. Counterfactual simulations suggest that the BRT would have improved if buses had been faster and if the network had expanded into neighboring municipalities.

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**Keywords**: bus rapid transit, congestion, public transit

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# 1 Introduction

In many developing countries, urbanization proceeds at an astonishing pace. The number of people living in urban areas in Asia increased by more than a billion people from 1980 to 2010, and the same figure for Africa is expected to triple between 2018 and 2050 (ADB, 2012; UN, 2019). Traffic is growing worse in many burgeoning cities, leading to unsustainable commuting times and deteriorating air quality (e.g. Brinkman, 2016; Simeonova et al., 2019; Lu et al., 2017). Cities now face a menu of policy options for alleviating congestion, including investments in public transit infrastructure, such as light rail, subways, or busways. How they implement such investments will have lasting effects, shaping commuting patterns for decades.

A small, but growing literature studies the effects of improved public transit on congestion and other commuting outcomes in developing country cities. Much of the literature focuses on some of the best implementations, but these are often expensive and difficult to replicate in cities with limited resources and weak governance. For instance, although subways have been shown to increase public transit ridership (Gonzalez-Navarro and Turner, 2018), reduce congestion (Yang et al., 2018; Gu et al., 2019), and improve air quality (Gendron-Carrier et al., 2018), building and operating such systems is costly. Many cities are instead turning to Bus Rapid Transit (BRT), which uses a network of dedicated busways to provide similar transport services as subways at a fraction of the cost. The highest quality BRT implementations, such as Bogotá's TransMileno and Lahore's BRT, have been shown to increase welfare, output, and overall public transit use (Tsivanidis, 2019; Majid et al., 2018). However, evidence on the effects of cheaper, lower quality implementations, which are more common in the developing world, is lacking.

In this paper, we contribute to this evidence by studying how the *TransJakarta* BRT system affected commuting outcomes for city residents. There are now BRTs in over 170 cities, including many in low and middle-income countries, with more planned for development.[1] TransJakarta was Southeast Asia's first BRT system and has become the world's largest system, with 12 primary routes and more than 200 stations. It serves a population of more than 30 million people living in Greater Jakarta, the world's second largest agglomeration and home to some of the world's worst traffic. It was also one of the least costly BRTs to develop, costing $1.4 million per kilometer, compared to $12.5 million per kilometer in Bogotá, Columbia (Flyvbjerg et al., 2008).

To evaluate the impact of TransJakarta, we use high quality data from two unique cross-sectional surveys: the 2002 household travel survey (known as the *Home Visit Survey* or HVS), fielded before the BRT opened, and the 2010 Commuter Survey (CS), fielded 6 years afterward. Both surveys were designed as 3 percent samples of the city's population, and over 160,000 households were interviewed in each wave. The data contain responses from nearly all communities (*kelurahan*) in Greater Jakarta, with a median of 300 observations per community per wave. The timing and representativeness of these data enable us to accurately assess changes in community-level outcomes. These surveys also provide information on household demographics and incomes, and they measure regular commuting patterns

[1] BRTs operate 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).

from travel diaries. We combine these data with community level aggregates from the household census in 2000 and 2010, as well as a variety of geospatial datasets.

We first examine how proximity to the BRT system affects commuting behavior. To address the endogenous placement of BRT stations, we construct two different comparison groups for communities close to BRT stations: (1) communities that were eventually treated by subsequent extensions to the BRT system, and (2) communities located close to a set of planned lines that have not yet been constructed. Further, we use an inverse probability weighting (IPW) approach that explicitly adjusts for potential *ex ante* differences in observable, pre-determined characteristics 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.

We find that BRT station proximity did not reduce incentives to own motor vehicles. Instead, from 2002 to 2010, motorcycle ownership increased throughout the city, from 37 percent of households owning at least one motorycle in 2002 to a staggering 75.8 percent in 2010, and TransJakarta did little to curb this rising motorization. Although we do find small positive effects of BRT station proximity on choosing the BRT as a main or alternative mode for transport, the overall mode share of 4.3 percent in 2010 is small compared to other BRT systems. For instance, in Bogotá, Colombia, the TransMilenio BRT had attained a 26 percent mode share after 7 years of operation. Over this period, the major changes in Jakarta's commuting choices came from people substituting away from public transport and into private vehicles, trends that are precisely what a well-designed BRT system would hopefully negate or counteract.

Despite low ridership, if the BRT resulted in a small reduction in vehicle volumes along service corridors, traffic congestion might have attenuated (Anderson, 2014). However, because the BRT system was built by converting mixed-use lanes into busways, the reduction in road capacity could have instead exacerbated congestion. Using origin-by-destination travel time regressions, we find that after TransJakarta was built, trips taken along its corridors had longer durations, suggesting that the BRT worsened congestion instead of alleviating it. Increased delays are found for most modes of transit, including the traditional public bus system, cars, and motorcycles—and were largest during peak travel times. The effects on trains were insignificant, which is expected given that the BRT system did not compete with trains for space. Our results are robust to a number of controls for differential increases in demand that might have explained the observed increase in travel times.

Next, we explore whether a better implementation of the BRT system could have improved ridership. BRT implementations vary widely: high-quality systems have fully segregated busways, GPS-based service planning, peak frequency buses, and comfortable stations. In addition, well-implemented systems have stations whose placements are more optimal. Differences in implementation quality affect key system attributes — such as operating speed, comfort, and the span of its network — and may contribute to different outcomes. However, there is no exogenous variation in these attributes that we can use to quantify the relative importance of different mechanisms. To better understand why TransJakarta's ridership was so low, we develop an equilibrium model of commuting behavior and use it to simulate the impact of improving the BRT.

In the model, commuters choose a mode of transit and a departure time to maximize utility. They have preferences over many different choice attributes, some of which may be unobserved. Preferences are modeled using 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). To account for the endogeneity of travel speeds along a particular route, we implement a novel instrumental variables (IV) strategy for estimating demand that uses cost shifters from traffic on overlapping routes. The IV has a strong first stage and generates more realistic substitution patterns than naive OLS estimates. Traffic routes are also congestible, and as more vehicles travel simultaneously along the same routes, travel times increase. Following Couture et al. (2018) and Akbar and Duranton (2017), we specify and estimate Cobb-Douglas cost-of-travel functions that capture these relationships. We also implement an IV strategy that relies on time-of-day demand shifters to identify cost curve parameters.

We use the model to simulate different counterfactual improvements in BRT system attributes. We first predict how changing those attributes results in changes in demand. Consider, for example, an increase in BRT comfort. This should raise demand for the BRT, leaving fewer vehicles on the roads. Now, based on the travel cost curves, travel times along those roads should fall slightly, and that could encourage greater private transport ridership, counteracting the positive BRT ridership effects. We iterate between changes in demand and travel costs until we converge at a new counterfactual equilibrium.

Our findings from policy simulations suggest that TransJakarta's slow, uncomfortable buses limit demand. A 20 percent increase in BRT speeds or a 20 percent increase in comfort would both increase BRT ridership by 50 percent. Expanding the network by building TransJakarta's planned lines would similarly increase ridership, but such a policy would presumably be more costly. However, if the BRT system were improved, much of the increase in ridership would come from individuals substituting away from other public transit modes. A similar increase in overall total public transit ridership that would result from these BRT improvements could be achieved with a moderate congestion charge levied for operating private modes in the city center during peak times.

This paper contributes to a growing literature evaluating the impacts of different transport policies in developing country cities.[2] It also complements a sizeable literature estimating the costs and benefits of public transit in developed countries (e.g. Voith, 1991; Baum-Snow and Kahn, 2000; Baum-Snow et al., 2005; Winston and Maheshri, 2007; Parry and Small, 2009). A large body of transportation research also evaluates BRT systems, but that literature tends to focus on performance metrics which may be less useful for program evaluation, 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).

Two recent papers similarly evaluate the impact of high-quality implementations of BRT systems in developing country cities. Tsivanidis (2019) finds that Bogotá's TransMilenio system increased average welfare by 1.5 percent and output by 1.1 percent, net of construction costs, while Majid et al. (2018) finds that the BRT system in Lahore increased overall public transit use by 30 percent. However, both systems are atypical as they represent among the best BRT implementations.[3] Our paper evaluates a

[2] Apart from several previously cited studies of improved infrastructure (subways and BRT systems), Hanna et al. (2017) study the congestion effects of HOV policies in Jakarta, while Davis (2008) and Viard and Fu (2015) examine the effects of odd-even license plate policies on driving and pollution in different contexts. Ang et al. (2018) study the effects of speed limits on traffic accidents and driving times in Sao Paolo, Brazil.

[3] For instance, among BRT corridors whose operating speed data were available, the operating speed of both TransMilenio and the Lahore BRT are around 26 km/hr, which is significantly faster than the operating speed of the median BRT system of 21 km/hr (or 20 km/hr for the subset in developing country cities). In contrast, the operating speed of TransJakarta is around 19 km/hr. Moreover, TransMilenio corridors were regularly considered the Gold standard of BRT implementation (ITDP, 2017).

lower quality implementation that is more commonly seen in developing country cities.[4] The lackluster findings of TransJakarta may also provide insight for why several BRT systems have recently failed and been dismantled.[5]

Our work also contributes to several strands of literature on estimating equilibrium models of urban travel. Small and Verhoef (2007) survey travel demand models that focus on mode choice, but we extend those models to encorporate departure time choices to evaluate the impact of more flexible transport policies, like congestion pricing. For travel cost functions, 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).[6] Our model is closest in spirit to Akbar and Duranton (2017), which attempts to separately identify cost curves from demand, but instead of estimating the deadweight loss of congestion, our focus is on using the model to explore mechanisms behind TransJakarta's low ridership and ways to improve it.

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 discusses our reduced form results of the impact of station proximity on vehicle ownership, commuting choices, and congestion. Section 6 presents a model of equilibrium commuting choices and describes how we use our data to identify parameters, estimate them, and conduct policy simulations. Section 7 presents results of estimating the model and simulating counterfactual policies. Section 8 concludes.

## 2 Congestion in Greater Jakarta 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, including the districts and municipalities of Bogor, Bekasi, Depok, and Tangerang. Together, this metropolis is known as Greater Jakarta (*Jabodetabek*) and was home to over 31 million people in 2015, making it one of the world's largest agglomerations.[7] According to several independent assessments, Jakarta also has some of the world's worst traffic, making traversing the city both frustrating and unpredictable.[8]

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[4]The Institute for Transportation and Development Policy (ITDP) regularly rates BRT systems according to various technical criteria. Of the 122 corridors around the world that it has evaluated, most have mediocre-to-poor quality and achieve less than its Silver standard. Only roughly 11 percent attained the Gold standard (ITDP, 2017). None of TransJakarta's corridors received a Gold standard, and only one received the Silver standard in 2013.

[5]Systems constructed in several countries, including Thailand (Bangkok), Taiwan (Taichung), and India (Dehli, Pune, Indore, Jaipur), were subsequently dismantled (Pojani and Stead, 2017).

[6]An important exception is Geroliminis and Daganzo (2008), which uses high frequency vehicle counts data from road censors in Yokohama, Japan.

[7]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 world's second most populous agglomeration after the greater Tokyo area, while Brinkhoff (2017) lists Jakarta as the world's fourth most populous agglomeration.

[8]From data on vehicle starts, stops, and idling times, Castrol (2015) measured traffic congestion in 78 cities worldwide and found that Jakarta had the worst traffic in the world. Waze (2016) used floating car data from its driving app to construct a driver satisfaction index for 186 cities, finding that Jakarta had the 10th worst overall driver satisfaction and the 2nd worst traffic rating. However, in 2016, the INRIX Global Traffic Scorecard ranked Jakarta 22nd out of 1064 cities in terms of peak hours spent in congestion, with 22 percent of overall driving time spent in congestion (INRIX, 2016). Note that Jakarta does not ap-

Rapid growth and weak urban planning have both led to chronic congestion in Jakarta. Income growth has spurred demand for private vehicles, as cars and motorcycles are often seen as positive signals of social status (Susilo and Joewono, 2017). On the other hand, national policies such as fuel subsidies and road construction programs have also encouraged greater private vehicle ownership (Savatic, 2016; Hook and Replogle, 1996). The various agencies responsible for managing land use and urban planning in Jakarta have also generally been ineffective in dealing with rising motorization (Susantono, 1998; Goldblum and Wong, 2000).[9]

After several failed attempts at mass transit, Jakarta's governor Sutiyoso (1997-2007) developed the TransJakarta BRT system to alleviate congestion.[10] BRT systems provide dedicated right of way lanes for buses and use a network of stations where buses pick up and drop off passengers. TransJakarta began operation in 2004 with an initial 13.6 km north-south corridor, but it expanded services throughout DKI Jakarta over time. By January 2018, TransJakarta had 12 operating corridors and more than 200 stations, and it was the world's largest BRT system, with a total system length of over 200 km.

Although the system is expansive, it operates on less than 3 percent of DKI Jakarta's total road length. By only serving the DKI Jakarta area, its corridors do not connect workers in the surrounding municipalities to jobs in the center. Panel A of Figure 1 provides a map of the system's corridors, which depicts both the locations of lines and stations as of mid-2010 (in black), and the locations of eventually constructed lines and stations (in red). In mid-2010, the system had 159 stations on 9 corridors, but by January 2018, the system had expanded to 196 stations and 12 corridors.

A major benefit of BRT systems is that they are cheaper to construct and easier to expand than public transit alternatives, such as subways or light rail. For instance, constructing a BRT system typically costs 4-20 times less than an light rail system and 10-100 times less than a subway system (Wright and Hook, 2007). In fact, TransJakarta BRT was relatively inexpensive even for a BRT system: its construction cost was $1.4 million per km, compared to TransMilenio's $12.5 million per km (Flyvbjerg et al., 2008) or Lahore BRT's $11 million per km (Majid et al., 2018).

Although constructing TransJakarta was relatively inexpensive, the cost savings often reflected lower quality infrastructure design. Instead of creating new lanes with overpasses separating BRT buses from other traffic, the system largely converted existing roadspace into busway lanes. Satellite imagery confirms that the number of lanes reserved for mixed traffic fell after the BRT system was implemented.[11] The system's design also did not include passing lanes, creating bottlenecks when TransJakarta buses broke down. Finally, the original TransJakarta buses only had a single front passenger door, slowing boarding and alighting speeds (ITDP, 2017).[12]

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pear on other international traffic monitoring surveys, such as the Tom Tom Traffic Congestion Index, and the methodologies between international comparisons differ.

[9] Hook and Replogle (1996) discusses how some policies to encourage private, motorized transport use may stem from crony capitalism under the Suharto regime.

[10] Unsuccessful transit efforts in Jakarta included establishing a curbside bus-only lane (which was poorly enforced), a monorail line (which was started but never completed), and a subway system, which was only completed in April 2019 (Ernst, 2005).

[11] Appendix Figure A.1 uses Digital Globe satellite imagery to monitor changes in the number of lanes between 2003 (before the system opened) and 2010 (see also the example in Appendix Figure A.2). Overall, the average road around TransJakarta BRT stations lost 1.2 lanes from 2003 to 2010, our sample endpoint. 9 Corridor 1 stations (45 percent) saw no lane reductions. The average corridor 1 station lost only a single lane. 60.5 percent of bronze stations and 46.4 percent of basic stations lost 2 or more lanes of traffic after the BRT was constructed.

[12] Several other implementation problems also plagued TransJakarta during its initial roll out. Funding for TransJakarta came entirely from the DKI Jakarta government, but decisions about the system's design, procurement, and operation were split

As TransJakarta expanded, newer lines tended to have poorer service quality than the original corridor. The Institute for Transportation and Development Policy (ITDP) scores all BRT systems on various criteria and issues standards for their implementation and performance.[13] In 2014, ITDP scored different TransJakarta corridors, and these scores are reported in Table 1. No corridor reached the "Gold" standard attained by TransMilenio, and only Corridor 1 had attained a "Silver" rating. The remaining corridors, developed subsequently to Corridor 1, were rated either "Bronze" or "Basic BRT".

As part of a feasibility study for Greater Jakarta's Integrated Transportation Master Plan, JICA (2004b) contains maps of several BRT corridors and stations that were planned for completion by 2010. These planned lines, which extend beyond the DKI Jakarta boundary, appear in red in Figure 1, Panel B. Although the planned lines were encorporated into Jakarta's Master Spatial Plan for 2010, they have yet to be developed, largely due to jurisdictional issues between the DKI Jakarta government and the surrounding municipalities (JICA, 2004a).

## 3 Data

To study how Jakarta's BRT system impacted commuting outcomes for residents, we combine several high-quality, spatially disaggregated data sources. These include two rounds of high-frequency commuter travel surveys, population censuses, and geospatial datasets. We briefly describe these data sources here, leaving many details for Appendix C.

**Commuter Travel Surveys.** Our main analysis uses two rounds of unique commuter travel surveys, conducted by the Japan International Cooperation Agency (JICA) in 2002 and 2010. JICA researchers designed and fielded these surveys as part of their Study on Integrated Transportation Master Plan (SITRAMP), a technical assistance project designed to promote policies encouraging greater mobility in Jakarta. The first round of the household travel survey, known as the Home Visit Survey (HVS), was conducted in 2002 and recorded detailed information on the regular travel patterns, mode choices, vehicle ownership, and demographic characteristics of more than 160,000 households.[14] A second round, the 2010 Commuter Survey (CS), was a follow-up to the first survey and contained similar information on nearly 179,000 households.[15]

The JICA surveys have several features that are unique to an urban developing country setting. First, the surveys are large and representative at the community (*kelurahan*) level, which is the lowest admin-

between two different agencies: the Department of Transportation (*Dinas Perhubungan*, or *Dishub*) and TransJakarta. Because DisHub earned significant revenues by selling and allocating bus route licenses to bus companies, they were unwilling to eliminate bus services that competed with BRT routes. As a result, competing bus services continued to run in mixed traffic lanes parallel to the new busways (ITDP, 2017). Moreover, existing bus services were not integrated with the new BRT corridors and stations, resulting in the absence of a feeder bus system.

[13] ITDP scores BRT systems based on several criteria, including: (i) BRT basics (dedicated right of way lanes, busway alignment, etc.); (ii) service planning (multiple routes, location in high demand corridors, etc.); (iii) infrastructure (passing lanes at stations, minimum bus emissions, etc.); (iv) station attributes (distance between stations, safety, comfort, etc.); (v) communications; and (vi) access and integration. Points are also deducted for several reasons, including: (i) slow speeds; (ii) poorly enforced right of way; (iii) poor maintenance; (iv) low peak or off-peak frequency. Based on these scores, systems (and corridors within systems) are assigned standards ratings: Gold, Silver, Bronze, or Basic BRT. Gold-standard BRT systems are consistent with international best practices, achieving high levels of operational performance and service quality.

[14] Household income and expenditure were also collected, but these measures are discretized into 7 bins, instead of being reported as continuous variables.

[15] These sample sizes are quite large and similar to those used in various waves of the U.S. National Household Travel Survey (NHTS), which covers the entire United States. The 2017 NHTS had a sample of 130,000 households.

istrative unit in Indonesia and comprises our main spatial unit of analysis.[16] Both waves were designed to be 3 percent samples of households in the city and contain observations in almost all of the roughly 1,600 communities in Greater Jakarta. In 2002 and 2010, the median community had over 200 and 300 individual-level observations, respectively. The spatial coverage and representativeness allow us to calculate neighborhood-level means with relative accuracy, an unusual feature for an urban developing country setting. Although the data represent repeated cross sections of the Greater Jakarta population, in some analyses, we use survey weights to aggregate the data by community-year, obtaining a panel of neighborhoods.

Another critical feature of the dataset is its trip-level information. The surveys collected data on trips regularly taken during a typical workday for all respondents in each household. In 2002, the HVS asked respondents about all trips regularly taken on a typical weekday (Tuesday-Thursday) for all purposes, including work-related trips, school trips, and trips for leisure or shopping. The 2010 CS only asked about trips made for school or work purposes. Therefore, we only consider work and school-related trips in our analysis. In both years, the trip-level data contain a variety of attributes, including origin and destination information by community, trip purposes, modes used for all links on the trip chain, transfers, departure times, arrival times, and costs or fees incurred during travel.

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). After dropping observations with missing modes, travel times, 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). Following Akbar and Duranton (2017), we denote these trips as the set of "well-defined trips". Note that trip distances are imprecisely measured, because exact departure and arrival addresses and trip routes were not recorded in the data. We use centroid distance (as the crow flies) between communities to measure trip distance.[17]

**Community-Level Characteristics: Demographics and Economic Activity** We combine the commuter survey data with a variety of datasets to measure community-level attributes. First, we construct community-level demographic characteristics by aggregating the individual-level data from the 2000 and 2010 Indonesian Population Censuses. The census data allow us to construct multiple measures, including the size of the local population, levels of educational attainment, and migration shares. Second, as a proxy for community-level economic activity, we use satellite data on nighttime light intensity produced by the United States Air Force Defense Meteorological Satellite Program (DMSP).

**Geospatial Data on Administrative Boundaries, Infrastructure, and Topography.** Our analysis relies on administrative shapefiles containing community-level boundaries, created by Indonesia's national statistical agency, *Badan Pusat Statistik* (BPS). We also use on detailed digital maps of Jakarta's roads, railroads, and BRT lines and stations. Some of these maps were produced by JICA for their field work and policy reports. Others were derived from Open Street Map and produced by the authors using GIS

[16]Greater Jakarta is divided into roughly 1,600 *kelurahan*, which we term communities in our analysis. In the year 2000, the median community in Greater Jakarta had an area of 3.2 square kilometers and was home to nearly 9,000 residents. In 2010, the median community had a population of nearly 13,000. Communities in Greater Jakarta tend to be smaller than both counties and zip codes in major U.S. urban areas; for instance, the New York-Newark-Jersey City, NY-NJ-PA Metropolitan statistical area consisted of 23 counties and 576 zip codes.

[17]For trips that take place entirely within the same community, we use an average distance measure. This is calculated by randomly sampling 100 points in each community and calculating the average distance between those points.

software. Data on locations of planned stations are from JICA. Finally, we use the *Harmonized World Soil Database (HWSD)* to construct basic topographic characteristics of these communities (e.g., ruggedness and elevation).

# 4 Characterizing Greater Jakarta's Urban Form

To put TransJakarta in context, this section describes Greater Jakarta's evolving spatial structure and its commuting patterns. We first summarize economic and demographic characteristics of the metropolitan area. We then link these characteristics to a description of residents' commuting mode choices. Finally, we summarize their commuting trips.

**Residential and Workplace Locations** Employment in Jakarta is largely service-sector oriented, and most employers are located in DKI Jakarta. Figure 2, Panel A presents a map of employer locations, showing the probability that an individual works in a community based on the 2010 CS data. The greatest employment probabilities in Greater Jakarta are found in the center of the city; however, some employment has shifted away from the city center and other centers are located in different places in the metropolitan region. From 2000 to 2010, Greater Jakarta also experienced population rapid growth, adding 7 million more people to its total population. This amounts to an annual population growth rate of 3.6 percent per year. However, growth was more pronounced in the peripheral regions of the metropolitan area, just outside of DKI Jakarta borders (depicted in thick black) and symptomatic of urban sprawl. Panel B of Figure 2 depicts population growth across communities, with darker areas corresponding to faster growth.

Because such a large share of Greater Jakarta's population does not reside in DKI Jakarta but instead lives in the surrounding municipalities, the TransJakarta BRT system does not adequately connect workers and firms. In Appendix Table A.1, we report the share of the population in 2002 that lives and works within different distances of BRT stations (built by 2010). In 2002, only 12.7 percent of the population of Greater Jakarta lived and worked within 1 km of a BRT station. This share fell to 9.4 percent in 2010, as workers and firms continued locating beyond the central city where BRT stations are located.

**Vehicle Ownership and Commuting Mode Choice** Between 2002 and 2010, the number of workers living farther from their jobs increased, stimulating demand for travel (Turner, 2012). Over the same period, Jakarta also experienced a dramatic increase in vehicle ownership, especially motorcycles. Panel A of Figure 3 shows that the share of households owning at least one motorcycle more than doubled, from 37.0 percent in 2002 to a staggering 75.8 percent in 2010. Although some of the expansion in motorcycle ownership could be explained by per-capita income gains, 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).[18] Car ownership also increased from 2002 to 2010, but not as dramatically as motorcycle ownership.[19]

[18] Yagi et al. (2012) also document rising motorcycle ownership but use a different data source: the number of registered vehicles in DKI Jakarta. During the same time, the number of registered cars doubled, while the number of registered motorcycles more than quadrupled. Note also that according to the 2010 CS over 20 percent of households owned more than one motorcycle, and nearly one third of the lowest-income households surveyed owned a motorcycle.

[19] Income growth also explains some of these findings, and Senbil et al. (2007) shows that the share of motorcycle and car ownership in Greater Jakarta increases with income. However, unlike the case of cars, the share of motorcycle ownership

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.[20] Using this definition, Panel B of Figure 3 shows how changes in vehicle ownership have significantly altered mode choice patterns. In 2002, the traditional public bus system was the most popular commuting mode with a 52.3 percent share, but by 2010, this share had fallen to 23.4 percent.[21] By 2010, the most popular commuting mode was private motorcycles. During the sample period, 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 may 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).[22]

**Commuting Characteristics** Table 2 contains summary statistics for all well-defined trips. 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. In 2002, 50 percent of trips in the data took place within a single community, and this share increased slightly in 2010.

In Appendix Table A.2, we regress log travel times on trip characteristics and a year indicator to measure overall changes in travel times. Column 1, which only controls for distance, demonstrates that overall travel times fell by 11.6 percent between 2002 and 2010. However, nearly all of this reduction can be explained by differences in trip characteristics, departure times, mode choices, and the mix of origins and destinations. When we control for these effects in Column 4, the time savings fall to 3.2 percent. Although statistically significant, this effect is not economically meaningful, representing only a minute of time savings for an average trip duration.

## 5 Did TransJakarta Change Commuting Behavior or Reduce Congestion?

This section presents our reduced-form estimates of the impact of TransJakarta BRT on mode choice, vehicle ownership, and congestion. We begin by motivating our identification strategy to address endogeneity in the placement of BRT stations. Next, we estimate the average treatment effect on the treated (ATT) of TransJakarta station proximity on outcomes. Finally, we examine whether the BRT alleviated congestion by measuring its impact on travel times for other modes along BRT corridors.

actually declines for the top 3 income groups in the JICA data. See Appendix Figure A.3 for more detail.

[20]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.

[21]The traditional public bus system consists of several independent private bus operators with fleets of minivans and small buses. Although they follow set routes in Jakarta, traditional public buses do not keep a fixed schedule, and drivers are compensated on a per-fare basis, so that they compete for riders. Traditional buses 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).

[22]Note that BRT's small mode share also persists in data collected subsequent to our sample, even after TransJakarta was transfered to private management and service quality improved. In 2014, BPS conducted a commuter survey in Greater Jakarta and found that the overall TransJakarta mode share was only 2.5 percent (see Appendix Figure A.4). Witoelar et al. (2017) also find similar mode share results for a survey of females in DKI Jakarta in 2016.

### 5.1 Comparing Treated and Almost-Treated Neighborhoods

A primary concern in studying the impact of BRT station proximity is that because station locations are not randomly assigned, naive estimates may be confounded with selection bias. To illustrate this concern, Table 3 summarizes a number of community-level characteristics. Each variable was measured before the TransJakarta BRT system became operational in 2004. The first set of columns report statistics for the 140 "treated" communities, defined as communities located within 1 km of the nearest BRT station in mid-2010.[23] The second set of columns reports the difference in means between these treated communities and the other 1,359 "non-treated" communities in Greater Jakarta that were located more than 1 km away from a BRT station by mid-2010.

Panel A shows that compared to all non-treated communities, communities close to BRT stations are denser, more educated, and have a greater share of migrants arriving in the last five years (henceforth "recent migrants") from different districts. These differences are all significant at the 1 percent level.[24] Panel B suggests that individuals living in treated communities tend to be older and earn more income than individuals in non-treated communities. They are also more likely to own a motorized vehicle, less likely to take public transport or taxi services, and are more likely to choose cars as their main mode of transport. Finally, Panel C suggests that relative to non-treated communities, treated communities were closer to the city center and had a smaller land area, lower elevation, and greater nighttime light intensity in 1992. Overall, these findings suggest that BRT stations were constructed in positively selected areas.

We address the potentially endogenous placement of BRT stations by limiting our comparison group to 134 "almost-treated" communities — defined as the subset of non-treated communities that were either: (i) within 1 km of a planned BRT station that was eventually constructed after mid-2010; or (ii) within 1 km of a planned BRT line in 2010 (as depicted in Figure 1). Column 5 reports the unadjusted difference in means between treated and almost-treated communities. Several differences in Column 3 become statistically insignificant, while those that remain significant tend to be much smaller in magnitude. The major exception is that the migration patterns between treated and almost-treated communities differ; relative to the treated communities, almost-treated communities have a greater share of recent migrants, possibly reflecting recent sprawl into these areas.

We further improve identification using propensity-score re-weighting. The weights come from a first-step estimation of the probability of BRT station proximity as a function of predetermined community-level variables, such as population density, education, income, economic growth, and migrant shares, all of which may have influenced station locations.[25] Column 6 reports differences in weighted means

[23]TransJakarta surveys of ridership indicated that nearly 90 percent of customers walked less than 1 km to the BRT stations (ITDP, 2017, p. 951). Note that in constructing distance variables, we coded a community as "close" to a BRT station if at least some portion of the community's polygon was less than 1 km from a BRT station. This differs slightly from the typical centroid distance measure.

[24]In comparing communities based on their pre-treatment characteristics, we regress the outcome variable on a treatment indicator, clustering standard errors at the sub-district level. Significance levels are taken from the p-values of these treatment indicators. See the notes to Table 3 for more detail.

[25]This vector includes 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 district) in the neighborhood, and population density. From the 2002 HVS data, we also include shares of the population with different income levels and shares of trips made from the community into communities located in DKI Jakarta. Finally, we include log distance to *Kota Tua*, the original center of the city, as well as elevation, ruggedness, night light intensity in 1992, night light intensity growth between 1992 and 2002, and the area of the neighborhood. Appendix Table A.3 reports our estimated propensity scores across all neighborhoods (Column 1) and for the treated vs. planned and eventual comparison (Column 2). Despite using only a

between treated and almost-treated communities. Overall, the differences in weighted means fall substantially and are only significant in a handful of cases.

### 5.2 Average Treatment Effects of Station Proximity on Treated Communities

To obtain ATT estimates of proximity to a BRT station, we estimate parameters of the following regression equation:

$$\Delta y_c = \alpha + \theta T_c + \mathbf{x}_c' \beta + \varepsilon_c \quad (1)$$

where $c$ indexes communities, $\Delta y_c$ is the before-after change in outcome $y_{ct}$ for community $c$, $\mathbf{x}_c$ is a vector of predetermined controls (described in Footnote 25), and $\varepsilon_{ct}$ 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; $\theta$ measures the close-proximity treatment effect.

As discussed above, we address the non-random assignment of $T_c$ by first limiting our sample to only treated and almost-treated communities. We then implement 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 likely influenced the selection. In particular, we implement both the Robins et al. (1995) two-step, double-robust estimator for $\theta$ and the Oaxaca-Blinder re-weighting 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.

Table 4 reports estimates of $\theta$, with robust standard errors, clustered at the subdistrict (*kecamatan*) level in parentheses.[26] These results shows scant evidence that close proximity to a BRT station affected vehicle ownership (Rows 1–2). We observe no robust, statistically significant differences in vehicle ownership growth between close-proximity communities and almost-treated communities. Although the confidence intervals vary in length, our estimates of the impact on growth in motorcycle ownership are fairly precise: we can reject that BRT access reduced motorcycle ownership growth by 4 percent. This is a small effect given that the median community experienced a 39.4 percent increase in motorcycle ownership, and it is equal to about one fifth of the standard deviation of community-level motorcycle ownership growth. The precise null is also disappointing in light of the potential for public transport to reduce incentives to own motor vehicles.

We do find evidence for small positive effects of proximity to BRT stations on choosing BRT as the main and/or alternative mode of transport (Rows 3 and 4), although the estimates are not always robustly significant.[27] Column 4 reports the preferred, Oaxaca-Blinder estimate of a 4.3 percentage point increase in the likelihood of choosing BRT as a main or alternative mode. However, this statistically significant difference is not economically meaningful relative to the widespread increase in motorcycles ownership and use of other public transit. The final set of rows examine the impact of BRT proximity on

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.5 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 overlap improves with the treated and almost-treated comparison.

[26] *Kecamatan* is the second-lowest administrative unit in Indonesia. In Jakarta, an average *kecamatan* comprises roughly six communities (*kelurahan*).

[27] These mode share outcomes are equal to zero in 2002, since this mode was unavailable at baseline.

changes in other mode shares, finding no significant differences.

Our results on the impact of TransJakarta on mode choice and vehicle ownership compare unfavorably to other, better implemented systems. For example, the impact of station proximity on BRT adoption is much smaller than estimates of effects in Lahore, Pakistan where the BRT system increased public transit use by an estimated 30 percent in nearby areas during the same period of operation (Majid et al., 2018). Similarly, Bogotá's TransMilenio BRT system, which opened in 2000, had attained a mode share of approximately 26% by 2007 (Cain et al., 2007).

Furthermore, we also find that even for neighborhoods with the greatest station proximity, TransJakarta BRT use is quite small relative to other settings. To demonstrate this, we estimate a partially linear regression function of the following form:

$$y_c = \alpha + f(d_c) + \mathbf{x}_c'\beta + \varepsilon_c \,, \tag{2}$$

where $c$ indexes communities, $y_c$ denotes community $c$'s BRT mode share in 2010, $d_c$ is a continuous measure of distance to the closest BRT station in 2010, and $\mathbf{x}_c$ is a vector of predetermined controls (described in Footnote 25). The distance function, $f(\cdot)$ is allowed to be flexible, and we estimate (2) semi-parametrically, following Robinson (1988). The resulting estimate in Figure 4 shows that the BRT mode share peaks out at just over 6 percent at areas very close to stations, dipping to below 4 percent in intermediate distances. As we show next, these null results for the effects of TransJakarta on vehicle ownership and mode choice are robust to many different empirical specifications.

**Continuous Treatment.** Appendix Table A.4 reports results from linear regressions of changes in vehicle ownership and commuting modes on a continuous measure of distance to stations. Column 1 reports OLS estimates, while in Columns 2-4, we use planned and eventual station distances as instrumental variables for actual station distances. All regressions include the same set of pre-determined controls as in (1). These results largely support our main findings that BRT-station proximity neither curbed vehicle ownership nor increased public transit use.

**Varying Treatment and Non-Treatment Definitions.** The one-kilometer threshold we use to define a community's treatment status is often used in empirical work and consistent with walking behavior of commuters in Jakarta (see Footnote 23). Appendix Table A.5 shows that our mode-choice results are robust to alternative distance thresholds used to define treatment status. Alternatively, spillovers of the treatment effect between closely located treated and non-treated neighborhoods could be producing our null results. Appendix Table A.6 shows that our main results are mostly unchanged when we drop neighborhoods that are greater than 1 km but less than 2 km away from BRT stations in 2010.

**Alternative Propensity Score Specifications.** We next explore the robustness of our estimates to different choices for pre-determined controls variables in estimating the propensity score ($\mathbf{x}_c$). Appendix Table A.7 reports how our original Oaxaca-Blinder estimates (Column 4 of Table 4, reported in Column 1) change when we use only geographic controls (Column 2), only demographic controls (Column 3), or the full set of pre-determined covariates (Column 4).[28] Overall, our main results remain robust to these different specifications.

[28] The original, geographic, and demographic controls are described in Footnote 25. The full set of baseline controls includes baseline measures of vehicle ownership, mode choice shares, incomes, and various light intensity measures.

In Appendix Table A.8, we also implement two different machine learning procedures to select controls for the propensity score and estimate treatment effects. Columns 1 and 2 report our original linear regression with controls and logistic reweighting estimates (Columns 2 and 3 of Table 4). In Column 3, we implement the Belloni et al. (2014) post-double selection estimator, selecting separate controls for the propensity score and the outcome equation by choosing from the large set of controls discussed in Footnote 28 to minimize a Lasso objective function. In Columns 4 and 5, we used generalized boosted regression models to estimate the propensity score, following McCaffrey et al. (2004). Point estimates and confidence intervals under these approaches are very similar to our original results.

**Treatment Effect Heterogeneity.** Appendix Table A.9 explores the possibility that the muted effects were driven by competing heterogeneous treatment effects. Separate analyses by gender (Columns 2 and 3), education (Columns 4 and 5), and total monthly household expenditures (Columns 6 and 7) show that our main null results are fairly robust across these different splits.[29]

**Sorting.** Sorting may drive our results if, for example, areas with BRT stations attracted migrants who were less likely to demand public transportation. Appendix Table A.10 increasingly adds a series of (bad) demographic controls to our original Oaxaca-Blinder specification (Table 4, Column 4). Column 2 controls for changes in density and migration shares, Column 3 adds changes in education shares, and Column 4 adds changes in monthly household expenditure 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.[30]

**Effects on Demographics and Housing.** Although our main results focus on the effects of the TransJakarta BRT system on vehicle ownership and mode choice, we present a similar set of results for changes in demographic and housing outcomes in Appendix B. We find no significant effects on changes in population density or average years of schooling. However, we do find faster growth in the number of single family homes in non-treated areas, which could either reflect lower density sprawl in non-treated areas or densification near treated areas. These results survive a similar set of robustness checks as do our main results presented in Table 4.

### 5.3 Effects on Travel Times and Congestion

A well-designed transit system could reduce congestion despite low ridership. If transit lines are located on important and frequently used corridors, a small reduction in vehicle volumes along those corridors could substantially increase speeds and reduce travel times.[31] However, a transit system that reduces road capacity could plausibly do the opposite. As we discuss in Section 2, the TransJakarta BRT system

[29]We find some suggestive evidence, however, that the main or alternative BRT effect may be coming from males. Witoelar et al. (2017) show that many females are concerned about safety while riding the BRT. TransJakarta has enacted several policies trying to increase female ridership, including providing female-only BRT cars.

[30]If people with strong tastes for public transportation moved in to treated areas, this would cause us to overestimate the average impacts of the program in the absence of sorting. The absence of strong program impacts reduces concerns over this type of sorting bias.

[31]As Anderson (2014) points out for the case of the Los Angeles bus and rail lines, these congestion-reducing effects are one way to rationalize public transport subsidies despite low ridership.

was built by taking away lanes of traffic from other modes and dedicating them for BRT buses. This reduction of traffic lanes could have exacerbated congestion and increased travel times for other modes traveling along BRT corridors.[32]

Using pooled 2002 and 2010 trip data from the JICA surveys, we examine how the BRT system impacted travel times for other modes along its service corridors. To do so, we estimate parameters of the following regression equation:

$$y_{iodt} = \alpha_{od} + \gamma_t + \delta_1 \text{BRT}_{ot} + \delta_2 \text{BRT}_{dt} + \beta \left( \text{BRT}_{ot} \times \text{BRT}_{dt} \right) + \mathbf{x}'_{iodt}\theta + \varepsilon_{odt} \tag{3}$$

where $y_{iodt}$ is the log travel time for a trip taken by individual $i$ from origin community $o$ to destination community $d$ in year $t$, the BRT variables are indicators for whether origin $o$ or destination $d$ is within 1 km of a BRT station in year $t$, $\alpha_{od}$ is a separate fixed effect for each origin and destination pair (effectively controlling for distance), $\gamma_t$ is a year fixed effect, $\mathbf{x}_{iodt}$ is a vector of controls (including as a baseline separate purpose-by-year, mode-by-year, and departure hour-by-year indicators), and $\varepsilon_{odt}$ is an error term.

In Table 5, we report the estimate of the interaction term for the origin and destination BRT indicators, $\beta$. This coefficient measures the differential growth in travel times for routes that begin and end 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 (Row 2-5). Column 1 shows that travel times along BRT corridors increased by an average of 12.9 percent between 2002 and 2010. These effects are large and significant for many modes, including the non-BRT public buses (Row 2), private cars (Row 3), and motorcycles (Row 4). Also, as expected, the impact on private cars is the largest, at 20.4 percent, relative to smaller effects on public buses and private motorcycles. The impact on travel times for trains (Row 5) is much smaller and not statistically significant. This is expected because train travel is not congestible; train tracks are elevated in central Jakarta and do not compete with the BRT for road space.[33]

One plausible explanation for these findings is that they reflect differential increases in demand for travel along BRT corridors. In Column 2 of Table 5, we add controls for the number of trips taken each year for each origin-destination pair, while in Column 3, we additionally add controls for changes in community-level population density at the origin and destination. In Column 4, we add separate intercepts for each origin-by-year and destination-by-year; this allows us to control flexibly for changes in commuting trends specific to residential or workplace locations. These time-varying controls should capture much of the differential demand variation, but when we include them, they only slightly attenuate point estimates.[34]

In Column 5, we estimate spillover effects by restricting attention only to non-peak trips.[35] This

[32] Ernst (2005, p.23) makes a related observation, noting: "[c]ongestion has increased for mixed traffic on the corridor".

[33] The results in Table 5 use survey weights to adjust for differences in population origin and destination locations. We report the unweighted version of this table in Appendix Table A.11, which shows qualitatively similar results, although there are some differences in the magnitude of the point estimates.

[34] The specification in Column 4 also partially addresses concerns that the effects may be driven by changes to Jakarta's HOV policy. Initially, the HOV policy applied only to certain highly travelled routes on weekday mornings from 6-10 AM. However, 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).

[35] 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.

specification reveals that during off-peak times, the BRT system had no differential impact on travel times for other modes. This suggests that the negative spillovers occur during peak times, precisely when a public transit system should be reducing (instead of exacerbating) traffic congestion.

Overall, these results suggest that instead of improving traffic congestion in Jakarta, the BRT system may actually have had adverse consequences by taking away crucial road space that could have been used for other modes.[36] While the potential for similarly implemented BRT systems to exacerbate congestion has been proposed in anecdotes and in the media, our study is, to our knowledge, the first rigorous demonstration of this negative spillover.[37] We explore robustness of these findings below.

**Closer Route Comparisons.** One concern with the previous analysis is that trips along BRT corridors may not be comparable to trips made further away. Appendix Table A.12 reports estimates of $\beta$ by only using comparison routes that begin and end within 10 km of a BRT station (Row 2), within 5 km of a BRT station (Row 3), and within 3 km of a BRT station (Row 4). Although the magnitude of the effects fall somewhat, the point estimates are still positive and significant, particularly in the most demanding specification (Column 4, with origin-by-destination fixed effects). In Row 5, we compare trips along BRT corridors to trips along planned or eventual BRT corridors, and again we find similar results.

**Varying Treatment Distances.** In Appendix Figure A.6, we re-estimate equation (3) by including several separate BRT distance indicators, where $d$ ranges from 1 to 5 km, and their interaction terms. After estimating this regression, we plot the coefficient estimates on these different indicators (i.e. $\beta(d)$) as a function of distance $d$. This figure demonstrates that the negative externality impacts of the BRT system are highly localized. The travel time impacts of the system are positive for trips beginning and ending very close to BRT stations, but dissipate at larger levels of distance.

**Heterogeneity by BRT Standard.** Finally, in Appendix Table A.13, we examine the extent to which our estimates of the BRT system's impacts on congestion vary by corridor quality. We find that for corridor 1, which had attained the highest service standards, there were no differences from other trips in terms of travel times. We also find that off-peak travel times fell along corridor 1 by 16.4 percent (Column 5). As a result, the entire negative effect of the BRT system on congestion is explained by the other lines on the system, which were implemented with lower service standards.

### 5.4 Discussion

What explains TransJakarta's low rates of adoption and its apparent lack of success in reducing congestion? One hypothesis is that TransJakarta's low mode share may result from capacity constraints: the system might have been full and could not carry more passengers. However, evidence presented in Figure 5 shows little support for this hypothesis. Panel A plots the average total number of weekday riders on the BRT, showing that between 2004 and 2014, TransJakarta's average weekday ridership increased by a factor of 6, from 52,400 to 368,000. However, Panel B shows that over this same period, the total length of busways also increased by a factor of nearly 13. As a result, the total number of weekday riders per km of busway fell substantially (Panel C). From a peak of over 5 thousand weekday riders per km in 2005,

[36] Duranton and Turner (2011) show that the benefits of wider highways decline in the long run as people drive more. Arguably, the (short-run) costs of narrower roads that we find here may similarly decline in the long run as people adjust their commuting and residential choices.

[37] Misra (2016) describes how the BRT system in Delhi similarly worsened traffic along service corridors.

by 2014, the system had less than 2 thousand riders per km in 2014. Compared to Bogotá's Transmilenio BRT system, which carried 9.5 thousand weekday riders per km in 2013, TransJakarta's performance has been relatively poor. Similarly, Adiwianto (2010) also found that the number of passengers per bus per km had fallen by more than a third, from over 4 to less than 2.5 between 2004 and 2009.

If capacity constraints do not explain TransJakarta's low ridership, high fare costs also probably do not play a role (Sayeg, 2015). TransJakarta charges a flat fare for riding anywhere on the system, and the low cost of Rp 3,500 (or USD 0.26 in 2017 dollars) has remained constant since the system opened. In real terms, the price of riding the BRT has fallen substantially, as the fare index shows in Figure 5, Panel D.

A more promising hypothesis is that TransJakarta's poor performance reflects the quality of its implementation: its slow speeds, lack of comfort, and limited network extent. During our study period, TransJakarta had considerable difficulty enforcing bus lane segregation which may have congested bus lanes, slowing them down (Radford, 2016).[38] Another oft-cited complaint relates to bus comfort. 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), and such findings were corroborated in a recent survey of females in DKI Jakarta (Witoelar et al., 2017). Finally, the relatively small extent of the network may have reduced ridership. Although the BRT stations serve the city center and help individuals reach jobs, they may not be well targeted to residential areas, particularly those lying beyond DKI Jakarta borders.[39]

Our data do not provide exogenous variation in these system attributes. To better quantify the mechanisms behind low ridership, we specify and estimate an equilibrium commuting model that predicts how individuals make commuting decisions. We use this model to simulate the effects of improving shortcomings of the BRT system, such as its speed, comfort, and network extent, to see what would have happened to ridership if those aspects had been improved. The next section describes this commuting model and explains how we use our data to estimate model parameters.

## 6 Estimating an Equilibrium Model of Jakarta's Morning Commute

This section describes an equilibrium model of commuting decisions. In the model, individuals choose transport modes and departure times to maximize utility. When making these choices, commuters have preferences over many different attributes of modes and departure times, and some choice characteristics may be unobserved. We formulate demand using a nested logit model to allow for realistic substitution patterns. Because the time it takes to travel along a particular route, a key attribute of commuting choices, is determined in equilibrium, we adopt a novel instrumental variables strategy that relies on demand from overlapping routes to estimate preference parameters.

Travel times increase as more people drive on the same routes at similar times of day. Following Couture et al. (2018) and Akbar and Duranton (2017), we estimate Cobb-Douglas cost-of-travel functions that capture this relationship, mapping the total number of vehicles on roads at particular times to travel

[38] In addition, TransJakarta has had 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).

[39] 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.

times for different transport modes. We also describe an instrumental variables strategy that relies on demand shifters to identify travel cost curve parameters.

After estimating parameters for both demand and travel costs, we use the model to conduct counterfactual simulations that shed light on mechanisms behind TransJakarta's low ridership. We first map simulated policies into changes in mode-by-departure time choice characteristics. Then, we predict how changing those attributes results in changes in demand. These demand shifts imply different traffic patterns, and we use the average travel cost relationships to estimate how the new traffic impacts travel times. These changed travel times, in turn, generate demand responses, and we iterate between changes in demand and travel cost curves until we converge at a new counterfactual equilibrium.

### 6.1 Setup: Locations and Products

Greater Jakarta consists of a finite set of subdistricts (kecamatan), 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.[40] For simplicity, we assume that $N_{od}$, the number of commuters traveling from origin sub-district $o$ to destination sub-district $d$, is fixed. We let the index $t = 1, ..., T$ refer to these different origin-by-destination commuting markets.

In market $t$, commuters choose both a mode of travel and a departure time window. We index modes by $m$, which include: (1) the TransJakarta BRT system; (2) the commuter rail train; and (3) other public transit (i.e. the traditional public bus system); (4) motorcycles; (5) cars; and (6) non-motorized transit.[41] These modes are nested within two categories, $h \in \{\text{public}, \text{private}\}$. For congestible modes, individuals also choose a departure (or start) time-window, denoted by $s \in \{s_b, s_p, s_a\}$, where $s_b$ denotes *before peak time* (departing from 1-6 AM), $s_p$ denotes *peak time* (departing from 7-9 AM), and $s_a$ denotes *after peak time* (departing from 10 AM or later). The nested structure of this choice set is depicted in Figure 6.[42] Let $j = (h, m, s)$ denote a typical element (product) of this choice set.

### 6.2 Nested Logit Demand

The indirect utility that commuter $i$ obtains from choosing product $j$ in market $t$ is given by:

$$V_{ijt} = \mathbf{x}'_{jt}\beta - \alpha p_{jt} + \xi_j + \Delta\xi_{jt} + \varepsilon_{ijt} \qquad i = 1, ..., N_t, \qquad j = 1, ..., J, \qquad t = 1, ..., T, \tag{4}$$

where $p_{jt}$ denotes the travel cost (in minutes per kilometer) for choice $j$ in market $t$, $\mathbf{x}_{jt}$ is a vector of characteristics of choice $j$ in market $t$, $\xi_j$ is an unobserved product effect common to all markets, $\Delta\xi_{jt}$ is an unobserved product characteristic for product $j$ in market $t$, and $\varepsilon_{ijt}$ is a mean-zero error term. Indirect utility thus consists of a mean-utility portion, $\delta_{jt}$, which is equal for all consumers, and a mean

[40] Although our original survey data were coded at the community (*kelurahan*) level, we aggregated locations to subdistricts in this analysis in order to reduce noise in the calculation of market shares.

[41] The JICA travel surveys ask about a much more detailed set of mode choices, but we aggregate similar modes to simplify the model. Taxis and motorcycle-taxi (*ojek*) choices were assigned to the appropriate vehicles. Non-motorized transit includes walking and bicycling.

[42] For simplicity, we assume that both the TransJakarta BRT and trains are not congestible, so there is no departure time window for these choices. Ignoring departure times for these modes seems sensible if we consider the effects of congestion pricing, which will only be charged for other modes of transit (e.g. cars and motorcycles during peak times).

zero error term, representing individual-specific deviations from mean utility. We normalize parameters for the indirect utility of non-motorized transit ($j = 0$) to zero, so that $V_{i0t} = \varepsilon_{i0t}$.

We further assume that the error term takes the following form:

$$\varepsilon_{ijt} = \overline{\varepsilon}_{iht} + (1 - \rho)\overline{\varepsilon}_{ihjt}$$

where $\overline{\varepsilon}_{iht}$ represents an error component varying across consumers and mode types (public vs. private), while $\overline{\varepsilon}_{ihjt}$ varies across consumers and modes for each mode type $h$. Following Cardell (1997), we assume that $\overline{\varepsilon}_{iht}$ and $\overline{\varepsilon}_{ihjt}$ have the unique distribution such that $\varepsilon_{ijt}$ is i.i.d with the Type I Extreme Value (Gumbel) distribution. The parameter $\rho$ measures preference correlation within nests. As $\rho$ tends to 1, the within-mode-type correlation of utility levels across products tends to 1, and as $\rho$ tends to 0, the model collapses to a standard logit model.

Berry (1994) shows that by share inversion, we can obtain a simple linear regression equation for estimating preference parameters:

$$\ln(s_{jt}) - \ln(s_{0t}) = \mathbf{x}'_{jt}\beta - \alpha p_{jt} + \rho \ln\left(s_{j|h}\right) + \xi_j + \Delta\xi_{jt} \tag{5}$$

where $s_{j|h}$ market share of mode $j$ conditional on mode type $h$, and the $\xi_j$'s are estimated using product-specific intercepts.

### 6.3 Estimating Demand: Empirical Strategy

**Data: Shares and Choice Characteristics** We use data from the 2010 Commuter Survey (CS) to estimate the model. This survey allows us to estimate mode shares for each market, $s_{jt}$, and it also provides measures of choice characteristics. A product's travel time per kilometer, $p_{jt}$, which is the inverse of speed, includes both actual travel time on the mode and also access time, where access time reflects time spent walking to stations.[43] Monthly transport costs per kilometer include both the costs of driving (petrol) and fares from taking public transit. A product's comfort is the self-reported averages (by market) of responses to a question about mode comfort in the 2010 CS data, where respondants score each mode on a 5-point scale.

**Accounting for Missing Modes** The raw data contain trips for 7,703 pairs of origin-by-destination kecamatan, out of a possible $17,689$ pairs ($133 \times 133$). However, most of those trips are sparsely populated in the raw survey data, and we only estimate the model on the 1,381 markets with at least 20 observations in the JICA trip data. This is roughly 18% of the markets in the survey data and 7.8% of the full possible trip origin-destination matrix.

Even with this sample restriction, there are still many markets with products that have zero mode shares. Of the 15,191 product $\times$ market observations in our main estimation sample (i.e. 1,381 markets $\times$ 11 products), 3,968 (26.12%) have zero mode shares for either the products or the outside option. To account for this, we add a small positive value to the missing mode shares (0.001), and subtract an

[43] We assume that individuals walk to train or BRT stations at 5 km per hour, abstracting from time spent waiting at stations. Access time for other modes is set to zero. Trip distances are defined as above, except that we aggregate to sub-district level markets using the average trip distance for all trips originating and terminating within each sub-district.

appropriate amount away from the outside option or the other mode shares to ensure that all shares sum to 1. In estimating the model, we also include an indicator variable for whether or not the shares were missing in the original data.

**Identification: Instrumental Variables Strategy** An ideal transport demand experiment would measure how individuals respond to randomly-assigned choice characteristics, varying travel times, access to public transport infrastructure, and other factors.[44] However, because we work with observational data, identification requires a strategy to address the endogeneity of travel times, motivating the use of instrumental variables. A good IV for demand parameters would isolate changes in travel times that come from shifts in travel costs. Possible cost-curve 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 IVs. Instead, to instrument for travel times, we use time-specific cost shifters driven by variation in the demand for other, overlapping routes.

Figure 7 illustrates our IV strategy. Panel A depicts a trip from a hypothetical community $B$ to community $A$ during departure-time window $s$, indicated by the grey arrow. Our IV 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 start time $s$, indicated by the blue arrow. For this to be a valid IV, 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 $A$.[45]

One concern with this IV 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 7, 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 $A$. We mitigate these concerns by ignoring all routes that originate or terminate in subdistricts adjacent to the origin and destination subdistrict we are instrumenting when we construct our overlapping routes IVs. The final instrument vector combines this overlapping routes IV with additional instruments, including the sums of other product characteristics in other markets (i.e. sums of elements of $\mathbf{x}_{kt}$ for $k \neq j$). Such IVs are commonly used in estimating differientiated product demand systems (e.g. Berry et al., 1995; Nevo, 2001).

### 6.4 Demand Results

If we ignore the potential for within-nest preference correlation, setting $\rho = 0$, the market share equation (5) becomes a standard logit expression. Columns 1-4 of Table 6 present estimates of the parameters from (5) under this assumption, while Column 5 allows for non-zero $\rho$. Columns 1 and 2 report fixed effects least squares (FELS) parameter estimates, where we include alternative-specific constants ($\xi_j$),

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

[45] As we discuss in Section 6.5, our data do not provide information about specific routes taken for trips, so we use distance-minimizing routes in calculating this IV. Misspecified routes would lead to a weak first stage relationship, but we do not find this to be the case.

while Columns 3-6 report GMM estimates, where we instrument for the endogenous $p_{jt}$ using the IVs described above. Robust standard errors are clustered at the market level. In Columns 1 and 2, coefficients on both travel time costs per km and log monthly travel costs per km are statistically significant and appropriately signed. However, the impact of time costs on demand is relatively small relative to the impact of mode comfort. In the FELS specification (col 2), the parameter estimates imply consumers are willing to travel 7.6 more minutes per km ((-1) $\times$ 0.267 / -0.035) for a marginal increase in safety.[46]

Columns 3-6 report diagnostics suggesting a well-specified IV model. The Kleibergen-Papp $F$-Stat, a generalization of the first-stage $F$-statistic with multiple instruments, is large, and the Kleibergen and Paap (2006) LM test rejects the null of weak instruments of the endogenous price variable. Based on the Hansen (1982) test, we cannot reject the null hypothesis that the IVs are uncorrelated with the error term and are correctly excluded from the second stage. These results also show a slightly reduced willingess to pay for a marginal increase in mode safety. Based on the GMM results in Column 6, commuters are only willing to travel 0.4 more minutes per km ((-1) $\times$ 0.215 / -0.031) for a marginal safety increase.

Finally, the estimate of $\rho$ in Column 6 is large, and $0 < \rho < 1$, consistent with random utility maximization (McFadden, 1978). Since $\rho$ is estimated to be greater than 0, there is positive preference correlation both across products within mode types, rejecting a standard logit model.

### 6.5 Cobb-Douglas Cost-of-Travel Functions

Roads are congestible by multiple transport modes, and different 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. We specificy these congestion effects using flexible Cobb-Douglas functions with separate elasticities for different modes.

In order to estimate cost-of-travel functions, we need data on the number of different types of vehicles on different types of roads at different times. Let $\tau_{od}$ 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 $\tau_{od}$. However, our data do not provide any individual-specific route information. Although we know the community where a trip begins and ends, we do not know the exact roads an individual regularly uses when moving from $o$ to $d$. We therefore need an assumption about how individuals choose their routes.

**Assumption 6.1.** (Distance-Minimizing Routes) *For any route $\tau_{od}$ 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.

[46] Marginal willingness to pay for increased safety is obtained by totally differentiating indirect utility and setting it equal to zero. See Train (2009) for more details.

To measure traffic, we combine the regular trip information with assumed routes to count the number of vehicles that come from routes that traverse community $k$ (i.e. $\tau'$ 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 6.2.** (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 $\tau_{od}$ from community $o$ to community $d$, the amount of time an individual spends in community $k \in \mathcal{K}(\tau_{od})$ is proportional to $A_k / \sum_{l \in \mathcal{K}(\tau_{od})} A_l$.*

This assumption states that while traversing route $\tau_{od}$, 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 $k$ (calculated as described in Footnote 17). Although somewhat restrictive, this assumption is a useful first approximation and reflects the limits of our available data.

Let $p_{odms}$ denote the cost of travel, in minutes per km, for using mode $m$ at start time $s$ 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:

$$p_{odms} = N_{ods}^{\theta_m} \exp\left\{\mathbf{w}'_{ods}\beta_m + u_{odms}\right\} \qquad \text{for } \ m \in \{M, B\} \tag{6}$$

Here, $N_{ods}$ denotes the total number of vehicles on route $od$ at time $s$ (calculated with Assumptions 6.1 and 6.2 above), $\mathbf{w}_{ods}$ denotes a vector of characteristics of route $od$, and $u_{odms}$ is an error term. The parameter $\theta_m$ is a cost elasticity, while $\beta_m$ maps various route-specific features into travel times. Taking logs yields the following linear equations:

$$\log p_{odms} = \theta_m \log N_{ods} + \mathbf{w}'_{ods}\beta_m + u_{odms} \tag{7}$$

To identify 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 shift 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.

### 6.6 Cost of Travel Results

Table 7 reports estimates of the average travel cost curve, using the pooled trip-level data to estimate equation (7). 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 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 Bogotá by Akbar and Duranton (2017), who argue that when cities have many small, redundant routes, they may allow for better traffic absorption because cars and motorcycles can use other routes if one road is badly congested.[47]

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). 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 is expected: given motorcycles' maneuverability, their speeds may be less responsive to increases in total vehicles. Figure 8 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 7. 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 the total number of vehicles increases substantially.

## 7 Policy Simulations

In this section, we use the model to conduct counterfactual policy simulations to understand ways to improve takeup of the TransJakarta BRT system and the mechanisms behind its low demand. We examine three counterfactual experiments: (1) increasing BRT speeds; (2) improving BRT comfort; and (3) expanding the BRT network. We contrast these findings with the effects of congestion pricing.

**Increasing BRT Speeds** As discussed above, one key concern with TransJakarta's implementation is that BRT buses are frequently cited as being well below international standards. We model a 10 or 20 percent increase in BRT travel speeds and study what happens to commuting outcomes in equilibrium as travelers respond.

**Improving BRT Comfort** Another oft-cited deterrent to riding public transport is that public transport options are not comfortable for riders. To model improvements to BRT comfort, we simply increase the value of the stated comfort scores for this mode by 10 and 20 percent for each market and simulate new counterfactual equilibria.

**Building Planned BRT Lines** In addition to improving BRT comfort and speed, we also study what would have happened to BRT adoption if the network had expanded. In this policy simulation, we construct the network's planned lines (depicted in Figure 1), expanding the network beyond the DKI

[47] An important difference between these results and those presented in Akbar and Duranton (2017) is that our cost curves use the total vehicles traveled along specific routes on the right-hand-side, not the total number of travelers for the entire city.

Jakarta boundary. This effectively reduces BRT access time for commuters living in communities near the planned stations. We study how this access time reduction increases demand for ridership.

**Congestion Pricing** Finally, we contrast the BRT policy simulations with the effects of congestion pricing, another policy that economists, urban planners, and transportation researchers have extolled for decades (Vickrey, 1963). By charging road user fees for vehicles operating on high-demand corridors during peak times, congestion pricing induces drivers to internalize the negative travel-cost 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, the program has yet to be implemented (Sugiarto et al., 2015). To simulate 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 (cars or motorcycles) that either originate or terminate in DKI Jakarta will be charged a single flat fee, similar to the London congestion pricing scheme (Leape, 2006). We vary this fee by Rp 30,000 (or \$3.30 in 2010 USD) and Rp 50,000 (or \$5.50 in 2010 USD).[48]

**Limitations** Because our model is used to simulate the impact of improving TransJakarta, 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. 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 such transport initiatives were enacted. Moreover, we also ignore the impact of any policies on vehicle ownership.[49] Despite these simplifications, our model still provides a way to assess the short run impacts of improvements in TransJakarta, which shed light on the mechanisms behind low transit ridership.

### 7.1 Results

Table 8 shows the results of counterfactual simulations on overall mode choices, departure times, and decisions to use public transport. In Column 1, we report the baseline mode share, departure time window shares, and public vs. private shares.[50] The remaining columns of this table report the changes in these shares if different types of counterfactual policies were implemented. Columns 2 and 3 report changes in shares if BRT speeds increased by 10 and 20 percent, Columns 4 and 5 report changes in shares if BRT comfort was increased by 10 and 20 percent, while Column 6 reports changes in shares if the planned BRT lines were constructed. Columns 7 and 8 contrasts these findings with the effects of a Rp 30,000 or an Rp 50,000 congestion toll.

To obtain simulation results, we begin by initially changing mode chares, where we simply alter the choice attributes and study the resulting impact on demand. This change results in new traffic patterns, which in turn affect travel times for different modes. The new travel times will again affect demand,

[48] These congestion charges are similar in orders of magnitude to those implemented by electronic road pricing in Singapore in 2010, namely per-use tolls that vary between SGD 1 (or USD 0.73) and SGD 4 (USD 2.90) (Agarwal et al., 2015).

[49] 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.

[50] The departure time window shares are conditional on choosing a congestible mode, and the public vs. private mode shares are conditional on choosing a non-outside option.

which will again affect traffic patterns, and we iterate until the overall change in mode shares between iterations is small.[51]

Columns 2-6 show that improvements in BRT speed, comfort, and network extent would generate positive increases in BRT mode shares. Increasing BRT speeds by 20 percent or comfort by 20 percent would increase BRT's mode share by roughly 3 percentage points (pp) on average, an increase of nearly 50 percent. This suggests that both attributes similarly limit demand for TransJakarta. We also find that expanding the BRT network, a potentially more expensive option, would increase ridership by 3.2 pp, a similarly sized effect. However, increasing each of these aspects alone would only increase TransJakarta's ridership to roughly 10 percent, which is still much smaller than other BRT implementations. Moreover, most of the increase in BRT ridership comes from substitution away from other public transit modes, and not from private modes. This leads to relatively small effects on total public transport ridership.[52]

In Columns 7 and 8, we compare the findings on improving the BRT system with the impact of congestion pricing. Overall, we find that congestion pricing has a modest impact on mode shares, encouraging slight reductions in 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 a 3 to 8 pp decrease in the share of travelers commuting during peak times, and an increase in commuters leaving before peak time and afterward. Notably, the overall effects on public transit ridership from the Rp 50,000 congestion price are of similar orders of magnitude as the effects on public transit ridership from improving BRT speeds or comfort by 20 percent.

Overall, these policy simulations suggest that low BRT ridership reflects its the quality of its implementation. Ridership is significantly reduced by slow speeds, a lack of comfort, and a limited network structure. Improving speeds by effectively segregating the bus lanes or improving bus comfort seems to be a more cost effective option for increasing ridership than expanding the network. However, improving these aspects would generally lead to reductions in demand for other public transport modes and would not increase total public transit ridership by a substantial amount. The magnitude of the effects of improving BRT speeds on overall public transit ridership is also similar to the effects of implementing a London-style congestion charge in the city.

# 8 Conclusion

This paper presents estimates of the impact of the TransJakarta BRT system on commuting outcomes in the greater Jakarta metropolitan region. Using new, high quality datasets, we find both that the BRT system did not reduce incentives for motorization in Jakarta, and we also found that it had modest impacts on transit ridership. We further show that the system exacerbated congestion along its service corridors, the opposite of what a well-designed public transport initiative is supposed to achieve. Therefore, our

[51] We use demand parameters from Column 6 of Table 6 and the linear cost-of-travel parameters from Column 4 of Table 7 for these simulations. Let $s_{jt}(k)$ denote the predicted product shares for iteration $k$. We iterate until the sum of the absolute difference between predicted mode shares in different iterations is less than 1, i.e. $\sum_j \sum_t |s_{jt}(k) - s_{jt}(k-1)| < 1$. Because most simulations result in fairly small changes in demand, we converge to a new equilibrium typically after 1-2 iterations. For more details, see Appendix D.

[52] In simulations not shown, we found that a 40 percent increase in speeds, which would have increased speeds to the level of Bogotá's TransMilenio system, would have lead to an increase in the BRT mode share by 4.7 pp.

results suggest that the early experiences of TransJakarta can be viewed as a cautionary tale for rapidly growing cities. The findings on increased congestion from road capacity reduction also potentially explain why several lower quality BRT implementations, such as those in Dehli and Bangkok, have been abandoned (Pojani and Stead, 2017). However, whether the effects found in this context are generalizable to the large number of other settings with lower quality BRT implementations remains an important and open question.

Using an equilibrium commuting model, we find that improving TransJakarta by increasing bus speeds and comfort, effectively bringing service quality up to that of Gold-Standard BRT implementations, would significantly increase ridership. We also find that TransJakarta's ridership is similarly hindered by its limited network extent. This suggests that an improved BRT implementation might have changed outcomes for city residents. However, even if TransJakarta had been improved, much of the increase in its mode share would have come at the expense of other public transit modes. Similar effects on overall public transit ridership could have been achieved through a simple congestion charge.

Further research could improve upon some of the limitations of the current model. For example, allowing commuters to respond to BRT improvements by altering their residential and workplace locations would improve our understanding on the possible impacts of such policies in the long run (e.g. Ahlfeldt et al., 2015; Tsivanidis, 2019). Additionally, encorporating demand heterogeneity, possibly through random coefficients logit models (e.g. Berry et al., 1995; Nevo, 2001), could be used to better explore the equity and efficiency tradeoffs of different urban transport policies.

Finally, additional unmodeled aspects are also possibly very important and would be worth pursuing further. For example, TransJakarta station infrastructure is difficult for commuters to access, sidewalks around stations are deteriorating, and in the areas around many stations, there is little transit-oriented commercial or residential development. These factors could limit the potential complementarities between walking and the BRT system, but the size of these effects is an open question (Cervero, 2013; Cervero and Dai, 2014; Hass-Klau, 1997; Witoelar et al., 2017).

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**Table 1:** BRT Standards by Corridor, as of 2014

| Corridor | Description | Opening Date | Standard |
|---|---|---|---|
| 1 | Kota - Blok M | 15 January 2004 | Silver |
| 2 | Pulo Gadung - Harmoni | 15 January 2006 | Bronze |
| 3 | Kalideres - Pasar Baru | 15 January 2006 | Bronze |
| 4 | Pulo Gadung - Dukuh Atas 2 | 27 January 2007 | Bronze |
| 5 | Ancol - Kampung Melayu | 27 January 2007 | Bronze |
| 6 | Dukuh Atas 2 - Ragunan | 27 January 2007 | Bronze |
| 7 | Kampung Melayu - Kampung Rambutan | 27 January 2007 | Basic BRT |
| 8 | Lebak Bulus - Harmoni | 21 February 2009 | Basic BRT |
| 9 | Pluit - Pinang Ranti | 31 December 2010 | Basic BRT |
| 10 | Tanjung Priok - PGC 2 | 31 December 2010 | Basic BRT |
| 11 | Kampung Melayu - Pulo Gebang | 28 December 2011 | Basic BRT |
| 12 | Penjaringan - Tanjung Priok[22][23] | 14 February 2013 | Basic BRT |
| 13 | Ciledug - Tendean - Blok M | TBD | |

*Notes:* Ratings for different corridors are from ITDP (2014).

**Table 2:** Summary Statistics on Well-Defined Trips

| | 2002 ($N$ = 653,814) | 2010 ($N$ = 541,630) | $\Delta$ |
|---|---|---|---|
| **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 |

*Notes:* Authors' calculations on well-defined trips, using the 2002 HVS and the 2010 CS 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 3:** Summary Statistics on Communities: Pre-Treatment Characteristics

| | $d\,(\mathbf{BRT}) \leq 1$ | | All Non-Treated | | Planned or Eventually Treated | | |
|---|---|---|---|---|---|---|---|
| **Panel A: Census 2000** | **Mean (sd) (1)** | **N (2)** | **Δ Mean (3)** | **N (4)** | **Δ Mean (5)** | **Δ Wt. Mean (6)** | **N (7)** |
| Log Population Density | 10.13 (0.80) | 140 | 2.17*** | 1359 | 0.54*** | -0.15 | 109 |
| Average Years of Schooling | 8.16 (0.80) | 140 | 3.22*** | 1359 | 0.81*** | 0.32* | 109 |
| % of recent migrants from a diff. district | 10.18 (4.45) | 140 | 1.46 | 1359 | -4.30*** | 0.53 | 109 |
| % of recent migrants from a diff. province | 8.44 (4.07) | 140 | 1.81** | 1359 | -3.58*** | 0.45 | 109 |
| | $d\,(\mathbf{BRT}) \leq 1$ | | All Non-Treated | | Planned or Eventually Treated | | |
| **Panel B: JICA 2002** | **Mean (sd) (1)** | **N (2)** | **Δ Mean (3)** | **N (4)** | **Δ Mean (5)** | **Δ Wt. Mean (6)** | **N (7)** |
| Age | 31.16 (2.11) | 132 | 3.66*** | 1358 | 1.78*** | 0.36 | 109 |
| Female (0 1) | 0.47 (0.03) | 132 | 0.02*** | 1358 | 0.00 | 0.00 | 109 |
| Monthly Income < Rp 1 mil | 0.40 (0.14) | 132 | -0.24*** | 1358 | 0.05* | -0.00 | 109 |
| Monthly income Rp. 1-1.5 mil | 0.21 (0.06) | 132 | 0.05*** | 1358 | -0.03** | -0.01 | 109 |
| Monthly income Rp. 1.5-2 mil | 0.13 (0.04) | 132 | 0.06*** | 1358 | -0.00 | 0.01 | 109 |
| Monthly income Rp. 2-3 mil | 0.12 (0.06) | 132 | 0.06*** | 1358 | -0.01 | 0.00 | 109 |
| Monthly income Rp. 3-4 mil | 0.05 (0.04) | 132 | 0.03*** | 1358 | -0.01 | -0.01* | 109 |
| Monthly income Rp. 4-5 mil | 0.03 (0.03) | 132 | 0.02*** | 1358 | -0.00 | 0.00 | 109 |
| Monthly Income > Rp 5 mil | 0.05 (0.06) | 132 | 0.03*** | 1358 | 0.00 | 0.00 | 109 |
| Own a Car (0 1)? | 0.25 (0.16) | 132 | 0.14*** | 1358 | -0.01 | -0.00 | 109 |
| Motorcycle Ownership (2002) | 0.38 (0.11) | 132 | 0.08*** | 1358 | -0.06** | -0.01 | 109 |
| Number of cars | 0.31 (0.24) | 132 | 0.19*** | 1358 | 0.00 | -0.00 | 109 |
| Number of motorcycles | 0.44 (0.15) | 132 | 0.11*** | 1358 | -0.06* | -0.01 | 109 |
| Main Mode: Train | 0.03 (0.03) | 132 | -0.00 | 1358 | 0.01 | 0.00 | 109 |
| Main Mode: Other Public Transport | 0.51 (0.13) | 132 | -0.05** | 1358 | 0.03 | 0.02 | 109 |
| Main Mode: Taxi / Ojek / Bajaj | 0.06 (0.05) | 132 | -0.08*** | 1358 | 0.02*** | 0.01 | 109 |
| Main Mode: Car | 0.19 (0.14) | 132 | 0.11*** | 1358 | -0.00 | -0.00 | 109 |
| Main Mode: Motorcycle | 0.22 (0.09) | 132 | 0.02 | 1358 | -0.06*** | -0.03 | 109 |
| Main Mode: Non-Motorized Transit | 0.00 (0.00) | 132 | -0.01*** | 1358 | -0.00** | -0.00 | 109 |
| | $d\,(\mathbf{BRT}) \leq 1$ | | All Non-Treated | | Planned or Eventually Treated | | |
| **Panel C: GIS Variables** | **Mean (sd) (1)** | **N (2)** | **Δ Mean (3)** | **N (4)** | **Δ Mean (5)** | **Δ Wt. Mean (6)** | **N (7)** |
| Area | -0.20 (0.78) | 140 | -1.44*** | 1360 | -0.62*** | -0.07 | 109 |
| Log Dist. to City Center | 8.82 (0.74) | 140 | -1.55*** | 1360 | -0.72*** | 0.16 | 109 |
| Elevation | 13.01 (9.71) | 140 | -113.51*** | 1360 | -3.24* | 0.40 | 109 |
| Ruggedness | 0.15 (0.15) | 140 | -0.02 | 1360 | 0.04** | -0.07 | 109 |
| Light Intensity (1992) | 62.71 (1.10) | 139 | 39.06*** | 1357 | 8.83*** | -0.03 | 109 |

*Notes:* Authors' calculations. Each observation is a community (*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 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 communities and all other communities ("non-treated"), and columns 5 (6) report the weighted difference in means (number of observations) between the close-proximity communities and communities within 1 km of either a planned BRT line that has yet to be constructed or a planned BRT station that was constructed after mid 2010. The weights are generated by a first-step propensity score estimation. The signifance stars in this table are computed by regressing the outcome variable on a treatment indicator, restricting the sample in columns 5 and to only treated and planned communities and using propensity-score reweighting. In these regressions, we cluster standard errors at the sub-district (*kecamatan*) level, and significance levels are from the p-values of these treatment indicators. */**/*** denotes significance at the 10% / 5% / 1% levels.

**Table 4:** ATT Estimates of BRT Station Proximity: Vehicle Ownership and Mode Choice

| | Treated vs. Planned | | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Δ Share Owning Car | -0.003 | 0.001 | -0.001 | -0.035 |
| | (0.029) | (0.042) | (0.036) | (0.063) |
| Δ Share Owning Motorcycle | 0.002 | -0.001 | -0.012 | 0.010 |
| | (0.018) | (0.023) | (0.025) | (0.028) |
| Δ Main Mode Share: BRT | 0.031** | 0.013 | -0.005 | 0.020 |
| | (0.013) | (0.020) | (0.030) | (0.019) |
| Δ Main or Alternative Mode Share: BRT | 0.072*** | 0.022 | 0.003 | 0.043* |
| | (0.019) | (0.024) | (0.042) | (0.025) |
| Δ Main Mode Share: Car | -0.001 | 0.006 | -0.016 | -0.011 |
| | (0.020) | (0.029) | (0.023) | (0.027) |
| Δ Main Mode Share: Motorcycle | -0.044* | 0.001 | 0.043 | 0.027 |
| | (0.024) | (0.034) | (0.052) | (0.030) |
| Δ Main Mode Share: Train | 0.012 | -0.002 | -0.012 | 0.004 |
| | (0.010) | (0.016) | (0.033) | (0.018) |
| Δ Main Mode Share: Other Public Transport | 0.011 | -0.017 | -0.009 | -0.041 |
| | (0.023) | (0.032) | (0.032) | (0.029) |
| Δ Main Mode Share: Taxi | -0.009 | -0.004 | -0.003 | -0.003 |
| | (0.006) | (0.006) | (0.009) | (0.007) |
| Δ Main Mode Share: Non-Motorized Transit | 0.000 | 0.002 | 0.002 | 0.002 |
| | (0.003) | (0.003) | (0.005) | (0.004) |
| $N$ | 241 | 241 | 241 | 241 |
| 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 community is within 1 km of a BRT station. Columns 1-4 restrict the non-treated sample to include only almost-treated communities. Column 2 includes pre-treatment controls, and Columns 3 reports a double-robust specification that both includes controls and reweights almost-treated communities by $\hat{\kappa} = \hat{P}/(1-\hat{P})$, where $\hat{P}$ is the estimated probability that the community is within 1 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 slightly across outcomes but include as many 132 "treated" communities and 109 "almost-treated" communities. */**/*** denotes significance at the 10% / 5% / 1% levels.

**Table 5:** Negative Spillovers: Impact of BRT on Travel Times

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| 1. All Trips | 0.129*** | 0.125*** | 0.120*** | 0.099*** | 0.037 |
| | (0.017) | (0.017) | (0.017) | (0.019) | (0.029) |
| $N$ | 1137900 | 1137900 | 1119916 | 1137898 | 696308 |
| Adjusted $R^2$ | 0.449 | 0.449 | 0.447 | 0.464 | 0.423 |
| Adjusted $R^2$ (within) | 0.030 | 0.030 | 0.030 | 0.029 | 0.035 |
| 2. Public Bus Trips | 0.123*** | 0.123*** | 0.119*** | 0.090** | 0.021 |
| | (0.035) | (0.036) | (0.036) | (0.040) | (0.048) |
| $N$ | 450485 | 450485 | 447243 | 450412 | 278479 |
| Adjusted $R^2$ | 0.399 | 0.399 | 0.398 | 0.412 | 0.371 |
| Adjusted $R^2$ (within) | 0.022 | 0.022 | 0.022 | 0.021 | 0.025 |
| 3. Private Car Trips | 0.204*** | 0.190*** | 0.168*** | 0.196*** | 0.134 |
| | (0.060) | (0.060) | (0.060) | (0.060) | (0.126) |
| $N$ | 69352 | 69352 | 68839 | 69227 | 39871 |
| Adjusted $R^2$ | 0.499 | 0.500 | 0.499 | 0.498 | 0.439 |
| Adjusted $R^2$ (within) | 0.037 | 0.038 | 0.039 | 0.038 | 0.042 |
| 4. Private Motorcycle Trips | 0.134*** | 0.132*** | 0.128*** | 0.105*** | 0.042 |
| | (0.024) | (0.024) | (0.025) | (0.027) | (0.044) |
| $N$ | 424837 | 424837 | 413752 | 424782 | 257124 |
| Adjusted $R^2$ | 0.421 | 0.421 | 0.418 | 0.433 | 0.390 |
| Adjusted $R^2$ (within) | 0.024 | 0.025 | 0.023 | 0.024 | 0.032 |
| 5. Train Trips | 0.006 | 0.007 | -0.017 | -0.082 | 0.130 |
| | (0.161) | (0.162) | (0.165) | (0.180) | (0.501) |
| $N$ | 35900 | 35900 | 35379 | 35744 | 22225 |
| Adjusted $R^2$ | 0.483 | 0.483 | 0.481 | 0.451 | 0.405 |
| Adjusted $R^2$ (within) | 0.058 | 0.058 | 0.058 | 0.056 | 0.078 |
| Year FE | Yes | Yes | Yes | Yes | Yes |
| Origin × Destination FE | Yes | Yes | Yes | Yes | Yes |
| Number of Trips | | Yes | Yes | Yes | Yes |
| Origin Population Density | | | Yes | | Yes |
| Destination Population Density | | | Yes | | Yes |
| Origin × Year FE | | | | Yes | Yes |
| Destination × Year FE | | | | Yes | Yes |
| Only Non Peak-Time Trips | | | | | Yes |

*Notes:* Each cell in this regression corresponds to a separate estimate of $\beta$ from the specification (3) to assess the differential impact on travel times for trips originating and terminating within 1 km of a BRT station. The dependent variable is log travel times, and the parameters are estimated from the pooled 2002 HVS / 2010 CS sample. In row 1, we use all trips, while the other rows restrict the sample to public bus trips (row 2), private car trips (row 3), private motorcycle trips (row 4), and train trips (row 5). In column 1, we include separate year fixed effects and origin-by-destination community FE (effectively controlling for distance). 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 population density. Column 4 adds separate origin-by-year and destination-by-year fixed effects. Column 5 restricts the sample of column 3 to only include non-peak time trips. All columns include separate purpose-by-year effects, mode-by-year effects, and departure-hour-by-year indicators. Robust standard errors, two-way clustered by origin and destination community, are reported in parentheses. */**/*** denotes significance at the 10% / 5% / 1% levels.

**Table 6:** Travel Demand Curves

| | Simple Logit | | | | Nested Logit (GMM) | |
|---|---|---|---|---|---|---|
| | FELS | | GMM | | | |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Total Time Cost (min/km) | -0.035*** | -0.035*** | -0.034*** | -0.035*** | -0.030*** | -0.031*** |
| | (0.003) | (0.003) | (0.005) | (0.005) | (0.005) | (0.005) |
| Log Monthly Travel Costs (per km) | -0.520*** | -0.512*** | -0.454*** | -0.453*** | -0.163*** | -0.167*** |
| | (0.054) | (0.053) | (0.047) | (0.048) | (0.046) | (0.047) |
| Mode Comfort | | 0.267** | | 0.195 | | 0.215* |
| | | (0.131) | | (0.130) | | (0.127) |
| $\rho$ | | | | | 0.755*** | 0.750*** |
| | | | | | (0.030) | (0.030) |
| $N$ | 15191 | 15191 | 15191 | 15191 | 15191 | 15191 |
| $N$ Markets | 1381 | 1381 | 1381 | 1381 | 1381 | 1381 |
| Adj. $R^2$ | 0.511 | 0.512 | 0.397 | 0.398 | 0.456 | 0.457 |
| Adj. $R^2$ (Within) | 0.398 | 0.399 | 0.445 | 0.445 | 0.499 | 0.499 |
| Regression $F$-Stat | 1984.3 | 1493.7 | 1815.0 | 1383.9 | 2488.0 | 2001.6 |
| Kleibergen-Paap LM Test Stat | . | . | 266.6 | 265.9 | 266.4 | 265.8 |
| Kleibergen-Paap $F$-Stat | . | . | 115.7 | 115.7 | 115.8 | 115.8 |
| Hanson $J$-Stat | . | . | 172.8 | 172.3 | 153.8 | 152.5 |
| Choice-Specific Constants | Yes | Yes | Yes | Yes | Yes | Yes |

*Notes:* This table reports estimates of the aggregate logit demand curve, using the linear equation specified in (5). Columns 1-2 are estimated using fixed-effects least squares (FELS), while columns 3-6 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 × departure window), and an indicator for whether or not the mode share was missing in the original data. Robust standard errors, clustered by market (origin-by-destination kecamatan), are reported in parentheses. */**/*** denotes significance at the 10% / 5% / 1% levels.

**Table 7:** 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 | -0.091* | 0.016*** | 0.115*** | 0.935*** | 1.191*** | 0.858*** |
| | (0.002) | (0.012) | (0.050) | (0.002) | (0.021) | (0.153) | (0.212) | (0.206) |
| Log Total Vehicles (squared) | | 0.000 | 0.015* | | -0.007*** | -0.137*** | -0.182*** | -0.120*** |
| | | (0.001) | (0.008) | | (0.002) | (0.023) | (0.032) | (0.031) |
| 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) |
| $N$ | 1124075 | 1124075 | 1124075 | 1124075 | 1124075 | 1124075 | 550813 | 482558 |
| $N$ Clusters | 1528 | 1528 | 1528 | 1528 | 1528 | 1528 | 1517 | 1526 |
| Adj. $R^2$ | 0.446 | 0.446 | 0.446 | 0.056 | 0.055 | 0.054 | 0.065 | 0.046 |
| Regression $F$-Stat | 962.194 | 722.587 | 579.315 | 1300.419 | 839.090 | 645.023 | 424.778 | 286.958 |
| Kleibergen-Paap $F$-Stat | . | . | . | 2349.211 | 211.396 | 93.971 | 52.729 | 79.703 |
| Cragg-Donald Wald $F$-Stat | . | . | . | 1.26e+05 | 9970.957 | 3247.972 | 2016.678 | 1567.590 |
| Hansen $J$ test p-value | . | . | . | 521.034 | 511.091 | 495.992 | 424.486 | 423.343 |
| Total Vehicles, Mean E | 0.008 | 0.009 | -0.108 | 0.016 | 0.005 | -0.013 | -0.019 | -0.013 |
| Total Vehicles, Max E | 0.008 | 0.006 | 0.011 | 0.016 | 0.123 | 1.089 | 1.396 | 0.994 |
| 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 2002 HVS / 2010 CS trip data. 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 significance at the 10% / 5% / 1% levels.

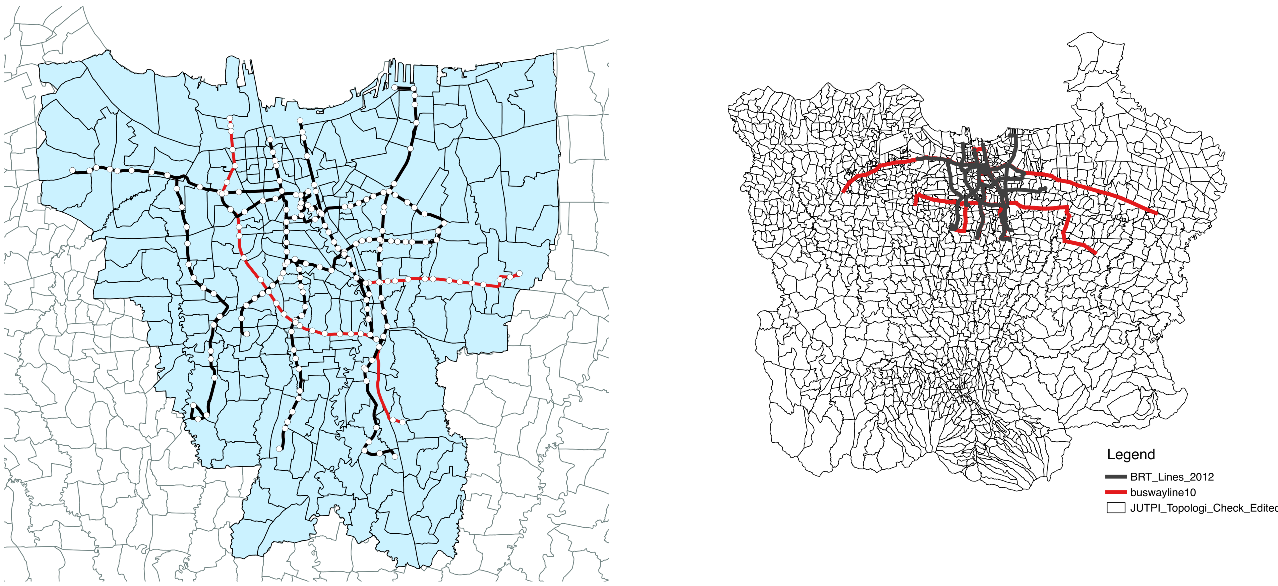
**Table 8:** Policy Simulations: Results for Mode and Departure Time Window Choice

| | | BRT Speed | | BRT Comfort | | Expand BRT Lines | Congestion Pricing (Rp '000) | |
|---|---|---|---|---|---|---|---|---|
| | **Baseline (1)** | **+10% (2)** | **+20% (3)** | **+10% (4)** | **+20% (5)** | **Planned (6)** | **+30 (7)** | **+50 (8)** |
| TransJakarta BRT | 7.08 | 2.18 | 2.99 | 1.45 | 3.06 | 3.27 | 0.10 | 0.25 |
| Train | 6.57 | -0.49 | -0.67 | -0.42 | -0.87 | -0.69 | 0.07 | 0.18 |
| Other Bus | 17.36 | -1.07 | -1.45 | -0.69 | -1.45 | -1.46 | 0.20 | 0.47 |
| Car | 15.74 | -0.11 | -0.16 | -0.07 | -0.16 | -0.20 | 0.33 | 0.37 |
| Motorcycle | 51.66 | -0.48 | -0.68 | -0.26 | -0.57 | -0.87 | -0.72 | -1.32 |
| Non-Motorized | 1.59 | -0.02 | -0.03 | -0.01 | -0.02 | -0.04 | 0.02 | 0.05 |
| Before Peak | 46.59 | 0.08 | 0.12 | 0.02 | 0.03 | 0.09 | 2.44 | 6.51 |
| Peak | 39.21 | 0.08 | 0.08 | 0.01 | 0.02 | 0.18 | -3.11 | -8.05 |
| After Peak | 14.20 | -0.16 | -0.20 | -0.02 | -0.05 | -0.27 | 0.66 | 1.54 |
| Private | 31.51 | 0.62 | 0.88 | 0.34 | 0.75 | 1.12 | 0.39 | 0.93 |
| Public | 68.49 | -0.62 | -0.88 | -0.34 | -0.75 | -1.12 | -0.39 | -0.93 |

*Notes:* This table reports simulation results for the average mode shares, departure time windows, and public vs. private shares across markets. Column 1 reports baseline shares, while the remaining columns report changes in shares under different counterfactual policies (listed in the column headers). The departure time window shares are conditional on choosing a congestible mode, and the public vs. private mode shares are conditional on choosing a non-outside option. We use demand parameters from Column 6 of Table 6 and the linear cost-of-travel parameters from Column 4 of Table 7 for these simulations. Let $\widehat{s}_{jt}^{k}$ denote the predicted product shares for iteration $k$. We iterate until the sum of the absolute difference between predicted mode shares in different iterations is less than 1, i.e. $\sum_j \sum_k \left|\widehat{s}_{jt}^{k} - \widehat{s}_{jt}^{k}\right| < 1$. Because most simulations result in fairly small changes in demand, we converge to a new equilibrium typically after 1-2 iterations.

**Figure 1:** TransJakarta BRT: Eventually Constructed and Planned Lines

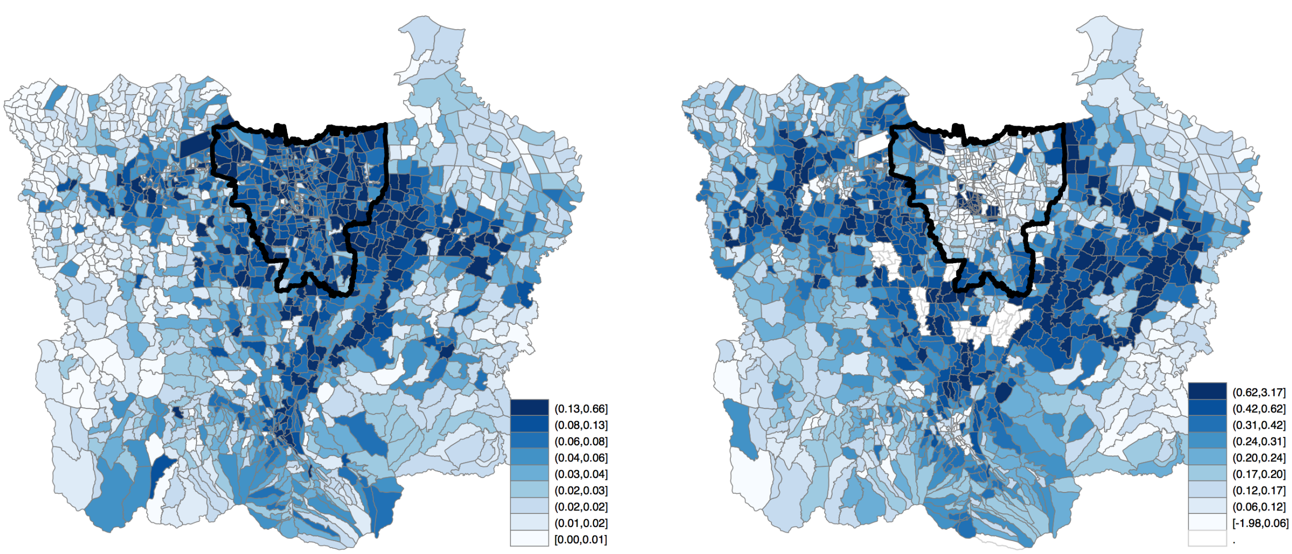
**(A)** Mid 2010 vs. Eventually Constructed | **(B)** Mid 2010 vs. Planned Lines




*Notes*: Panel A plots the locations of actual lines and stations as of mid-2010 (in black) and the locations of eventually constructed lines and stations (in red). As of mid-2010, the system had 159 stations on 9 corridors, but this was increased to 196 stations along 12 corridors as of January 2018. Panel B plots the locations of actual BRT lines (in black) and planned BRT lines that have yet to be constructed (in red). The locations of actual and eventually constructed BRT lines were traced from Open Street Map and TransJakarta data. Locations of planned lines are from JICA (2004a).

**Figure 2:** Employment Shares and Population Growth by Community

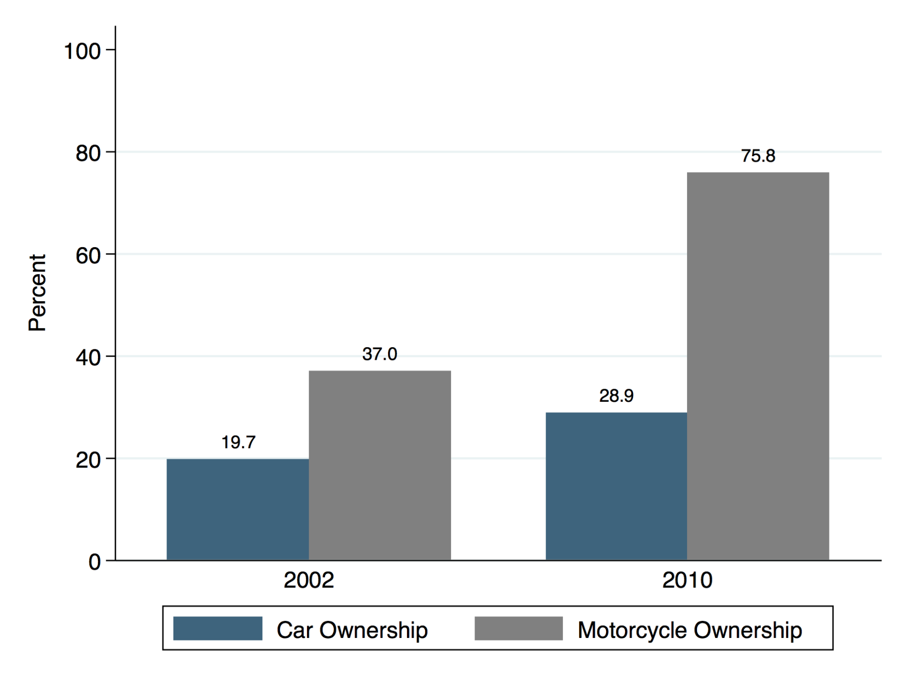
**(A)** Employment Share (2010) | **(B)** Population Growth (2000-2010)



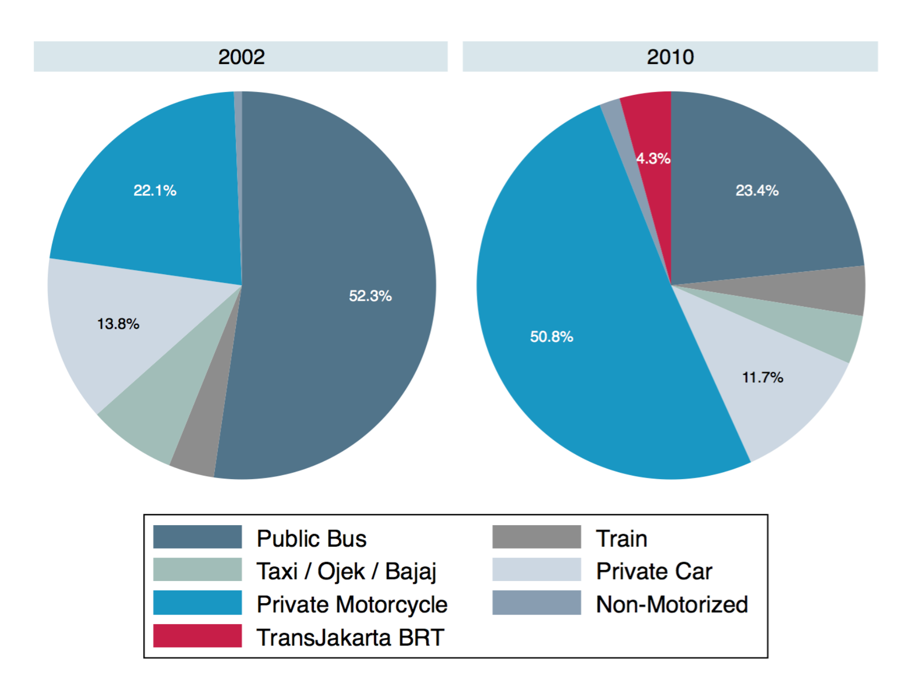

*Notes*: Authors' calculations, using data from the 2010 CS data in Panel A and the 2000 and 2010 population censuses in Panel B. Darker shading corresponds to greater unconditional employment probabilities (Panel A) and more rapid population growth, in percent changes (Panel B). The thick dark border denotes the boundaries of DKI Jakarta, the special capital region.

**Figure 3:** Changes in Vehicle Ownership and Mode Choice

(A) Panel A: Vehicle Ownership

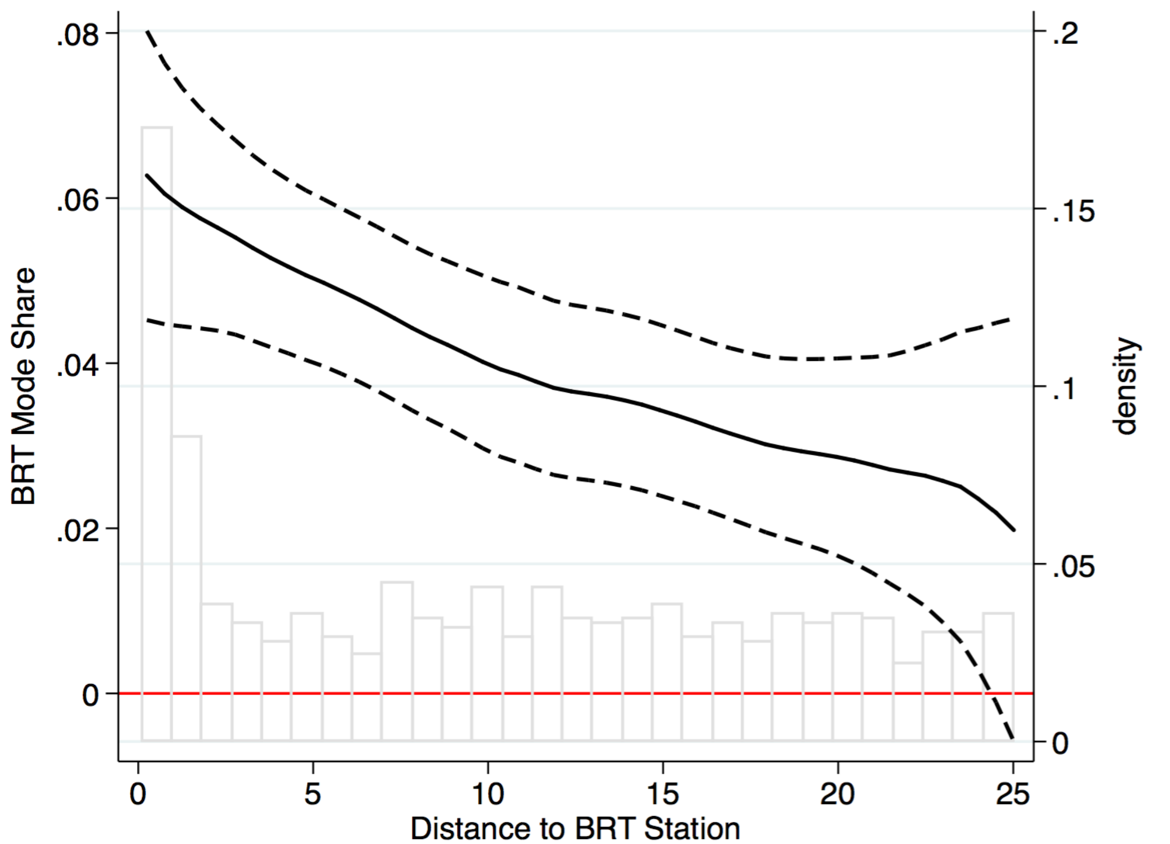



(B) Panel B: Mode Choice




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

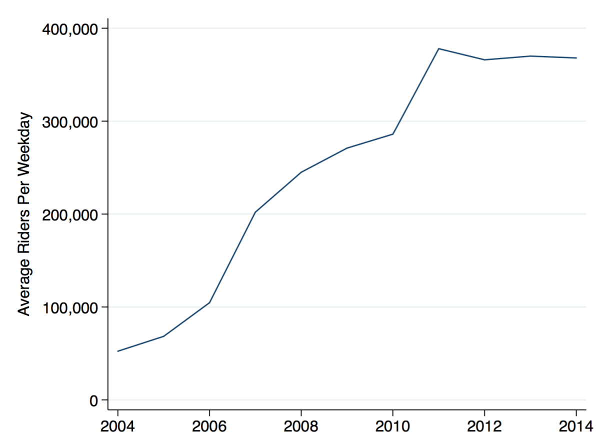
**Figure 4:** Semiparametric Effect: BRT Mode Share




*Notes*: This figure reports regressions of the neighborhood BRT mode share on a flexible function of distance and a linear function of control variables. This partially linear regression equation is described in (2) 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 district) in the neighborhood, and population density. From the 2002 HVS data, we also include shares of the population with different income levels and shares of trips made from the neighborhood into DKI Jakarta. Finally, we also include log distance to *Kota Tua*, the original center of the city, as well as elevation, ruggedness, night light intensity in 1992, night light intensity growth between 1992 and 2002, and the area of the neighborhood.

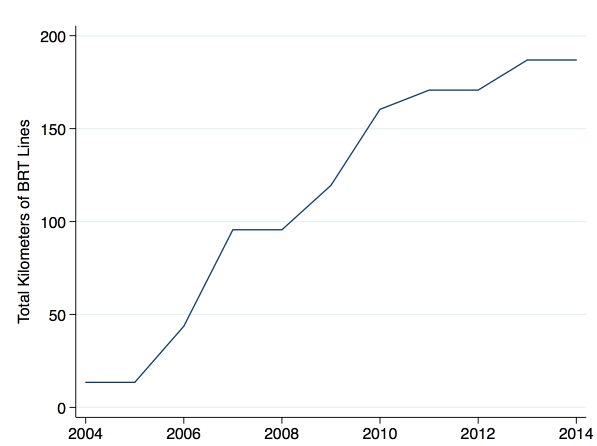
**Figure 5:** TransJakarta Ridership Statistics

**(A)** Average Weekday Riders

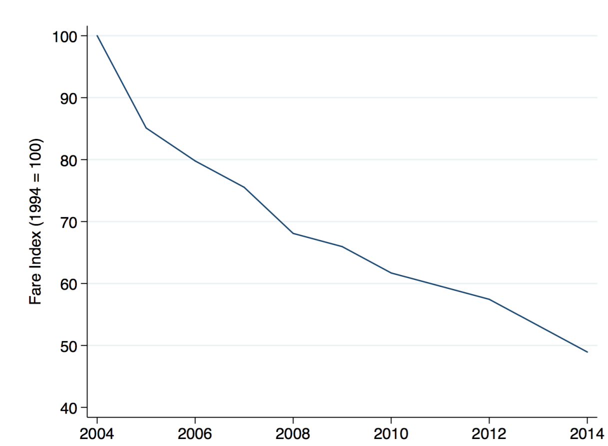



**(C)** Riders Per Km


**(B)** Total Busway Km

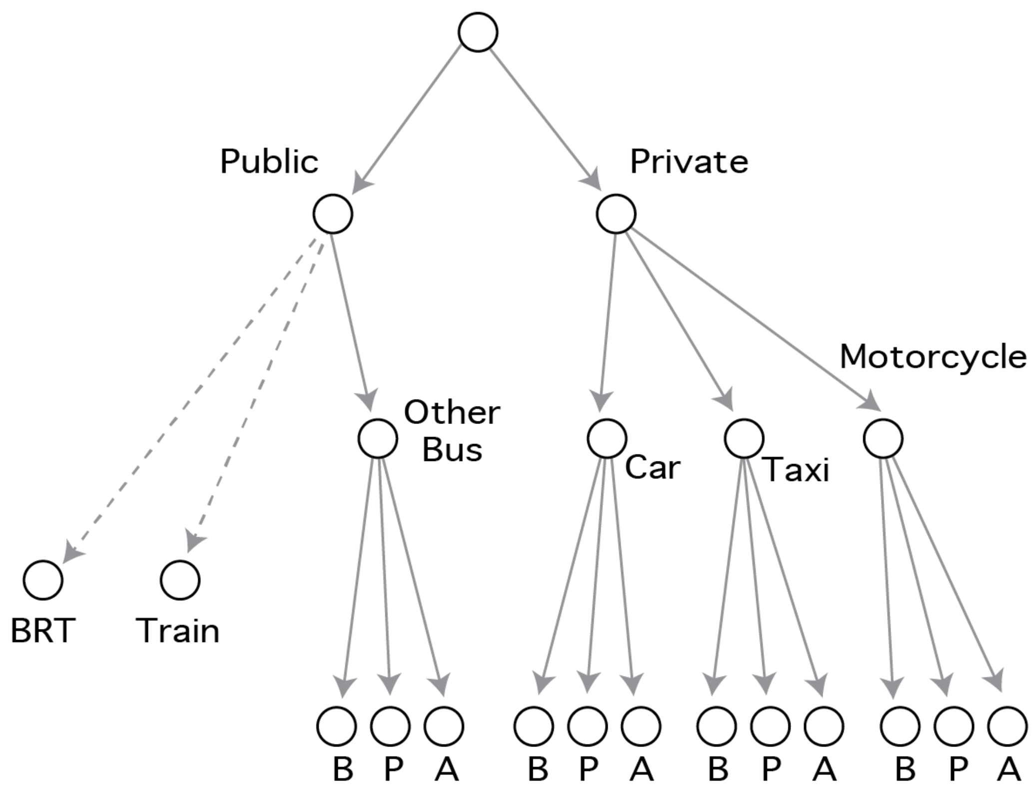



**(D)** Fare Cost Index (1994 = 100)



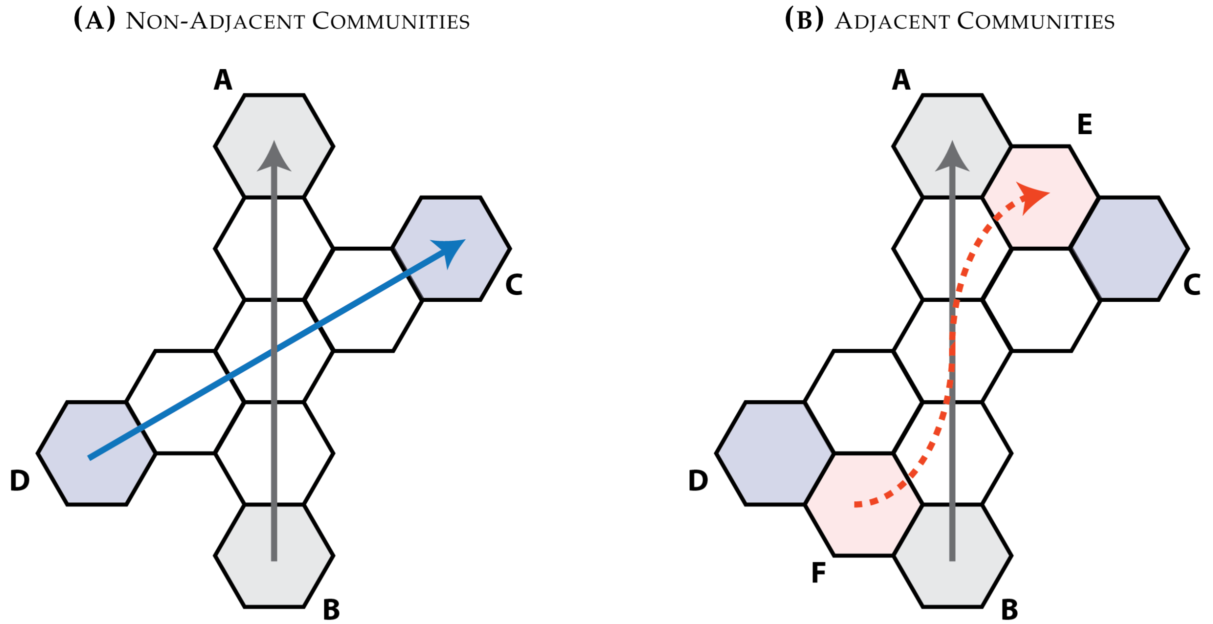

*Notes*: Panel A plots the average total riders per weekday on the TransJakarta BRT system, using data from Sayeg (2015). Panel B plots the expansion in kilometers of the TransJakarta BRT system. The data are derived from the traced BRT lines and opening dates, and calculated using GIS software. Panel C is a ratio of the data plotted in Panel A and Panel B. Panel D is a real fare cost index, reported by Sayeg (2015).

**Figure 6:** Choice Set: Nested Logit Structure



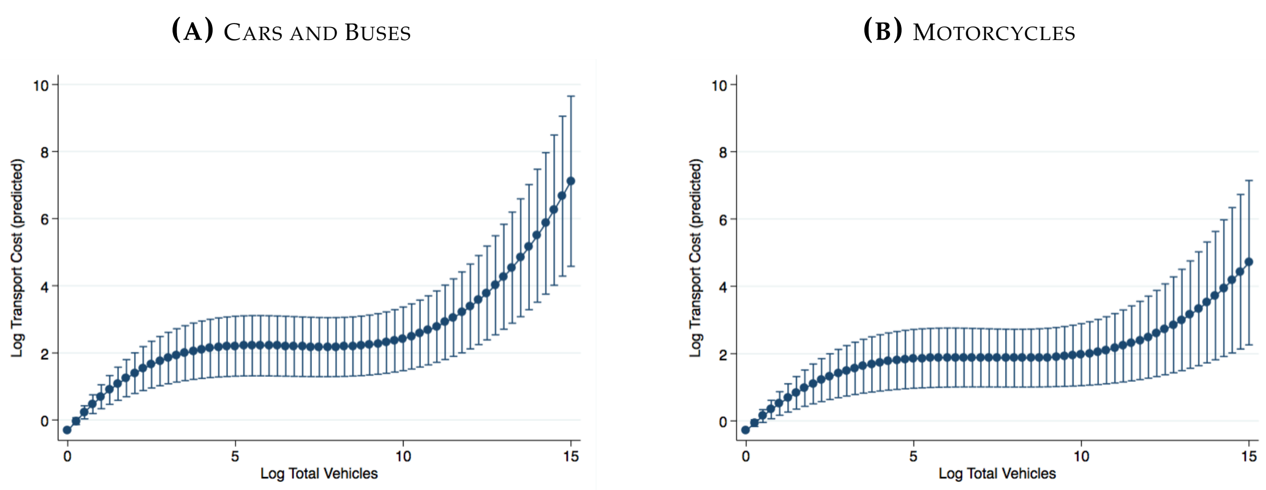

*Notes*: This diagram depicts the nested structure of mode choice and departure time windows. The first level is a choice of mode types (public or private). The second level depicts choices of modes within each type. The final level depicts departure time windows: "B" indicates before peak time (1-6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

**Figure 7:** Demand IV: Traffic from Overlapping Routes




*Notes*: This diagram illustrates the instrumental variable (IV) 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 IV to exclude trips that originate and end in adjacent communities.

**Figure 8:** Estimated Cost-of-Travel Curves by Transport Mode




*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 7, 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:** Residence and Workplace Distance to BRT Stations (2002)

| | | Workplace Distance to BRT Stations (km) | | | | | |
|---|---|---|---|---|---|---|---|
| | | **0-1** | **1-2** | **2-3** | **3-4** | **4-5** | **5+** |
| | **0-1** | 12.7 | 2.7 | 1.0 | 0.5 | 0.4 | 1.4 |
| Residential | **1-2** | 2.8 | 7.0 | 0.8 | 0.4 | 0.3 | 0.8 |
| Distance | **2-3** | 1.1 | 0.9 | 3.4 | 0.3 | 0.2 | 0.5 |
| to BRT | **3-4** | 0.6 | 0.5 | 0.3 | 2.3 | 0.2 | 0.4 |
| Stations (km) | **4-5** | 0.5 | 0.3 | 0.2 | 0.2 | 1.7 | 0.6 |
| | **5+** | 2.5 | 1.1 | 0.6 | 0.4 | 0.7 | 49.7 |

*Notes:* This table reports the percent of the population in 2002 and living and working within different distances of BRT stations built by mid 2010, based on the JICA data. The rows and columns list different bins of distances to BRT stations, with distances measured in kilometers.

**Table A.2:** Log Travel Time Regressions

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| YEAR IS 2010 (0 1) | -0.116*** | -0.107*** | -0.087*** | -0.080*** |
| | (0.007) | (0.009) | (0.010) | (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 2002 HVS / 2010 CS trip data. 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, are reported in parentheses. */**/*** denotes significance at the 10% / 5% / 1% levels.

## **Table A.3:** Neighborhood Propensity Score

| | Treated vs. All Non-Treated | Treated vs. Planned + Eventual |
|---|---|---|
| | (1) | (2) |
| Population Density (2000) | -0.003 | -0.043 |
| | (0.009) | (0.034) |
| Share of 5-Year District Migrants (2000) | -0.004*** | -0.015* |
| | (0.001) | (0.009) |
| Monthly Income < Rp 1 mil (%, 2002) | 0.083 | 0.441* |
| | (0.057) | (0.252) |
| Monthly Income > Rp 5 mil (%, 2002) | 0.041 | 0.443 |
| | (0.083) | (0.468) |
| No Primary School Share (2002) | -0.007*** | -0.011 |
| | (0.002) | (0.014) |
| College Completion Share (2002) | 0.001 | 0.006 |
| | (0.002) | (0.010) |
| Share of Commuting Trips to/from DKI Jakarta | -0.036** | -0.155* |
| | (0.017) | (0.089) |
| Log Dist. to City Center | 0.105 | 1.137* |
| | (0.120) | (0.595) |
| Log Dist. to City Center (Squared) | -0.007 | -0.077** |
| | (0.007) | (0.038) |
| Elevation | 0.001*** | 0.011*** |
| | (0.000) | (0.004) |
| Night Light Intensity (1992) | 0.038*** | 0.092 |
| | (0.009) | (0.061) |
| $\Delta$ Night Light Intensity (1992-2002) | 0.029*** | 0.045 |
| | (0.009) | (0.066) |
| Ruggedness | 0.021 | 0.302 |
| | (0.028) | (0.202) |
| Area | -0.016* | -0.035 |
| | (0.008) | (0.044) |
| $N$ | 1487 | 241 |
| Pseudo $R^2$ | 0.718 | 0.460 |
| Log Likelihood | -125.8 | -89.6 |
| LR $\chi^2$ | 74.6 | 61.1 |

*Notes:* This table reports marginal effects of our estimated propensity score model. This propensity score is estimated with a logit regression, where the dependent variable is an indicator for whether or not community $c$ is within 1 km of the nearest BRT station, and the independent variables are a vector of pre-treatment variables, $x_c$. Column 1 includes results comparing treated communities to all non-treated communities, while Column 2 restricts the comparison to only planned or eventually treated neighborhoods. Robust standard errors, clustered at the sub-district (*kecamatan*) level, appear in parentheses. */**/*** denotes significance at the 10% / 5% / 1% levels.

**Table A.4:** Effects of Continuous BRT Station Distance

| | OLS | IV (2SLS) | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Δ Share Owning Car | 0.000<br>(0.002) | -0.000<br>(0.002) | 0.381<br>(4.058) | -0.000<br>(0.002) |
| Δ Share Owning Motorcycle | -0.003<br>(0.002) | -0.002<br>(0.002) | 0.002<br>(0.162) | -0.002<br>(0.002) |
| Δ Main Mode Share: BRT | -0.001<br>(0.001) | -0.001<br>(0.001) | -0.012<br>(0.130) | -0.001<br>(0.001) |
| Δ Main or Alternative Mode Share: BRT | -0.001<br>(0.001) | -0.002<br>(0.002) | 0.038<br>(0.305) | -0.002<br>(0.002) |
| Δ Main Mode Share: Car | 0.002<br>(0.001)* | 0.002<br>(0.001)* | 0.031<br>(0.232) | 0.002<br>(0.001)** |
| Δ Main Mode Share: Motorcycle | -0.000<br>(0.003) | 0.001<br>(0.003) | 0.135<br>(1.125) | 0.001<br>(0.003) |
| Δ Main Mode Share: Train | -0.001<br>(0.001) | -0.001<br>(0.001) | 0.094<br>(0.739) | -0.001<br>(0.001) |
| Δ Main Mode Share: Other Public Transport | 0.001<br>(0.002) | 0.002<br>(0.002) | -0.420<br>(3.249) | 0.001<br>(0.002) |
| Δ Main Mode Share: Taxi | 0.001<br>(0.002) | -0.001<br>(0.002) | 0.156<br>(1.188) | -0.001<br>(0.002) |
| Δ Main Mode Share: Non-Motorized Transit | -0.001<br>(0.001) | -0.001<br>(0.001) | 0.016<br>(0.135) | -0.001<br>(0.001) |
| $N$ | 696 | 696 | 696 | 696 |
| Controls | X | X | X | X |
| Planned IV | . | X | . | X |
| Eventual IV | | . | X | X |

*Notes:* Each cell reports the coefficient from a regression of the given dependent variable (listed in the left-most column) on a continuous measure of distance to the nearest BRT station. The regression includes all communities within 10 km of the nearest BRT station. Column 1 reports OLS estimates, while in columns 2-4, we use planned and eventual distances to stations as instrumental variables for actual distance to stations. All regressions also include the same set of pre-determined controls as in (1). Robust standard errors, clustered at the sub-district level, are reported in parentheses. */**/*** denotes significance at the 10% / 5% / 1% levels.

**Table A.5:** ATT Estimates on Vehicle Ownership and Mode Choice: Varying $d$

| | $d = 0.5$ | $d = 1$ | $d = 1.5$ | $d = 2$ | $d = 2.5$ | $d = 3$ |
|---|---|---|---|---|---|---|
| | **(1)** | **(2)** | **(3)** | **(4)** | **(5)** | **(6)** |
| Δ Share Owning Car | 0.031<br>(0.038) | -0.035<br>(0.063) | -0.028<br>(0.045) | -0.025<br>(0.046) | -0.052<br>(0.063) | -0.126<br>(0.095) |
| Δ Share Owning Motorcycle | 0.066<br>(0.045) | 0.010<br>(0.028) | -0.001<br>(0.039) | 0.057<br>(0.034)* | 0.187<br>(0.048)*** | 0.241<br>(0.065)*** |
| Δ Main Mode Share: BRT | 0.029<br>(0.037) | 0.020<br>(0.019) | -0.017<br>(0.025) | -0.017<br>(0.031) | -0.026<br>(0.037) | -0.008<br>(0.035) |
| Δ Main or Alternative Mode Share: BRT | 0.094<br>(0.061) | 0.043<br>(0.025)* | 0.019<br>(0.029) | 0.008<br>(0.033) | -0.082<br>(0.049)* | 0.028<br>(0.052) |
| Δ Main Mode Share: Car | 0.081<br>(0.046)* | -0.011<br>(0.027) | -0.014<br>(0.037) | -0.013<br>(0.035) | -0.128<br>(0.074)* | -0.218<br>(0.090)** |
| Δ Main Mode Share: Motorcycle | -0.028<br>(0.046) | 0.027<br>(0.030) | 0.035<br>(0.041) | 0.060<br>(0.060) | 0.093<br>(0.070) | 0.084<br>(0.080) |
| Δ Main Mode Share: Train | 0.010<br>(0.032) | 0.004<br>(0.018) | -0.023<br>(0.029) | -0.008<br>(0.021) | 0.011<br>(0.041) | 0.057<br>(0.049) |
| Δ Main Mode Share: Other Public Transport | -0.095<br>(0.038)** | -0.041<br>(0.029) | 0.026<br>(0.028) | -0.007<br>(0.030) | 0.040<br>(0.048) | 0.043<br>(0.066) |
| Δ Main Mode Share: Taxi | 0.000<br>(0.013) | -0.003<br>(0.007) | -0.012<br>(0.008) | -0.022<br>(0.010)** | -0.017<br>(0.011) | 0.017<br>(0.023) |
| Δ Main Mode Share: Non-Motorized Transit | 0.002<br>(0.007) | 0.002<br>(0.004) | 0.004<br>(0.007) | 0.007<br>(0.008) | 0.028<br>(0.011)** | 0.025<br>(0.020) |
| Controls | X | X | X | X | X | X |
| Oaxaca-Blinder | X | X | X | X | 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 community is within $d$ km of a BRT station, where $d$ is listed in the column header, ranging from $d = 0.5$ in column 1 to $d = 3$ in Column 6. All columns report results of a control function specification based on a Oaxaca-Blinder decomposition, described in Kline (2011), analagous to the estimates in Column 4 of Table 4. Robust standard errors, clustered at the sub-district level, are reported in parentheses. */**/*** denotes significance at the 10% / 5% / 1% levels.

**Table A.6:** ATT Estimates on Vehicle Ownership and Mode Choice: Dropping $d \in (1, 2]$

| | Treated vs Planned + Eventual | | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| $\Delta$ Share Owning Car | -0.003 | 0.009 | -0.001 | -0.019 |
| | (0.028) | (0.042) | (0.036) | (0.070) |
| $\Delta$ Share Owning Motorcycle | 0.014 | 0.038 | -0.012 | 0.055 |
| | (0.018) | (0.032) | (0.025) | (0.036) |
| $\Delta$ Main Mode Share: BRT | 0.033** | -0.011 | -0.005 | -0.019 |
| | (0.013) | (0.031) | (0.030) | (0.030) |
| $\Delta$ Main or Alternative Mode Share: BRT | 0.087*** | 0.009 | 0.003 | 0.031 |
| | (0.019) | (0.036) | (0.039) | (0.035) |
| $\Delta$ Main Mode Share: Car | 0.004 | 0.047 | -0.016 | -0.025 |
| | (0.022) | (0.033) | (0.022) | (0.044) |
| $\Delta$ Main Mode Share: Motorcycle | -0.060** | 0.004 | 0.043 | 0.083 |
| | (0.024) | (0.049) | (0.050) | (0.067) |
| $\Delta$ Main Mode Share: Train | 0.013 | -0.013 | -0.012 | 0.000 |
| | (0.011) | (0.022) | (0.031) | (0.022) |
| $\Delta$ Main Mode Share: Other Public Transport | 0.022 | -0.024 | -0.009 | -0.018 |
| | (0.025) | (0.039) | (0.030) | (0.041) |
| $\Delta$ Main Mode Share: Taxi | -0.010 | -0.002 | -0.003 | -0.025** |
| | (0.007) | (0.009) | (0.009) | (0.012) |
| $\Delta$ Main Mode Share: Non-Motorized Transit | -0.001 | -0.000 | 0.002 | 0.004 |
| | (0.004) | (0.007) | (0.005) | (0.012) |
| Controls | . | X | X | X |
| Logistic Reweighting | . | . | X | . |
| Oaxaca-Blinder | . | . | . | X |

*Notes:* This table is identical to Table 4 except that we drop all communities that were greater than 1 km but less than 2 km from the closest BRT station. 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 community is within 2 km of a BRT station. Column 2 includes pre-treatment controls, and Column 3 reports a double-robust specification that both includes controls and reweights non-treated communities by $\hat{\kappa} = \hat{P}/(1-\hat{P})$, where $\hat{P}$ is the estimated probability that the community is within 1 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 4 to account for the generated $\hat{\kappa}$ weights. */**/*** denotes significance at the 10% / 5% / 1% levels.

**Table A.7:** ATT Estimates: Robustness to Propensity Score Specifications

| | Original | Geographic X | Demographic X | Full X |
|---|---|---|---|---|
| | **(1)** | **(2)** | **(3)** | **(4)** |
| Δ Share Owning Car | -0.035 | -0.026 | -0.016 | -0.048 |
| | (0.063) | (0.059) | (0.038) | (0.066) |
| Δ Share Owning Motorcycle | 0.010 | -0.003 | -0.007 | -0.004 |
| | (0.028) | (0.021) | (0.022) | (0.018) |
| Δ Main Mode Share: BRT | 0.020 | 0.011 | 0.026 | 0.026 |
| | (0.019) | (0.016) | (0.019) | (0.020) |
| Δ Main or Alternative Mode Share: BRT | 0.043* | 0.038* | 0.058** | 0.051* |
| | (0.025) | (0.020) | (0.027) | (0.028) |
| Δ Main Mode Share: Car | -0.011 | -0.014 | -0.016 | -0.021 |
| | (0.027) | (0.027) | (0.026) | (0.025) |
| Δ Main Mode Share: Motorcycle | 0.027 | 0.022 | -0.021 | 0.005 |
| | (0.030) | (0.024) | (0.030) | (0.029) |
| Δ Main Mode Share: Train | 0.004 | -0.005 | 0.013 | 0.014 |
| | (0.018) | (0.014) | (0.017) | (0.018) |
| Δ Main Mode Share: Other Public Transport | -0.041 | -0.017 | 0.001 | -0.026 |
| | (0.029) | (0.024) | (0.025) | (0.025) |
| Δ Main Mode Share: Taxi | -0.003 | 0.001 | -0.008 | 0.001 |
| | (0.007) | (0.007) | (0.006) | (0.005) |
| Δ Main Mode Share: Non-Motorized Transit | 0.002 | 0.002 | 0.004 | 0.000 |
| | (0.004) | (0.004) | (0.003) | (0.005) |
| Oaxaca-Blinder | X | X | 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 community is within 1 km of a BRT station. All columns report estimates of a control function specification based on a Oaxaca-Blinder decomposition, described in Kline (2011). Column 1 reports our original estimates (Table 4, Column 4), while Columns 2-4 vary the set of controls used in estimating the propensity score. Robust standard errors, clustered at the sub-district level, are reported in parentheses. */**/*** denotes significance at the 10% / 5% / 1% levels.

**Table A.8:** ATT Estimates on Vehicle Ownership and Mode Choice: Lasso Robustness

| | Original | | Lasso | TWANG | |
|---|---|---|---|---|---|
| | **(1)** | **(2)** | **(3)** | **(4)** | **(5)** |
| Δ Share Owning Car | 0.001 | -0.001 | 0.029 | 0.035 | 0.035 |
| | (0.042) | (0.036) | (0.046) | (0.045) | (0.046) |
| Δ Share Owning Motorcycle | -0.001 | -0.012 | -0.023 | 0.003 | -0.001 |
| | (0.023) | (0.025) | (0.020) | (0.019) | (0.019) |
| Δ Main Mode Share: BRT | 0.013 | -0.005 | 0.016 | 0.002 | 0.007 |
| | (0.020) | (0.029) | (0.019) | (0.027) | (0.025) |
| Δ Main or Alternative Mode Share: BRT | 0.022 | 0.003 | 0.029 | 0.012 | 0.019 |
| | (0.024) | (0.042) | (0.023) | (0.036) | (0.032) |
| Δ Main Mode Share: Car | 0.006 | -0.016 | 0.004 | 0.009 | 0.007 |
| | (0.029) | (0.022) | (0.025) | (0.035) | (0.035) |
| Δ Main Mode Share: Motorcycle | 0.001 | 0.043 | -0.036 | 0.015 | 0.003 |
| | (0.034) | (0.051) | (0.029) | (0.039) | (0.036) |
| Δ Main Mode Share: Train | -0.002 | -0.012 | 0.004 | -0.013 | -0.006 |
| | (0.016) | (0.033) | (0.015) | (0.028) | (0.024) |
| Δ Main Mode Share: Other Public Transport | -0.017 | -0.009 | 0.016 | -0.010 | -0.009 |
| | (0.032) | (0.032) | (0.024) | (0.033) | (0.032) |
| Δ Main Mode Share: Taxi | -0.004 | -0.003 | 0.001 | -0.004 | -0.004 |
| | (0.006) | (0.009) | (0.004) | (0.005) | (0.005) |
| Δ Main Mode Share: Non-Motorized Transit | 0.002 | 0.002 | -0.000 | 0.002 | 0.001 |
| | (0.003) | (0.005) | (0.004) | (0.005) | (0.005) |
| Controls | X | X | . | X | X |
| Logistic Reweighting | . | X | . | . | . |
| Lasso Double-Selected Controls | . | . | X | . | . |
| TWANG Reweighting (`es mean`) | . | . | . | X | . |
| TWANG Reweighting (`ks max`) | . | . | . | . | 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 community is within 1 km of a BRT station. Columns 1 and 2 report our original linear regression with controls and logistic reweighting estimates (columns 2 and 3 of Table 4). Column 3 provides Belloni et al. (2014) post-double selection treatment effect estimates. We first select separate controls for the propensity score and the outcome equation by choosing from the large set of controls discussed in Footnote 28 to minimize a Lasso objective function. We then regress the outcome on the union of the selected controls. In columns 4 and 5, we used generalized boosted regression models to estimate the propensity score, following McCaffrey et al. (2004). Column 4 uses the average standardized effect size of pre-treatment variables for assessing balance between treated and control groups (`es mean`), while Column 5 uses the maximum Kolmogorov-Smirnov $p$-values for weighted pre-treatment variables for assessing balance (`ks max`). Robust standard errors, clustered at the sub-district level, are reported in parentheses. */**/*** denotes significance at the 10% / 5% / 1% levels.

**Table A.9:** ATT on Vehicle Ownership and Mode Choice: Heterogeneity

| | | Gender | | Education | | Monthly HH Expenditure | |
|---|---|---|---|---|---|---|---|
| | All (1) | Male (2) | Female (3) | Low (4) | High (5) | Low (6) | High (7) |
| Δ Share Owning Car | -0.035 | -0.028 | -0.043 | 0.013 | -0.047 | -0.040 | -0.094 |
| | (0.063) | (0.064) | (0.062) | (0.067) | (0.063) | (0.070) | (0.096) |
| Δ Share Owning Motorcycle | 0.010 | 0.013 | 0.007 | 0.028 | 0.007 | 0.041 | 0.002 |
| | (0.028) | (0.029) | (0.027) | (0.031) | (0.030) | (0.036) | (0.031) |
| Δ Main Mode Share: BRT | 0.020 | 0.021 | 0.020 | 0.024 | 0.020 | 0.021 | 0.020 |
| | (0.019) | (0.019) | (0.019) | (0.018) | (0.021) | (0.022) | (0.019) |
| Δ Main or Alternative Mode Share: BRT | 0.043* | 0.048* | 0.038 | 0.020 | 0.044 | 0.033 | 0.057** |
| | (0.025) | (0.026) | (0.024) | (0.027) | (0.028) | (0.032) | (0.026) |
| Δ Main Mode Share: Car | -0.011 | -0.010 | -0.012 | 0.004 | -0.004 | -0.003 | -0.051 |
| | (0.027) | (0.028) | (0.027) | (0.021) | (0.028) | (0.018) | (0.053) |
| Δ Main Mode Share: Motorcycle | 0.027 | 0.032 | 0.024 | 0.024 | 0.025 | 0.037 | 0.052 |
| | (0.030) | (0.032) | (0.029) | (0.037) | (0.029) | (0.037) | (0.043) |
| Δ Main Mode Share: Train | 0.004 | 0.005 | 0.003 | -0.002 | -0.000 | -0.002 | 0.008 |
| | (0.018) | (0.017) | (0.018) | (0.022) | (0.019) | (0.020) | (0.018) |
| Δ Main Mode Share: Other Public Transport | -0.041 | -0.047 | -0.034 | -0.053 | -0.037 | -0.045 | -0.026 |
| | (0.029) | (0.029) | (0.029) | (0.042) | (0.029) | (0.038) | (0.027) |
| Δ Main Mode Share: Taxi | -0.003 | -0.002 | -0.003 | -0.001 | -0.005 | -0.014 | 0.002 |
| | (0.007) | (0.006) | (0.009) | (0.009) | (0.007) | (0.023) | (0.018) |
| Δ Main Mode Share: Non-Motorized Transit | 0.002 | 0.003 | 0.002 | 0.003 | 0.001 | 0.006 | -0.004 |
| | (0.004) | (0.005) | (0.004) | (0.006) | (0.005) | (0.006) | (0.006) |
| Oaxaca-Blinder | X | X | X | X | X | 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 community is within 1 km of a BRT station. All columns report results of a control function specification based on a Oaxaca-Blinder decomposition, described in Kline (2011). Column 1 reproduces our original results (Column 4 of Table 4). In the remaining columns, the dependent variable is the community-level average of the outcome variable for males (Column 2), females (Column 3), below median years of schooling (Column 4), above median years of schooling (Column 5), below median monthly household expenditure (Column 6), and above median monthly household expenditure (Column 7). Robust standard errors, clustered at the sub-district level, are reported in parentheses. */**/*** denotes significance at the 10% / 5% / 1% levels.

**Table A.10:** ATT Estimates on Vehicle Ownership and Mode Choice: (Bad) Controls

| | Treated vs. Planned + Eventual | | | |
|---|---|---|---|---|
| | **(1)** | **(2)** | **(3)** | **(4)** |
| Δ Share Owning Car | -0.035 | -0.032 | -0.020 | -0.011 |
| | (0.063) | (0.067) | (0.064) | (0.050) |
| Δ Share Owning Motorcycle | 0.010 | 0.009 | 0.013 | 0.023 |
| | (0.028) | (0.028) | (0.027) | (0.025) |
| Δ Main Mode Share: BRT | 0.020 | 0.019 | 0.009 | 0.012 |
| | (0.019) | (0.019) | (0.021) | (0.022) |
| Δ Main or Alternative Mode Share: BRT | 0.043* | 0.040 | 0.024 | 0.028 |
| | (0.025) | (0.026) | (0.027) | (0.027) |
| Δ Main Mode Share: Car | -0.011 | -0.011 | -0.008 | -0.002 |
| | (0.027) | (0.029) | (0.029) | (0.023) |
| Δ Main Mode Share: Motorcycle | 0.027 | 0.028 | 0.048 | 0.042 |
| | (0.030) | (0.030) | (0.037) | (0.038) |
| Δ Main Mode Share: Train | 0.004 | 0.003 | -0.005 | -0.006 |
| | (0.018) | (0.019) | (0.022) | (0.021) |
| Δ Main Mode Share: Other Public Transport | -0.041 | -0.040 | -0.047 | -0.045 |
| | (0.029) | (0.029) | (0.029) | (0.030) |
| Δ Main Mode Share: Taxi | -0.003 | -0.002 | 0.001 | -0.005 |
| | (0.007) | (0.007) | (0.007) | (0.006) |
| Δ Main Mode Share: Non-Motorized Transit | 0.002 | 0.003 | 0.002 | 0.003 |
| | (0.004) | (0.005) | (0.006) | (0.006) |
| 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 Monthly HH 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 community is within 1 km of a BRT station. All columns report results of a control function specification based on a Oaxaca-Blinder decomposition, described in Kline (2011). Column 1 reproduces our original results (Column 4 of Table 4). In Column 2, we add controls for changes in community-level population density and the share of recent province-level and district-level migrants. In Column 3, we add 7 controls for changes in different levels of educational attainment. In Column 4, we add 7 additional controls for changes in the share of households with different monthly household expenditures. Robust standard errors, clustered at the sub-district level, are reported in parentheses. */**/*** denotes significance at the 10% / 5% / 1% levels.

**Table A.11:** Negative Spillovers: Unweighted Results

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| 1. All Trips | 0.124*** | 0.121*** | 0.115*** | 0.090*** | 0.025 |
| | (0.017) | (0.017) | (0.018) | (0.020) | (0.028) |
| $N$ | 1137900 | 1137900 | 1119916 | 1137898 | 696308 |
| Adjusted $R^2$ | 0.427 | 0.427 | 0.426 | 0.442 | 0.405 |
| Adjusted $R^2$ (within) | 0.024 | 0.025 | 0.024 | 0.024 | 0.030 |
| 2. Public Bus Trips | 0.115*** | 0.115*** | 0.111*** | 0.082** | 0.025 |
| | (0.032) | (0.032) | (0.033) | (0.036) | (0.045) |
| $N$ | 450485 | 450485 | 447243 | 450412 | 278479 |
| Adjusted $R^2$ | 0.396 | 0.396 | 0.395 | 0.407 | 0.367 |
| Adjusted $R^2$ (within) | 0.021 | 0.021 | 0.021 | 0.020 | 0.025 |
| 3. Private Car Trips | 0.230*** | 0.214*** | 0.189*** | 0.229*** | 0.178 |
| | (0.062) | (0.062) | (0.061) | (0.058) | (0.132) |
| $N$ | 69352 | 69352 | 68839 | 69227 | 39871 |
| Adjusted $R^2$ | 0.480 | 0.481 | 0.481 | 0.474 | 0.413 |
| Adjusted $R^2$ (within) | 0.026 | 0.027 | 0.028 | 0.027 | 0.031 |
| 4. Private Motorcycle Trips | 0.138*** | 0.136*** | 0.132*** | 0.098*** | 0.025 |
| | (0.024) | (0.024) | (0.024) | (0.025) | (0.038) |
| $N$ | 424837 | 424837 | 413752 | 424782 | 257124 |
| Adjusted $R^2$ | 0.403 | 0.403 | 0.401 | 0.415 | 0.375 |
| Adjusted $R^2$ (within) | 0.023 | 0.023 | 0.022 | 0.022 | 0.029 |
| 5. Train Trips | -0.017 | -0.017 | -0.032 | -0.040 | 0.217 |
| | (0.160) | (0.160) | (0.165) | (0.173) | (0.462) |
| $N$ | 35900 | 35900 | 35379 | 35744 | 22225 |
| Adjusted $R^2$ | 0.464 | 0.464 | 0.463 | 0.431 | 0.383 |
| Adjusted $R^2$ (within) | 0.048 | 0.048 | 0.048 | 0.047 | 0.065 |
| Year FE | Yes | Yes | Yes | Yes | Yes |
| Origin × Destination FE | Yes | Yes | Yes | Yes | Yes |
| Number of Trips | | Yes | Yes | Yes | Yes |
| Origin Population Density | | | Yes | | Yes |
| Destination Population Density | | | Yes | | Yes |
| Origin × Year FE | | | | Yes | Yes |
| Destination × Year FE | | | | Yes | Yes |
| Only Non Peak-Time Trips | | | | | Yes |

*Notes:* This table reports results analagous to Table 5, except that this table uses the raw travel diary data, while Table 5 uses survey weights. Each cell in this regression corresponds to a separate estimate of $\beta$ from the specification (3) 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 HVS / 2010 CS 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 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, mode-by-year effects, and departure-hour-by-year indicators. Robust standard errors, two-way clustered by origin and destination community, are reported in parentheses. */**/*** denotes significance at the 10% / 5% / 1% levels.

**Table A.12:** Negative Spillovers: Varying Treatment Comparisons

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| 1. All Trips (Original) | 0.129*** | 0.125*** | 0.120*** | 0.099*** | 0.037 |
| | (0.017) | (0.017) | (0.017) | (0.019) | (0.029) |
| $N$ | 1137900 | 1137900 | 1119916 | 1137898 | 696308 |
| Adjusted $R^2$ | 0.449 | 0.449 | 0.447 | 0.464 | 0.423 |
| Adjusted $R^2$ (within) | 0.030 | 0.030 | 0.030 | 0.029 | 0.035 |
| VS. Other Trips w. O-D $\leq$ 10 km of BRTs | 0.116*** | 0.110*** | 0.101*** | 0.104*** | 0.045 |
| | (0.018) | (0.019) | (0.019) | (0.018) | (0.029) |
| $N$ | 601338 | 601338 | 596640 | 601336 | 355637 |
| Adjusted $R^2$ | 0.468 | 0.468 | 0.467 | 0.479 | 0.435 |
| Adjusted $R^2$ (within) | 0.034 | 0.035 | 0.035 | 0.034 | 0.043 |
| VS. Other Trips w. O-D $\leq$ 5 km of BRTs | 0.077*** | 0.061*** | 0.060*** | 0.087*** | 0.028 |
| | (0.021) | (0.022) | (0.023) | (0.020) | (0.030) |
| $N$ | 390004 | 390004 | 389351 | 390003 | 226083 |
| Adjusted $R^2$ | 0.457 | 0.457 | 0.457 | 0.468 | 0.414 |
| Adjusted $R^2$ (within) | 0.035 | 0.036 | 0.036 | 0.035 | 0.042 |
| VS. Other Trips w. O-D $\leq$ 3 km of BRTs | 0.054** | 0.041 | 0.042 | 0.097*** | 0.045 |
| | (0.024) | (0.025) | (0.026) | (0.022) | (0.035) |
| $N$ | 289079 | 289079 | 288892 | 289078 | 164525 |
| Adjusted $R^2$ | 0.449 | 0.449 | 0.448 | 0.459 | 0.397 |
| Adjusted $R^2$ (within) | 0.030 | 0.030 | 0.030 | 0.029 | 0.034 |
| vs. Eventual and Planned Lines | 0.136*** | 0.120*** | 0.117*** | 0.045** | 0.019 |
| | (0.027) | (0.029) | (0.029) | (0.023) | (0.036) |
| $N$ | 283737 | 283737 | 282331 | 283541 | 156207 |
| Adjusted $R^2$ | 0.553 | 0.554 | 0.552 | 0.561 | 0.542 |
| Adjusted $R^2$ (within) | 0.032 | 0.033 | 0.033 | 0.032 | 0.036 |
| Year FE | Yes | Yes | Yes | Yes | Yes |
| Origin $\times$ Destination FE | Yes | Yes | Yes | Yes | Yes |
| Number of Trips | | Yes | Yes | Yes | Yes |
| Origin Population Density | | | Yes | | Yes |
| Destination Population Density | | | Yes | | Yes |
| Origin $\times$ Year FE | | | | Yes | Yes |
| Destination $\times$ Year FE | | | | Yes | Yes |
| Only Non Peak-Time Trips | | | | | Yes |

*Notes:* The first row of this table is identical to row 1 of Table 5. In subsequent rows, we restrict our estimate of $\beta$ from the specification (3) to only use comparison routes that begin and end within 10 km of a BRT station (row 2), within 5 km of a BRT station (row 3), within 3 km of a BRT station (row 4), or within 1 km of planned or eventual corridors (row 5). The dependent variable is log travel times, and the parameters are estimated from the pooled 2002 HVS / 2010 CS sample. 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 population density. Column 4 adds separate origin-by-year and destination-by-year fixed effects. Column 5 restricts the sample of Column 3 to only include non-peak time trips. All columns include separate purpose-by-year effects, mode-by-year effects, and departure-hour-by-year indicators. Robust standard errors, two-way clustered by origin and destination community, are reported in parentheses. */**/*** denotes significance at the 10% / 5% / 1% levels.

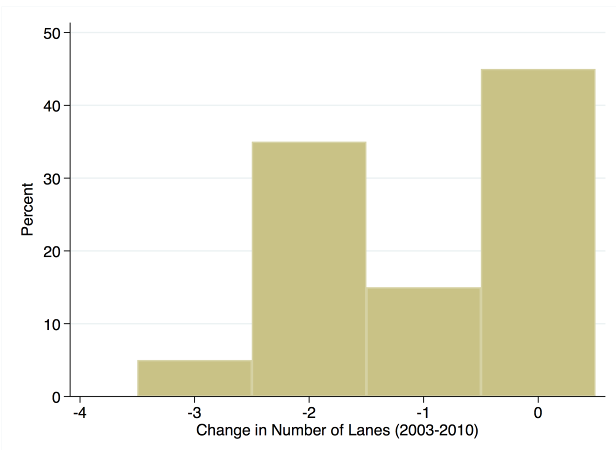
**Table A.13:** Negative Spillovers: Corridor 1 vs. Other Corridors

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| All Trips (Corridor 1 Line) | -0.021 | -0.031 | -0.040 | 0.000 | -0.164*** |
| | (0.073) | (0.073) | (0.073) | (0.061) | (0.063) |
| All Trips (Other Lines) | 0.137*** | 0.133*** | 0.126*** | 0.103*** | 0.047 |
| | (0.016) | (0.017) | (0.017) | (0.019) | (0.029) |
| $N$ | 1137900 | 1137900 | 1119916 | 1137898 | 696308 |
| Adjusted $R^2$ | 0.447 | 0.447 | 0.446 | 0.463 | 0.422 |
| Adjusted $R^2$ (within) | 0.027 | 0.028 | 0.027 | 0.027 | 0.033 |
| Year FE | Yes | Yes | Yes | Yes | Yes |
| Origin × Destination FE | Yes | Yes | Yes | Yes | Yes |
| Number of Trips | | Yes | Yes | Yes | Yes |
| Origin Population Density | | | Yes | | Yes |
| Destination Population Density | | | Yes | | Yes |
| Origin × Year FE | | | | Yes | Yes |
| Destination × Year FE | | | | Yes | Yes |
| Only Non Peak-Time Trips | | | | | Yes |

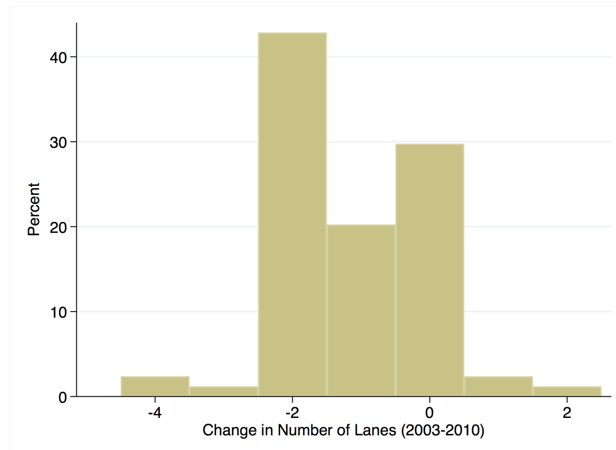
*Notes:* In this table, we report estimates of $\beta$ from a specification similar to that used in Table 5, except that introduce two different sets of BRT indicators: (1) whether or not a trip originates (or terminates) within 1 km of a Corridor 1 BRT station, and (2) whether or not a trip originates (or terminates) within 1 km of a different BRT station. The dependent variable is the log travel times, and the parameters are estimated from the pooled 2002 HVS / 2010 CS sample. In column 1, we include separate year fixed effects and origin-by-destination community 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, mode-by-year effects, and departure-hour-by-year indicators. Robust standard errors, two-way clustered by origin and destination community, are reported in parentheses. */**/*** denotes significance at the 10% / 5% / 1% levels.

**Figure A.1:** Histograms of Changes in Number of Road Lanes, by BRT Standard (2003-2010)

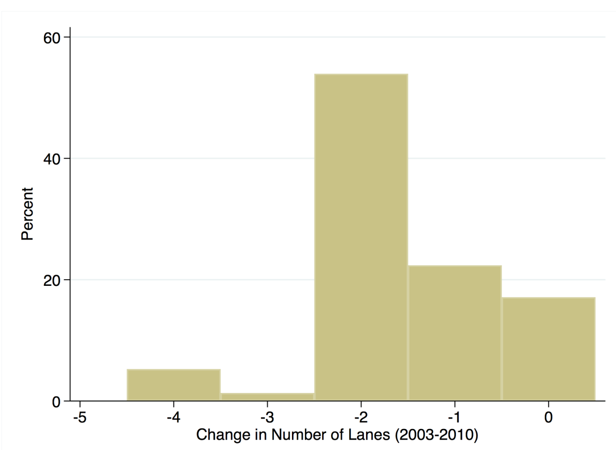
**(A)** Silver




**(C)** Basic




**(B)** Bronze




*Notes*: This figure provides histograms of changes in the number of lanes of traffic on roads parallel to BRT corridors and stations from 2003 to 2010. To construct this figure, we used Google Earth Pro's satellite imagery, provided by Digital Globe, to visually inspect images of BRT station locations in 2003 (before those stations were constructed) and in 2010 (after those stations had become operational). For each image (see the example in Figure A.2), we counted the number of lanes of traffic in both directions. We then plotted histograms of the change in the number of lanes across BRT corridors of different standards.

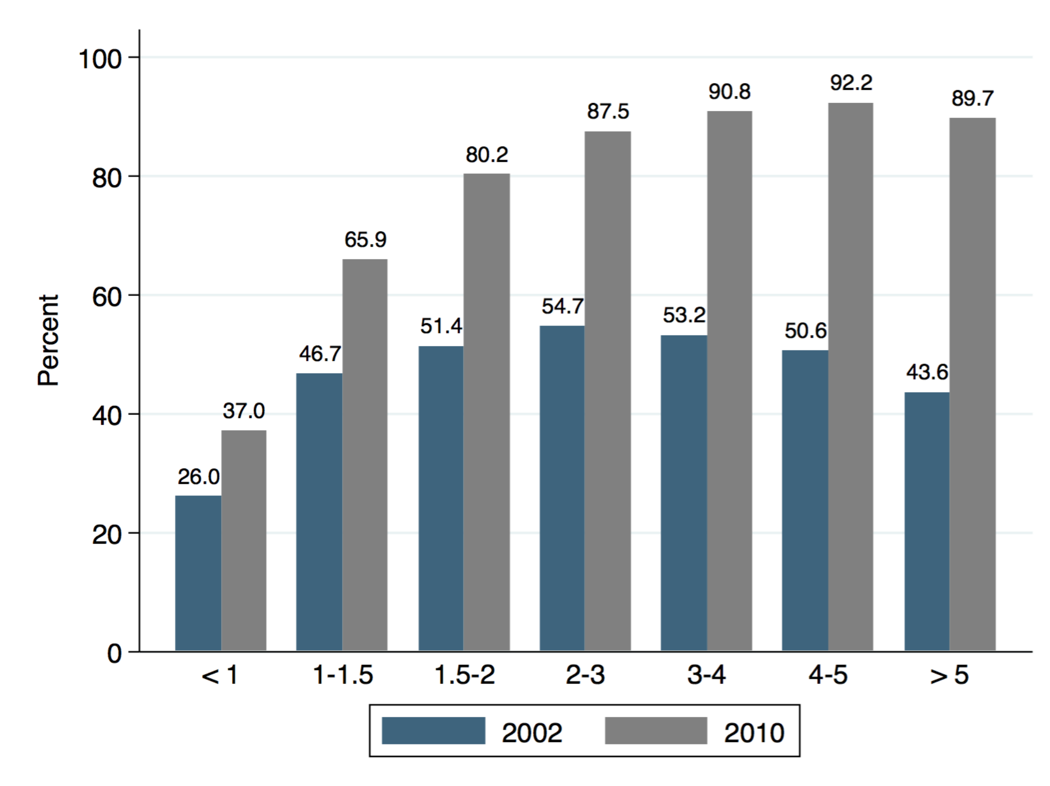
**Figure A.2:** Example of Changes in Number of Road Lanes: Harmoni Sentral Station

**(A)** 2003 **(B)** 2010

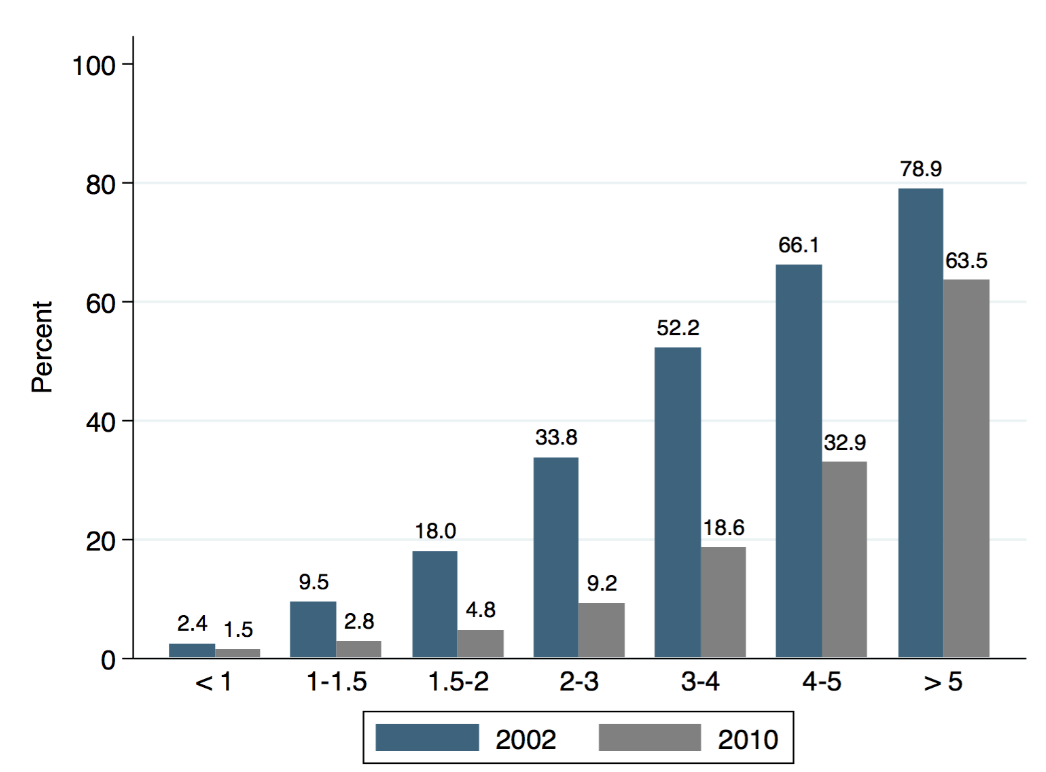
*Notes*: This figure provides an example of changes in the number of road lanes from Google Earth Pro's satellite imagery, provided by Digital Globe. The two images depict the area around Harmoni Sentral Station ($6.1656°$S, $106.8203°$E) in 2003 and 2010. Although the resolution of the 2003 image is somewhat coarser than the 2010 image, it shows that there were 10 lanes (5 in each direction) in 2003 and only 8 lanes (4 in each direction) in 2010. We sometimes used nearby imagery along the same roads as the stations to calculate these changes.

**Figure A.3:** Vehicle Ownership by Income, 2002-2010

**(A)** MOTORCYCLES

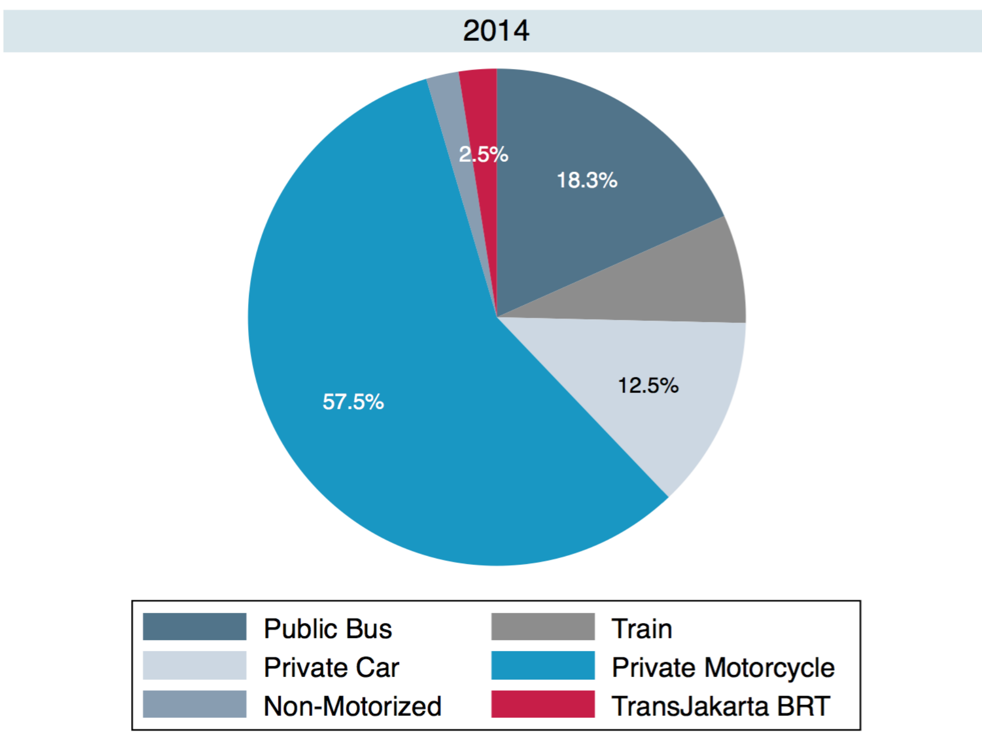



**(B)** CARS




*Notes:* This figure plots the share of households owning different types of motor vehicles by nominal income (in millions of Indonesian Rupiah) for 2002 and 2010, based on the JICA data.

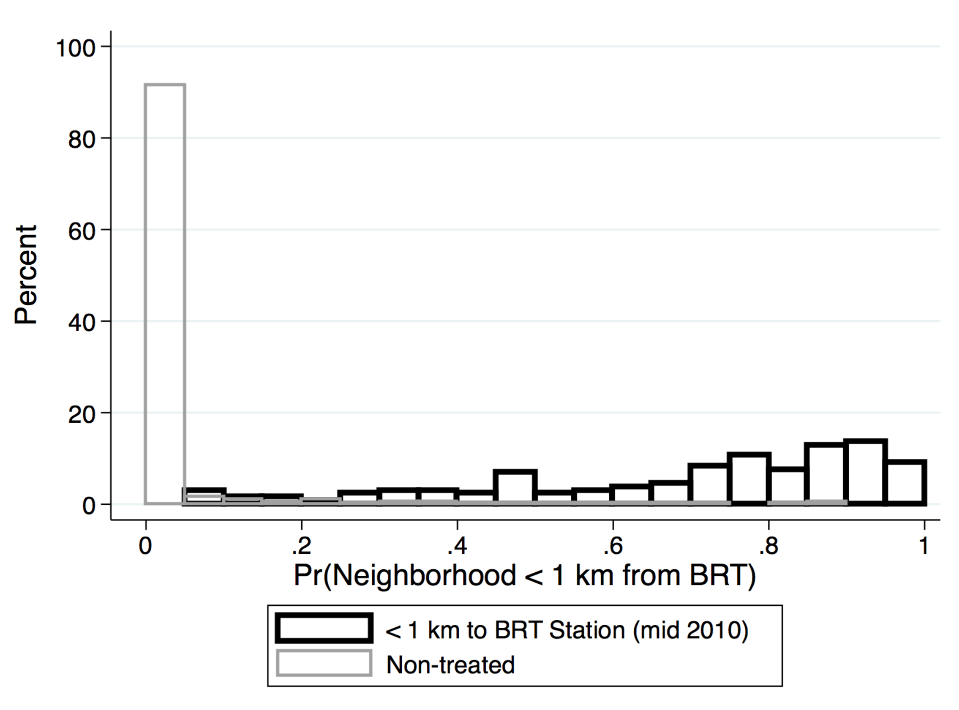
**Figure A.4:** Mode Choice in 2014



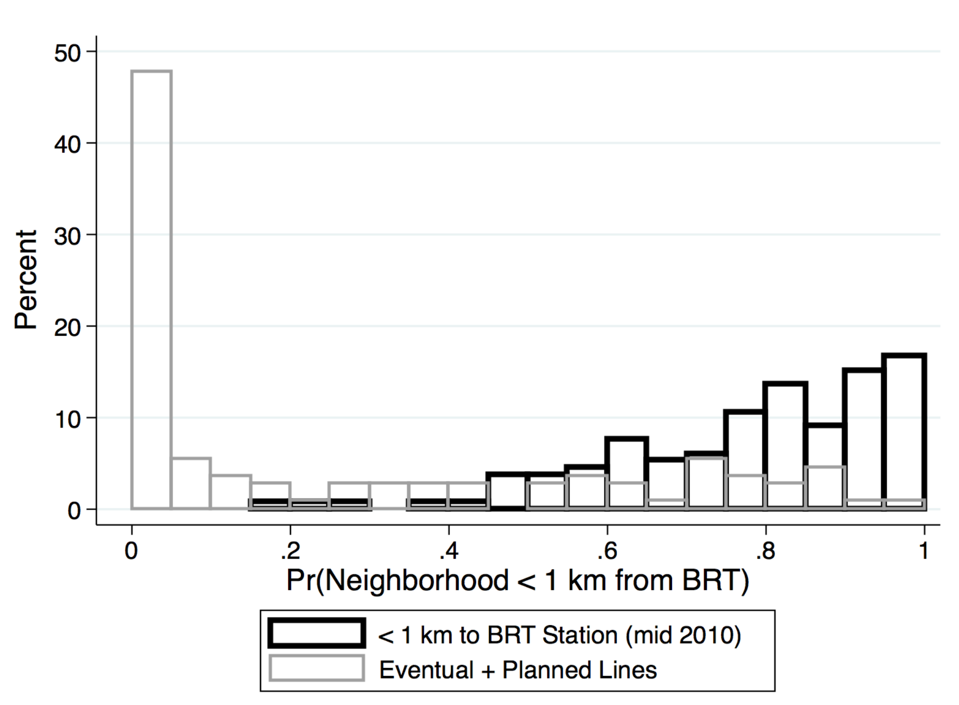

*Notes*: Authors calculations, based on BPS (2014). Note that these data are not completely comparable to those reported in Figure 3, Panel B, because BPS (2014) did not report the use of taxi/ojek/bajaj separately in tabulating the results of the 2014 Jakarta Commuter Survey.

**Figure A.5:** Distribution of Neighborhood Propensity Scores

(A) Treated vs. Non-Treated

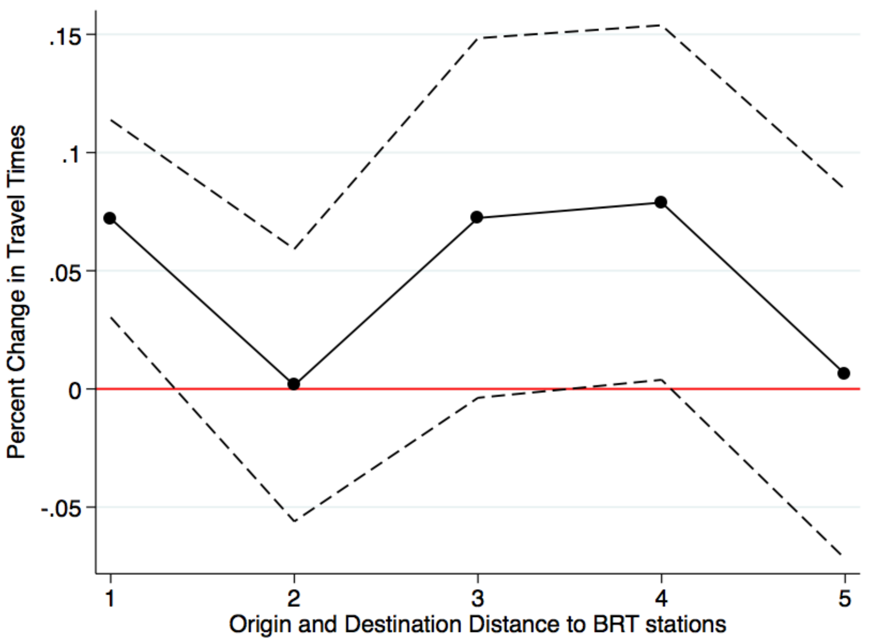



(B) Treated vs. Placebo




*Notes:* This figure plots the distribution across communities 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 kelurahan within 1 km of the closest BRT station to all other communities, while Panel B restricts the comparison to only the planned or eventually treated communities.

**Figure A.6:** Negative Spillovers: Impact of BRT on Travel Times by Distance




*Notes*: This figure reports estimates of $\beta$ from the specification (3) 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 HVS / 2010 CS sample. In this specification, we include indicators for whether or not a trip originates or terminates within $d$ km of a BRT station, with $d \in \{1, 2, 3, 4, 5\}$ and we plot separate effects of the different distance-specific 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.

# B Reduced Form Results: Demographics and Housing

In Table B.1, we report similar results of the effects of TransJakarta BRT station proximity on demographic and housing outcomes. We find no significant effects on changes in population density or average years of schooling. The estimates on changes in the shares of recent migrants are also insignificant, though the results are fairly imprecisely estimated. The growth of lower-middle income residents (monthly incomes between 1 and 1.5 million Rp.) increased by 4.3 percent in response to the BRT system, but the effects of the BRT system on the growth of the other income shares were insignificantly different from zero.

To construct housing outcomes, we use the 2000 and 2010 Census data, which include information on the household's building type. These building types are aggregated into three categories: (1) single family homes; (2) multi-family units (containing 2-4 households); or (3) larger residential structure with 5 or more households (which we term a "high rise" residence). Housing characteristics were also recorded, including whether or not the home had access to piped water, its own or a shared toilet, and state-provided electricity.

We find that almost treated areas experienced a 14.1 percent increase in residential building construction growth relative to treated areas. This growth seems strongest for single family homes, as there were no differences larger multi-family or high rise residential structures, and on the whole no differences in population density. This evidence suggests that instead of attracting higher density, transit-oriented development in areas near stations, lower density sprawl seems to have taken place in non-treated areas.

These results on demographic and housing outcomes survive a similar set of robustness checks as do our main results on mode choice and vehicle ownership:

- **Continuous Treatment.** See Appendix Table B.2.
- **Varying Treatment and Non-Treatment Definitions.** See Appendix Table B.3 and Appendix Table B.4.
- **Alternative Propensity Score Specifications.** See Appendix Table B.5 and Appendix Table B.6.

**Table B.1:** ATT Estimates of BRT Station Proximity: Demographic and Housing Outcomes

| | Treated vs. Planned | | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Δ Population density | -0.123** | -0.002 | 0.025 | -0.003 |
| | (0.051) | (0.028) | (0.029) | (0.039) |
| Δ % recent migrants from w/in Jakarta | 4.572*** | 0.288 | 0.856 | 0.870 |
| | (1.473) | (0.796) | (0.763) | (1.164) |
| Δ % recent migrants from outside Jakarta | 4.111*** | 0.086 | 0.827 | 0.299 |
| | (1.384) | (0.787) | (0.664) | (1.042) |
| Δ Average Years of Schooling | -0.282*** | 0.068* | 0.052 | 0.072 |
| | (0.096) | (0.038) | (0.049) | (0.064) |
| Δ Log Number of Residential Buildings | -0.475*** | -0.137* | -0.008 | -0.141* |
| | (0.115) | (0.069) | (0.028) | (0.082) |
| Δ Log Number of Single Family Buildings | -1.461*** | -0.612** | -0.107* | -0.434 |
| | (0.516) | (0.301) | (0.065) | (0.331) |
| Δ Log Number of Multi-Family Buildings | -0.702*** | 0.009 | 0.051 | -0.016 |
| | (0.182) | (0.103) | (0.048) | (0.105) |
| Δ Log Number of High Rise Buildings | 0.066 | 0.017 | -0.015 | -0.040 |
| | (0.131) | (0.089) | (0.130) | (0.130) |
| Δ % Buildings with clean water | -0.003 | 0.013 | 0.020 | -0.004 |
| | (0.025) | (0.017) | (0.016) | (0.019) |
| Δ % Buildings with electricity | -0.009 | 0.008** | 0.005* | 0.006 |
| | (0.006) | (0.004) | (0.003) | (0.005) |
| Δ % Buildings with own toilet | -0.042* | 0.003 | 0.004 | -0.009 |
| | (0.023) | (0.009) | (0.009) | (0.016) |
| Monthly income < Rp. 1 mil, Delta | -0.032 | 0.015* | 0.014 | 0.010 |
| | (0.024) | (0.009) | (0.009) | (0.011) |
| Monthly income Rp. 1-1.5 mil, Delta | 0.030 | 0.045** | 0.047*** | 0.043* |
| | (0.019) | (0.019) | (0.017) | (0.022) |
| Monthly income Rp. 1.5-2 mil, Delta | -0.028* | -0.024 | -0.028 | -0.024 |
| | (0.017) | (0.018) | (0.022) | (0.022) |
| Monthly income Rp. 2-3 mil, Delta | -0.011 | 0.001 | 0.014 | 0.017 |
| | (0.018) | (0.015) | (0.017) | (0.018) |
| Monthly income Rp. 3-4 mil, Delta | 0.006 | -0.006 | -0.003 | -0.008 |
| | (0.012) | (0.014) | (0.012) | (0.015) |
| Monthly income Rp. 4-5 mil, Delta | 0.015 | -0.008 | -0.006 | 0.000 |
| | (0.010) | (0.011) | (0.018) | (0.013) |
| Monthly income > Rp. 5 mil, Delta | 0.025 | -0.019 | -0.034 | -0.025 |
| | (0.021) | (0.022) | (0.023) | (0.024) |
| $N$ | 241 | 241 | 241 | 241 |
| 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 community is within 1 km of a BRT station. Columns 1-4 restrict the non-treated sample to include only almost-treated communities. Column 2 includes pre-treatment controls, and Columns 3 reports a double-robust specification that both includes controls and reweights non-treated communities by $\hat{\kappa} = \hat{P}/(1-\hat{P})$, where $\hat{P}$ is the estimated probability that the community is within 1 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 slightly across outcomes but include as many 132 "treated" community and 109 "almost-treated" community. */**/*** denotes significant at the 10% / 5% / 1% levels.

## Table B.2: Effects of Continuous BRT Station Distance

| | OLS | IV (2SLS) | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Δ POPULATION DENSITY | -0.004<br>(0.003) | -0.005<br>(0.004) | -0.081<br>(0.773) | -0.004<br>(0.004) |
| Δ % RECENT MIGRANTS FROM W/IN JAKARTA | -0.018<br>(0.116) | -0.104<br>(0.104) | -13.364<br>(129.017) | -0.094<br>(0.101) |
| Δ % RECENT MIGRANTS FROM OUTSIDE JAKARTA | -0.131<br>(0.098) | -0.248<br>(0.091)*** | -9.768<br>(93.923) | -0.240<br>(0.092)*** |
| Δ AVERAGE YEARS OF SCHOOLING | 0.005<br>(0.006) | 0.004<br>(0.006) | -0.674<br>(6.673) | 0.004<br>(0.006) |
| MONTHLY INCOME < RP. 1 MIL, DELTA | 0.001<br>(0.002) | 0.001<br>(0.002) | -0.020<br>(0.217) | 0.001<br>(0.002) |
| MONTHLY INCOME RP. 1-1.5 MIL, DELTA | 0.002<br>(0.002) | 0.002<br>(0.002) | -0.079<br>(0.652) | 0.002<br>(0.002) |
| MONTHLY INCOME RP. 1.5-2 MIL, DELTA | -0.001<br>(0.002) | -0.000<br>(0.002) | -0.316<br>(2.417) | -0.000<br>(0.002) |
| MONTHLY INCOME RP. 2-3 MIL, DELTA | -0.000<br>(0.002) | -0.001<br>(0.002) | 0.237<br>(1.837) | -0.001<br>(0.002) |
| MONTHLY INCOME RP. 3-4 MIL, DELTA | -0.000<br>(0.001) | 0.000<br>(0.001) | 0.075<br>(0.569) | 0.000<br>(0.001) |
| MONTHLY INCOME RP. 4-5 MIL, DELTA | -0.000<br>(0.001) | -0.000<br>(0.001) | 0.025<br>(0.198) | -0.000<br>(0.001) |
| MONTHLY INCOME > RP. 5 MIL, DELTA | 0.000<br>(0.001) | -0.000<br>(0.001) | 0.052<br>(0.409) | 0.000<br>(0.001) |
| Δ LOG NUMBER OF RESIDENTIAL BUILDINGS | -0.011<br>(0.011) | 0.010<br>(0.012) | 1.873<br>(18.162) | 0.008<br>(0.012) |
| Δ LOG NUMBER OF SINGLE FAMILY BUILDINGS | -0.033<br>(0.035) | 0.050<br>(0.039) | 6.961<br>(37.083) | 0.040<br>(0.038) |
| Δ LOG NUMBER OF MULTI-FAMILY BUILDINGS | 0.028<br>(0.023) | 0.013<br>(0.021) | 1.025<br>(6.143) | 0.014<br>(0.021) |
| Δ LOG NUMBER OF HIGH RISE BUILDINGS | 0.047<br>(0.023)** | 0.016<br>(0.021) | 11.445<br>(268.890) | 0.018<br>(0.021) |
| Δ % BUILDINGS WITH CLEAN WATER | 0.005<br>(0.003) | 0.002<br>(0.003) | 1.714<br>(51.099) | 0.002<br>(0.003) |
| Δ % BUILDINGS WITH ELECTRICITY | 0.005<br>(0.002)** | 0.004<br>(0.002) | 1.547<br>(46.228) | 0.004<br>(0.002)* |
| Δ % BUILDINGS WITH OWN TOILET | -0.001<br>(0.004) | -0.003<br>(0.004) | 0.993<br>(29.784) | -0.003<br>(0.004) |
| *N* | 705 | 705 | 705 | 705 |
| CONTROLS | X | X | X | X |
| PLANNED IV | . | X | . | X |
| EVENTUAL IV | | . | X | X |

*Notes:* Each cell reports the coefficient from a regression of the given dependent variable (listed in the left-most column) on a continuous measure of distance to the nearest BRT station. The regression includes all communities within 10 km of the nearest BRT station. Column 1 reports OLS estimates, while in columns 2-4, we use planned and eventual distances to stations as instrumental variables for actual distance to stations. All regressions also include the same set of pre-determined controls as in (1). Robust standard errors, clustered at the sub-district level, are reported in parentheses. */**/*** denotes significant at the 10% / 5% / 1% levels.

**Table B.3:** ATT Estimates on Demographics and Housing: Varying $d$

| | $d = 0.5$ | $d = 1$ | $d = 1.5$ | $d = 2$ | $d = 2.5$ | $d = 3$ |
|---|---|---|---|---|---|---|
| | **(1)** | **(2)** | **(3)** | **(4)** | **(5)** | **(6)** |
| Δ Population density | 0.065 | -0.003 | -0.099 | -0.107 | -0.092 | -0.185 |
| | (0.066) | (0.039) | (0.062) | (0.073) | (0.074) | (0.075)** |
| Δ % Recent migrants from w/in Jakarta | 2.044 | 0.870 | 0.713 | 0.554 | 0.735 | -4.759 |
| | (1.808) | (1.164) | (1.227) | (1.479) | (1.783) | (2.848)* |
| Δ % Recent migrants from outside Jakarta | 1.516 | 0.299 | 0.295 | -0.198 | -0.530 | -4.809 |
| | (1.709) | (1.042) | (1.173) | (1.345) | (1.623) | (2.868)* |
| Δ Average Years of Schooling | 0.180 | 0.072 | -0.092 | -0.056 | -0.036 | -0.048 |
| | (0.109) | (0.064) | (0.112) | (0.121) | (0.121) | (0.127) |
| Monthly income < Rp. 1 mil, Delta | 0.001 | 0.010 | 0.011 | 0.004 | -0.004 | -0.033 |
| | (0.022) | (0.011) | (0.013) | (0.016) | (0.016) | (0.023) |
| Monthly income Rp. 1-1.5 mil, Delta | -0.020 | 0.043 | 0.029 | 0.003 | -0.028 | -0.046 |
| | (0.035) | (0.022)* | (0.018) | (0.024) | (0.030) | (0.052) |
| Monthly income Rp. 1.5-2 mil, Delta | -0.035 | -0.024 | -0.019 | 0.017 | 0.012 | 0.023 |
| | (0.053) | (0.022) | (0.026) | (0.037) | (0.031) | (0.041) |
| Monthly income Rp. 2-3 mil, Delta | -0.027 | 0.017 | 0.032 | 0.037 | 0.062 | 0.114 |
| | (0.031) | (0.018) | (0.018)* | (0.021)* | (0.035)* | (0.054)** |
| Monthly income Rp. 3-4 mil, Delta | -0.008 | -0.008 | -0.024 | -0.012 | 0.033 | 0.081 |
| | (0.019) | (0.015) | (0.013)* | (0.014) | (0.023) | (0.043)* |
| Monthly income Rp. 4-5 mil, Delta | 0.040 | 0.000 | -0.006 | 0.002 | 0.024 | 0.041 |
| | (0.021)* | (0.013) | (0.014) | (0.012) | (0.018) | (0.029) |
| Monthly income > Rp. 5 mil, Delta | 0.051 | -0.025 | -0.014 | -0.042 | -0.103 | -0.197 |
| | (0.032) | (0.024) | (0.027) | (0.030) | (0.038)*** | (0.065)*** |
| Δ Log Number of Residential Buildings | -0.049 | -0.141 | -0.303 | -0.341 | -0.319 | -0.368 |
| | (0.078) | (0.082)* | (0.103)*** | (0.137)** | (0.151)** | (0.179)** |
| Δ Log Number of Single Family Buildings | -0.298 | -0.434 | -1.082 | -1.275 | -1.490 | -1.633 |
| | (0.369) | (0.331) | (0.491)** | (0.764)* | (0.717)** | (0.740)** |
| Δ Log Number of Multi-Family Buildings | -0.127 | -0.016 | -0.266 | -0.296 | -0.218 | -0.315 |
| | (0.067)* | (0.105) | (0.200) | (0.236) | (0.328) | (0.457) |
| Δ Log Number of High Rise Buildings | 0.291 | -0.040 | -0.076 | 0.137 | 0.035 | -0.158 |
| | (0.244) | (0.130) | (0.200) | (0.163) | (0.189) | (0.421) |
| Δ % Buildings with clean water | 0.014 | -0.004 | 0.035 | 0.022 | 0.041 | -0.032 |
| | (0.019) | (0.019) | (0.035) | (0.046) | (0.048) | (0.099) |
| Δ % Buildings with electricity | 0.001 | 0.006 | -0.002 | 0.014 | 0.053 | 0.007 |
| | (0.006) | (0.005) | (0.014) | (0.018) | (0.040) | (0.090) |
| Δ % Buildings with own toilet | 0.027 | -0.009 | -0.030 | -0.031 | 0.023 | -0.017 |
| | (0.029) | (0.016) | (0.025) | (0.039) | (0.061) | (0.110) |
| Controls | X | X | X | X | X | X |
| Oaxaca-Blinder | X | X | X | X | 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 community is within $d$ km of a BRT station, where $d$ is listed in the column header, ranging from $d = 0.5$ in Column 1 to $d = 3$ in Column 6. All columns report results of a control function specification based on a Oaxaca-Blinder decomposition, described in Kline (2011), analagous to the estimates in Table 4, Column 4. Robust standard errors, clustered at the sub-district level, are reported in parentheses. */**/*** denotes significant at the 10% / 5% / 1% levels.

**Table B.4:** ATT Estimates on Demographics and Housing (Dropping Too Close)

| | TREATED VS PLANNED + EVENTUAL | | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Δ POPULATION DENSITY | -0.178** | -0.046 | 0.025 | -0.153 |
| | (0.068) | (0.056) | (0.028) | (0.133) |
| Δ % RECENT MIGRANTS FROM W/IN JAKARTA | 5.795*** | -1.530 | 0.856 | 2.415 |
| | (1.629) | (1.187) | (0.727) | (1.737) |
| Δ % RECENT MIGRANTS FROM OUTSIDE JAKARTA | 5.183*** | -1.870 | 0.827 | 0.737 |
| | (1.611) | (1.279) | (0.652) | (1.717) |
| Δ AVERAGE YEARS OF SCHOOLING | -0.405*** | -0.017 | 0.052 | -0.157 |
| | (0.115) | (0.069) | (0.051) | (0.253) |
| MONTHLY INCOME < RP. 1 MIL, DELTA | -0.051* | 0.005 | 0.014 | -0.024 |
| | (0.027) | (0.016) | (0.010) | (0.019) |
| MONTHLY INCOME RP. 1-1.5 MIL, DELTA | 0.024 | 0.045 | 0.047*** | 0.020 |
| | (0.025) | (0.033) | (0.017) | (0.028) |
| MONTHLY INCOME RP. 1.5-2 MIL, DELTA | -0.026 | -0.014 | -0.028 | 0.032 |
| | (0.019) | (0.022) | (0.021) | (0.034) |
| MONTHLY INCOME RP. 2-3 MIL, DELTA | -0.015 | 0.001 | 0.014 | 0.038 |
| | (0.022) | (0.026) | (0.017) | (0.023) |
| MONTHLY INCOME RP. 3-4 MIL, DELTA | 0.012 | 0.005 | -0.003 | 0.005 |
| | (0.013) | (0.020) | (0.013) | (0.021) |
| MONTHLY INCOME RP. 4-5 MIL, DELTA | 0.021* | -0.004 | -0.006 | 0.006 |
| | (0.011) | (0.013) | (0.018) | (0.016) |
| MONTHLY INCOME > RP. 5 MIL, DELTA | 0.042* | -0.032 | -0.034 | -0.058* |
| | (0.022) | (0.028) | (0.023) | (0.031) |
| Δ LOG NUMBER OF RESIDENTIAL BUILDINGS | -0.665*** | -0.319** | -0.008 | -0.249 |
| | (0.121) | (0.155) | (0.029) | (0.202) |
| Δ LOG NUMBER OF SINGLE FAMILY BUILDINGS | -2.128*** | -1.440** | -0.107 | -0.549 |
| | (0.610) | (0.685) | (0.065) | (0.891) |
| Δ LOG NUMBER OF MULTI-FAMILY BUILDINGS | -1.056*** | -0.140 | 0.051 | -0.408 |
| | (0.199) | (0.236) | (0.049) | (0.400) |
| Δ LOG NUMBER OF HIGH RISE BUILDINGS | 0.126 | 0.047 | -0.015 | -0.134 |
| | (0.166) | (0.113) | (0.138) | (0.393) |
| Δ % BUILDINGS WITH CLEAN WATER | -0.003 | 0.042** | 0.020 | -0.025 |
| | (0.033) | (0.021) | (0.015) | (0.047) |
| Δ % BUILDINGS WITH ELECTRICITY | -0.015* | 0.015** | 0.005* | 0.004 |
| | (0.008) | (0.006) | (0.003) | (0.009) |
| Δ % BUILDINGS WITH OWN TOILET | -0.055 | 0.004 | 0.004 | -0.073* |
| | (0.036) | (0.016) | (0.009) | (0.042) |
| CONTROLS | . | X | X | X |
| LOGISTIC REWEIGHTING | . | . | X | . |
| OAXACA-BLINDER | . | . | . | X |

*Notes:* This table is identical to Table B.1 except that we drop all communities that were greater than 1 km but less than 2 km from the closest BRT station. 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 community is within 2 km of a BRT station. Column 2 includes pre-treatment controls, and Column 3 reports a double-robust specification that both includes controls and reweights non-treated communities by $\hat{\kappa} = \hat{P}/(1-\hat{P})$, where $\hat{P}$ is the estimated probability that the community is within 1 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 4 to account for the generated $\hat{\kappa}$ weights. */**/*** denotes significant at the 10% / 5% / 1% levels.

**Table B.5:** ATT Estimates on Demographics and Housing: Robustness to Propensity Score Specifications

| | Original | Geographic X | Demographic X | Full X |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Δ Population density | -0.003 | -0.016 | -0.015 | 0.037 |
| | (0.039) | (0.041) | (0.039) | (0.034) |
| Δ % recent migrants from w/in Jakarta | 0.870 | 2.807** | 0.534 | 1.429 |
| | (1.164) | (1.317) | (1.183) | (1.164) |
| Δ % recent migrants from outside Jakarta | 0.299 | 2.603** | -0.110 | 0.956 |
| | (1.042) | (1.157) | (1.072) | (1.034) |
| Δ Average Years of Schooling | 0.072 | -0.072 | 0.067 | 0.064 |
| | (0.064) | (0.067) | (0.059) | (0.063) |
| Monthly income < Rp. 1 mil, Delta | 0.010 | 0.009 | 0.012 | 0.006 |
| | (0.011) | (0.023) | (0.010) | (0.011) |
| Monthly income Rp. 1-1.5 mil, Delta | 0.043* | 0.048** | 0.033** | 0.041* |
| | (0.022) | (0.023) | (0.016) | (0.022) |
| Monthly income Rp. 1.5-2 mil, Delta | -0.024 | -0.026 | -0.025 | -0.016 |
| | (0.022) | (0.017) | (0.017) | (0.023) |
| Monthly income Rp. 2-3 mil, Delta | 0.017 | 0.005 | 0.004 | 0.005 |
| | (0.018) | (0.019) | (0.013) | (0.018) |
| Monthly income Rp. 3-4 mil, Delta | -0.008 | -0.005 | -0.009 | -0.003 |
| | (0.015) | (0.015) | (0.013) | (0.016) |
| Monthly income Rp. 4-5 mil, Delta | 0.000 | -0.004 | 0.001 | 0.000 |
| | (0.013) | (0.012) | (0.011) | (0.013) |
| Monthly income > Rp. 5 mil, Delta | -0.025 | -0.018 | -0.008 | -0.024 |
| | (0.024) | (0.020) | (0.019) | (0.023) |
| Δ Log Number of Residential Buildings | -0.141* | -0.204* | -0.192*** | -0.031 |
| | (0.082) | (0.114) | (0.073) | (0.064) |
| Δ Log Number of Single Family Buildings | -0.434 | -0.762 | -0.483* | -0.023 |
| | (0.331) | (0.486) | (0.275) | (0.306) |
| Δ Log Number of Multi-Family Buildings | -0.016 | -0.091 | -0.309** | 0.070 |
| | (0.105) | (0.134) | (0.140) | (0.084) |
| Δ Log Number of High Rise Buildings | -0.040 | -0.105 | 0.093 | -0.042 |
| | (0.130) | (0.128) | (0.133) | (0.123) |
| Δ % Buildings with clean water | -0.004 | -0.005 | 0.011 | -0.006 |
| | (0.019) | (0.021) | (0.022) | (0.024) |
| Δ % Buildings with electricity | 0.006 | 0.004 | 0.004 | 0.003 |
| | (0.005) | (0.005) | (0.004) | (0.005) |
| Δ % Buildings with own toilet | -0.009 | -0.004 | -0.023 | -0.003 |
| | (0.016) | (0.017) | (0.015) | (0.019) |
| Oaxaca-Blinder | X | X | 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 community is within 1 km of a BRT station. All columns report estimates of a control function specification based on a Oaxaca-Blinder decomposition, described in Kline (2011). Column 1 reports our original estimates (Table B.1, Column 4), while Columns 2-4 vary the set of controls used in estimating the propensity score. Robust standard errors, clustered at the sub-district level, are reported in parentheses. */**/*** denotes significant at the 10% / 5% / 1% levels.

**Table B.6:** ATT Estimates on Demographics and Housing: Lasso Robustness

| | Original | | Lasso | TWANG | |
|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) |
| Δ Population density | -0.002 | 0.025 | 0.019 | 0.013 | 0.016 |
| | (0.028) | (0.029) | (0.024) | (0.024) | (0.024) |
| Δ % recent migrants from w/in Jakarta | 0.288 | 0.856 | 1.958** | 1.345 | 1.367 |
| | (0.796) | (0.700) | (0.959) | (0.903) | (0.920) |
| Δ % recent migrants from outside Jakarta | 0.086 | 0.827 | 1.830** | 1.305 | 1.326 |
| | (0.787) | (0.651) | (0.846) | (0.857) | (0.875) |
| Δ Average Years of Schooling | 0.068* | 0.052 | 0.035 | 0.087** | 0.091** |
| | (0.038) | (0.050) | (0.043) | (0.043) | (0.043) |
| Monthly income < Rp. 1 mil, Delta | 0.015* | 0.014 | 0.012 | 0.014 | 0.013 |
| | (0.009) | (0.009) | (0.009) | (0.009) | (0.009) |
| Monthly income Rp. 1-1.5 mil, Delta | 0.045** | 0.047*** | 0.038** | 0.048*** | 0.047*** |
| | (0.019) | (0.017) | (0.016) | (0.016) | (0.016) |
| Monthly income Rp. 1.5-2 mil, Delta | -0.024 | -0.028 | -0.020 | -0.032 | -0.034 |
| | (0.018) | (0.023) | (0.017) | (0.021) | (0.021) |
| Monthly income Rp. 2-3 mil, Delta | 0.001 | 0.014 | -0.012 | 0.012 | 0.010 |
| | (0.015) | (0.018) | (0.013) | (0.015) | (0.014) |
| Monthly income Rp. 3-4 mil, Delta | -0.006 | -0.003 | -0.000 | -0.006 | -0.007 |
| | (0.014) | (0.012) | (0.010) | (0.015) | (0.015) |
| Monthly income Rp. 4-5 mil, Delta | -0.008 | -0.006 | -0.002 | -0.017 | -0.015 |
| | (0.011) | (0.018) | (0.011) | (0.020) | (0.019) |
| Monthly income > Rp. 5 mil, Delta | -0.019 | -0.034 | -0.007 | -0.017 | -0.015 |
| | (0.022) | (0.022) | (0.021) | (0.024) | (0.026) |
| Δ Log Number of Residential Buildings | -0.137* | -0.008 | -0.130* | -0.027 | -0.023 |
| | (0.069) | (0.030) | (0.071) | (0.030) | (0.030) |
| Δ Log Number of Single Family Buildings | -0.612** | -0.107 | -0.673* | -0.180* | -0.175* |
| | (0.301) | (0.066) | (0.342) | (0.099) | (0.099) |
| Δ Log Number of Multi-Family Buildings | 0.009 | 0.051 | -0.040 | 0.026 | 0.029 |
| | (0.103) | (0.050) | (0.092) | (0.052) | (0.053) |
| Δ Log Number of High Rise Buildings | 0.017 | -0.015 | -0.031 | -0.088 | -0.060 |
| | (0.089) | (0.136) | (0.100) | (0.155) | (0.141) |
| Δ % Buildings with clean water | 0.013 | 0.020 | -0.002 | 0.018 | 0.017 |
| | (0.017) | (0.016) | (0.019) | (0.017) | (0.017) |
| Δ % Buildings with electricity | 0.008** | 0.005* | 0.004 | 0.004 | 0.004 |
| | (0.004) | (0.003) | (0.005) | (0.003) | (0.003) |
| Δ % Buildings with own toilet | 0.003 | 0.004 | 0.002 | 0.007 | 0.008 |
| | (0.009) | (0.009) | (0.011) | (0.008) | (0.008) |
| Controls | X | X | . | X | X |
| Logistic Reweighting | . | X | . | . | . |
| Lasso Double-Selected Controls | . | . | X | . | . |
| TWANG Reweighting (es mean) | . | . | . | X | . |
| TWANG Reweighting (ks max) | . | . | . | . | 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 community is within 1 km of a BRT station. Columns 1 and 2 report our original linear regression with controls and logistic reweighting estimates (Columns 2 and 3 of Table B.1). Column 3 provides Belloni et al. (2014) post-double selection treatment effect estimates. We first select separate controls for the propensity score and the outcome equation by choosing from the large set of controls discussed in Footnote 28 to minimize a Lasso objective function. We then regress the outcome on the union of the selected controls. In Columns 4 and 5, we used generalized boosted regression models to estimate the propensity score, following McCaffrey et al. (2004). Column 4 uses the average standardized effect size of pre-treatment variables for assessing balance between treated and control groups (es mean), while Column 5 uses the maximum Kolmogorov-Smirnov $p$-values for weighted pre-treatment variables for assessing balance (ks max). Robust standard errors, clustered at the sub-district level, are reported in parentheses. */**/*** denotes significant at the 10% / 5% / 1% levels.

# C Data Appendix

**Commuter Travel Surveys.** Our trip-level data come from two cross-sectional surveys of households conducted by the Japan International Cooperation Agency (JICA) study teams in 2002 and 2010. The 2002 survey, known as the Home Visit Survey (HVS), was part of the *Study on Integrated Transportation Master Plan* (SITRAMP). SITRAMP was a technical assistance project intended to anticipate future transportation challenges in the Jabodetabek metropolitan area. HVS was collected, among others, to establish a person-trip origin-destination (PTOD) matrices for urban transportation planning purposes (JICA, 2004b).

The 2002 HVS's sampling strategy was designed to capture trip characteristic information for approximately 3 percent of the Jabodetabek population. Ultimately, its sample included 163,334 households across 1,485 communities (*kelurahan*) (JICA, 2004b, Table 1.8.3). HVS collected information on the demographic and socio-economic characteristics of households and their members, as well as trip information of household members. The trip information module included questions on the origin and destination of trips as well as their modes of transport (including transfers), and departure and arrival times. According to background reports, the 2002 survey was a massive undertaking, with 2,418 enumerators each making approximately 70 home visits over a 3 month period (July-September) (JICA, 2004a).

For 2010, the trip-level data come from the 2010 Commuter Survey (CS). This survey was also collected by the JICA study team under the *Jabodetabek Urban Transport Policy Integration Project* (JUTPI). The 2010 CS was similarly designed to capture trip characteristics for 3 percent of the Jabodetabek population (or around 180,000 households in 2010). Its final sample included around 180,000 households in 1,499 communities (OCAC, 2011, Table 1.2.1).

As an update to the HVS data, the survey contained modules that were similar to the 2002 HVS (OCAC, 2011). The survey was also another large data collection effort, employing 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).

**Census Data.** We use the 2000 and 2010 population census microdata to construct aggregate community-level characteristics. These population censuses provide complete enumerations of the Indonesian population. These censuses collect individual-level demographic information such as age, gender, education, and migration status in the past five years. In addition, they also collect information about the physical characteristics of buildings and individual residences. These datasets were collected by Indonesia's national statistical agency, *BPS Indonesia*.

**NOAA Data on Light Intensity.** To proxy for economic activities at the local level, we make use of an innovative technique, developed by Henderson et al. (2012), which uses satellite data on nighttime lights. Daily between 8:30 PM and 10:00 PM local time, satellites from the United States Air Force Defense Meteorological Satellite Program (DMSP) record the light intensity of every 30-arc-second-square of the Earth's surface (corresponding to roughly 0.86 square kilometers). DMSP cleans this daily data, dropping anomalous observations, and provides the public with annual averages of light intensity from multiple satellites. After averaging the data across multiple satellites, we obtain annual estimates of light intensity for every 30-arc-second square of the Earth's surface in 1992 and 2002. We construct log average night light intensity in 1992 as a pre-treatment baseline measure of each community's development and we measure the log difference between average night light intensity in 1992 and 2002 as a proxy for urban growth.[51]

**Elevation.** We construct the topographical variables using raster data from the Harmonized World Soil Database (HWSD), Version 1.2 (Fischer et al., 2008). The digital elevation map records the median elevation (in meters) of

[51] The DMSP-OLS Nighttime Lights Time Series Version 4 datasets can be downloaded here: `http://ngdc.noaa.gov/eog/dmsp/downloadV4composites.html`.

each 5 arc minute $\times$ 5 arc minute pixel (roughly 10 km$^2$).[52]

**Ruggedness.** A 30 arc-second ruggedness raster was computed for Indonesia according to the methodology described by Sappington et al. (2007). The authors propose a Vector Ruggedness Measure (VRM), which captures the distance or dispersion between a vector orthogonal to a topographical plane and the orthogonal vectors in a neighborhood of surrounding elevation planes. To calculate the measure, one first calculates the $x$, $y$, and $z$ coordinates of vectors that are orthogonal to each 30-arc second grid of the Earth's surface. These coordinates are computed using a digital elevation model and standard trigonometric techniques.

Given this, a resultant vector is computed by adding a given cell's vector to each of the vectors in the surrounding cells; the neighborhood or window is supplied by the researcher. Finally, the magnitude of this resultant vector is divided by the size of the cell window and subtracted from 1. This results in a dimensionless number that ranges from 0 (least rugged) to 1 (most rugged).[53]

For example: on a $(3 \times 3)$ flat surface, all orthogonal vectors point straight up, and each vector can be represented by $(0, 0, 1)$ in the Cartesian coordinate system. The resultant vector obtained from adding all vectors is equal to $(0, 0, 9)$, and the VRM is equal to $1 - (9/9) = 0$. As the $(3 \times 3)$ surface deviates from a perfect plane, the length of the resultant vector gets smaller, and the VRM increases to 1.

[52] Raster files from the HWSD project are publicly available at http://www.fao.org/soils-portal/soil-survey/soil-maps-and-databases/harmonized-world-soil-database-v12/en/.

[53] The authors have generously provided a Python script for computing their Vector Ruggedness Measure (VRM) in ArcView. The script and detailed instructions for installation can be found here: https://www.arcgis.com/home/item.html?id=9e4210b3ee7b413bbb1f98fb9c5b22d4.

# D Counterfactuals Appendix

**Nested Logit Choice Probabilities.** Let $B_1$ denote the set of mode-time products for public modes, let $B_2$ denote the set of mode-time products for private modes, and let $B(j)$ denote the nest in which product $j$ lies (i.e. either $B_1$ or $B_2$, depending on the product). Based on the specification of indirect utility in (4) and the nested logit error term assumptions, the share of market $t$ choosing product $j$ is given by:

$$s_{jt} = \frac{\exp\left\{\frac{V_{jt}}{(1-\rho)}\right\}\left(\sum_{k\in B(j)} \exp\left\{\frac{V_{kt}}{(1-\rho)}\right\}\right)^{-\rho}}{1+\left(\sum_{k\in B_1} \exp\left\{\frac{V_{kt}}{(1-\rho)}\right\}\right)^{1-\rho}+\left(\sum_{k\in B_2} \exp\left\{\frac{V_{kt}}{(1-\rho)}\right\}\right)^{1-\rho}} \tag{D.1}$$

where $V_{jt}$ is the mean utility of product $j$ in market $t$, given by:

$$V_{jt} = \mathbf{x}'_{jt}\beta - \alpha p_{jt} + \xi_j + \Delta\xi_{jt}$$

The share of individuals in market $t$ choosing the outside option is given by:

$$P_{0t} = \frac{1}{1+\left(\sum_{k\in B_1} \exp\left\{\frac{V_{kt}}{(1-\rho)}\right\}\right)^{1-\rho}+\left(\sum_{k\in B_2} \exp\left\{\frac{V_{kt}}{(1-\rho)}\right\}\right)^{1-\rho}}$$

These expressions are just standard nested logit choice market shares with an outside option (see Train, 2009).

Estimating (5) delivers estimates of $\beta$, $\alpha$, the $\xi_j$'s, and $\rho$, and we plug those estimates into the (D.1), together with the structural residuals, $\Delta\xi_{jt}$, to obtain predicted shares. Our counterfactuals use demand parameters from Column 6, Table 6 for these estimates. A plot of these predicted shares vs. actual shares is given in Figure D.1, Panel A.

**Counterfactual Simulations.** To conduct counterfactuals, we perform the following iterative procedure:

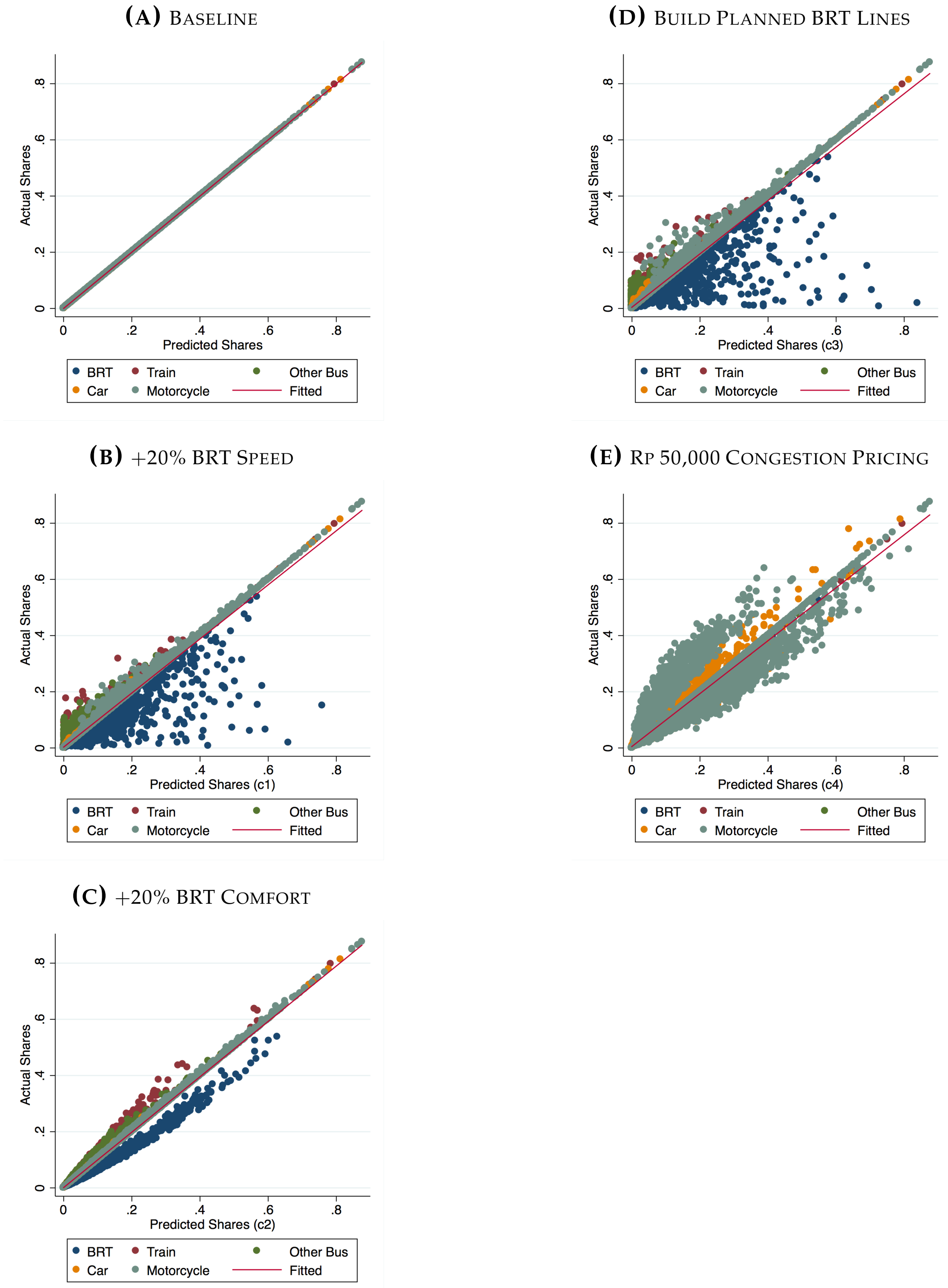
- **Step 0**: We change the product characteristics, $x \to \widetilde{x}$, and use the nested logit share equation, (D.1), to predict changes in market shares, $s_{jt}(\widetilde{x})$. Call this market share $s_{jt}(0)$.
- **Step 1**: The new market shares lead to different traffic patterns, and we use the average travel cost relationships to estimate how the new traffic impacts travel times. We use the linear cost-of-travel parameters from Column 4, Table 7 to update prices. Let $p_{jt}(0)$ denote the updated prices.
- **Step 2**: Based on the new prices, we update market shares in accordance with (D.1). Let $s_{jt}(1)$ denote the predicted product shares for this first iteration.

We repeat Steps 1 and 2 until the change between predicted market shares is "small". Formally, let $s_{jt}(k)$ denote the predicted product shares for iteration $k$. We repeat steps 1 and 2 until the sum of the absolute difference between predicted mode shares in different iterations is less than 1, i.e.

$$\sum_j \sum_t |s_{jt}(k) - s_{jt}(k-1)| < 1.$$

Because most simulations result in fairly small changes in demand, we converge to a new equilibrium typically after 1-2 iterations.

**Figure D.1:** Predicted vs. Actual Shares: Baseline and Counterfactuals




*Notes*: This figure shows predicted vs. actual shares under the baseline scenario (Panel A) and different counterfactual scenarios (Panels B-E).