Life in the Slow Lane: Unintended Consequences of Public Transit in Jakarta*

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Abstract

We study how TransJakarta, one of the world's largest BRT systems, impacted commuting outcomes in Jakarta, Indonesia from 2002 to 2010. Using planned lines for identification, we find that BRT station proximity neither reduced vehicle ownership nor travel times, and it did not increase commuter flows. Instead, the BRT exacerbated congestion along service corridors. To evaluate welfare effects, we calibrate a quantitative spatial general equilibrium model with multiple congestible transport networks. Counterfactual simulations suggest that implementation improvements, including increasing the quality of expansion corridors, would significantly improve welfare with only modest costs.

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1 Introduction

In many burgeoning cities of the developing world, traffic congestion is growing worse. Rapid increases in population and vehicle ownership have led to unsustainable commuting times and deteriorating air quality (e.g. Brinkman, 2016; Lu et al., 2017; Simeonova et al., 2019). Cities now face a menu of policy options for alleviating congestion, including investments in public transit. How cities design and implement public transit infrastructure today will shape commuting patterns for decades.

In this paper, we study the commuting effects of *TransJakarta*, a public transit system in Jakarta, Indonesia, one of the world's largest and most congested megacities. TransJakarta is a Bus Rapid Transit (BRT) system that uses a network of busways to provide similar transport services to those of subways but at a fraction of the costs. It is now the world's largest BRT with 13 primary routes and more than 200 stations. However, TransJakarta had many problems with service quality during its first six years of operation that reduced operational speeds and increased waiting times. As a result, we find that the system induced few effects on vehicle ownership, mode choice, and commuter flows. Planners expanded the system by converting surface-based lanes into busways, and as a result, we find that the system also exacerbated congestion along service corridors. We find that the overall welfare effects of the system were small, even accounting for its relatively low construction costs.

Our results are important for several reasons. First, a growing body of evidence suggests that although costly, urban transit investments can provide important benefits for commuters. For example, in many settings, subway systems have been shown to reduce congestion (Yang et al., 2018; Gu et al., 2019), improve air quality (Gendron-Carrier et al., 2018), and increase public transit ridership (Gonzalez-Navarro and Turner, 2018). The highest quality BRT implementations have also been shown to substantially increase welfare, output, and overall public transit use (Tsivanidis, 2019; Majid et al., 2018). However, we lack evidence on the effects of cheaper, lower quality implementations which are more common in low and middle-income countries (LMICs) characterized by weak governance and high levels of poverty.

Second, our setting, Greater Jakarta, is one of the largest agglomerations in the developing world, with a population of more than 31 million people in 2015. Like many rapidly growing cities in LMICs, Jakarta experienced rising traffic congestion due to rapid motorization and weak urban planning. Buses are also frequently used in Jakarta, similar to other cities in developing countries, and a BRT system represents an affordable upgrade that could potentially improve mobility.[1] Cheaper, lower quality BRT systems may be more attractive for LMIC cities facing resource constraints. Our work highlights the dangers of such choices: poorly implemented urban transport infrastructure can fail to curb rising motorization and actually increase congestion, instead of alleviating it. Our findings may also provide insights for why several BRTs have recently failed and been dismantled.[2]

Finally, our results may inform policymakers, who are often interested in understanding how changes to the design of urban transit systems could improve ridership, congestion, and welfare. We extend

[1]According to a recent World Bank Urban Transport Strategy, "[in] most cities in the developing world, buses are the backbone of the motorized transport system and will remain so for the foreseeable future" (World Bank, 2002, p. 80).

[2]BRT systems are now operational in nearly 100 LMIC cities, and more BRTs are planned for development, but implementation quality varies widely (BRT+ Centre of Excellence and EMBARQ, 2019). At the same time, many existing BRTs — such as in Bangkok, Taichung (Taiwan), and a number of Indian cities (Dehli, Pune, Indore, Jaipur) — has been recently dismantled (Pojani and Stead, 2017).

the quantitative spatial general equilibrium model of Allen and Arkolakis (2020) to study the effects of these design changes. Our extension allows for endogenous route choices across multiple congestible urban transport networks, highlighting how these networks interact. The framework provides a comprehensive method for quantifying the long run impacts of many different policy changes on welfare and economic activity.

To study the effects of TransJakarta, we use high quality data from two cross-sectional surveys of commuters conducted by the Japan International Cooperation Agency (JICA): the 2002 Home Visit Survey (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 Greater Jakarta's population, and in each wave, over 160,000 households responded to questions about vehicle ownership, mode choices, and commuting patterns. The data contain responses from nearly all communities (*kelurahan*) in the city. We combine these data with community level aggregates from the household census in 2000 and 2010, as well as a variety of other geospatial datasets.

To address endogenous station placement, 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 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 show that reweighting balances both baseline characteristics and pre-treatment trends in outcomes.

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 motorcycle in 2002 to a staggering 75.8 percent in 2010. Although we find small positive effects of BRT station proximity on choosing the BRT as a main or alternative mode for transport, TransJakarta's overall mode share of 4.3 percent in 2010 — after six years of operation — is small compared to other BRTs. For instance, in Bogotá, Colombia, TransMilenio had attained a 26 percent mode share after 7 years of operation. In this period, the major changes in Jakarta's commuting choices came from people substituting away from public transport and into private vehicles, trends that a well-designed transit system would hopefully negate or counteract. Commuting gravity regressions also reveal that despite targeting important commuter routes, the system did not significantly increase commuter flows, consistent with the low ridership effects.

Despite low ridership, TransJakarta may have alleviated traffic congestion if it had reduced vehicle volumes along its strategically located service corridors (Anderson, 2014). However, planners expanded the system by converting mixed-use lanes into busways, and we find that this reduced road capacity actually exacerbated congestion. Using origin-by-destination travel time regressions, we find that after TransJakarta was built, trips taken along expansion corridors had longer durations. These congestion effects were largest during peak times, but they were not significant for TransJakarta's initial corridor, which was better implemented. We also find no significant changes in train trips, which is expected given that the BRT did not compete with trains for space. Our results are robust to a number of controls for differential increases in demand that might otherwise explain the observed increase in travel times.

Next, we investigate the overall welfare effects of TransJakarta and examine whether a better BRT implementation could have reduced congestion. BRT implementations vary widely—high-quality systems have fully segregated busways, rapid bus speeds, and optimal station placements—and differences in implementation quality may contribute to different outcomes. In the absence of exogenous variation in these attributes, we specify and calibrate a quantitative spatial general equilibrium model. We analyze policies through counterfactual simulations to better understand how to cost-effectively improve the system.

Our model extends the framework developed by Allen and Arkolakis (2020) to allow for endogenous route choices across multiple congestible urban transport networks, generalizing the two-network case presented in Fan et al. (2021). Workers choose where to live, where to work, and which route to take when commuting to maximize utility. Routes are congestible, and as more commuters travel along the same routes, travel times increase. Despite the complicated feedback between route choices, traffic congestion, and residential and workplace locations, the framework remains analytically tractable. We describe how reduced-form parameters estimated from both gravity commuting regressions and origin-by-destination travel time regressions can be used to calibrate the model.

We use the model to simulate the welfare effects of both removing and improving the BRT system. We find that as implemented, the BRT system improves welfare modestly, with estimates far below similar estimates in the literature. We also find that if planners had created new BRT lanes instead of converting mixed-use lanes into busways, or if BRT buses had been faster, the welfare effects of TransJakarta would have been considerably enhanced. Expanding the network by building planned lines could also increase welfare, but the benefits depend on how the new lines would be implemented.

This paper contributes to a growing literature evaluating the impacts of different transport policies in developing country cities.[3] It also complements a sizable 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). In particular, two recent papers also study 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.[4] Our paper evaluates a lower quality implementation that is more commonly seen in LMICs.

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, and Section 4 discusses reduced form results of the impact of station proximity on vehicle ownership, mode choice, commuter flows, and congestion. Section 5 presents the model, and Section 6 explains how we estimate certain parameters of the model and calibrate others. Section 7 presents the results of

[3]Apart from previously cited studies of infrastructure improvements, 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. Akbar and Duranton (2017) study the welfare effects of congestion in Bogotá, Colombia.

[4]For instance, both TransMilenio and Lahore's BRT operate at around 26 km/hr, which is significantly faster than the median BRT's operating speed of 21 km/hr. Moreover, TransMilenio corridors are regularly considered the Gold standard of BRT implementation (ITDP, 2017).

simulating counterfactual policies, and 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 (*Daerah Khusus Ibu Kota Jakarta*, or DKI Jakarta) is surrounded by a greater metropolitan area that includes 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.[5] According to several assessments, Jakarta has some of the worst traffic in the world, making traversing the city challenging and unpredictable.[6]

Rapid growth and weak urban planning have both led to chronic congestion in Jakarta. Income growth has spurred demand for private vehicles which are often seen as positive signals of social status (Susilo and Joewono, 2017). National fuel subsidies and road construction programs have also encouraged greater use of private vehicles (Savatic, 2016; Hook and Replogle, 1996). Moreover, agencies responsible for managing land use and urban planning in Jakarta have generally been ineffective in dealing with rising motorization (Susantono, 1998; Goldblum and Wong, 2000).

After several failed attempts at mass transit, Jakarta's governor Sutiyoso (1997-2007) developed the TransJakarta BRT system to help alleviate congestion.[7] BRT systems provide dedicated right-of-way lanes for buses and use a network of stations to pick up and drop off passengers. TransJakarta began operating in 2004 with Corridor 1, an initial 12.9 km north-south corridor. This line traversed one of the most important thoroughfares connecting residents to Jakarta's central business district and financial center. Over time, TransJakarta expanded services throughout DKI Jakarta. As of this writing, it is the world's largest BRT system, with 13 operating corridors, more than 200 stations, and a total system length of more than 200 km.[8]

Despite its size compared to other systems, TransJakarta 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 living in the surrounding municipalities to jobs in the center. Panel A of Figure 1 provides a map of BRT corridors, depicting both the 9 lines and 159 stations constructed by mid-2010 (in black) and the locations of eventually constructed lines and stations (as of January 2018, in red). Policymakers had intended for a much larger expansion, but planned lines have yet to be developed, largely due to jurisdictional issues between the DKI Jakarta government and surrounding municipalities (JICA, 2004a). These planned lines, which extend beyond the DKI Jakarta boundary, appear in red in Figure 1, Panel B.[9]

[5] 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.

[6] Various traffic congestion indices compiled from GPS data have ranked Jakarta's traffic as the worst (or second-worst) among the world's major cities (Castrol, 2015; Waze, 2016). In 2016, 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).

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

[8] Prior to BRT implementation, surface travel along Corridor 1's route was significantly slower, especially during peak hours (see online Appendix Table A.1). At the same time, communities along Corridor 1 were closer to the city center, had slower pre-trend growth in car and motorcycle ownership, and faster growth in light intensity (see online Appendix Table A.2).

[9] Maps of the BRT corridors and stations that had been planned for completion by 2010 were contained in a feasibility study for Greater Jakarta's Integrated Transportation Master Plan (JICA, 2004b).

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 typically costs 4-20 times less than a light rail system and 10-100 times less than a subway system (Wright and Hook, 2007). In fact, TransJakarta was relatively inexpensive even for a BRT system, costing only $1.5 million per km to construct, compared to TransMilenio's $8.9 million per km (Hidalgo and Graftieaux, 2008) or Lahore Metrobus's $11 million per km (Majid et al., 2018). However, TransJakarta's low costs reflect both poor service quality and low quality infrastructure design.

During its first few years of operation, TransJakarta had many service quality problems that reduced operational speeds and increased waiting times. First, BRT buses only had a single front passenger door, slowing boarding and alighting speeds (ITDP, 2017). Second, TransJakarta had many difficulties scheduling buses and managing their departure and arrival to stations, creating uncertainty and delays (Radford, 2016). Finally, TransJakarta often failed to enforce bus lane segregation, particularly outside of Corridor 1. During rush hour, mixed-traffic incursions would sometimes congest the dedicated bus lanes, slowing them down (Radford, 2016).[10] These service quality problems led to long waiting times, as evidenced by results of a UN-sponsored survey of TransJakarta riders in January 2014. In that survey, nearly 48 percent of riders considered waiting times to be "very long" or "long", indicating problems with reliability (Sayeg and Lubis, 2014).

Moreover, TransJakarta was constructed with several low quality infrastructure choices, reducing ridership and hindering performance. Instead of creating new lanes with overpasses separating BRT buses from other traffic, the system largely converted existing road space into busway lanes. Satellite imagery confirms that the number of lanes reserved for mixed traffic fell after the BRT system was implemented.[11] Second, the system's design also did not include passing lanes, potentially creating bottlenecks when TransJakarta buses broke down. Third, station access often required traversing long walkways or climbing steep stairs, creating difficulties for many pedestrians (ITDP, 2017).[12] Finally, although the BRT network serves jobs in the city center, it is not well targeted to residential areas, particularly low income communities or those lying beyond DKI Jakarta borders (Wentzel, 2010).

As TransJakarta expanded, newer lines tended to have poorer service quality than the original corridor. In 2014, the Institute for Transportation and Development Policy (ITDP), which rates BRT systems on various criteria and issues performance standards, 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".[13]

[10] A regulation protecting TransJakarta's dedicated lanes from mixed-traffic incursions was only issued in 2007 (*Perda* DKI No. 8/2007) and even after the regulation was issued, its enforcement was relatively lax.

[11] Online Appendix Figures A.1 and A.2 use Digital Globe satellite imagery to monitor changes in the number of lanes between 2003 (before the system opened) and 2010. Overall, the average road near TransJakarta BRT stations lost 1.2 lanes from 2003 to 2010. For Corridor 1, roads around nine stations (45 percent) saw no lane reductions, and roads around the average station lost only a single lane. In contrast, 60.5 percent of stations along the lower quality Bronze corridors and 46.4 percent of stations around Basic BRT corridors lost 2 or more lanes of traffic after the BRT was constructed.

[12] ITDP (2017) cites pedestrian access problems as one of the worst deficiencies of the system, increasing access times and deterring ridership.

[13] ITDP scores BRT systems based on several criteria, including: (1) BRT basics (dedicated right of way lanes, busway alignment, etc.); (2) service planning (multiple routes, corridor location, etc.); (3) infrastructure (passing lanes, minimum bus emissions, etc.); (4) station attributes; (5) communications; and (6) access and integration. Points are also deducted for several reasons, including: (1) slow speeds; (2) poorly enforced right of way; (3) poor maintenance; (4) low bus frequency. Based on these

Using data described in the next section, we find that despite having a dedicated lane, BRT buses were on average as slow as traditional buses that used mixed-traffic lanes. Table 2 compares average door-to-door speeds for TransJakarta and the traditional public bus system to average door-to-door speeds for motorcycles. Column 1 shows that the BRT is 20 percent slower than motorcycles and has similar speeds to other public buses, after controlling for trip-purpose indicators, departure-hour indicators, and origin-by-destination fixed effects. These trends are similar when restricting the sample to trips that originate and terminate within 1 km of a BRT station (column 2). However, we find an exception for Corridor 1 trips (column 3), where BRT speeds do not significantly differ from motorcycle speeds. These results are consistent with lower service quality and implementation problems for extensions to the system beyond Corridor 1.

Despite slow speeds, TransJakarta compares favorably to other public transit modes along dimensions of safety and comfort, important factors that affect travel demand. Table 3 reports results of regressing perceptions of mode safety and comfort on different transit modes (with the commuter rail as the left-out mode), based on 2010 JICA commuter travel survey data (described in more detail below).[14] Commuters rate the BRT 5-7 percent higher on safety than trains (columns 1-2), and they consider the BRT to be just as comfortable as riding a commuter train (columns 3-4). Other public transport, which includes the traditional public bus system, is rated significantly lower on both safety and comfort. To the extent that people prioritize safety and comfort over speed, they may choose the BRT over other transport modes.

3 Data

To study how TransJakarta impacted commuting outcomes for residents, we combine several high-quality, spatially disaggregated data sources. These include two rounds of detailed commuter travel surveys, population censuses, and geospatial datasets. We briefly describe these data sources here, leaving many details for online Appendix B. Online Appendix C also uses these data to describe how Greater Jakarta's urban form, vehicle ownership, and commuting patterns have evolved over time.

Commuter Travel Surveys. Our main analysis uses two rounds of commuter travel surveys, conducted by 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 encourage 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. 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]

scores, systems are assigned standard ratings: Gold, Silver, Bronze, or Basic BRT. Gold-standard systems are consistent with international best practices, achieving high levels of operational performance and service quality.

[14]We estimated a regression of the log of a 5-point index of perceived safety (columns 1 and 2) and comfort (columns 3 and 4) on mode indicators. Controls include mode indicators, trip-purpose indicators, and departure-hour indicators, with origin and destination fixed effects in columns 2 and 4.

[15]These large sample sizes are comparable to those used in various waves of the U.S. National Household Travel Survey (NHTS), representative of the entire United States. For instance, the 2017 NHTS had a sample of 130,000 households.

The JICA surveys have several unique features for an urban LMIC setting. First, the surveys are large and representative at the community (*kelurahan*) level, which is the lowest administrative unit in Indonesia and comprises our main spatial unit of analysis. 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.[16] Moreover, in both waves, the median community had over 200 individual-level observations. The spatial coverage and representativeness allow us to calculate community-level means with relative accuracy, an unusual feature for an urban developing country setting. Although the data represent repeated cross sections of Greater Jakarta's population, in some analyses, we use survey weights to aggregate the data by community-year, obtaining a panel of communities.

The surveys also collected detailed trip-level data, for trips regularly taken during a typical workday for all household respondents. 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. 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, departure times, arrival times, and costs or fees incurred during travel.

The entire pooled trip-level dataset contains information on nearly 1.4 million trips that were either work or school-related (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). 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 several additional datasets to measure community-level attributes. First, we construct community-level demographic characteristics by aggregating individual-level data from the 2000 and 2010 Indonesian Population Censuses. The census data provide 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 U.S. Air Force Defense Meteorological Satellite Program (DMSP). Third, we use business directory listing data from the 2016 Economic Census to construct measures of workplace employment at the community level. Finally, to assess pre-trends in vehicle ownership, we use information from the triennial administrative census known as *Podes* (or Village Potential). The 1996 and 2000 rounds provide information on the total number of households owning cars and motorcycles in each community, which we use to construct ownership share measures.

Geospatial Data on Administrative Boundaries, Infrastructure, and Topography. Our analysis relies

[16] In the year 2000, the median community in Greater Jakarta had an area of 3.2 square km 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 within a single community, we use an average distance measure, similar to the disconnection index from the urban planning literature (Harari, 2020). This is calculated by randomly sampling 100 points in each community and calculating the average distance between those points.

on administrative shapefiles containing community-level boundaries, created by Indonesia's national statistical agency, *Badan Pusat Statistik* (BPS). We also use detailed digital maps of Jakarta's roads, railroads, and BRT lines and stations. Some of these maps, such as the locations of planned lines and stations, were produced by JICA, while others were derived from Open Street Map and produced by the authors using GIS software. Finally, we use the *Harmonized World Soil Database* (HWSD) to construct basic topographic characteristics (e.g., ruggedness and elevation).

4 Did TransJakarta Change Commuting Behavior or Reduce Congestion?

This section presents reduced-form estimates of the impact of TransJakarta on commuting outcomes. We begin by motivating our identification strategy to address endogeneity in the placement of BRT stations. Next, we use a semi-parametric difference-in-differences approach to estimate the average treatment effect on the treated (ATT) of TransJakarta station proximity on mode choice and vehicle ownership. We also estimate a gravity commuting model to explore how TransJakarta affected commuter flows. Finally, we examine whether the BRT alleviated congestion by estimating its impact on travel times for other travel modes along BRT corridors.

4.1 Comparing Treated and Almost-Treated Communities

A primary concern with studying the impact of BRT station proximity on commuting behavior is that because station locations are not randomly assigned, naive estimates may be confounded with selection bias. To illustrate this concern, in Table 4, we compare several characteristics of communities that are close to BRT stations to those that are farther away. The first set of columns reports statistics for the 140 "treated" communities, defined as communities located within 1 km of the nearest BRT station in mid-2010.[18] 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 more than 1 km away from a BRT station in mid-2010. Each variable was measured before the TransJakarta system became operational in 2004.

Panel A shows that compared to non-treated communities, communities close to BRT stations were denser, more educated, and had a greater share of recent migrants (who moved in from other districts in the last five years). These differences are all significant at the 1 percent level.[19] Panel B suggests that individuals living in treated communities earned more on average than individuals in non-treated communities. They were also more likely to own a motorized vehicle, less likely to take public transit or taxi services, and more likely to choose cars as their main mode of transport. Panel C suggests that treated communities were smaller in land area and closer to the city center. Overall, these findings suggest that BRT stations were constructed in positively selected areas.

[18]TransJakarta surveys of ridership indicated that nearly 90 percent of customers walked less than 1 km to BRT stations (ITDP, 2017, p. 951). 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.

[19]To compare 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 4 for more detail.

We begin to address the endogenous placement of BRT stations by limiting our comparison group to 109 "almost-treated" communities — defined as the subset of non-treated communities that were either: (1) within 1 km of a planned BRT station that was eventually constructed after mid-2010; or (2) 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 are much smaller in magnitude. The major exception is the difference in migration patterns between treated and almost-treated communities; relative to the treated communities, almost-treated communities had 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 baseline variables, including population density, education, income, economic growth, and migrant shares, all of which may have influenced station locations.[20] Column 6 reports differences in weighted means between treated and almost-treated communities. Overall, the differences in weighted means fall substantially and are only marginally significant for a single variable (average years of schooling).

In the next section, we report semi-parametric difference-in-differences estimates of the impact of BRT station proximity. A key concern with this approach is that the change in outcomes for comparison communities may not be a valid counterfactual for what would have happened to treated communities if BRT stations had not been constructed (Gibbons and Machin, 2005; Billings, 2011). To assess the common trends assumption, in Panel D of Table 4, we use *Podes* and night lights data to examine trend differences in vehicle ownership before the BRT was implemented.[21] Column 5 shows that in treated communities, there was slower growth in both car and motorcycle ownership from 1996-2000, as well as more rapid growth in light intensity from 1998-2003, although the pre-trend differences in motorcycle ownership growth are insignificant. However, Column 6 shows that reweighting eliminates any significant pre-trend differences.[22]

4.2 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:

$$\Delta y_c = \alpha + \theta T_c + \mathbf{x}_c' \beta + \varepsilon_c \ , \tag{1}$$

[20]This vector includes several community-level variables measured in the 2000 census, including population shares with different levels of educational attainment, the share of recent migrants (from another district), 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 land area. Online Appendix Table A.3 reports propensity score estimates. Despite using only a parsimonious set of variables in $\mathbf{x}_c$, our model explains a large amount of treatment variation, with the propensity scores having pseudo-R^2's of between 0.5 and 0.6. Online Appendix Figure A.3 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.

[21]*Podes* data are only available every 3-4 years. Because the vehicle ownership measures recorded in *Podes* are based on surveys of community heads instead of household surveys, measurement error is likely. However, misreporting errors are unlikely to change over time or differ systematically between treated and control groups.

[22]Online Appendix Figure A.4 also shows that propensity score reweighting eliminates level and trend differences in night-time lights from 1992-2013.

where c indexes communities, Δy_c is the 2002 to 2010 change in the outcome for community c, $\mathbf{x}_c$ is a vector of predetermined controls (described in Footnote 20), and ε_c 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, so that θ measures the close-proximity treatment effect.

In estimating equation (1), we limit the sample to only treated and almost-treated communities, and we implement double-robust estimators that, in addition to controlling for $\mathbf{x}_c$, reweigh the almost-treated communities according to their odds of treatment. In particular, we implement both the Robins et al. (1995) two-step, double-robust estimator for θ and the Oaxaca-Blinder re-weighting approach of Kline (2011). Both approaches allow us to assign greater counterfactual weight to non-treated communities with similar baseline levels of density, migration, education, and income.

Table 5 reports estimates of θ, with robust standard errors, clustered at the subdistrict (*kecamatan*) level in parentheses.[23] These results show that close proximity to a BRT station did not affect vehicle ownership (Rows 1–2). Although confidence intervals vary in length, our estimates of the impact on growth in motorcycle ownership are 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 from 2002 to 2010, and it is equal to about one fifth of the standard deviation of community-level motorcycle ownership growth.

This null result is surprising because the bias of our difference-in-differences estimates is probably negative. The unadjusted comparisons from Table 4 suggest that non-treated areas had lower baseline levels of private vehicle ownership and faster pre-treatment growth. If these trends continued, we would expect that non-treated communities would have experienced more rapid motorization than treated communities in the absence of treatment. Though our reweighting approach adjusts for these differences, any remaining unobserved common trend violations should induce a negative bias. The fact that we find precise zeros despite this potential negative bias corroborates our finding that TransJakarta did not have an impact.

However, we do find evidence for small positive effects of station proximity on choosing the BRT as the main and/or alternative mode of transport (Rows 3 and 4), although the estimates are not always significant.[24] 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 motorcycle ownership. The final set of rows examine the impact of BRT station proximity on changes in other mode shares, finding no significant differences.

TransJakarta's impacts on mode choice and vehicle ownership compare unfavorably to systems better implemented elsewhere. For example, these estimates are much smaller than similar estimates of effects in Lahore where the BRT system increased public transit use by an estimated 30 percent in nearby areas (Majid et al., 2018). Similarly, Bogotá's TransMilenio BRT system, which opened in 2000, had attained a mode share of approximately 26 percent by 2007 (Cain et al., 2007).

Even for communities with the greatest station proximity, we find that TransJakarta BRT use is quite small relative to other settings. To demonstrate this, we estimate a partially linear regression function of

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

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

the following form:

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

where 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 20). The distance function, $f(\cdot)$ is allowed to be flexible, and we estimate (2) semi-parametrically, following Robinson (1988). The resulting estimate in Figure 2 shows that the BRT mode share peaks out at just over 6 percent at areas very close to stations, decreasing to below 4 percent in intermediate distances.

Robustness. We conducted several checks to verify that the null results on vehicle ownership and the small effects on mode choice are robust to many different empirical specifications. These are described briefly here, but an expanded discussion can be found in online Appendix A.2.

The one-kilometer threshold we use to define a community's treatment status is often used in empirical work, and it is also consistent with commuting behavior in Jakarta (see Footnote 18). However, our null results are also robust to continuous distance specifications (online Appendix Table A.4), to using alternative distance threholds to define treatment (online Appendix Table A.5), to specifications that drop closely-located treated and almost treated communities (online Appendix Table A.6), and to using destination locations, instead of origin locations, to measure station distance (online Appendix Table A.7).

We also explore robustness to different specifications of the propensity score. Online Appendix Table A.8 varies the set of pre-determined controls used to estimate the propensity score ($\mathbf{x}_c$), while online Appendix Table A.9 uses two different machine-learning procedures to select controls for the propensity score and estimate treatment effects. Point estimates and confidence intervals under all of these approaches are very similar to our original results.

In online Appendix Table A.10, we explore the possibility that TransJakarta's muted effects were driven by competing heterogeneous treatment effects. Our main results are largely robust to sample splits by gender, education, and total monthly household expenditures.[25] Finally, in online Appendix Table A.11, we add a series of (bad) demographic controls to assess the extent to which sorting is driving our results. Controls for compositional changes, measured by changes in migration shares, educational changes, and monthly household expenditure, do not alter our main conclusions.[26]

Effects on Demographics and Housing. Although our main results focus on the effects of TransJakarta on vehicle ownership and mode choice, we also present a similar set of results for changes in demographic, employment, and housing outcomes in online Appendix D. We find no significant effects on changes in population density, employment, 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.

[25]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.

[26]If people with strong preferences for public transportation moved into treated areas, this would cause us to overestimate the average impacts of the program. The absence of strong program impacts reduces concerns over this type of sorting bias. Our concern here is if areas with BRT stations attracted more affluent migrants who were less likely to demand public transportation.

4.3 Gravity Commuting Regressions

While TransJakarta did not affect vehicle ownership or mode choice for commuters living near stations, it might have improved mobility by increasing commuting flows along its service corridors. Such effects would have important implications for welfare and would demonstrate how TransJakarta reorganized the city's spatial distribution of economic activity (Tsivanidis, 2019).

To examine how TransJakarta impacted commuting flows, we estimate parameters of a gravity commuting equation, following McDonald and McMillen (2010) and Ahlfeldt et al. (2015). Our main specification is given by:

$$\ln \pi_{odt} = \alpha_{od} + \gamma_t + \theta_1 \mathrm{BRT}_{ot} + \theta_2 \mathrm{BRT}_{dt} + \theta_3 \left(\mathrm{BRT}_{ot} \times \mathrm{BRT}_{dt}\right) + \mathbf{x}'_{odt}\beta + \varepsilon_{odt} \ , \tag{3}$$

where π_{odt} is the unconditional probability that a worker lives in community o and commutes to community d in year t, α_{od} is an origin-by-destination fixed effect, γ_t is a year effect, and BRT_{ot} and BRT_{dt} are indicators for whether communities o or d were within 1 km of a BRT station in year t. The vector $\mathbf{x}_{odt}$ includes time-varying observable characteristics of the origin-destination pair, and ε_{odt} is an error term. The parameter θ_3 measures the extent to which commuting flows from o to d were impacted by proximity to BRT stations.

To measure π_{odt}, we use the JICA trip data, restricted to outbound trips to work or school, and we use sampling weights to accurately calculate π_{odt} from survey responses. We also aggregate data to the sub-district (*kecamatan*) level to reduce noise and concerns about sampling error for bilateral pairs with small numbers of reported commuters. Additionally, our baseline specification restricts estimation of (3) to include only bilateral pairs with 10 or more commuters in both survey waves.

Table 6 reports results of estimating equation (3) with two different estimators. Panel A reports fixed effects least squares estimates, where the dependent variable is the log of the commuting probability, while Panel B reports Poisson Pseudo Maximum Likelihood (PPML) estimates with fixed effects, following Correia et al. (2020). In columns 1-4, these specifications are cross-sectional, so we only include fixed effects for each origin and destination location separately.[27] In columns 1 and 3, we do not include any BRT indicators and find a semi-elasticity of commuting with respect to travel times of approximately -0.059 in Panel A and -0.133 in Panel B, which implies that each additional minute of travel time reduces the flow of commuters by roughly 6 to 13 percent. Note that these estimates have a similar order of magnitude to the 7 percent commuting semi-elasticity reported in Ahlfeldt et al. (2015, Table III), for Greater Berlin in 2008. Online Appendix Figure A.5 also presents a residual-on-residual plot of the regression in Table 6, Column 3. This figure shows that the log-linear functional form of (3) does a good job of fitting the data.

Columns 2 and 4 show that in both 2002 and in 2010, BRT station infrastructure was positively and significantly correlated with commuting flows, with a large semi-elasticity of 1.186 for 2010 in Panel A (or 2.878 in 2010, Panel B). However, the commuting semi-elasticity estimates are large and significant for 2002 as well, suggesting that BRT stations were targeted to areas with larger pre-existing commuting flows. This makes it challenging to assign a causal interpretation to these cross-sectional correlations.

To make progress on identification, in columns 5 and 6 of Table 6, we estimate (3) with panel data. We

[27] A full set of origin-by-destination pair fixed effects, represented in α_{od}, would absorb all of the variation in the data.

include year effects and replacing the separate origin and destination fixed effects with a full set of origin-by-destination fixed effects, year effects, and separate indicators for each origin-district-by-year and each destination-district-by-year. This specification enables us to study changes in bilateral commuting flows over time, and to see whether those changes are correlated with the construction of nearby BRT station infrastructure. Column 5 includes no additional controls, while column 6 adds controls for time-varying population density in origin community o and destination community d.

In columns 5 and 6, we report small negative estimates of θ_3, but they are not significantly different from zero. As reported in online Appendix Table A.12, we find similar results when we use all observations to estimate the gravity commuting regressions. Online Appendix Table A.13 also shows similar results if we restrict estimates to bilateral commuting pairs beginning and terminating within 5 km of actual and planned BRT stations. Overall, these findings suggest that while the BRT station infrastructure was built to connect important and highly traversed commuting corridors, it did not significantly increase commuting flows.[28]

4.4 Effects on Travel Times and Congestion

A well-designed transit system could reduce congestion despite low ridership. If transit lines are located on important corridors, even a small reduction in vehicle volumes along those corridors could substantially increase speeds and reduce travel times.[29] However, a transit system that reduces road capacity could plausibly do the opposite. As we discuss in Section 2, TransJakarta 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.[30]

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:

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

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 o or d are within 1 km of a BRT station in year t (as defined above), α_{od}, α_{ot}, and α_{dt} are separate fixed effects for each origin-by-destination, origin-by-year, and destination-by-year pair, respectively, $\mathbf{x}_{iodt}$ is a vector of controls (including as a baseline separate purpose-by-year, mode-by-year, and departure hour-by-year indicators), and ε_{odt} is an error term.

In Table 7, we report the estimate of the interaction term for the origin and destination BRT indicators, β. 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 for other routes between 2002

[28] In online Appendix Table A.14, we explore the extent to which Corridor 1 affected commuting flows differently than the other corridors. Although the area around Corridor 1 was associated with higher levels of flows in both 2002 and 2010, in the panel specification, we find no significant effects on commuting flows for either corridor.

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

[30] In an early assessment of TransJakarta, Ernst (2005, p.23) makes a related observation, noting: "[c]ongestion has increased for mixed traffic on the corridor" as a result.

and 2010. Beyond controlling for distance with origin-by-destination fixed effects, the origin-by-year and destination-by-year specific intercepts also allow us to control flexibly for changes in commuting trends specific to each residential and workplace location. All columns also include a control for the total number of trips taken each year from community o to community d, which should partially address differential variation in demand.

In Panel A, column 1, we show that overall travel times along BRT corridors increased by an average of 9.9 percent from 2002 to 2010. We attribute this effect to the fact that when the BRT system was expanded, lanes that had been reserved for mixed traffic were converted into BRT lanes. In Column 2, we replace the BRT indicators from (4) with separate indicators for Corridor 1 and the other corridors. This column shows that for Corridor 1, which had attained the highest service standards and was constructed without taking away lanes, there were no differences from other trips in terms of travel times. The negative spillover effects of the BRT system seem to come entirely from the other corridors, which were constructed with lower quality infrastructure. Column 3 shows that these effects are insignificant for off-peak travel times overall.[31] This suggests that the negative spillovers occur during peak times, precisely when a public transit system should be alleviating traffic congestion, instead of exacerbating it. In column 4, we also find that off-peak travel times fell along Corridor 1 by 16.3 percent.[32]

The results from Panel A suggest that the BRT expansion significantly increased congestion along some of the most important commuting routes in the city. Instead of improving traffic congestion in Jakarta, the BRT system exacerbated it by taking away crucial road space that could have been used for other modes.[33] While the potential for similarly implemented BRT systems to exacerbate congestion has been proposed in anecdotes and in the media, these results are, to our knowledge, the first rigorous demonstration of this negative spillover.[34]

Train Trips as a Placebo. In Table 7, Panel B, we repeat the same specifications as in Panel A, but we restrict the sample to train trips. We find that travel times for train trips were not significantly impacted by the BRT system. This is expected given that train tracks are elevated in central Jakarta and do not compete with the BRT for road space.

Robustness Checks. We conducted several checks to verify that the effects of lane reductions on travel times from Table 7 are robust to many different empirical specifications and potential confounders. These are described briefly here, and in more detail in online Appendix A.4.

Online Appendix Table A.17 reports the impact of the BRT system on different transport modes. We find effects that are large and significant for many road-based modes, including private cars, private motorcycles, and traditional public buses. As expected, the impact on private cars is the largest, at 19.6 percent, relative to smaller effects on motorcycles and public buses.

[31] A peak-time trip is defined as an outbound trip departing from 7-9 AM or a return trip departing from 4-7 PM.

[32] Equation (4) includes a demanding set of controls. In online Appendix Table A.15, we iteratively add controls and fixed effects until we obtain our preferred specification. We find that the effects remain robust to these different specifications. Moreover, the results in Table 7 also use survey weights to adjust for differences in population origin and destination locations. The unweighted version of this table appears in online Appendix Table A.16. Results are quantitatively similar, although there are some differences in the magnitude of the point estimates.

[33] 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.

[34] Misra (2016) describes how the BRT system in Delhi, which was removed, similarly worsened traffic along service corridors.

In online Appendix Table A.18, we investigate whether our findings for Corridor 1 were driven by the contemporaneous expansion of a high-occupancy vehicle (HOV) policy (Hanna et al., 2017). Jakarta's HOV policy was first implemented in 1992 on a 6.2 km portion of the route covered by Corridor 1, but in December 2003, it was expanded to cover the entire corridor (as shown in online Appendix Figure A.6). If the HOV policy drove our Corridor 1 results, we should see weaker negative spillovers for the "Original HOV" segments relative to the segments affected by the HOV extension. We do not find any heterogeneous effects, suggesting that the HOV policy does not explain the lack of negative spillover along Corridor 1.

Next, we investigate the concern that trips along BRT corridors may not be comparable to trips made further away. Online Appendix Table A.19 reports estimates of β by only using comparison routes that begin and end within 10 km of a BRT station (Panel A), within 5 km of a BRT station (Panel B), and within 3 km of a BRT station (Panel C). Although the effect magnitudes vary somewhat, the point estimates are still positive and significant. In Panel D, we compare trips along BRT corridors to trips along planned or eventual BRT corridors. Again we find similar qualitative results, although our estimates are smaller and less precise.

In a similar spirit, online Appendix Figure A.7 reports the results of re-estimating the overall BRT effect from equation (4) by including several separate BRT distance indicators, where d ranges from 1 to 5 km, and their interaction terms. 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.

Finally, in online Appendix Table A.20, we explore whether the BRT system's infrastructure impacted travel times differently on different routes based on initial levels of traffic. Intuitively, routes that were already quite congested should have grown even worse as a consequence of the BRT taking away lanes, while other routes should be less impacted. We find that the BRT effects seem to be more pronounced for initially high delay routes, as expected.

4.5 Discussion

What explains TransJakarta's low mode share and its apparent failure to increase commuting flows and reduce congestion? One hypothesis is capacity constraints: it is possible that the system was at capacity and could not carry more passengers. Evidence presented in Figure 3 shows little support for this hypothesis. Panel A plots the average total number of weekday riders on the BRT. Between 2004 and 2014, TransJakarta's ridership increased by a factor of 6, from 52,400 to 368,000 per weekday. However, Panel B shows that over this same period, the total length of busways increased even more—by a factor of nearly 13. As a result, the total number of weekday riders per km of busway fell substantially (Panel C). By 2014, the system had less than 2 thousand riders per km in 2014, down from a peak of over 5 thousand weekday riders per km in 2005. Compared to Bogotá's TransMilenio BRT, which carried 9.5 thousand weekday riders per km in 2013, TransJakarta's performance has been relatively poor.

Low ridership could also result from high fare costs. However, 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 (Sayeg, 2015). In real terms, the price of riding the BRT has actually fallen substantially, as the fare index shows in Figure 3, Panel D.

A more convincing hypothesis is that TransJakarta's poor performance reflects the quality of its implementation: ridership was deterred by slow speeds and limited network extent. Our data do not provide exogenous variation in these system attributes. To better quantify the welfare effects of the existing BRT system, and to assess the costs and benefits from improving TransJakarta, we specify a quantitative spatial general equilibrium model with traffic congestion. We use reduced form estimates from this section, along with additional calibrated parameters, to simulate the effects of different BRT system improvements. The next section describes the model, and the following section explains how we take the model to the data.

5 Model

In this section, we present a quantitative spatial general equilibrium model with traffic congestion and discuss how it can quantify the welfare effects of modifying transport infrastructure in Jakarta. The model modestly extends the framework introduced by Allen and Arkolakis (2020) to allow for multiple transit networks, generalizing the two-network case presented in Fan et al. (2021). We present the essential features of the model in this section, leaving many details and derivations for Appendix E.

Individuals and Routes. Let $\nu \in [0,1]$ index individuals, and let $i \in \{1, 2, ..., N\}$ index locations (subdistricts, or *kecamatan*) in Greater Jakarta. The city has a fixed aggregate population of commuters, given by $\overline{L}$. An individual who lives in location i, works in location j, and commutes via route r of length K_r has the following indirect utility function:

$$V_{ij,r}(\nu) = \left[\frac{u_i w_j}{\prod_{l=1}^{K_r} t_{r_{l-1},r_l}\left(m_{r_{l-1},r_l}\right)} \right] \varepsilon_{ij,r}(\nu) \ , \tag{5}$$

where u_i denotes the amenity value of residential location i, w_j denotes the wage at workplace location j, and $\varepsilon_{ij,r}(\nu)$ is a Fréchet distributed idiosyncratic preference term, specific to each workers's residence location, workplace location, and route choice, with shape parameter $\theta > 0$. The shape parameter governs commuter heterogeneity; as θ grows large, commuters become less differentiated and make more similar choices, holding the values of u_i and w_j fixed. Individuals choose where to live, where to work, and which route to take to maximize $V_{ij,r}(\nu)$.

Locations in the city are connected by multiple transport networks, indexed by $m = 1, ..., M$, and workers use these networks to commute between different locations. We assume that Greater Jakarta has three transport networks: (1) BRT; (2) trains; and (3) surface (used by motorcycles, cars, and traditional public buses), so that $M = 3$.[35] Let $t_{kl}(m) \geq 1$ measure the disutility of moving directly from location k to location l using network m.[36] Crucially, $t_{kl}(m)$ is determined in equilibrium and depends on the route and location choices of all workers in the city.

A route from i to j represents a sequence of edges along different networks that link origin i to destination j. For example, a commuter from i to j may take the surface transport network from i to k,

[35] This approach ignores different mode choices within the surface network. It also assumes that traffic congestion depends on the total volume of commuters on the surface network, and not on the mix of vehicles.

[36] Note that if no direct link exists for network m, we set $t_{kl}(m) = \infty$. To exclude self loops, we also set $t_{kk}(m) = \infty$ for all k and m.

the BRT from k to l, the BRT from l to m, and the surface network again from m to j. In this example, the route has a length of 4. Transport costs are multiplicative, and for a general route r of length K_r, the total cost of commuting is given by:

$$TC(r) = \prod_{l=1}^{K_r} t_{r_{l-1},r_l}\left(m_{r_{l-1},r_l}\right) ,$$

where m_{r_{l-1},r_l} indexes the network chosen on link l of route r. Let $\mathcal{R}_{ij}$ denote the (countably infinite) set of all of possible routes from i to j.

Commuter Flows and Welfare. From properties of the Fréchet distribution, the probability that a worker chooses to live in i, work in j, and commute by $r \in \mathcal{R}_{ij}$ is given by:

$$\pi_{ij,r} = \frac{u_i^\theta w_j^\theta \left(\prod_{l=1}^{K_r} t_{r_{l-1},r_l}\left(m_{r_{l-1},r_l}\right)^{-\theta}\right)}{\sum_{i=1}^N \sum_{j=1}^N \sum_{r' \in \mathcal{R}_{ij}} u_i^\theta w_j^\theta \left(\prod_{l=1}^{K_{r'}} t_{r'_{l-1},r'_l}\left(m_{r'_{l-1},r'_l}\right)^{-\theta}\right)} . \tag{6}$$

By summing (6) across all routes, we can show that the total number of commuters who live in i and work in j is given by:

$$L_{ij} = u_i^\theta w_j^\theta \tau_{ij}^{-\theta} \overline{L}\,\overline{W}^{-\theta} . \tag{7}$$

This equation shows that the model admits a gravity formulation for bilateral commuting flows, as in McDonald and McMillen (2010) and Ahlfeldt et al. (2015). In equation (7), τ_{ij} measures the (endogenous) transportation costs from i to j, given by:

$$\tau_{ij} \equiv \left[\sum_{r \in \mathcal{R}_{ij}} \left(\prod_{l=1}^{K_r} t_{r_{l-1},r_l}\left(m_{r_{l-1},r_l}\right)^{-\theta}\right)\right]^{-\frac{1}{\theta}} . \tag{8}$$

This a sum of the total costs of commuting across all routes from i to j, where those costs are determined in equilibrium by each of the least cost routing choices made by different workers in the city. The term $\overline{W}$ in equation (7) is also the expected welfare of a resident in the city, given by:

$$\overline{W} = \mathbb{E}\left[\max_{i,j,r} V_{ij,r}(\nu)\right] = \left(\sum_{i=1}^N \sum_{j=1}^N \tau_{ij}^{-\theta} u_i^\theta w_j^\theta\right)^{\frac{1}{\theta}} . \tag{9}$$

Wages, Productivity, and Residential Amenities. Each location produces a homogeneous product that is costlessly traded between locations in the city. Labor is the only input into production, which takes place under perfect competition and constant returns to scale at the level of the firm. We assume that productivity in location j and residential amenities in location i are given by:

$$A_j = \overline{A}_j \left(L_j^F\right)^\alpha \quad \text{and} \qquad u_i = \overline{u}_i \left(L_i^R\right)^\beta . \tag{10}$$

Here, $\overline{A}_j$ and $\overline{u}_i$ respectively measure location fundamentals contributing to productivity in j and residential amenities in i. The total number of workers in location j is given by L_j^F, so that α measures the strength of (net) local agglomeration externalities. Similarly, L_i^R measures the total number of residents in location i, and β measures the size of (net) residential externalities. Because land prices do not enter the model, α and β may be negative (see Section 6 below).

Traffic Congestion. For simplicity, we assume that all networks are congestible.[37] We also assume that the direct cost of traversing a particular link using network m depends on the total traffic flowing through that link using network m, as follows:

$$t_{kl}(m) = \bar{t}_{kl}(m) \left[\Xi_{kl}(m)\right]^{\lambda} \ , \tag{11}$$

where $\bar{t}_{kl}(m)$ measures the exogenous component of transport costs for network m, $\Xi_{kl}(m)$ measures the total traffic over link (k, l) using network m, and $\lambda > 0$ measures the strength of traffic congestion.

Consumers' endogeneous route choices result in traffic volumes that vary over different links. Variation in traffic along a link depends on *link intensity*, a measure of the expected number of times that link (k, l) on network m is used in commuting between i and j:

$$\pi_{ij}^{kl}(m) = \sum_{r \in \mathcal{R}_{ij}} \left[\frac{\pi_{ij,r}}{\sum_{r' \in \mathcal{R}_{ij}} \pi_{ij,r'}} \right] n_r^{kl}(m) \ . \tag{12}$$

In this expression, the term in brackets is the probability that route r is chosen among all routes linking i to j and $n_r^{kl}(m)$ is the number of times the link (k, l) on network m is used along that route. Using this expression for link intensity, the total traffic $\Xi_{kl}(m)$ over link (k, l) and network m can be written as follows:

$$\Xi_{kl}(m) = \sum_{i=1}^{N} \sum_{j=1}^{N} \pi_{ij}^{kl}(m) L_{ij} \ .$$

Combined with (11), this expression shows the feedback between workers' route choices and traffic, which endogenously changes commuting costs.

Parameterizing Transport Costs. For networks $m = 1, 2, 3$, we assume that:

$$t_{kl}(m) = \left[\text{distance}_{kl}(m) \times \text{speed}_{kl}^{-1}(m) \right]^{\delta_0} \left[\Gamma(m) \right]^{\gamma_m} , \tag{13}$$

where δ_0 is the time elasticity of transport costs, and $\Gamma(m) \equiv \exp\{\mathbb{1}_m\}$ is a network-specific indicator, raised to the power γ_m. We set $\delta_0 = 1/\theta$ to imply a distance elasticity for commuting flows of negative one, following Allen and Arkolakis (2020) and a large gravity literature (e.g. Disdier and Head, 2008; Chaney, 2018).

We also set $\gamma_3 = 0$ for the surface network ($m = 3$), so that $\Gamma(m)^{\gamma_m}$ measures the disutility of commuting via network m relative to the surface network, holding travel times constant. If BRT or train networks create greater disutility from travel than surface-based modes, perhaps because of waiting times or lower comfort, we would expect that $\gamma_1 > 0$ and $\gamma_2 > 0$.[38]

[37] For instance, congestion for public transit modes, for example BRT buses or trains, might occur as the number of riders increases.

[38] For instance, in January 2014, a UN-sponsored survey of TransJakarta BRT riders found that nearly 30 percent of riders

We also assume that $\text{speed}_{kl}^{-1}(m)$ is given by:

$$\text{speed}_{kl}^{-1}(m) = \left[m_0 \times \left[\frac{\Xi_{kl}(m)}{\text{lanes}_{kl}(m)} \right]^{\delta_1} \times \varepsilon_{kl}(m) \right], \tag{14}$$

where $\text{lanes}_{kl}(m)$ measures the number of lanes from k to l on network m. Combining (13) and (14), we obtain equation (11) with

$$\bar{t}_{kl}(m) = \left[\text{distance}_{kl}(m) \times m_0 \times \text{lanes}_{kl}(m)^{-\delta_1} \times \varepsilon_{kl}(m) \right]^{\frac{1}{\theta}} \left[\Gamma(m) \right]^{\gamma_m},$$

and $\lambda = \delta_1/\theta$.

Equilibrium and Counterfactuals. Given location fundamentals, $\{\overline{A}_i, \overline{u}_i\}$ for $i = 1, ..., N$, the aggregate labor endowment, $\overline{L}$, and the exogenous components of transport costs for all networks: $\{\bar{t}_{kl}(m)\}$, an *equilibrium* is a distribution of economic activity, $\{L_i^F, L_i^R\}$ and aggregate welfare, $\overline{W}$, such that:

1. The equilibrium distribution of economic activity ensures that commuting markets clear (i.e. $L_i^R = \sum_j L_{ij}$ and $L_i^F = \sum_i L_{ij}$, where bilateral commuting flows L_{ij} take the gravity form of (7)).

2. Given equilibrium transport costs, agents choose optimal routes for commuting, following equation (6).

3. Given the equilibrium distribution of economic activity, the exogenous components of transport costs for all networks, and agents' optimal route choices, equilibrium transport costs are determined by traffic congestion, following equation (11).

In online Appendix E, we present the equilibrium equations of the model, which express the distribution of economic activity as a function of the model's parameters, $\{\alpha, \beta, \theta, \lambda, \gamma_1, \gamma_2\}$, location fundamentals, and transport networks. Despite the complicated feedback between economic activity, traffic congestion, and commuting route choices, the model remains analytically tractable. The equilibrium expressions account for optimal routing choices and the resulting traffic patterns and congestion they imply. Our results closely follow derivations for a single congestible transport network from Allen and Arkolakis (2020). As long as all transport networks have the same congestion elasticity, λ, the multi-network equilibrium is quite similar to the single-network case. The multi-network equilibrium will also be unique provided that productivity and amenities are weakly net dispersive.

To determine how the distribution of economic activity and welfare would change under different configurations of the transportation network, we follow the "exact-hat algebra" approach (Dekle et al., 2008). Online Appendix E also shows how to express the system of equilibrium equations in changes form. We discuss parameter choices in the next section, and we conduct counterfactuals using a nested fixed-point algorithm to solve the exact hat equations for the resulting changes in welfare, workplace populations, and residential populations, again following Allen and Arkolakis (2020).

considered the BRT buses to either be "uncomfortable" or "very uncomfortable" (Sayeg and Lubis, 2014). Such findings were also corroborated in a recent survey of females in DKI Jakarta (Witoelar et al., 2017).

6 Taking the Model to the Data

In this section, we first describe how the model's key parameters, $\{\theta, \alpha, \beta, \lambda, \gamma_1, \gamma_2\}$, are either estimated or calibrated. When possible, we estimate these parameters with our data, but in some cases we choose values from prior work. In our counterfactual simulations below, we explore robustness of these choices to different parameter values. Online Appendix Table A.22 summarizes the different sets of model parameters that we use for counterfactual simulations. After discussing each parameter, we explain how to use data on commuter flows to approximate traffic, a key input to the exact hat counterfactuals exercise.

Estimating θ. Our preferred estimate of the commuter heterogeneity parameter, θ, is equal to 5.36. To obtain this value, we begin by following Ahlfeldt et al. (2015) to estimate the semi-elasticity of commuting with respect to travel times from a least squares gravity commuting regression (column 4 of Table 6). This estimate, $\widehat{\nu} \equiv \widehat{\theta\kappa} = 0.059$, is a combination of the commuting cost parameter that maps the log of the disutility from commuting to travel times, κ, and the heterogeneity parameter, θ. We convert this to an estimate of θ using the value of $\kappa = 0.011$ from Ahlfeldt et al. (2015).[39] This leads to our preferred value of $\theta = 5.36$, which is between the average value of 3.02 obtained by Tsivanidis (2019) for high and low skilled workers in Bogota and the value of 6.83 obtained by Ahlfeldt et al. (2015) for commuters in Berlin.

Calibrating α and β. Following Allen and Arkolakis (2020), we set the productivity spillover parameter, $\alpha = -0.12$, and the residential spillover parameter, $\beta = -0.1$, based on estimates obtained by Ahlfeldt et al. (2015) for Berlin. Note that α and β are both negative because there is no direct land consumption in the model.[40]

Estimating λ. Our reduced form estimates of how the BRT increased congestion for other modes, reported in Table 7, identify what happens to travel times when a lane of traffic was taken away from traditional surface based modes for use by the BRT. Our controls in those specifications attempt to proxy for changes in travel patterns and traffic, so what remains is the impact of the lane change. In other words, our reduced form regressions estimate the following parameter:

$$\widehat{\beta}_{RF} = \frac{-\partial \ln \left(\text{travel time}_{kl}\right)}{\partial \, \text{lanes}_{kl}(m)} = \frac{-\partial \ln \left(\text{speed}_{kl}^{-1}(m)\right)}{\partial \, \text{lanes}_{kl}(m)} \ ,$$

where we use a negative sign to indicate that the BRT took away lanes of traffic (as opposed to adding them), and where we express the change in terms of the inverse of speed (because distance is held constant). In online Appendix E.7, we explain how this estimate can be converted into an estimate of δ_1. When combined with a value of θ, this delivers an estimate of λ, the traffic congestion elasticity. Using

[39] Note that Tsivanidis (2019) also provides an estimate of $\kappa = 0.012$ which is very close to that obtained by Ahlfeldt et al. (2015).

[40] We follow Allen and Arkolakis (2020) in setting $\alpha = -0.12$ to combine the positive local estimated agglomeration externality of 0.08 (Table V, Column 1 of Ahlfeldt et al., 2015) with the negative congestion force arising from the fact that floorspace is used to produce goods (proxied by the share of firm expenditure on commercial floorspace of 0.20). Similarly, β combines the positive residential externality of 0.15 (Table V, Column 1 of Ahlfeldt et al., 2015) with the negative congestion force of -0.25 arising from floorspace consumption. Ideally, we would have used values of α and β for Bogota from Tsivanidis (2019). Combining the estimated agglomeration externality for Bogota with the congestion force arising from floorspace being used in the production of goods, we would obtain $\alpha = 0.056$. In most cases, this value is small enough to ensure a unique equilibrium, but not always. However, obtaining β from Tsivanidis (2019) is not straightforward, because in that model, residential externalities are based on the share of college workers in each location, not the total workplace population.

this approach, our baseline estimate of $\lambda = 0.055$ implies that a 10 percent increase in traffic increases transport costs by 0.5 percent.[41] This estimate is comparable to the value of $\lambda = 0.071$ used by Allen and Arkolakis (2020).

Estimating γ_1 and γ_2. Parameters γ_1 and γ_2 are chosen to adjust relative transport costs across networks to match survey data on mode choices. In online Appendix E.8, we describe a procedure for estimating γ_1 and γ_2. The approach requires expressing the probability that network m is chosen as a ratio of link intensities and inverting the resulting market shares, as in Berry (1994). The estimation equation we use is the following:

$$\ln(p_{ij}(m)) - \ln(p_{ij}(\text{surface})) = \widetilde{\gamma_m}\mathbb{1}_m + \delta\left[\ln(\text{trav. time}_{ij}(\text{surface})) - \ln(\text{trav. time}_{ij}(m))\right] + \boldsymbol{\theta}_{ij} + \varepsilon_{ijm}\ , \tag{15}$$

where i and j denote origin and destination sub-districts, m indexes networks, the left-hand side is the log of the share of people choosing network m minus the log of the share of people who choose surface-based modes, $\mathbb{1}_m \equiv \ln(\Gamma(m))$ is a network-specific indicator, and $\boldsymbol{\theta}_{ij}$ is a full set of origin-by-destination fixed effects. The parameter of interest is $\widetilde{\gamma_m} \equiv -\gamma_m\theta$.

In online Appendix Table A.21, we provide estimates of $\widetilde{\gamma_1}$ and $\widetilde{\gamma_2}$, which are both negative as expected. Working with our preferred estimate of $\theta = 5.36$ and the estimates of $\widetilde{\gamma_1}$ and $\widetilde{\gamma_2}$ from column 2, this implies that $\gamma_1 = 0.646$ and $\gamma_2 = 0.652$. Holding lanes and speeds fixed, these parameter values imply that the utility cost of commuting via the BRT (trains) is 1.91 (1.92) times that of surface-based modes.[42]

Approximating Traffic from Commuter Flows. Though we have data on commuter flows and the shares of people who choose different modes at different locations, we do not observe traffic between locations on different networks in Jakarta. To approximate traffic in a way that is consistent with the model, we first use average speeds calculated from the 2010 JICA data to estimate the link intensity of network m on link (k,l), forming an estimate $\widetilde{\pi}_{ij}^{kl}(m)$ of $\pi_{ij}^{kl}(m)$. Next, let $L_{ij}(m)$ denote the number of commuters from i to j who choose network m as their main transit network; this is readily observed from the trip surveys. Our approximation of traffic along each mode is given by:

$$\widetilde{\Xi}_{kl}(m) = \sum_{i=1}^{N}\sum_{j=1}^{N}\widetilde{\pi}_{ij}^{kl}(m)L_{ij}(m) \tag{16}$$

Essentially, instead of using the actual iceberg commuting costs, $t_{kl}(m)$, to construct link intensities in calculating traffic flows, we approximate it with data on average speeds by mode, where those average speeds are calculated from the 2010 JICA data. In online Appendix E.9, we derive a simple matrix formula that we use to implement (16) computationally.

[41] Note that if traffic and lanes are positively correlated, and if our controls in Table 7 do not fully capture traffic variation, estimates from this procedure should underestimate the congestion elasticity.

[42] Holding other aspects of transport costs constant across networks, the ratio of transport costs between network m and the surface network is given by $\Gamma(m)/\Gamma(\text{surface}) = \exp\{\gamma_m\}/1$.

7 Counterfactuals

In this section, we use the model to conduct three different counterfactual policies that alter the TransJakarta BRT system: (1) removing the system; (2) increasing BRT speeds and restoring lanes to other surface-based modes; and (3) building planned lines. For each counterfactual, we first specify the change in the exogenous portion of transport costs that would result from the policy change. Then, using parameter values discussed in Section 6, we follow the nested fixed-point algorithm described by Allen and Arkolakis (2020) to solve the model's exact-hat equilibrium equations for the resulting changes in welfare, workplace populations, and residential populations.

To establish a baseline, we first solve the model assuming no changes in transport costs. Online Appendix Figure A.8 produces a scatterplot comparing actual workplace and residential population counts to our baseline predictions. As can be seen, the vast majority of the data lies very close to the 45 degree line.[43] In describing our results, all changes in welfare, workplace, and residential population shares are expressed relative to this baseline.

Removing the BRT. To assess the overall welfare effect of the TransJakarta BRT system, we begin by examining what would have happened to Jakarta's overall spatial structure and welfare if the BRT had never been constructed. To conduct this simulation, we drastically inflate transport costs for the BRT, setting distance$_{kl}(m = 3)$ to a very large number in equation (13), and making it an infeasible choice. Table 8, row 2, column 1, shows that removing the BRT would reduce welfare, but only very slightly.

In columns 3-6 of Table 8, we use the change in welfare, $\widehat{\overline{W}}$, to calculate the net present value for removing the BRT system. Column 2 reports the present value of the benefit of the system. We obtain this value by applying the change in welfare to Jabodetabek's overall GDP from 2010 ($132,702.84 million USD, in 2010 dollars, from the World Bank's INDO-DAPOER database), and assuming this increase in GDP would be sustained for 50 years, discounted at an annual rate of 5 percent. Column 3 reports the present value of construction costs, assuming that these costs would occur in the first 3 years of system development. Column 4 reports the present value of the system's operating costs.[44] We find that removing the BRT would reduce the present value of welfare by $1.035 billion, but it would also save on $136 million in construction costs and $821.7 million in operating costs. In column 5, we show that removing the system has a net present value of -$77.8 million, which represents 0.003 percent of 2010 GDP (column 6). Although removing the system reduces welfare, the effects are relatively small when compared to Tsivanidis (2019), who finds that the net increase in welfare was 1.09 percent for TransMilenio in Bogota.

The small positive welfare benefits of BRT in our model may appear to contradict the modest impacts we found in our reduced-form evidence. Although the BRT system removes traffic lanes in certain areas and increases congestion along those routes, it still has a positive mode share and is valued by

[43] Discrepancies between actual and predicted totals under the baseline may be due to the fact that we had to approximate traffic counts, as described in Section 6.

[44] To obtain cost parameters for these counterfactual exercises, we used a capital cost value for Corridor 1 of $1.512 million per km, inflating the figure reported in Hidalgo and Graftieaux (2008) to 2010 dollars. We also used an average cost per km value of $1.297 for other corridor construction costs, obtained from various news sources. For TransMilenio capital costs, we used a value of $8.86 million per km, again inflating the figure reported in Hidalgo and Graftieaux (2008) to 2010 dollars. For all counterfactuals, we also assumed that the system's operating costs would be $45.01 million per year, consistent with 2010 fare recovery data from Jakarta's Department of Public Transportation (*Dinas Perhubungan*). Online Appendix B contains more details on these figures.

commuters, and it reduces congestion along Corridor 1, an important thoroughfare.[45] To explore what features of the model drive the positive welfare effects, we conduct several different counterfactual simulations for removing the BRT. Each panel of Figure 4 reports 50 different simulations where a single parameter is varied (listed in the panel title) and all other parameters are held constant at our preferred, baseline set of parameters. The varying parameters are plotted on the x-axis, and $\widehat{\overline{W}}$, our measure of the increase in welfare from removing the BRT, is plotted on the y-axis. The red dashed lines in each panel also indicate our preferred parameter values (along the x-axis) and the level of $\widehat{\overline{W}}$ reported in Table 8 (along the y-axis).

Panel A shows that for relatively small values of θ, removing the BRT reduces welfare because people have strong idiosyncratic preferences for using that mode which is no longer available. As θ increases and workers become less differentiated, the costs of BRT removal become smaller and removing the BRT eventually becomes beneficial because of its impact on congestion. Panels B and C show that varying α and β do not substantially change the extent to which removing the BRT impacts welfare. This is because at our baseline value of $\theta = 5.364$, the relocation effects of removing the BRT on workplace and residential populations are quite small.[46]

Panel D shows that as the congestion parameter, λ, increases, it becomes less costly to remove the BRT system. With low levels of λ, transport costs do not vary as ridership increases and the value of preserving the BRT system is primarily a function of preference heterogeneity. A larger λ amplifies the costs of BRT-induced traffic congestion, and this increases the benefits from removing the BRT system.

Finally, Panels E and F vary γ_1 and γ_2. These two parameters rescale the way that BRT transport costs ($m = 1$) and train transport costs ($m = 2$) enter into the model, relative to surface-based transport costs ($m = 3$). Lower values of γ_1 imply that the BRT is more costly to use, reducing ridership and increasing the benefits of removing the BRT. As γ_1 increases to zero, it becomes more substitutable with surface-based modes, and the costs of removing the BRT increase. The effects of γ_2 have the opposite relationship because trains are a substitute for the BRT system.

Restoring Lanes and Increasing BRT Speeds. The counterfactual of removing the BRT system conflates the effects of three different policies: (1) removing a higher quality (and speedier) Corridor 1; (2) removing other, slower corridors; and (3) restoring mixed-traffic lanes currently occupied by the BRT system. To assess the welfare implications of the BRT in more detail, in Table 8, row 3, we report the results of a simulation where we keep the BRT infrastructure intact, but we restore lanes taken away by the BRT's expansion outside of Corridor 1. We find that restoring BRT lanes to surface-based modes, while still keeping the system in place, would have caused a positive increase in welfare in present value terms, raising Jabodetabek's GDP by \$1.989 billion.

If restoring lanes had increased construction costs for other corridors to the levels of Corridor 1 costs, this would have increased costs by only \$19.4 million in present value terms, leading to a net increase in welfare of 0.05 percent. Given the small cost differences between the construction costs of other corri-

[45] Online Appendix Table A.23, row 2, reports changes in average delay from removing the BRT (i.e. $\widehat{\text{delay}}_{kl} = \text{delay}'_{kl}/\text{delay}_{kl}$, where delay_{kl} is expressed in minutes per km) from this simulation. While removing the BRT decreases overall delay for surface-based modes, it increases delay along Corridor 1.

[46] Online Appendix Figure A.9 presents scatterplots comparing residential and workplace populations under the BRT removal simulation to those same variables from our baseline. For both plots, the vast majority of the data lies along the 45 degree line.

dors and Corridor 1, the failure to pay for these enhanced infrastructure investments represents a sizable missed opportunity for the city of Jakarta. Online Appendix Figure A.11 shows that by reducing congestion in the center, restoring BRT lanes would have brought some jobs and workers back to the city center and reduced economic activity in the periphery. As shown in Table 8, row 4, we obtain similar results if all BRT corridors had been built to Corridor 1 standards. This simulation both restores lanes taken away but it also increases the speeds of other BRT corridors to Corridor 1 speeds.

In row 5 of Table 8, we show what would have happened to welfare if TransJakarta had been built to TransMilenio standards. For this simulation, we again restore lanes taken away by the other corridors of the BRT system, but we also increase speeds to TransMilenio speeds (26.2 km per hour, as stated in Tsivanidis, 2019). These rapid speeds more than double the impacts on welfare. Even at nearly 8 times the cost of the Corridor 1 infrastructure, a gold-standard BRT in Jakarta would have increased welfare by 0.08 percent of GDP in net present value terms.[47]

Building Planned Lines. Next, we investigate the welfare and reallocation effects of building the additional 103 km of planned BRT lines, depicted in red in Figure 1. We conduct two different simulations: (1) a low-quality expansion, similar to the existing lower-quality corridors in terms of speeds, construction costs, and surface-lane removal; and (2) a high quality expansion, similar to TransMilenio in terms of speed and costs, and with no lane removal. Row 6 of Table 8 shows that the low quality expansion reduces welfare in net present value terms, presumably because of the increased congestion that would have occurred from the lane reductions.[48] Row 7 shows that the high quality expansion would have increased welfare, but large construction costs reduce its benefits. Online Appendix Figure A.14 shows that the low quality expansion would have pushed jobs and workers away from the center, while online Appendix Figure A.15 shows that the high quality expansion would have increased both residential and commercial activity in the center and around the areas near the newly created BRT stations.

Robustness to Different Parameter Values. In online Appendix Table A.24, we explore the robustness of all counterfactual simulations to different parameter values. In this table, each column is labeled by the set of parameter values taken from the corresponding panel of online Appendix Table A.22. Column 1 reproduces the changes in welfare from Table 8. Columns 2-4 explore the robustness to different values of θ, ranging from the Tsivanidis (2019) estimate of $\theta = 3.020$ (column 2) and the Ahlfeldt et al. (2015) estimate of $\theta = 6.830$ in column 3 to our PPML estimate of $\theta = 12.091$ in column 4. As is evident, the impacts of different counterfactual policies are qualitatively and quantitatively similar under these different parameter sets. As θ falls, the costs of BRT removal, the benefits of improving the BRT, and the benefits of building high quality planned lines all increase.

8 Conclusion

In this paper, we study the impact of the TransJakarta BRT system on commuting outcomes and welfare. Using new, high quality datasets, we find that the BRT system did not reduce incentives for motoriza-

[47]Online Appendix Figures A.13 and A.12 show that increasing BRT standards would have increased economic activity in the center and reduced it in the periphery. The relocation effects are larger for the TransMilenio standards than for the Corridor 1 standards simulation, as expected.

[48]Online Appendix Table A.23, row 6, shows that average delays increase substantially for surface-based modes after the low-quality planned lines are constructed.

tion in Jakarta and that it had modest impacts on transit ridership. We also show that the system did not increase commuter flows. As the system expanded, planners converted mixed-use lanes into BRT busways, which we find exacerbated congestion along service corridors, instead of alleviating it. Our reduced form results suggest that TransJakarta's low cost infrastructure and poor service quality represent a cautionary tale for rapidly growing cities. The findings on increased congestion from road capacity reductions may also help explain why several lower-quality BRT implementations, such as those in Dehli and Bangkok, have been abandoned (Pojani and Stead, 2017).

We also evaluate the welfare implications of TransJakarta and simulate the effects of counterfactual implementation improvements. To do so, we extend the quantitative spatial framework developed by Allen and Arkolakis (2020) to allow for route choices and traffic congestion across multiple congestible transport networks. We find that although TransJakarta modestly improves welfare, its benefits were small relative to the system's construction costs. However, we also find that improving the system, by bringing the expanded corridors to TransMilenio standards, would substantially increase the welfare effects of the system, even accounting for increases in costs. That these improvements were not part of the system's original implementation represents a significant missed opportunity.

Further research could improve upon some of the limitations of the current model. In particular, the assumption that residential, workplace, and commuting route choices are all governed by the same Fréchet parameter is particularly strong. Additional research to better connect the long standing mode choice literature in the economics of urban transportation (reviewed in Small and Verhoef, 2007) to this class of quantitative spatial general equilibrium models could be insightful. Moreover, extensions endogenizing vehicle ownership or allowing for parameter heterogeneity for different skill or income groups, as in Tsivanidis (2019), would also be useful.

Our results also focus on the period from 2002-2010, when TransJakarta was early in its operation. Any service quality improvements undertaken since the system was transferred to private management in 2014 are not reflected in these results. Moreover, additional aspects were not modeled but may be worth exploring. 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. The feeder bus system is also undergoing continual development and improvement. These factors could limit access and potential complementarities between walking and the BRT system, but their effects remain understudied (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	14 February 2013	Basic BRT

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

Table 2: Average Speeds by Mode (Relative to Motorcycle), 2010

	(1)	(2)	(3)	(4)
TransJakarta BRT	-0.199***	-0.366***	0.215	-0.373***
	(0.030)	(0.085)	(0.222)	(0.086)
Other Public Transport	-0.231***	-0.264***	-0.369***	-0.254***
	(0.008)	(0.037)	(0.037)	(0.040)
N	293465	24760	1996	22763
Adjusted R^2	0.523	0.489	0.664	0.469
Adjusted R^2 (within)	0.013	0.016	0.028	0.015
H_0: $\beta_{\text{BRT}} = \beta_{\text{BUS}}$, p-value	0.304	0.277	0.008	0.216
Purpose Indicators	X	X	X	X
Departure Hour Indicators	X	X	X	X
Origin × Destination FE	X	X	X	X
Only BRT Routes	.	X	X	X
... Corridor 1	.	X	X	.
... Other Corridors	.	X	.	X

Notes: This table reports differences in speeds, relative to motorcycle, for BRT and other public bus modes. We used the 2010 JICA survey data and regressed trip speeds on mode indicators, in addition to the controls listed in the rows. All columns include separate fixed effects for departure hour and purpose. Columns 2-4 include origin × destination fixed effects and focus only on observations along BRT routes. Column 3 only includes data from corridor 1 routes, while column 4 includes other BRT routes. Robust standard errors, two-way clustered at the origin and destination community level, are reported in parentheses. */**/*** denotes significant at the 10% / 5% / 1% levels.

Table 3: Self-Reported Safety and Comfort: Public Transport Modes (2010)

	DV: Safety		DV: Comfort	
	(1)	**(2)**	**(3)**	**(4)**
TransJakarta BRT	0.075***	0.052***	0.017	0.002
	(0.020)	(0.013)	(0.013)	(0.009)
Other Public Transport	-0.050**	-0.053***	-0.071***	-0.038***
	(0.020)	(0.017)	(0.013)	(0.011)
N	90022	90022	90022	90022
Adjusted R^2	0.019	0.220	0.019	0.221
Adjusted R^2 (within)	0.018	0.007	0.017	0.002
Departure Hour FE	Yes	Yes	Yes	Yes
Purpose FE	Yes	Yes	Yes	Yes
Origin FE	.	Yes	.	Yes
Destination FE	.	Yes	.	Yes

Notes: This table reports differences in self-reported safety and comfort for public transit modes, with the left-out mode being trains. We used the 2010 JICA survey data and regressed these self-reported values on mode indicators, in addition to the controls listed in the rows. All columns include separate fixed effects for departure hour and purpose; columns 2 and 4 additionally control for origin and destination fixed effects. Robust standard errors, two-way clustered at the origin and destination community level, are reported in parentheses. */**/*** denotes significance at the 10% / 5% / 1% levels.

Table 4: Summary Statistics on Communities: Pre-Treatment Characteristics

	$d\,(\textbf{BRT}) \leq 1$		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
Panel B: JICA 2002							
Monthly Income < Rp 1 mil	0.40 (0.14)	132	-0.24***	1358	0.05*	-0.00	109
Monthly income Rp. 1-5 mil	0.54 (0.12)	132	0.22***	1358	-0.05**	-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
Own a Motorcycle? (0 1)	0.38 (0.11)	132	0.08***	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
Panel C: GIS Variables							
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
Panel D: Pre-Trends (PODES, Night Lights)							
Δ % of HH w/ a Car (1996-2000)	-0.06 (0.22)	134	-0.07*	1271	-0.08**	-0.06	90
Δ % of HH w/ a Motorcyle (1996-2000)	-0.05 (0.30)	135	-0.07	1269	-0.05	0.00	90
Δ Night Light Intensity (1998-2003)	-0.24 (0.63)	140	2.19***	1359	1.68***	0.01	109

Notes: 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 located within 1 km of a BRT station in 2010. Columns 3 and 4 report the difference in means and number of observations between the close-proximity communities and all other communities ("All Non-Treated"). Columns 5-7 report the difference in means, difference in weighted means, and number of observations between the close-proximity communities and communities within 1 km of either a BRT line that has yet to be constructed or a planned BRT station that was constructed after mid 2010 ("Planned or Eventually Treated"). The weights are generated by a first-step propensity score estimation. The significance stars in this table are computed by regressing the outcome variable on a treatment indicator, restricting the sample in columns 5-7 to only treated and planned/eventually-treated 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 5: 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 6: Gravity Commuting Regressions

	Cross-Section					
	2002		2010		Panel	
Panel A: Fixed Effects Least Squares	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Travel Time	-0.058***		-0.059***			
	(0.002)		(0.002)			
BRT Route (OD)		1.176***		1.186***	-0.085	-0.089
		(0.089)		(0.099)	(0.070)	(0.069)
N	2210	2210	2210	2210	4402	4402
Adjusted R^2	0.620	0.063	0.550	0.097	0.879	0.880
Adjusted R^2 (within)	0.610	0.040	0.522	0.040	0.001	0.004
Panel B: Poisson Pseudo ML w/ FE	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Travel Time	-0.107***		-0.133***			
	(0.004)		(0.005)			
BRT Route (OD)		2.729***		2.878***	-0.008	-0.028
		(0.093)		(0.140)	(0.066)	(0.061)
N	2210	2210	2210	2210	4402	4402
Wald χ^2	847.069	861.424	672.641	425.186	0.877	11.107
Pseudo R^2	0.148	0.038	0.164	0.055	0.177	0.177
Origin FE	Yes	Yes	Yes	Yes	.	.
Destination FE	Yes	Yes	Yes	Yes	.	.
Origin × Destination FE	.	.	.	.	Yes	Yes
Year FE	.	.	.	.	Yes	Yes
Orig. District × Year FE	.	.	.	.	Yes	Yes
Dest. District × Year FE	.	.	.	.	Yes	Yes
O-D Density Controls	.	.	.	.	.	Yes

Notes: This table reports estimates of the gravity commuting regression equation, (3). We first aggregated the data to pairs of origin and destination subdistricts (*kecamatan*) and only use observations with 10 or more commuters in the raw survey data. Columns 1-4 report cross-sectional regressions and only include separate fixed effects for each origin and destination location. Columns 5-7 use panel data, with a full set of origin × destination fixed effects and year fixed effects. Column 7 adds origin district × year fixed effects and destination district × year fixed effects. Robust standard errors, two-way clustered at the origin and destination sub-district level, are reported in parentheses. */**/*** denotes significance at the 10% / 5% / 1% levels.

Table 7: Negative Spillovers: Impact of BRT on Travel Times

Panel A: All Trips	**(1)**	**(2)**	**(3)**	**(4)**
BRT Route	0.099***		0.037	
	(0.019)		(0.029)	
Corridor 1		0.003		-0.163**
		(0.061)		(0.064)
Other Corridors		0.104***		0.048*
		(0.019)		(0.029)
N	1137898	1137898	696308	696308
Adjusted R^2	0.464	0.464	0.423	0.423
Adjusted R^2 (within)	0.001	0.001	0.001	0.001
Panel B: Train Trips	**(1)**	**(2)**	**(3)**	**(4)**
BRT Route	-0.082		0.130	
	(0.180)		(0.501)	
Corridor 1		0.063		0.380
		(0.315)		(0.571)
Other Corridors		-0.122		0.095
		(0.171)		(0.468)
N	35743	35743	22224	22224
Adjusted R^2	0.451	0.451	0.405	0.405
Adjusted R^2 (within)	0.001	0.001	0.000	0.000
Origin $\times$ Destination FE	Yes	Yes	Yes	Yes
Origin $\times$ Year FE	Yes	Yes	Yes	Yes
Destination $\times$ Year FE	Yes	Yes	Yes	Yes
Only Non Peak-Time Trips			Yes	Yes

Notes: Each cell in this regression corresponds to a separate estimate of β from the specification (4) to assess the differential impact on travel times for trips originating and terminating within 1 km of a BRT station. The dependent variable is log travel times, and the parameters are estimated from the pooled 2002 HVS / 2010 CS sample. Panel A uses all trips, while Panel B only uses train trips. All columns include separate purpose-by-year effects, mode-by-year effects, and departure-hour-by-year indicators, as well as separate fixed effects for each origin $\times$ year and destination $\times$ year. Columns 3 and 4 restrict the sample to only include non peak-time trips. Robust standard errors, two-way clustered by origin and destination community, are reported in parentheses. */**/*** denotes significance at the 10% / 5% / 1% levels.

Table 8: Counterfactuals: Welfare

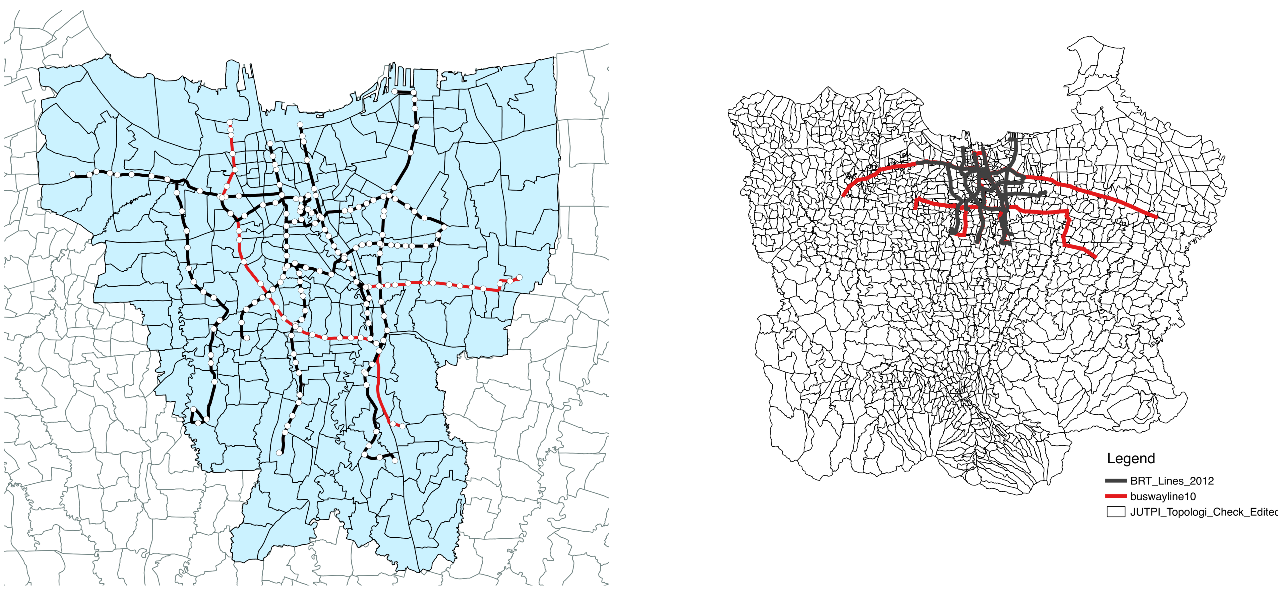
			Net Present Value (millions, 2010 USD)				
		$\widehat{W}$	Benefit	Capital Costs	Operating Costs	Total NPV	Total NPV / GDP (Percent)
	Description	(1)	(2)	(3)	(4)	(5)	(6)
1	Baseline	1.00000					
2	Removing the BRT	0.99957	-1035.1	-135.5	-821.7	-77.8	-0.003
3	Keeping BRT but Removing Spillovers	1.00082	1989.8	19.4	821.7	1148.7	0.047
4	Improving the BRT, Corridor 1 Standards	1.00083	2020.1	19.4	821.7	1179.1	0.049
5	Improving the BRT, TransMilenio Standards	1.00148	3574.5	771.9	821.7	1980.8	0.082
6	Building Planned Lines, Low Quality	0.99999	-33.4	127.3	821.7	-982.4	-0.041
7	Building Planned Lines, High Quality	1.00106	2567.4	869.4	821.7	876.3	0.036

Notes: All numbers are reported in millions of 2010 USD. Row 1 reports the baseline change in welfare (normalized to 1). Rows 2-7 report the change in welfare that would result from the counterfactuals described in the row titles. Net Present Value (NPV) columns report different elements of the following formula: $NPV = \sum_{t=0}^{50} (B_t - C_t) / (1+\beta)^t$, where $\beta = 0.05$ is the discount rate. Column 1 reports the counterfactual change in welfare, obtained directly from the simulation results. Column 2 applies the result from Column 1 as the NPV of the benefit of the policy, assuming that the policy would lead to a steady-state increase in GDP sustained over 50 years. Column 3 reports the NPV of capital costs (assuming they would accrue during the first 3 years), and column 4 reports the NPV of operating costs (assuming they would be constant across years and simulations). Column 5 is obtained by subtracting columns 3 and 4 from column 2. Column 6 expresses the results from column 5 as a percent of the NPV of GDP in 2010. Detailed cost information is described in footnote 44 and in Appendix B.

Figure 1: TransJakarta BRT: Eventually Constructed and Planned Lines

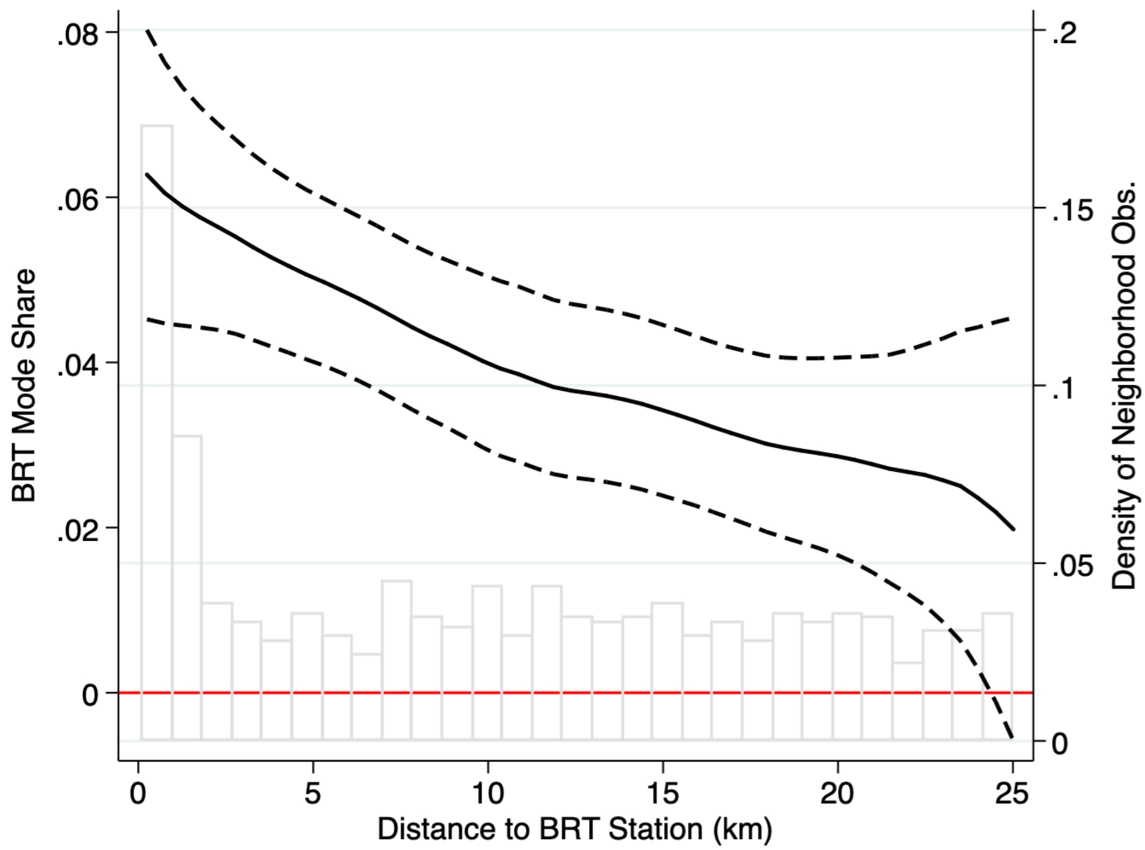
(A) MID 2010 VS. EVENTUALLY CONSTRUCTED

(B) MID 2010 VS. PLANNED LINES



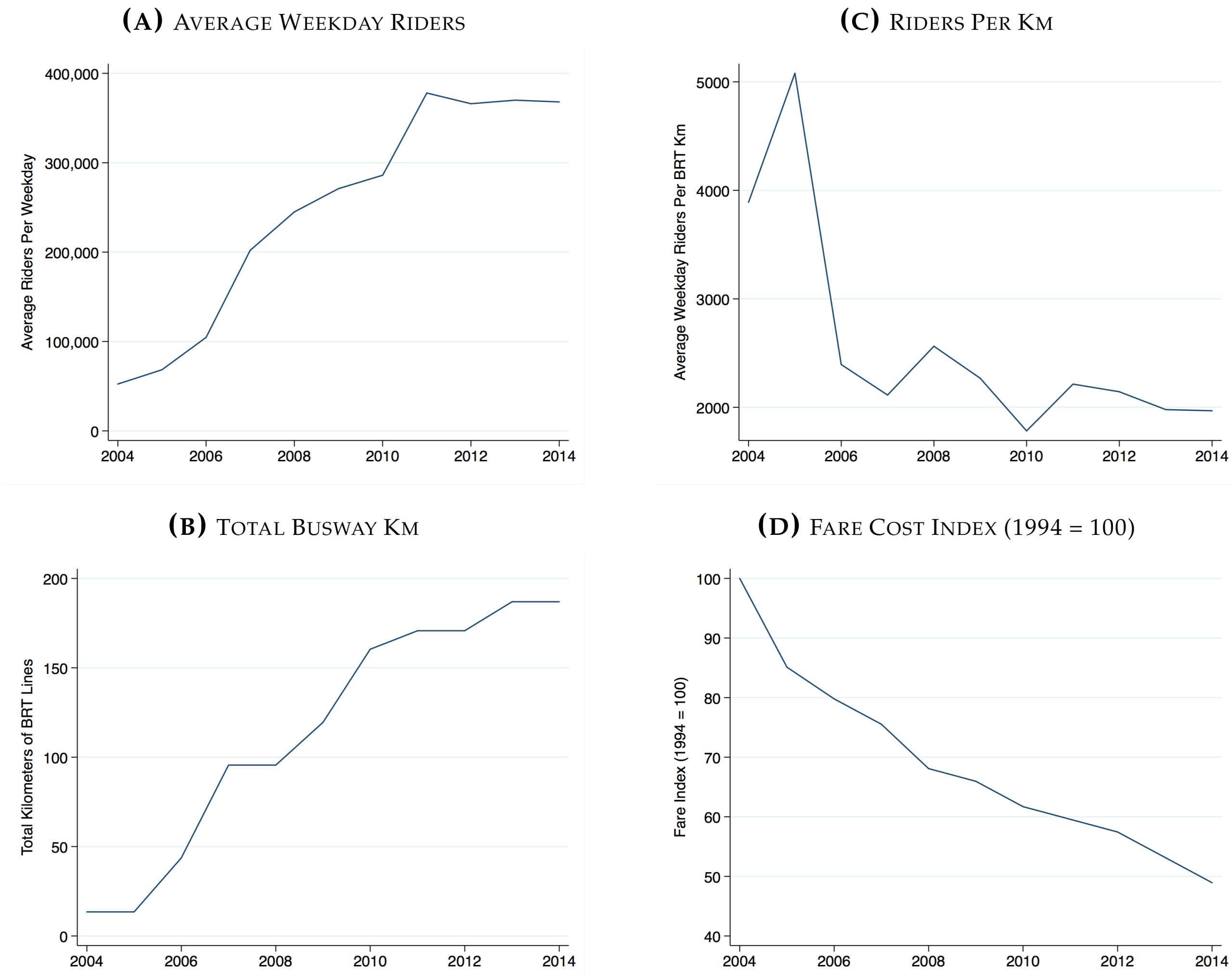
Notes: Panel A plots the locations of actual lines and stations as of mid-2010 (in black) and the locations of eventually constructed lines and stations (in red). As of mid-2010, the system had 159 stations on 9 corridors, but this was increased to 196 stations along 12 corridors as of January 2018. 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: Semiparametric Effect: BRT Mode Share



Notes: This figure reports the results of a partially linear regression of neighborhood BRT mode share (plotted on left y-axis) on a flexible function of distance to the nearest BRT station and a linear function of control variables. The 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. The black line corresponds to the estimated regression line, and the dashed lines represent pointwise 95% confidence bands. Control variables include 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, all from 2000 census data. 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. The grey bars in the figure report a histogram of average distance to the nearest BRT station across neighborhoods in Jakarta, with the density of neighborhood observations plotted on the right y-axis.

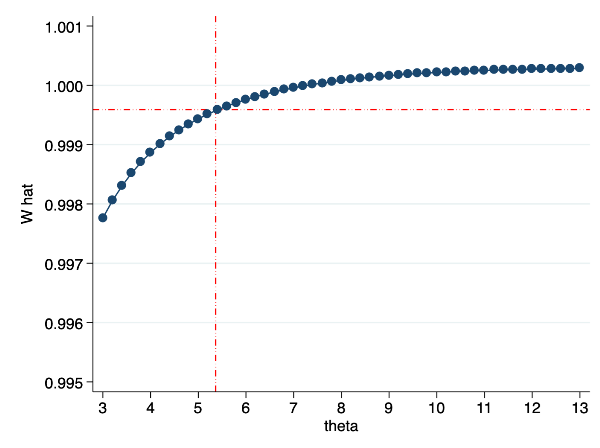
Figure 3: TransJakarta Ridership Statistics



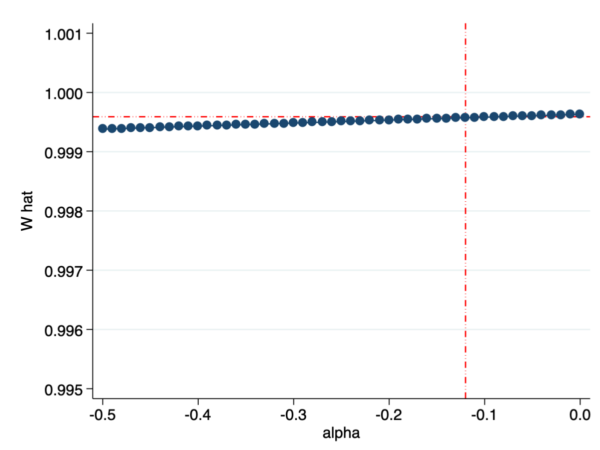
Notes: Panel A plots the average total riders per weekday on the TransJakarta BRT system, using data from Sayeg (2015). Panel B plots the expansion in kilometers of the TransJakarta BRT system. The data are derived from the traced BRT lines and opening dates, and calculated using GIS software. Panel 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 4: Welfare Effects of Removing the BRT: Varying Parameters

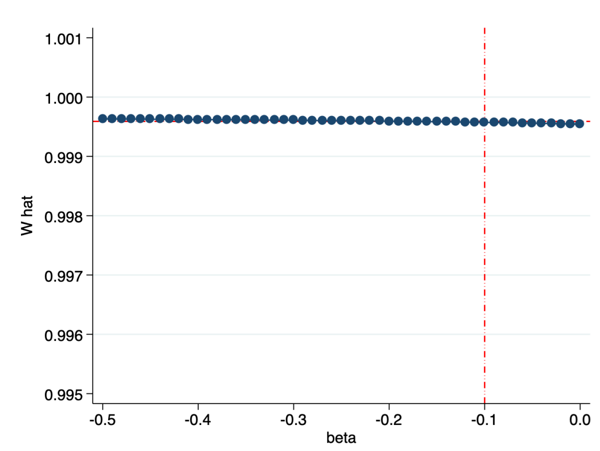
(A) Varying θ



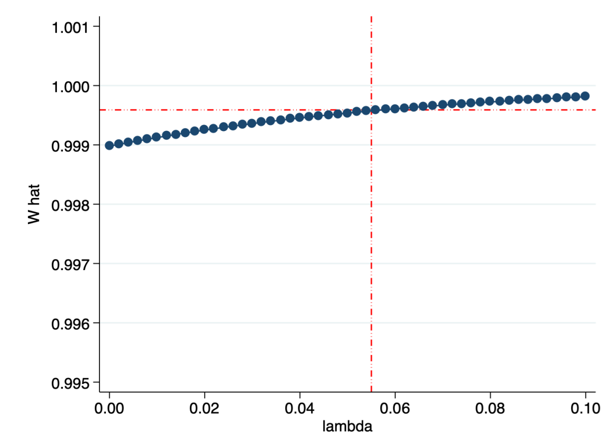
(B) Varying α



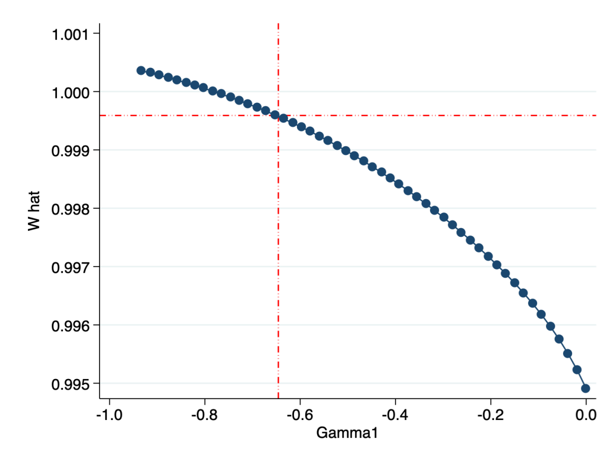
(C) Varying β



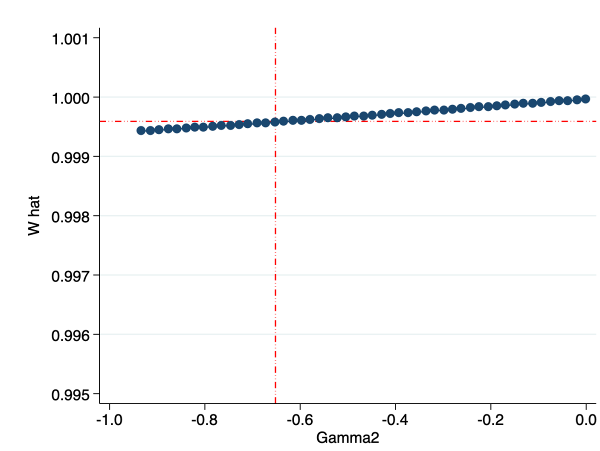
(D) Varying λ



(E) Varying γ_1



(F) Varying γ_2



Notes: This figure plots $\widehat{\widehat{W}}$ on the y-axis for different simulations undertaken with different parameter values, where those values are listed on the x-axis. Each panel conducts 50 different simulations, and the results of each simulation are indicated by separate points on the graph. In each panel, a single parameter is varied (listed in the panel title) and all other parameters are held constant at values taken from Appendix Table A.22, Panel A. The red dashed lines indicate our preferred parameter values (along the x-axis) and the level of $\widehat{\widehat{W}}$ reported in Table 8 (along the yx-axis).