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Connecting to economic opportunity

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Connecting to economic opportunity: The role of public transport in promoting women's employment in Lima[*]

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Abstract

Limited access to safe transportation is one of the greatest challenges to labor force participation faced by women in developing countries. This paper quantifies the causal impacts of improved urban transport systems in women´s employment outcomes, looking at Bus Rapid Transit (BRT) and elevated light rail investments in the metropolitan region of Lima, Perú. We find large gains in employment and earnings per hour among women, and not for men, due to these investments. Most of the gains arise on the extensive margin, with more women being employed, but employment does not appear to be of higher quality than that for comparison groups. We find also evidence of an increase in the use of public transport. Results are robust to alternative specifications and we do not find evidence that they are driven by neighborhood composition changes. Overall, these findings suggest that infrastructure investments that make it more convenient and safer for women to use public transport can generate important labor market impacts for women who reside in the area of influence of the improved infrastructure.

Keywords: Urban transport; gender; employment, impact evaluation

JEL Codes: J01; J16; O12; R40

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1. Introduction

Social and economic differences between women and men play a significant role in travel behavior, making gender one of the most important demographic determinants of travel patterns (Curtis & Perkings, 2006; Wachs, 1996). For example, women tend to work close to their home to facilitate household related travel (Sermons & Koppleman, 2001). In addition, as women tend to oversee multiple household responsibilities, they make more stops and more chained trips than men (Taylor & Mauch, 2000), and report making a considerable number of trips for family and personal business (Schintler, Root, & Button, 2000). Women also make a higher proportion of their trips by transit and walking, even when a private vehicle is available in the household (Peters, 1999; Peters, 2013). In addition to having different transport needs, women also frequently report feeling unsafe when using public transport systems, with sexual harassment and robbery being some of the key issues (Gardner et al., 2017; Gekoski et al., 2017).

There is limited research exploring women's needs and issues concerning public transportation use in developing countries (Kash, 2014). This poses a barrier for transportation planners who cannot effectively target policies to reduce the mobility and accessibility gap between men and women. Moreover, women tend to be underrepresented in the transportation-related jobs, from decision-making and planning roles, to operators of public transportation (Duchéne, 2011; Kunieda and Gauthier, 2007; Peters, 2006) which many argue may contribute to and reinforce gender biases in transport systems, and propagate systems developed towards men's needs (Peters, 2006). As a consequence, women in many developing countries continue to have reduced access to safe and adequate public transportation, which may potentially limit their mobility and accessibility to economic opportunities.

Unequal labor force participation between women and men is also a reality and it is more sharply observed in developing countries. While a myriad of socio-economic and overlapping factors affect the decision and ability of women to engage in the labor market including the level of economic development of cities, individual educational attainment, social dimensions (such as social norms influencing marriage, fertility, and women's role outside the household), and institutional settings (e.g. laws, protection, benefits) (Verick, 2014), access to transport is increasingly emerging as a key issue affecting women's labor force participation. A recent report by the International Labor Organization finds that limited access to safe transportation is the greatest challenge to labor force participation that women face in developing countries, reducing their participation probability by 15.5 percentage points (ILO, 2017). Furthermore, due to wage inequality and a higher prevalence of part-time work, women tend to have lower earnings, and in turn, access to lower quality modes of transport (Astrop & Palmer, 1996; Srinivasan & Rogers, 2005).

The role of urban transport in facilitating access to employment opportunities becomes even more relevant in contexts of rapid urban growth, such as the case of Latin America and the Caribbean (LAC)[1], where the increase in the value of centrally located land has pushed lower income and vulnerable populations to move to the outskirts of cities in search of affordable housing. As urban planning mechanisms are fragmented, urban peripheral growth tends to be sprawling, informal, and lacking in adequate transport infrastructure services. This, in turn, tends to increase both the monetary and time cost of transportation for the poor, and exacerbates the already low level of access to jobs and other economic opportunities among these vulnerable populations (Carruthers, Dick, and Saurkar, 2005). Data from CAF (2009, 2011) shows that in the largest 15 metropolitan areas in Latin America while bus users spend in average 59 minutes per trip, car users in the region spend in average 25 minutes per trip.

This paper studies the impacts of access to improved urban transport systems on women's employment outcomes. To our knowledge, it is the first causal study on this subject worldwide. We exploit the opening of two modes of urban transportation in the metropolitan region of Lima, Perú, namely a Bus Rapid Transit System (BRT) and an elevated light rail, better known as metro Line 1. Both the BRT and Line 1 are major transit investments that have increased the formality of the public transit system in Lima. The systems have considerably reduced travel times and increased connectivity between peripheral areas to major employment centers. In addition, they are equipped with lighting, security personnel, and security cameras at stations and on-board trains, which represent substantial improvements relative to the safety of the rest of the public transit in the city. We hypothesize that women in areas close to the system react to these changes by increasing their usage, therefore improving their accessibility to jobs.

To quantify the causal impacts of the introduction of the two transport systems (BRT and Line 1), we estimate difference-in-differences (DID) models using 2007 to 2017 data from the Peruvian National Household Survey (ENAHO, original Spanish acronym), which is collected on an annual basis and provides the geographic coordinates of the centroid of the block where the household resides. Our identification strategy compares changes in employment indicators for men and women living in areas that are closer to these transport systems versus those living in comparable

[1] According to the Atlantic Council (2014), Latin American countries have undergone unprecedented urbanization in the past 60 years. From 1950 to 2014, the share of the population in Latin America living in urban areas increased from 40% to around 80% and it is expected to increase to 90% by 2050.

areas that are further away and with limited access to these services. Given that we rely on repeated cross-sections, we test for changes in neighborhood composition and conduct tests of the parallel trends assumption, to rule out the possibility that those living in areas closer and farther to the systems were experiencing different trends before the urban transport systems were implemented.

Our findings apply to women as we do not find significant changes for men. Our results show, by the end of the analysis period, an increase of ten percentage points in the probability of being employed among women living closer to the systems when compared to women living farther away from the systems (an increase of 17% in the probability of employment, compared to the pre-intervention period). We also find large increases in both total earnings and hours worked, resulting in a 23% increase in earnings per hour. The analysis suggests that most of these results are being driven by women previously not in the labor force joining the labor market. To understand what drives the earnings results we attempt measuring job quality by looking at job benefits, the characteristics of the employing firm or self-employment activity, and the type of occupation. Overall, we do not find significant improvements in job conditions. Thus, while employment increases, and earnings per hour increase for women close to the improved public transport systems, these changes are not driven by women finding higher quality jobs.

We also find substantial increases in the use of public transport, again only for women, as measured by expenditures. The share of women spending positive amounts on public transport increases eight percentage points (10% increase with respect to the pre-intervention period), indicating that the opening of the BRT and Line 1 strongly pulled women into using public transport. Given that data prior to the intervention shows that a large majority of men and women rely on public transport for trips to and from work, this provides further evidence for the hypothesis that the increase in labor force participation is facilitated by the new transport systems. We conduct tests that allows us to rule out that these observed changes are driven by compositional changes in the education characteristics of those men and women who live in the area of influence of the BRT and Line 1. In addition, exploiting the fact that we have three years of pre-treatment (i.e. pre-BRT and Line 1) data, we run placebo regressions using only the pre-treatment period 2007-2009 and find that the null hypothesis of zero treatment effect for this period cannot be rejected for any of the outcomes. This suggests that the parallel trends assumption, needed for the validity of the DID estimator, holds. We also conduct several robustness checks, as well as heterogeneity analyses, finding that our main results are stable, and robust to specification changes.

The paper is structured as follows. The next section discusses in more detail the related literature highlighting the main contributions of this paper. Section three explains how urban transport systems operate in Lima, Perú. Section four describes the data used in the analysis. Section five presents some descriptive analysis to showcase the different patterns in travel behavior for men and women in the context of our study. Section six describes the methodology, while Section seven presents the main results of the paper. Section eight provides a discussion of the results and conclusions.

2. Related Literature

Much of the literature on gender issues and transport in developing countries has explored women's perception of accessing and using transport systems, finding that sexual harassment[2] is one of the main issues that affect women who use public transportation (Schulz & Gilbert, 1996; Gwilliam, 2003; Zermeno et al., 2009; Kash, 2014; Neupane & Chesney-Lind, 2014). Specifically, women report frequently feeling unsafe walking to a transit stop/station, waiting for the bus or train, and traveling in the system.

A handful of studies examine these security issues in informal versus formal public transit. For example, in a study conducted in Mexico City, female respondents said that the informal transport service was the most unsafe mode and that higher-quality public transportation (scheduled service, defined stops, cleaner buses) will lead to safer trips (Tudela Rivadeneyra et al., 2015). In Bogotá and Arequipa, riders of informal transportation services identified crime as one of the principal problems with the system, which was tied to the crowding during peak hours. In Bogotá, women were significantly more concerned about crime than men (Kash, 2014). Women in the slums in Delhi identified themselves as targets of sexual harassment while traveling to work, especially when walking to the stops of informal and public transportation, which in some cases affected their ability to retain jobs in distant areas from their homes (Anand & Tiwari, 2007).

Most of the strategies to create a more equal and fair access to women in public transportation have been targeted to improve women's personal security. Formal surveillance, with the presence of on-site security personnel, has been found as the most effective strategy to reduce sexual harassment at transit stations (Gekoski, et al., 2015; Loukaitou-Sideris, 2008). Other security

[2] Sexual harassment issues experienced by women in transit include staring, unwanted comments on physical appearance, men touching or rubbing against women, and groping (Gomez, 2000). While in developed countries sexual harassment in public transport has been reported to be more verbal than physical, subtle groping and unwanted touching are common in rush hours (Hsu, 2011; Gekoski, et al., 2015). In developing countries, this pattern is more pronounced (Zermeno, Pacido, Soto, & Yadin 2009).

measures that have been rated positively are good lighting at bus stops and adjacent streets, request-stop programs (which allow women to get out of the bus closer to their destination), public awareness campaigns denouncing sexual harassment, policing (in vehicles and stops), and public education (Zermeno et al., 2009; Loukaitou-Sideris, 2008). Some authors have also found benefits in women-only vehicles[3] (Zermeno, Pacido, Soto, & Yadin, 2009). However, this short-term solution does not necessarily change the behavior of the perpetrators and might be perceived as a segregation tool against women (Gardner, Cui, & Coiacetto, 2017).

Regarding the literature connecting transport infrastructure with unemployment and labor informality, this relationship is theorized to occur due to two main factors. First, the spatial mismatch hypothesis, posed by Kain (1968), who argues that the spatial segregation of low-income minorities from skill-appropriate job centers decreases the affordability of job searches and commutes, and thus increases unemployment rates among such isolated and predominately transit-dependent communities. Second, the reservation wage hypothesis that states that the wage at which a person is willing to supply labor is likely to be higher the higher the transport costs; therefore, increased transport costs are more likely to limit the geographic range of job opportunities (Patacchini & Zenou, 2005). As the impact of transportation costs is higher on less skilled workers who have lower wages, where women could be more concentrated, we would expect the search radius to be more limited for those workers the higher the transportation costs.

Overall, there are few studies that rigorously estimate the causal relationships between urban transport investments and employment outcomes (Yañez-Pagans et al., 2018). This responds to the empirical complexities that arise when trying to distinguish between impacts that can be attributed to transport investments versus those that result from the non-random placement of these investments (i.e. driven by demand considerations) and that might benefit populations that were already better connected, that were more employed, or had higher income, etc. There is also an important aspect of mobility and household dynamic location decisions. What is measured might not necessarily reflect the benefits obtained by the original population living in project-served areas, but could reflect that new populations, with distinct characteristics, are moving in (i.e. compositional changes).

There are several non-causal studies that analyze the changes on access to employment opportunities resulting from urban transport systems (Bocarejo & Oviedo, 2012; Delmelle & Casas, 2012; Bocarejo, Portilla & Meléndez, 2016; Venter et al., 2018). They do so by looking at

[3] This strategy has been implemented in cities such as Mexico City, Rio de Janeiro, Tehran, and Tokyo.

the reduction in travel times generated by improved transport systems across different areas in a city and considering how well they serve to connect low income or vulnerable populations to employment centers. Another group of studies looks at the correlation between employment outcomes and distance or access to urban transport systems, showing that nearness to a system is correlated with lower levels of unemployment (Sanchez, 1999) or with a lower probability of being informally employed (Oviedo-Dávila, 2017).

Studies trying to tackle attribution challenges are more limited and the majority have relied on a DID empirical strategy. For cities in the United States, studies have shown larger job growth in areas surrounding transport stations, particularly in downtown areas (Cervero & Landis, 1997 for subways) and for white-collar and high-wage employment (Guthrie & Yinling, 2016, for BRT). Studies also find increases in the propensity of suburban firms, previously not near a metro line, to hire minority populations, specifically Latinos (Holzer et al., 2003). In a related study, Scholl et al. (2018) study the overall labor market impact of the BRT system (trunk and feeder lines) in Lima, finding positive impacts on labor outcomes concentrated on individuals living close to the trunk line, and no impacts on individuals living in low income areas served by the feeders.

The role of transportation in shaping economic opportunities for women has not been explored in the literature to-date, and to the best of our knowledge, there are no causal studies looking at the effects of these investments on women´s labor market outcomes. This study thus makes two important contributions to the literature. First, it contributes to the limited causal evidence on the impacts of transport systems on employment. Second, and more importantly, it presents novel empirical evidence on the impacts on women that improved urban transport systems can generate.

3. Lima's Urban Transport System

Lima is the capital of Perú, and its metropolitan area (Lima-Callao), with a population of close to 10 million, represents about one-third of the population of the country and is one of the fastest growing urban areas in the LAC region. Its public transit system is highly chaotic and informal. Rooted in liberalization policies of the early 1990s, which eliminated fare regulations and barriers to entry, the system has been challenged by oversupply and generally poor levels of service quality. In addition, the city's transport network suffers from high levels of congestion, traffic accidents, and transport related air pollution (Bielich, 2009). Lower-income groups in Lima tend to have longer travel times, because of both longer distances and higher rates of dependency on informal public transit modes. They also make the largest share of their daily trips on foot—28%

of trips by the poor and 35% of trips among the extreme poor, followed by trips on traditional buses (Scholl et al., 2016).

Levels of sexual harassment of women in Lima's public transport system are among the highest in the Latin American region, with 78% of women reporting that they had been a victim in the past year while traveling in a transit vehicle or waiting at a bus stop or transit station (Galiani & Jaitman, 2016). Sixty four percent of women surveyed in the same study stated that they felt insecure or very insecure in Lima's public transit system, and 77% reported feeling unsafe if traveling at night in the system (Galiani & Jaitman, 2016).

Through a series of planning efforts over the past 20 years, the Metropolitan Area of Lima-Callao has begun slowly transforming its transport system. The Metropolitan Area Urban Transport Project, developed between 1996 and 2000, sought to increase mobility and reduce the social and environmental costs of transport. The project planned for the delivery of public transport by connecting the most populous areas of the city to important employment centers. The first part of this project implemented was the BRT line and was followed shortly after by the implementation of the metro Line 1. Although the two projects represent significant improvements to the city's transport system, mobility remains mostly informal (Darido et. al, 2015)[4]. While Lima's public transit system is one of the least secure in the region, women ranked Lima's Metro Line 1 to be the safest, followed by taxis, the BRT, buses, and finally microbuses (Galiani & Jaitman, 2016).

3.1. Bus Rapid Transit System

The BRT project in Lima, better known as the *Metropolitano*, connects two of the fastest-growing areas of the city and connects lower income neighborhoods in the northern and southern cones of the city with the financial district, major universities, and the historic downtown. The *Metropolitano* is the first line of a larger system planned for the city and was one of the first mass public transit system proposed for Lima. The corridor comprises 28.6 km of segregated busway, with 35 stations, two terminals, and a central transfer. It also includes feeder routes that extend up to 14 km and connect the two terminals with the surrounding and primarily low-income neighborhoods in the north and south cones. It serves one of the highest-demand corridors and offers late night and weekend service. It utilizes low emission articulated buses fueled by compressed natural gas and passing lanes, and multiple docking bays allow for express and

[4] There are no reliable figures on the share of trips of the system using the BRT or Line 1. An opinion survey on living conditions in the metropolitan area suggest that the two lines are used daily by around 10% of the population of Lima and 6.2% of the population of Callao (Lima Como Vamos, 2017, p. 43).

super express services between high demand stations. Wide doors and station designs provide for universal access (IDB, 2015).

Beginning operation in mid-2010, the system opened with only 22% of the planned articulated buses and five feeder routes in operation, in part because of low demand but also due to the unfinished infrastructure (Guerra Garcia, 2014). By 2014, the system was nearly fully operational, with the full fleet of 300 articulated buses operating and 222 feeder buses serving 20 feeder routes. In the same year, demand reached 660,000 card validations per day. By 2015, the system's demand was estimated to surpass 700,000 daily validations. Travel time savings of the system were considerable. Before the implementation of the system, the average trip time from one end of the trunk line to the other took on average 55 minutes, while the same trip would take 35 minutes on average in the BRT (Scholl et al., 2015).

3.2. Metro Line 1

Lima's metro Line 1, the first metro line for the city, is a 34.6 km elevated light rail that runs north-south along the eastern portion of the city and in parallel to the BRT line. The line was built in two stages. The first segment of the line began operating in January 2012 and connects Villa El Salvador, a low-income area, to central Lima. The second 12.4 km stretch runs from downtown Lima to San Juan de Lurigancho and opened in July 2014. With headways between 6 and 10 minutes, trains reach a maximum velocity of 100 kph and carry up to 1,000 to 2,000 passengers (AATE, 2013). As with the BRT system, several operational and infrastructure improvements have been implemented since it opened for service, including amplification of stations and the addition of trains to reduce overcrowding and headways. As of 2015, the system carried 320,000 passengers per day, surpassing demand forecasts. Currently, ridership is estimated to be 344,000 per day with headways of 4-6 minutes in the peak hours (Diario Correo, 2018).

4. Data

To investigate the effects of improved urban transport systems on employment outcomes we rely on data both before and after the implementation of the BRT and Line 1. Our main data source is the ENAHO, produced by Perú's National Institute of Statistics and Informatics (INEI, original Spanish acronym). The ENAHO is a continuous survey that generates quarterly indicators for poverty levels, employment, income, and living conditions of households distributed in both urban and rural areas in the country. It surveys approximately 3,000 households and 15,000 persons per year in the Lima metropolitan area. Our empirical analysis combines the annual cross-section ENAHO surveys for the period 2007 to 2017.

We also rely on three additional datasets that allow characterizing smaller geographical areas and measuring neighborhood characteristics prior to the entry into operation of the BRT and Line 1.

First, we use data from the 2008 Economic Census to characterize the conglomerate-level[5] potential as attractor or generator of work trips. We calculate for each conglomerate: the average number of occupied individuals per establishment; value added per employed individuals; and share of high skilled activities and non-tradable activities.

Second, we use data from the 2007 National Population Census to obtain conglomerate-level averages of the following household-level variables: percentage of households who use gas as cooking fuel, are connected to a public source of electricity, have a toilet inside the premises, have a water connection, have mud, wood or other low quality material walls, have dirt or bare concrete floor, live in an apartment, live in a rented house; the average number of rooms in the dwelling, household size, average years of education of the working age population (18-64), household head years of education, and household head age; percentage of indigenous population and female headed households; first principal component of household assets and services[6]; and conglomerate strata[7] and average income per capita according to the 2007 poverty map.

Third, we use a 2004 Origin-Destination (OD) survey, that was collected as part of the urban transport master plan for the metropolitan area of Lima and Callao (JICA, 2005), and prior to the implementation of the BRT and Line 1 systems. The OD survey collects individual-level data on trips for different Traffic Analysis Zones (TAZ).[8] With this information we create indicators of accessibility at the TAZ level, such as the average travel time of a trip to work in minutes and the

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[5] A conglomerate is a geographic area with approximately 140 private dwellings, defined by INEI to be the primary sampling unit in its surveys.

[6] The Principal Component Analysis (PCA) was calculated from dummies indicating if the household had the following assets or services: refrigerator, washing machine, music-player equipment, color TV, landline phone, cellphone, computer, and internet access.

[7] There are five socioeconomic status levels, ranging from A to E, A being the highest and E the lowest. According to the 2007 poverty map the percentages of the population associated to each level are: level A=5.6%, level B=10.9%, level C=18.5%, level D=27.7%, and level=37.3%.

[8] The 2004 OD survey defines 427 TAZ in the Lima metropolitan area. They vary in size and are constructed to capture homogeneous transport characteristics among the population within each zone. Close to downtown traffic zones are smaller (less than 1 km^2), while in the periphery traffic zones are larger (more than 20 km^2).

number of bus routes in a 500 meters radius. As the TAZ are larger than conglomerates, we assign to each conglomerate their corresponding TAZ values.

We analyze employment and quality of employment outcomes for individuals ages 18 to 64 using ENAHO data. Employed individuals are defined as working-age individuals who respond affirmatively to the question of whether they worked in the week prior to their interview and report positive earnings. We characterize quality of employment in several ways: (i) as working in formal firms (dummies for registered with the tax authority, carrying accounting books, or with more than five employees); (ii) as contributing to social security or under a formal contract (dummies for each); (iii) or as being in occupations associated to the top or bottom 25% of the earnings distribution in the ENAHO sample (dummies for each).[9] We also create two summary measures of quality of employment based on these variables: an index that adds up the five dummy variables in (i) and (ii) plus the dummy occupation in the top 25% of the earnings distribution (this index can assume values from 0 to 6); and a dummy variable equal to one when the index is positive.

5. Gender Differences in Travel and Employment Patterns in Lima

In this section we use baseline data from the 2004 OD survey to characterize transport patterns for men and women living in the metropolitan region of Lima and prior to the introduction of the BRT and Line 1. To facilitate the presentation, we aggregate the 427 TAZ in the OD survey into 14 zones, following an aggregation proposed by JICA (2005), and calculate statistics and identify gender gaps within those aggregated zones. Figure 1 compares average travel times in minutes for trips outside their TAZ, reported by men and women. Overall, looking at trips for all purposes (Panel A) and consistent with what is observed in other urban areas, women travel less time than men and this pattern is observed in almost all areas across the metropolitan region. When we look at the average travel times by area for women, we see that travel times are longer for those living further away from the city center, where the BRT and Line 1 are depicted. It is important to highlight that even though the BRT and Line 1 are depicted in the maps, these systems had not yet been built in 2004. When we look at average travel times for work-related trips (panel B), the gender differences tend to disappear, particularly for the more centrally located zones. This suggests that, conditional on working, men and women experience the same travel times when

[9] To assign jobs to the top or bottom 25% of the earnings distribution, we take the 341 occupations that appear in the ENAHO, rank them in the period 2005 to 2009 based on hourly earnings and identify them as appearing in the bottom or top quartile of the earnings distribution. We then classify all occupations in the period 2010-2017 based on the pre-intervention classification.

they are centrally located. For those who live farther away from the city center, men seem to have longer work-related trips.

Regarding the use of public transportation, Panel A in Figure 2 shows that the percentage of trips where public transport was the primary travel mode is larger for men than for women, and this difference increases as they move further away from the city center. When we look at work-related trips on Panel B, we see that both men and women rely almost equally on public transport to get to work. For most areas, except two, the share of public transport trips for work, among women is above 50%, and for large portions of the city the share is above 70%.

Figure 3 presents the percentage of trips that are conducted within the same traffic zone. This information can tell us how far women and men move in their daily trips. From the figure it is clear that a larger proportion of women tend to stay within their own traffic zone for their trips for all purposes (Panel A). Even though gender differences decrease when we examine work-related trips (Panel B), some differences remain, and women seem to work more within their own traffic zone.

Figure 4 presents the percentage of individuals who walk or bike as their primary travel mode. The comparison of panels A and B makes clear that walking or biking is relied on much more by women than by men, but also that they are in general a minority of the work trips (except in the southern part of the city). As in the other figures, once work trips are considered, the differences between men and women tend to disappear.

The analysis of the OD survey data shows that men and women have different travel behaviors and suggests that some of these differences may be explained by heterogeneity in their employment status. The fact that a lower percentage of women work and that, in general, bear most of the household work, is reflected in the large gender differences in transport patterns for the overall trips. Conditional on labor force participation, the survey suggests that women demand public transportation in similar ways as men do, but that they travel shorter distances and stay more within their own traffic zone. When looking at the use of public transport for the full sample (working and non-working people), a higher percentage of men use public transport and women seem to rely more on walking or biking trips. This is consistent with the fact that they are traveling shorter distances and could be also a reflection of the security concerns associated to traveling by public transport.

6. Methodology

We estimate the impacts of the introduction of the BRT and Line 1 on employment outcomes using a DID approach. We compare individuals before and after the introduction of the BRT and Line 1 living in treatment and control areas and use distance to these transport systems as an exogenous measure of exposure to the new infrastructure. We exploit the geographic coordinates (centroid of the city block) assigned for each household surveyed in the ENAHO to calculate the Euclidian distances of each household to the: i) closest BRT station; and ii) closest Line 1 station.[10] Treatment areas are defined as those within 1 km of the BRT or Line 1. This cutoff is based on the standard convention of an average walk speed of 5 km per hour (Levine and Norenzayan, 1999) and considers the distribution of walking times to access public transport. According to data from the 2011 OD survey, 90% of public transport users in Lima walk 12 minutes or less to reach public transportation (i.e. around 1 km).[11] We set as control areas those between 2 km and 5 km from the BRT or Line 1. At larger distances we should expect small effects of the new infrastructure on individuals; however, to prevent potential spatial spillovers on the control group, we drop from the sample households located within 1 km and 2 km. Figure 5 shows in blue the treatment areas for both the BRT and Line 1 and in red the control areas.[12]

Since the two systems run parallel and very close to each other along some segments of their alignments, it is not clear which of the two lines a person relatively close to both of them would take for a majority of their work-related trips, leading to potential overlap in the treatment samples. We define a single treatment group by pooling together households in the areas of influence or close to either system (BRT or Line 1) in most of our analyses. Even though we have limited power, we also explore the differential effects of the two systems. Moreover, we test for treatment effects heterogeneity across different distances to the systems, by comparing the impacts observed within the 1 km buffer versus those within 1 and 1.5 km. In this case and relying on

[10] We exclude the feeders from our analysis as they run in non-segregated roadways, do not have dedicated stations, and do not provide information on headways, while both BRT and Line 1 stations do. This can have important implications in the safety of women traveling in these systems. Moreover, Line 1 does not have an established system of feeders, only the BRT does. As we are pooling both systems together, we focus only on the areas of influence around the BRT trunk line and around Line 1.

[11] The survey indicates that 90% of passengers walk no more than 12 minutes (91% walk no more than 15 minutes) and 99% walk 20 minutes or less to reach public transportation.

[12] Based on our empirical strategy, 32,229 observations in the ENAHO fall within the treatment and control areas between 2007-2017. We eliminate 615 observations due to missing information in key variables of interest, and 4,947 due to improper geocoding. Our final estimation sample is 26,668 observations.

similar intuition to that in the main analysis, we drop households within 1.5 km and 2 km from the sample to avoid potential spatial spill overs.[13]

Since the BRT and Line 1 operations had a slow ramp-up since their official opening in 2010 (BRT) and 2011 (Line 1), it is of interest to understand the timing of the effects of the two systems. The standard DID model, allowing for time heterogeneity in effects, would be:

$$Y_{it} = \alpha + \sum_k \gamma_k P_{kt} + \delta T_i + \sum_k \beta_k P_{kt} T_i + \theta X_{it} + \eta_{dt} + \varepsilon_{it} \quad (1)$$

where Y_{it} is the outcome of interest (e.g. employment status) computed for the working-age (ages 18-64) individual *i* in time *t*, T_i is a dummy variable equal to 1 if individual *i* lives in the area of influence of the BRT or Line 1 and zero otherwise, the *k* dummies P_{kt} are equal to one for different sub-periods after the introduction of the lines (i.e. 2010-2011, 2012-2014, 2015-2017) and zero otherwise, and β_k are the coefficients of interest, measuring the effects of the improved systems in each sub-period *k*, X_{it} is a vector of individual- and household-level covariates for individual *i* in time *t*, η_{dt} represents district-year fixed effects, to control for potential within district (which is the level for many planning decisions, including transport and security) time-variant unobserved heterogeneity, and ε_{it} is an error term.[14] The covariates included in X_{it} are: age (and its square), an indicator variable for married or cohabitating status, a dummy variable for indigenous language as mother tongue by the individual, a dummy for whether the individual is currently enrolled in school, a dummy for single parent household, an indicator for female-headed household, number of household members, number of children under the age of 6 in the household, and the household dependency rate.[15]

As our interest is in the differential effects for men and women, we could either estimate (1) separately for men and women, and compare the respective coefficients, or modify (1) to allow for an interaction with a *female* dummy variable. To improve efficiency in our estimates we opt for the interacted model. This allows estimating the following model to capture the heterogeneous effects on women:

$$Y_{it} = \alpha + \sum_k \gamma_k P_{kt} + \delta T_{si} + \pi F_i + \sum_k \beta_k P_{kt} T_i + \sum_k \tau_k P_{kt} F_i + \zeta T_i F_i + \sum_k \lambda_k P_{kt} T_i F_i$$
$$+ \theta_M X_{it} + \theta_F X_{it} F_i + \eta_{dt} + \varepsilon_{it} \quad (2)$$

[13] This increases our total potential sample in the ENAHO to 41,776 observations, of which 34,105 have valid information and are used in the regressions.

[14] In all regressions, we cluster the standard errors at the district level to allow for arbitrary correlation within districts.

[15] The household dependency rate is defined as 1 minus the ratio of income earners over total members of the household.

where F_i is the *female* dummy, and everything else is defined in the same way as in (1). In equation (2) we are interested now in the coefficients β_k and λ_k. The DID estimate for the treatment effect for men is β_k and the DID estimate for the treatment effect for women is $(\beta_k + \lambda_k)$. The comparison of these two effects allows us to compute the differential treatment effects across gender. More specifically, the treatment effect for women and men differs by $(\beta_k + \lambda_k) - \beta_k = \lambda_k$, which is the coefficient of the triple interaction term in equation (2).

The specifications of equation (2) consider a pre-treatment period (2007-2009) and three post-treatment sub-periods (2010-2011, 2012-2014, 2015-2017). Although the BRT system started operations only in July 2010, we include the data for this entire year in the post-treatment period to avoid splitting the ENAHO sample within a year. In addition, Line 1 was also completed in stages, as discussed above, with the first stage being completed in 2011 and the second stage in 2014. Thus, the 2010-2011 period can be considered as the period when the BRT was transitioning into fully functional, while the 2012-2014 can be considered as the one where the BRT was already (mostly) working as planned, while Line 1 was transitioning into becoming fully operational. The period 2015-2017 is the one where both the BRT and Line 1 are fully operational.

To evaluate the consistency of our results across multiple specifications, we conduct some robustness checks. There could be a concern that the covariates included in a linear way in equation (2) may not be enough to properly account for differences in observable characteristics at baseline between treatment and control areas. To address any potential bias that could be generated by comparing areas that are not comparable, we select in a first stage the most comparable conglomerates, and then re-estimate equation (2) restricting the ENAHO sample to the selected conglomerates. To do this we take data from the 2007 Population Census, the 2008 Economic Census and the 2004 OD survey, aggregate them at the conglomerate level, and assign conglomerates to treatment and control groups based on the ENAHO individuals living in those conglomerates, and their distance to the BRT or Line 1 (i.e. the groups indicated in Figure 5). We then estimate at the conglomerate-level a propensity score model for the probability of being a treated conglomerate.[16] Based on the estimated propensity score we impose *overlap*

[16] The propensity score is estimated by a logit regression with the following conglomerate-level covariates: percentage of households who use gas as cooking fuel, are connected to a public source of electricity, have a toilet inside the premises, have a water connection, have mud, wood or other low quality material walls, have dirt of bare concrete floor, live in an apartment, live in rental housing; the average number of rooms in the premises, members of the household, years of education of the working age population (18-64), years of education of household head, age of household head; percentage of indigenous population, female headed households; first principal component of household assets and services; establishments per inhabitants (in logs); value added per employed individuals (in logs); conglomerate strata according to the poverty map; average income per capita according to the poverty map; road density; and share of high skilled activities and non-tradable activities.

between the treated and control conglomerates (i.e. we identify the comparable conglomerates as those that have *common support* in the propensity score distribution). For this we follow the propensity score trimming strategy proposed by Crump et. al. (2009).[17] We then estimate (2) using only households in the conglomerates that satisfy the common support condition.

DID models rely on the identification assumption that treatment and control observations follow parallel trends prior to the start of the treatment or intervention. To test whether this assumption is reasonable in our case, we use information from the baseline years 2007-2009, prior to the opening of the BRT and Line 1. More specifically, we estimate model (2) classifying 2007-2008 as baseline years and assuming 2009 is the treatment year. Any significant differences between these two periods would be an indication that trends between treatment and control areas are not parallel from 2007-2008 to 2009, which could indicate a violation of the key assumption underlying the validity of a DID model.

Finally, it is important to note that outcome variables related to earnings and hours worked are zero for those not employed. The same is true for expenditures in public transport for those not using this type of transport or no transport at all. This implies that it is not possible to take logarithm of these variables to obtain percentage changes when running the regressions. To avoid the problem that the logarithm of zero is undefined, we apply to those variables the inverse hyperbolic sine (IHS) transformation in all our estimations. This allows the same interpretation as a logarithm in a regression framework and it is defined at zero.[18] We refer to it as *IHS* from now on.

7. Results and Analysis

In this section we first discuss descriptive statistics of the outcomes and covariates used in our estimations and then discuss the main results obtained following the methodology described above. In addition, we report the results of the parallel trend tests and of heterogeneity analyses across different types of transport investments (BRT vs. Line 1) and different distances to the

[17] Specifically, we drop those conglomerates for which the propensity score is lower than an optimal cutoff value *q* or higher than (1-*q*). We obtain the values of *q*, following Crump et al. (2009), for the two propensity score estimations we perform (defining the treatment area as 1 km or 1.5 km around the lines). In both cases the values are close to 0.10 (0.1040 for 1 km and 0.1054 for 1.5 km), the rule of thumb suggested by Crump et al. (2009). This implies that our estimation sample decreases by 5,827 observations to 21,546 observations in the 1 km treatment area case (see Appendix Table A1), and by 6,283 observations to 27,822 in the 1.5 km treatment area case (results not presented, available upon request).

[18] The IHS transformation of y_i is equal to $\log(y_i + (y_i^2 + 1)^{1/2})$. See Burbidge, Magee and Robb (1988) for details.

lines (0 to 1 km vs. 1 to 1.5 km). In the Appendix we present the robustness results imposing overlap in the distributions of the propensity score for the treatment and control conglomerates.

7.1. Descriptive Statistics

Table 1 presents in panel A the summary statistics of the different outcomes of interest for control and treatment groups by gender in the period prior to the BRT and Line 1 opening (2007-2009) and in the post-intervention period (2010-2017). There are large gender differences in employment rates between men (80%) and women (60%). There is a predominance of self-employment over paid employment (employee); women are more likely to be homemakers and have lower quality jobs (according to our job quality index[19]) and be employed in occupations classified as in the bottom 25% of the ENAHO sample earnings distribution. These gender differences are also evident for earnings, hours worked and their ratio. A large proportion of the sample reports spending on public transport, however men tend to spend more than women. In terms of education, the average number of years of education is 11.8 for men and 11.1 for women. The latter is also reflected in the lower proportion of women with an education level of high school or higher.

Panel B in Table 1 evaluates how balanced the covariates are at baseline. This is done for the full sample and for the sample after imposing overlap (satisfying common support). Differences between treated and controls within gender groups and which are statistically significant at the 5% significance level are highlighted in bold. Results in this panel suggest that there are no major differences between treated and control observations in the baseline period for both men and women. Within the sample for men, before overlap, in the baseline there are less indigenous and married individuals in the treated areas. After imposing overlap, only the differences in marital status remains. Within the sample for women, the sample before overlap indicates that women in treated areas live in smaller households, are more likely to be head of household, and are older. After overlap, the age difference disappears, but women in treated areas are still more likely to head a household or live in larger families. It is important to note that it is not necessary for covariates to be balanced between treated and control individuals in a DID model, as one of the main advantages of this type of models is that it allows for systematic differences between the two groups, provided they are not changing over time. Nevertheless, if the treatment and

[19] This index groups six dummy indicators associated to formal employment and type of occupation: firm keeps accounting books, firm is registered, firm has more than five employees, employee contributes to social security, employee has a contract, and occupation is in the top 25% occupation rank according to average earnings per hour.

comparison conglomerates are very different, it weakens the credibility of the ex-ante assumption of parallel trends between the two groups.

7.2. Impacts on Employment, Earnings and Job Quality

We analyze now the results from estimating the DID model specified in equation (2). In all cases, the regressions include the full complement of individual and household level covariates discussed in Section 6, as well as district-year fixed effects. Standard errors are clustered at the district level. All the tables follow the same structure, with each column representing the regressions using a different outcome. In the interest of space, the first three rows of all tables (except for Table 6) show the estimated treatment impacts for women ($\hat{\beta}_k + \hat{\lambda}_k$). The next three rows show the estimated coefficients $\hat{\beta}_k$ associated with the treatment effects for men. The last three rows provide the *differential effect* of the BRT and Line 1 for women compared to the effect for men ($\hat{\lambda}_k$), which is the triple interaction term in (2).[20] All the regressions discussed in Tables 2 to 8 use the full estimation sample, before imposing overlap. We deem the results imposing overlap as robustness checks of our main results. A summary of the results for the main outcomes when imposing overlap is presented in Appendix Table A1.[21]

Column (1) in Table 2 provides the results for an employment indicator equal to one for all the individuals who declare working and have positive earnings, and zero otherwise. Columns (2) to (4) split employment into three categories (employee, self-employed, domestic worker). Column (5) shows a specific group among the non-employed which is of particular interest in the case of women, homemakers. While for men there are no statistically significant results, for women there are large statistically significant effects on employment and they are increasing over time in the order of 5 percentage points in the period 2010-2011, eight percentage points in the periods 2012-2014 and ten percentage points for 2015-2017. These effects imply increases of between 8.3% and 16.6% with respect to the pre-treatment employment rate among women living in the treatment area. The increase in employment appears to be driven by the increases in the employee and domestic worker categories (column 2 and 4), which are marginally significant, and by statistically significant large decreases in the homemaking category (column 5). The results in Table A1 in the Appendix, imposing overlap, show similar patterns.

[20] The full results for all regressions can be made available upon request.

[21] The Appendix only presents results for the main outcomes for the sake of space. The full set of results imposing overlap can be made available upon request.

Table 3 explores the impacts of the BRT and Line 1 on earnings. Columns (1) to (3) show results unconditional on employment status while columns (4) to (6) show results conditional on employment. As the outcomes in columns (1) to (3) are zero for those not working, we use the IHS transformation discussed above. Its interpretation is equivalent to that of a logarithmic transformation, which means that the coefficients can be interpreted as percentage changes[22]. Columns (1) and (4) show total labor earnings, columns (2) and (5) show total hours worked, and columns (3) and (6) show earnings per hour, calculated as the ratio of the two preceding columns. The unconditional effects are clear, with large increases for women in the three post-intervention periods in total earnings, hours worked, and earnings per hour. As column (3) shows there are increases in *hourly* earnings in the order of 12% to 23%. Conditional on employment, however, most effects go away or are marginally significant and, if any, there are some increases in hours worked but much smaller than those unconditional on employment (coefficients decrease to being as low as a quarter to as large as a half of the unconditional ones). Overall, this suggests that most of the results are being driven by a reduction on zero earnings and hours. This is consistent with the increase in employment rates discussed above. For males, however, the coefficients associated to earnings and hourly earnings conditional on employment are negative in the order of 12% to 24%. This does not necessarily mean that earnings decrease for this group, but more precisely that they might be increasing at a slower rate than the earnings for males in the control group. A potential explanation for this finding will be discussed when presenting the results in the next table. Table A1 shows that the results are quite stable despite the trimming of the sample when imposing overlap, and they are particularly strong for the last sub-period (2015-2017).

To understand what drives the earnings results, we analyze in Table 4 different job quality measures. Columns (3) to (5) attempt characterizing job quality with indicator measures of job formality derived from the characteristics of the employing firm or self-employment activity. The outcome in column (3) classifies as formal a firm if it keeps accounting books, in column (4) if the firm is registered,[23] and in column (5) if the firm has more than five employees. In columns (6) and (7) formality is defined by whether the individual contributes to social security or if he or she

[22] When regression models have log transformed outcomes the impact of a one-unit change in a covariate (X) is calculated by exponentiating the coefficient. In this case, the interpretation of impacts should be done as exp ($\hat{\beta}$) -1. For example, for a coefficient of 0.23 the effect is calculated as exp (0.23)-1=0.26. When the estimated coefficient is less than 0.10 the simple interpretation that a unit increase in X is associated with an average of 100*$\hat{\beta}$ percent increase in Y works well. When the coefficient is above 0.10 the simple interpretation will underestimate effects. For simplicity we report percentages changes using the simple interpretation throughout the text.

[23] This includes small firms registered in special categories with small tax burden.

has a formal contract. In columns (8) and (9) we characterize the type of occupation, based on its position in the earnings distribution of the ENAHO sample. Finally, as explained above, to summarize all these measures, and to try to minimize the possibility of finding effects purely due to testing hypothesis on multiple outcome variables, we create an index of job quality, which is equal to the sum of columns (3) to (7), the alternative measures of formality, and column (8), the indicator for occupation in the top quartile of the hourly earnings distribution. The index can assume values from 0 to 6. The results associated to the index are presented in column (1), while those associated to the indicator equal to one when the index is greater than zero (and zero otherwise) are presented in column (2). The results suggest that that there are no significant changes in job formality for women closer to the BRT and Line 1, and that there are, instead, increases in their participation in occupations that are in the bottom of the income distribution (increases of between 7 and 10 percentage points). Thus, while employment increases and earnings per hour increase for women close to the BRT and Line 1, these changes are not driven by women finding high quality jobs. For men, there are some negative effects on formality, which seem to be driven by a more rapid job inflow into smaller firms and this is also reflected in marginally higher participation in low-paid jobs and with no contributions to social security. For men we also see an increase of 7 to 11 percentage points in the share working in occupations in the bottom 25% of the earnings, which may explain the negative earnings among men found in Table 3. The results after imposing overlap remain unchanged (Table A1).

To better understand the effects captured so far, Table 5 explores some intermediate outcomes of interest and tests for potential composition effects that could be driving our results. Column (1) presents the results associated to an indicator variable equal to one if spending in public transport by the individual is greater than zero, and zero otherwise. Column (2) looks at changes in the intensive margin by looking at the IHS of individual monthly transport expenditures. We observe important changes in transport expenditures for women that are closer to the BRT and Line 1, both in the intensive and extensive margins. Specifically, we see an increase between 27% and 48% in public transport expenditures among women in the treatment areas. The results suggest that the opening of the BRT and Line 1 strongly pulled women into using public transport (8 percentage points increase in positive expenditures, i.e. a 10% increase compared to the pre-treatment period, by 2015-2017). This aligns with the increases in employment found in Table 2. In contrast, effects on intermediary outcomes for men are mostly absent, except some negative changes in the first post-treatment period, 2010-2011. The robustness checks imposing baseline overlap in conglomerates confirms the previous findings, showing that the impacts observed during the period 2015-2017 are the most robust.

To rule out the possibility that the effects could be driven by compositional changes in the characteristics of the individuals across areas, columns (3) and (4) in Table 5 analyze changes in the years of education of the individuals and in the proportion of the individuals with a high school education level or higher. The regressions show no statistically significant results, suggesting that the observed impacts are *not* driven by compositional changes in the education characteristics of those men and women who live in the areas of influence of the BRT and Line 1.

7.3. Parallel Trends Placebo Tests

When running DID regressions, it is important to test whether the parallel trends identifying assumption holds. If the treated and control groups do not follow parallel trends, then it is not valid to use the observed post-treatment outcomes for the controls, as counterfactual for the post-treatment outcomes for the treated. As explained above, exploiting the pre-treatment data, we run regressions estimating the treatment effects for the year 2009, with the 2007-2008 as the "placebo" pre-treatment period; we would expect the "placebo treatment effect" associated to the year 2009 to be zero. We test this in Table 6 for the main outcomes, and we find that the null hypothesis of no treatment effects cannot be rejected for any of the outcomes, either for men and women. That is, the results suggest that the identifying assumption justifying the DID estimation is valid, at least in terms of this limited placebo test. At the very least, the results suggest that there are no systematic differences between the treatment and control areas pre-treatment, that may affect the credibility of the empirical strategy.

7.4. Heterogeneity analyses

We conduct two types of heterogeneity analyses. The first one analyzes the differential impacts of proximity to the BRT versus proximity to Line 1; we classify households considering their closest distance to any of the lines. These results should be taken with caution, given that the two systems run parallel and very close to each other and there could be some ambiguity in treatment assignment (i.e. it is not clear which of the two systems would a person relatively close to both take for their work trips). The findings for the main outcomes are reported in Table 7 and indicate that the positive employment and earnings impacts for women can be attributed to both the BRT and Line 1. Moreover, the results highlight that changes in public transportation expenditures are mostly driven by changes in expenditure patterns for women close to Line 1.[24] Results after overlap are consistent.

In a second analysis we test for heterogenous effects across different distances to the system. We pool again the treated sample for Line 1 and the BRT and compare the impacts associated to individuals within the 1 km buffer (used up to now) versus those associated to individuals within the 1 to 1.5 km buffer. This analysis serves to explore whether treatment effects weaken as we move further away from the lines. Results are reported in Table 8 and confirm that the impacts are stronger for, or sometimes only coming from, the areas that are closer to the lines (0 - 1 Km). However, there are effects further away. Their lower statistical significance could respond to a power issue, as the treatment area is smaller in size, and thus encompasses less observations, when compared to the 0-1 km treatment area. We do not go beyond 1.5 km since 99% of respondents to the 2004 OD survey indicate that they do not walk more than this distance to reach public transportation. It is important to mention that there is a negative and significant impact on years of education, for women in the 2012-2014 period, for the 1-1.5 km treatment. This result would suggest a negative composition effect, but we do not consider this a very relevant result as it only appears for a sub-period, and then disappears, and goes in the opposite direction to the compositional changes one would expect to happen (i.e. more educated women moving into the influence area of the lines).

8. Discussion and conclusion

This paper investigates whether access to safer modes of public transport impacts women's labor market outcomes. We conduct the analysis in the metropolitan area of Lima, Perú, where access to this type of transportation remains a challenge. The identification strategy, based on a DID estimation, allows us to infer causal estimates of the implementation of two interventions, a BRT system and an elevated rail system, better known as Line 1 of the metro. Both systems have considerably reduced travel times and increased connectivity between peripheral areas of the city to major employment centers. In addition, the systems are equipped with infrastructure and technology that represent a substantial improvement relative to the safety of the rest of the public transit in the city. We hypothesize that these changes may have disproportionally encouraged women to use these systems and improved their accessibility to jobs when compared to men. We find large gains in employment for women. Proximity to the system results in 7.6 percentage

[24] Which is surprising given the lower fare for Line 1 (1.5 Soles in 2017) compared to the BRT (2.5 Soles in 2017).

points increase in the probability of being employed right after the BRT system was implemented (2012-2014) and 10 percentage points increase by the time both the BRT and Metro Line 1 are fully functional (2015-2017). These effects imply increases of between 8.3% and 16.6% with respect to the employment rate of treated women in the pre-treatment period. There are no effects for men. Employment gains are also reflected in larger earnings for women, between 11.5% and 23.3% with respect to treated women in the pre-treatment period. However, most of these gains seem to arise from changes on the extensive margin, with more women working. We do not find any significant effects on earnings for already employed women.

The increase employment for women does not appear to be of higher quality than that for comparison groups. We find no significant effect on different measures of formal employment and it is more likely that women are employed in occupations at the bottom 25% of the hourly earnings distribution. The magnitude of this effect ranges between 7.7 and 9.7 percentage points, which implies increases of between 19.3% and 27.5% with respect to the employment rate for treated women in the pre-treatment period.

To understand these results, we explore several mechanisms and find evidence of an increase in the use of public transport. Treated women are 8 percentage points more likely to report expenditures on public transport, which is reflected in 47% higher expenditures with respect to untreated women. We find no evidence of demographic composition impacts in the treatment areas, particularly when looking at changes in the levels of education of those living closer to the BRT and Line 1. Heterogeneity analyses show that results are also indistinguishable between the BRT and Line 1. Proximity to either one of them renders similar results. Extending the proximity cutoff from 1 km to 1.5 km does not modify the estimated impacts, but highlights that impacts are somehow stronger in areas closer to the system. A further robustness check that imposes a common support condition, selecting conglomerates that are more similar across conglomerate-level baseline characteristics, offers qualitatively similar impacts.

Overall, we believe these are novel and robust results. Tests of the parallel trends assumption (albeit limited), key for the validity of the DID estimation strategy, seem to justify the use of the DID method. However, one needs to be careful in interpreting the results, given that defining "treatment" and "control" groups is inherently difficult for these types of urban transport interventions. The definition of which areas are treatment and control is somewhat arbitrary, and individuals can move in and out of those areas over time (we do not find evidence of compositional changes, though). Even if the employment and (unconditional on employment) earnings and hourly earnings impacts are as large as our regression results suggest, we only have suggestive public transport expenditure evidence on the role the new lines had in promoting better labor outcomes for women. We would need to have individual-level transport use information (i.e., an OD survey) to unequivocally show a direct link between the usage of the two new public transport lines and labor outcomes. Unfortunately, there is no such source of information after the implementation of the two lines for Lima.

Keeping in mind these caveats, our findings provide strong suggestive evidence that infrastructure investments that make it more convenient and safer for women to use public transport can generate large labor market impacts for those women who reside in the areas of influence of the improved infrastructure. The extent to which women enter the labor market and the quality of the jobs they hold once their accessibility opportunities increase is still an area that needs to be further examined. Increasing their labor market participation and job quality may require additional structural interventions that go well beyond the reach of the transport sector. Regardless of this, the power of transport investments in facilitating access to opportunities and encouraging changes in time allocation decisions for women appears to be quite remarkable.

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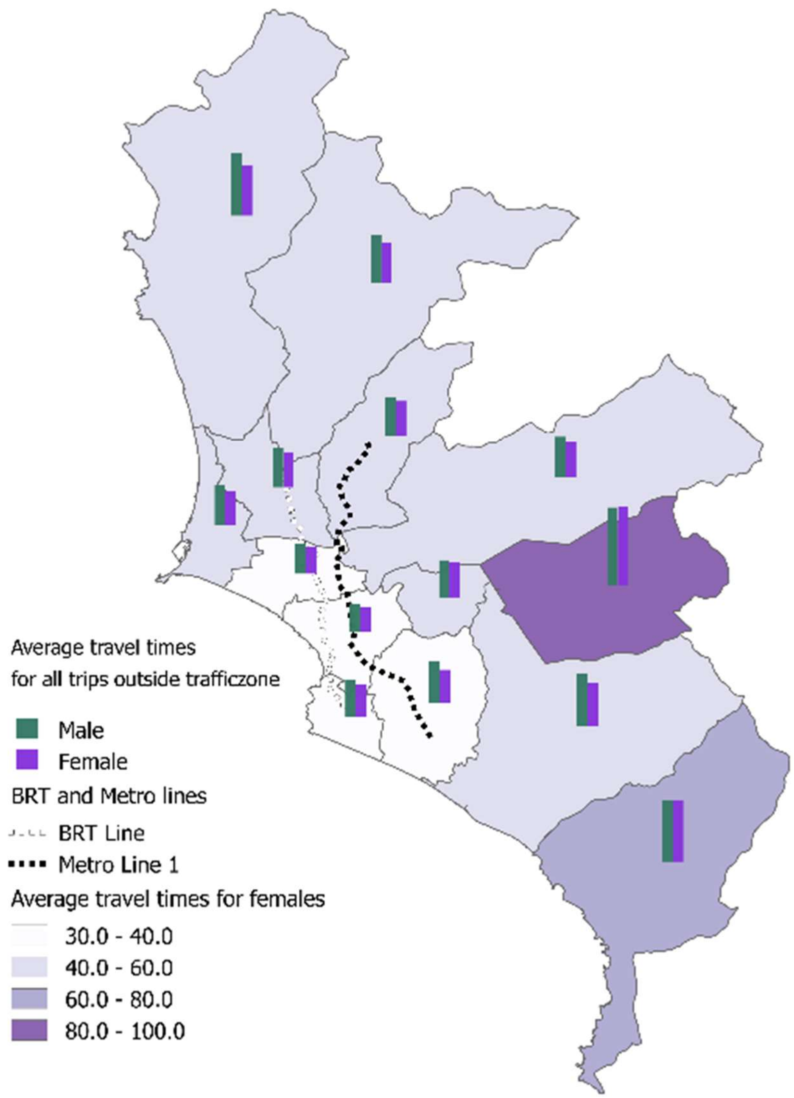
Figure 1. Average travel times for all trips outside traffic zone in minutes (2004)

a. All Purposes



b. Work Purpose

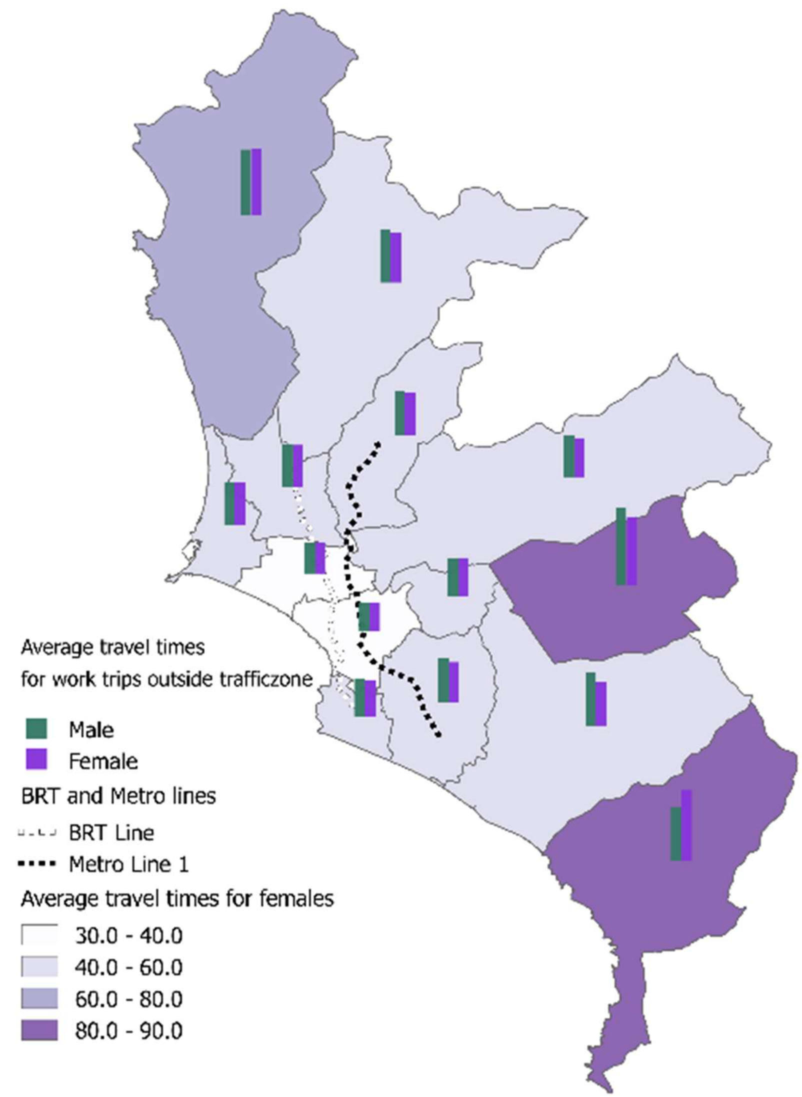
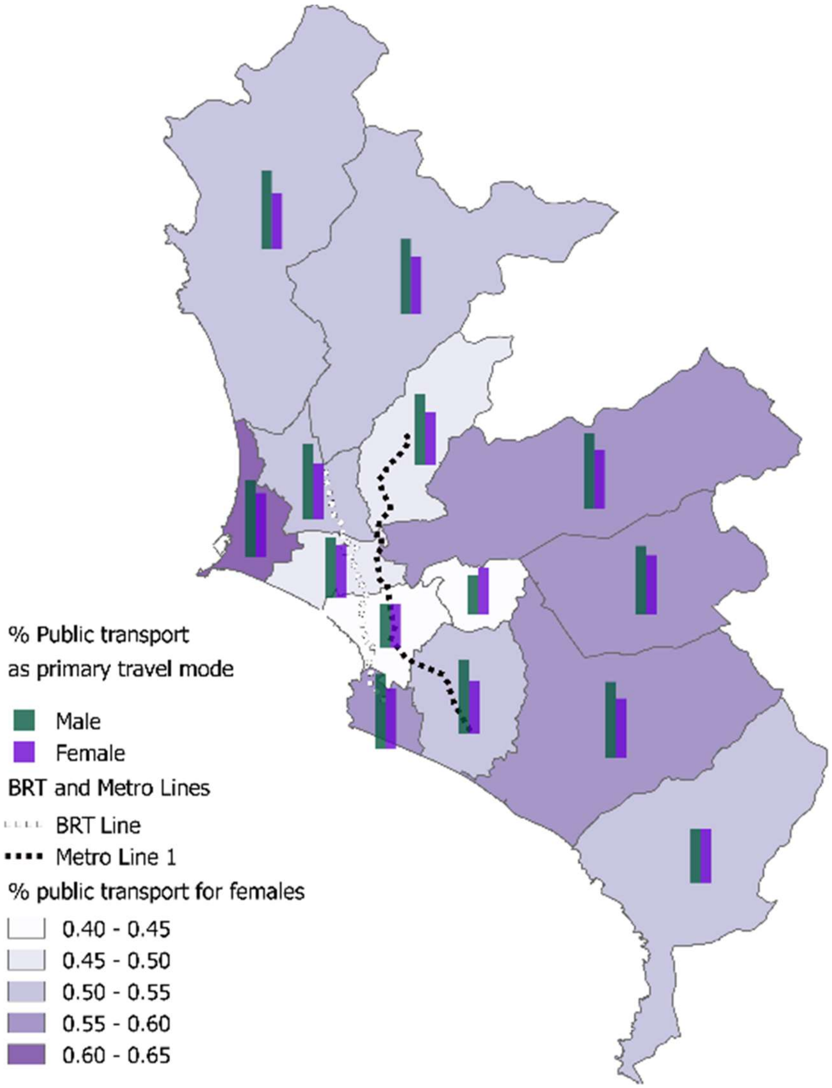


Figure 2. Percentage of public transport use as primary travel mode (2004)

a. All Purposes



b. Work Purpose

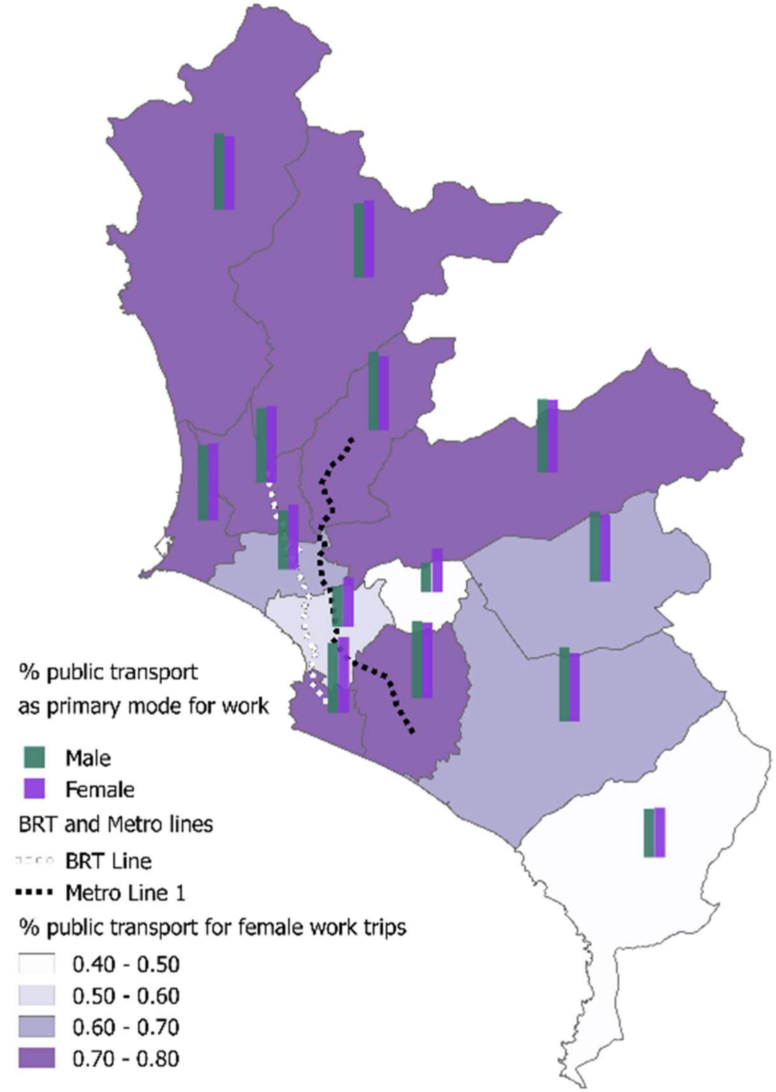


Figure 3. Percentage of trips within the same traffic zone (2004)

a. All Purposes **b. Work Purpose**

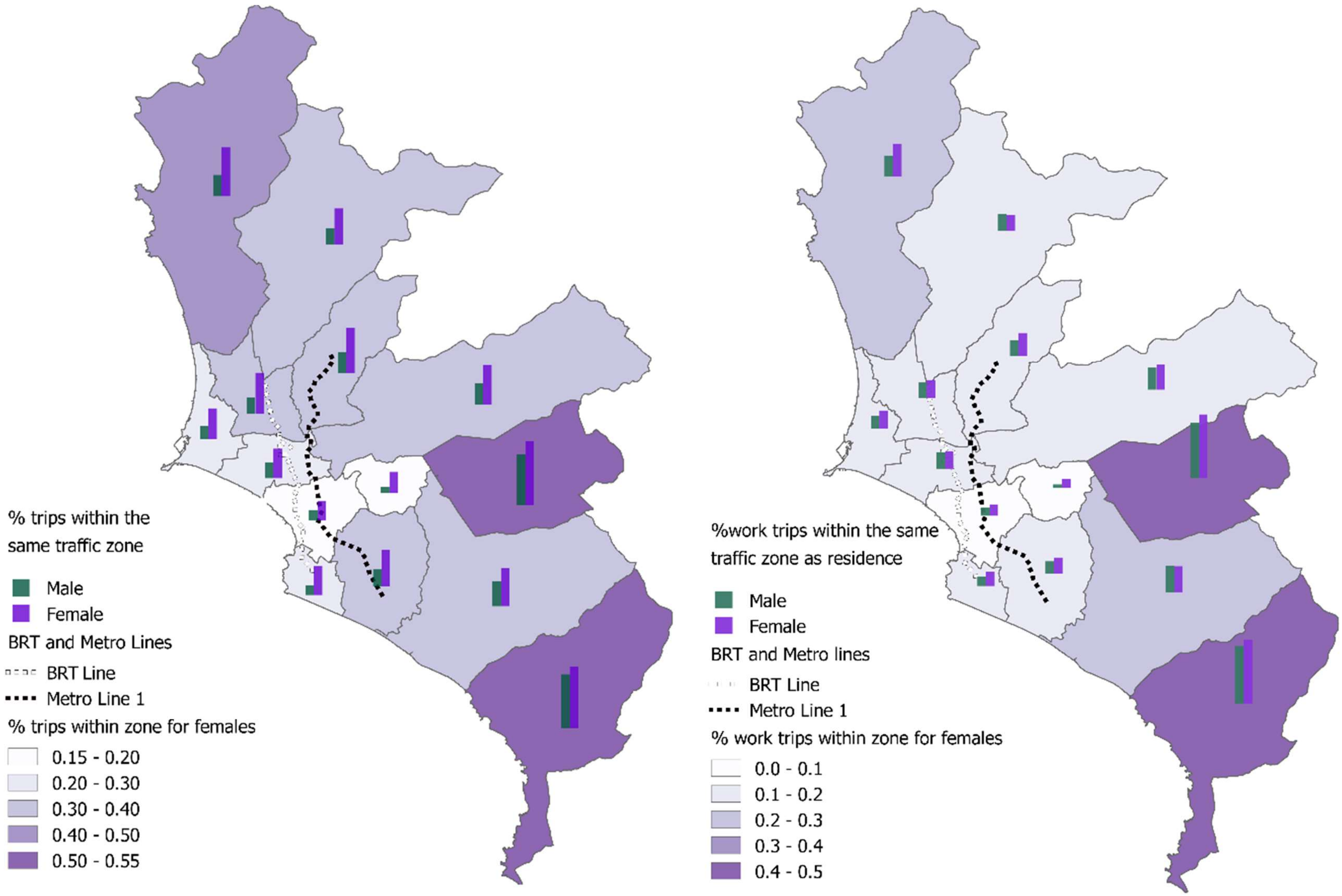


Figure 4. Percentage who walk or bike as primary travel mode (2004)

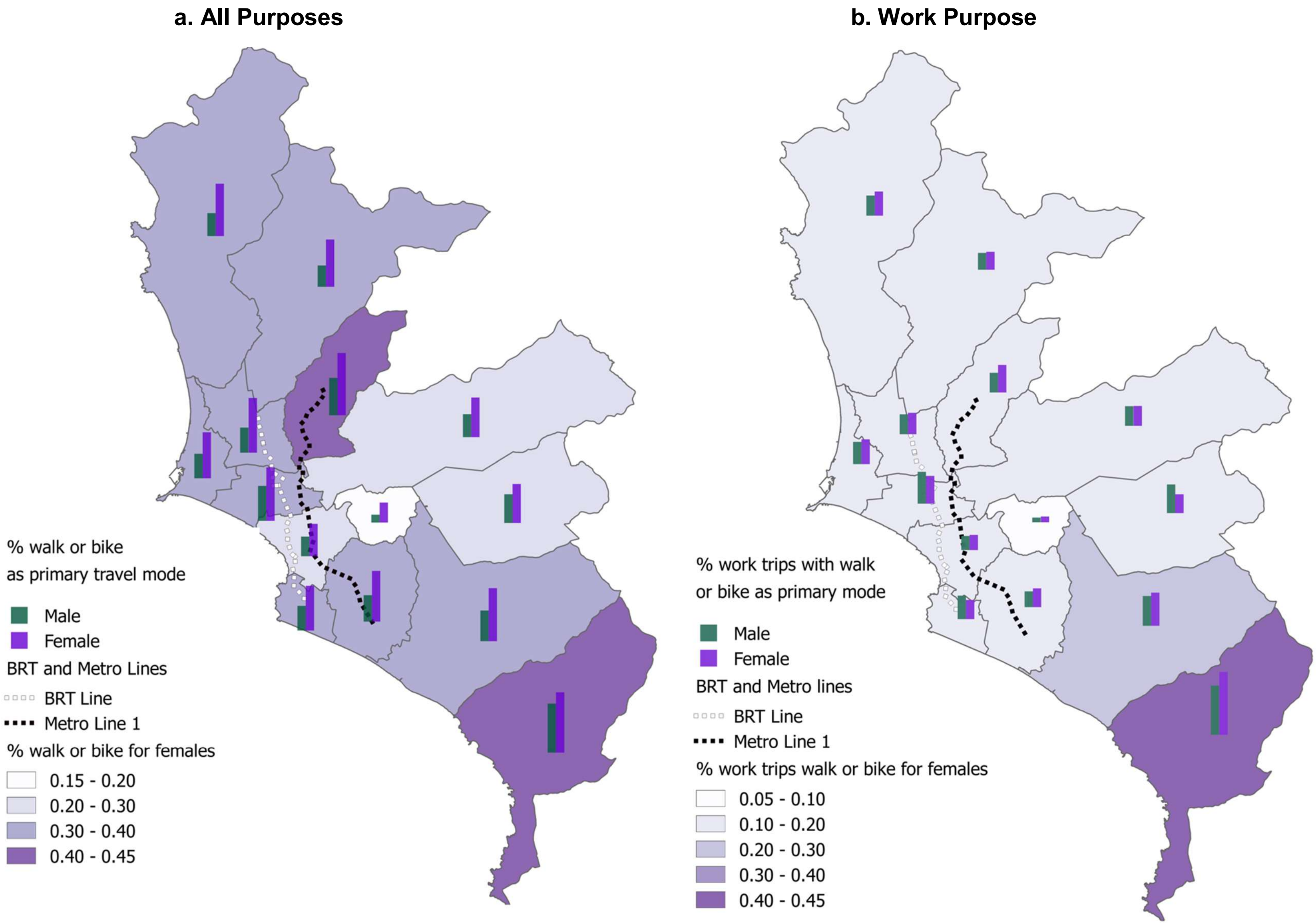


Figure 5. Treatment and control areas

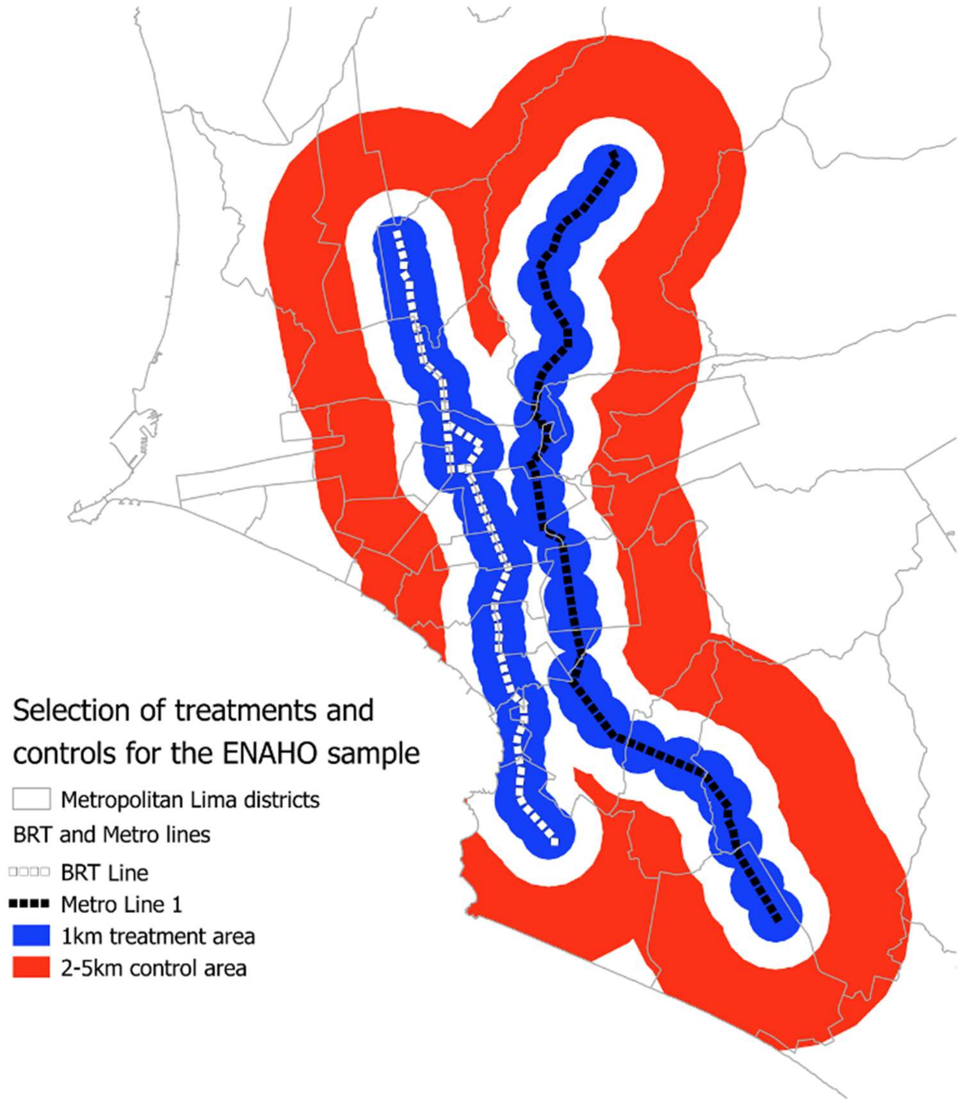


Table 1. Descriptive statistics outcomes and covariates

Panel A. Outcomes

	Males				Females			
	Controls		Treated		Controls		Treated	
	2007-2009	2010-2017	2007-2009	2010-2017	2007-2009	2010-2017	2007-2009	2010-2017
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Employment outcomes								
Employment	0.85	0.83	0.84	0.83	0.66	0.63	0.60	0.64
Employee	0.25	0.24	0.28	0.27	0.21	0.19	0.22	0.19
Self-employed	0.60	0.59	0.55	0.56	0.35	0.37	0.31	0.41
Domestic worker	0.00	0.00	0.00	0.00	0.11	0.07	0.08	0.05
Homemaker	0.03	0.04	0.03	0.04	0.22	0.24	0.24	0.22
Job quality outcomes								
Job quality index (0-6)	2.04	2.42	1.97	2.35	1.19	1.54	1.12	1.67
Job quality index dummy	0.63	0.67	0.63	0.67	0.36	0.44	0.36	0.48
Firm keeps accounting books	0.39	0.44	0.38	0.42	0.22	0.27	0.21	0.29
Firm is registered	0.33	0.51	0.31	0.48	0.18	0.31	0.16	0.34
Firm has more than 5 employees	0.44	0.46	0.45	0.43	0.27	0.31	0.25	0.32
Employee contributes to social security	0.44	0.50	0.42	0.49	0.22	0.30	0.23	0.32
Employee has a formal contract	0.35	0.40	0.31	0.39	0.23	0.27	0.19	0.29
Occupation is in top quartile of earnings	0.10	0.12	0.10	0.13	0.07	0.09	0.08	0.10
Occupation is in bottom quartile of earnings	0.30	0.24	0.29	0.25	0.40	0.34	0.36	0.32
Earnings and hours outcomes								
Hours	45.0	40.6	43.2	39.6	29.3	25.9	26.2	26.8
Monthly earnings (Soles 2017)	1,768	2,035	1,702	2,044	896	1,030	894	1,199
Hourly earnings (Soles 2017)	8.7	10.9	8.4	11.1	7.6	6.5	5.7	7.9
Intermediate outcomes and composition								
Public transport expenditure > 0	0.73	0.75	0.74	0.71	0.81	0.81	0.76	0.79
Monthly public transport expenditure (Soles 2017)	64.7	66.9	64.2	59.8	59.0	57.5	48.5	56.8
Years of education	11.8	12.1	11.9	12.4	11.0	11.6	11.2	12.1
High school eduaction level or more	0.79	0.84	0.81	0.87	0.72	0.77	0.74	0.83
Observations	1,108	4,766	1,200	5,540	1,293	5,412	1,331	6,018

Panel B. Covariates balance in 2007-2009

	Males				Females			
	Before overlap		After overlap		Before overlap		After overlap	
	Controls	Treated	Controls	Treated	Controls	Treated	Controls	Treated
Age	36.9	37.4	37.4	37.4	**36.8**	**37.9**	37.0	38.1
Indigenous ethnicity	**0.10**	**0.07**	0.08	0.08	0.11	0.10	0.10	0.11
Married or cohabiting with partner	**0.59**	**0.51**	**0.59**	**0.52**	0.53	0.51	0.53	0.51
Enrolled in school	0.10	0.10	0.11	0.10	0.10	0.09	0.10	0.09
Single parent household	0.04	0.05	0.04	0.05	0.10	0.08	0.08	0.09
Female headed household	0.17	0.18	0.18	0.18	**0.27**	**0.31**	**0.25**	**0.29**
Children under 6 years old in the household	0.45	0.42	0.45	0.43	0.47	0.45	0.46	0.45
Number of household members	4.85	4.70	4.94	4.75	**4.82**	**4.66**	**4.88**	**4.70**
Dependency Rate	0.36	0.36	0.36	0.36	0.37	0.37	0.37	0.38
Observations	1,108	1,200	905	1,005	1,293	1,331	1,075	1,118

Note: Figures in bold in Panel B indicate that the difference between treated and controls is statistically significant at the 5% significance level.

Table 2. Employment outcomes

Coefficient	Employment	Categories of employment: Employee	Self-employed	Domestic worker	Homemaker
	(1)	(2)	(3)	(4)	(5)
2010-2011 × treated BRT/Line 1 × Female	0.053**	0.021	0.009	0.022	-0.064***
	(0.022)	(0.028)	(0.021)	(0.015)	(0.017)
2012-2014 × treated BRT/Line 1 × Female	0.076***	0.024	0.027	0.026**	-0.052***
	(0.019)	(0.027)	(0.022)	(0.012)	(0.014)
2015-2017 × treated BRT/Line 1 × Female	0.101***	0.077**	-0.003	0.027*	-0.061***
	(0.025)	(0.033)	(0.025)	(0.014)	(0.019)
2010-2011 × treated BRT/Line 1 × Male	0.019	0.014	0.010	-0.005	-0.013
	(0.026)	(0.048)	(0.027)	(0.008)	(0.019)
2012-2014 × treated BRT/Line 1 × Male	0.002	-0.004	0.001	0.006	-0.010
	(0.027)	(0.028)	(0.025)	(0.008)	(0.012)
2015-2017 × treated BRT/Line 1 × Male	0.027	0.010	0.007	0.011	-0.007
	(0.017)	(0.026)	(0.027)	(0.009)	(0.014)
2010-2011 × treated BRT/Line 1 × (Female - Male)	0.034	0.008	-0.000	0.027*	-0.051**
	(0.031)	(0.038)	(0.023)	(0.013)	(0.025)
2012-2014 × treated BRT/Line 1 × (Female - Male)	0.074***	0.028	0.025	0.021	-0.042**
	(0.025)	(0.029)	(0.027)	(0.013)	(0.019)
2015-2017 × treated BRT/Line 1 × (Female - Male)	0.074**	0.067*	-0.010	0.016	-0.054**
	(0.029)	(0.034)	(0.029)	(0.014)	(0.020)
District-Year Fixed Effects	YES	YES	YES	YES	YES
Controls (linear and interacted with Female)	YES	YES	YES	YES	YES
Observations	26,668	26,668	26,668	26,668	26,668
Number of districts	32	32	32	32	32

Note: Standard errors in parentheses, clustered at the district level. *** p<0.01, ** p<0.05, * p<0.10.

Table 3. Earnings and hours outcomes

Coefficient	Unconditional on employment			Conditional on employment		
	IHS(Earnings)	IHS(Hours)	IHS(Earnings/hours)	IHS(Earnings)	IHS(Hours)	IHS(Earnings/hours)
	(1)	(2)	(3)	(4)	(5)	(6)
2010-2011 × treated BRT/Line 1 × Female	0.345**	0.321***	0.135*	-0.057	0.146*	0.037
	(0.151)	(0.109)	(0.069)	(0.087)	(0.083)	(0.070)
2012-2014 × treated BRT/Line 1 × Female	0.498***	0.423***	0.115**	-0.088	0.162*	-0.089*
	(0.138)	(0.083)	(0.047)	(0.052)	(0.084)	(0.044)
2015-2017 × treated BRT/Line 1 × Female	0.754***	0.518***	0.233***	0.020	0.130*	0.004
	(0.191)	(0.110)	(0.066)	(0.057)	(0.073)	(0.040)
2010-2011 × treated BRT/Line 1 × Male	-0.048	0.132	-0.088	-0.220***	0.070	-0.152**
	(0.196)	(0.106)	(0.073)	(0.073)	(0.047)	(0.064)
2012-2014 × treated BRT/Line 1 × Male	-0.182	0.075	-0.179**	-0.243***	0.096*	-0.235***
	(0.199)	(0.109)	(0.072)	(0.048)	(0.053)	(0.056)
2015-2017 × treated BRT/Line 1 × Male	0.102	0.198**	-0.013	-0.148**	0.107*	-0.118*
	(0.134)	(0.090)	(0.060)	(0.067)	(0.060)	(0.060)
2010-2011 × treated BRT/Line 1 × (Female - Male)	0.394	0.188	0.223**	0.162**	0.076	0.188***
	(0.252)	(0.138)	(0.104)	(0.065)	(0.076)	(0.068)
2012-2014 × treated BRT/Line 1 × (Female - Male)	0.680***	0.349***	0.294***	0.155**	0.066	0.146**
	(0.222)	(0.125)	(0.100)	(0.065)	(0.070)	(0.068)
2015-2017 × treated BRT/Line 1 × (Female - Male)	0.651**	0.319**	0.247**	0.168**	0.023	0.122*
	(0.246)	(0.137)	(0.098)	(0.069)	(0.073)	(0.068)
District-Year Fixed Effects	YES	YES	YES	YES	YES	YES
Controls (linear and interacted with Female)	YES	YES	YES	YES	YES	YES
Observations	26,668	26,668	26,668	19,427	19,427	19,427
Number of districts	32	32	32	32	32	32

Note: Standard errors in parentheses, clustered at the district level. *** p<0.01, ** p<0.05, * p<0.10. IHS() refers to the inverse hyperbolic sine transformation, see text for

Table 4. Job quality outcomes

Coefficient	Job quality index		Formality based on firm characteristics			Formality based on employee		Characteristics of occupation	
	Index value	Index value > 0	Keeps accounting books	Is registered	Has more than five employees	Contributes to social security	Has a formal contract	In top quartile of earnings	In bottom quartile of earnings
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
2010-2011 × treated BRT/Line 1 × Female	-0.045	-0.021	0.012	0.024	-0.026	-0.026	0.009	0.002	0.077***
	(0.091)	(0.025)	(0.021)	(0.018)	(0.024)	(0.024)	(0.025)	(0.017)	(0.026)
2012-2014 × treated BRT/Line 1 × Female	-0.081	-0.015	0.010	0.014	-0.015	-0.015	-0.007	-0.014	0.097***
	(0.122)	(0.027)	(0.023)	(0.026)	(0.036)	(0.036)	(0.029)	(0.012)	(0.026)
2015-2017 × treated BRT/Line 1 × Female	0.034	0.022	0.009	0.028	0.007	0.007	0.031	-0.004	0.071**
	(0.155)	(0.033)	(0.026)	(0.026)	(0.036)	(0.036)	(0.036)	(0.021)	(0.028)
2010-2011 × treated BRT/Line 1 × Male	-0.243	-0.055	-0.009	-0.031	-0.093***	-0.087*	-0.029	0.006	0.112***
	(0.184)	(0.033)	(0.049)	(0.049)	(0.034)	(0.044)	(0.038)	(0.019)	(0.032)
2012-2014 × treated BRT/Line 1 × Male	-0.288**	-0.075***	-0.042*	-0.048*	-0.080***	-0.076*	-0.025	-0.018	0.091**
	(0.106)	(0.025)	(0.024)	(0.025)	(0.026)	(0.038)	(0.027)	(0.015)	(0.035)
2015-2017 × treated BRT/Line 1 × Male	-0.178	-0.040*	-0.030	-0.033	-0.068**	-0.045	-0.009	0.008	0.071*
	(0.150)	(0.021)	(0.040)	(0.043)	(0.028)	(0.029)	(0.033)	(0.017)	(0.036)
2010-2011 × treated BRT/Line 1 × (Female - Male)	0.198	0.034	0.021	0.055	0.068*	0.020	0.038	-0.004	-0.035
	(0.183)	(0.045)	(0.054)	(0.050)	(0.036)	(0.044)	(0.038)	(0.025)	(0.034)
2012-2014 × treated BRT/Line 1 × (Female - Male)	0.207*	0.061*	0.052*	0.062**	0.064**	0.008	0.018	0.003	0.006
	(0.118)	(0.033)	(0.028)	(0.024)	(0.028)	(0.035)	(0.028)	(0.019)	(0.026)
2015-2017 × treated BRT/Line 1 × (Female - Male)	0.212*	0.062*	0.039	0.061*	0.075**	0.008	0.041	-0.012	-0.000
	(0.111)	(0.033)	(0.030)	(0.034)	(0.029)	(0.031)	(0.026)	(0.022)	(0.032)
District-Year Fixed Effects	YES	YES	YES	YES	YES	YES	YES	YES	YES
Controls (linear and interacted with Female)	YES	YES	YES	YES	YES	YES	YES	YES	YES
Observations	26,668	26,668	26,668	26,668	26,668	26,668	26,668	26,668	26,668
Number of districts	32	32	32	32	32	32	32	32	32

Note: Standard errors in parentheses, clustered at the district level. *** p<0.01, ** p<0.05, * p<0.10. Job quality index adds up dummies for columns (3) to (8) (index can take values 0 to 6). Classification in columns (8) and (9) based on occupation code, using earnings distribution for all occupation codes from 2005 to 2009.

Table 5. Intermediate outcomes

Coefficient	Intermediate outcomes: Public transport expenditure > 0	Intermediate outcomes: IHS(monthly public transport expenditure)	Composition effects: Years of education	Composition effects: High school education level or more
	(1)	(2)	(3)	(4)
2010-2011 × treated BRT/Line 1 × Female	0.001	0.080	-0.261	-0.036
	(0.018)	(0.111)	(0.324)	(0.042)
2012-2014 × treated BRT/Line 1 × Female	0.039	0.271*	-0.250	-0.022
	(0.031)	(0.154)	(0.243)	(0.024)
2015-2017 × treated BRT/Line 1 × Female	0.081***	0.477***	-0.209	-0.014
	(0.029)	(0.164)	(0.267)	(0.032)
2010-2011 × treated BRT/Line 1 × Male	-0.069**	-0.384**	-0.307	-0.036
	(0.033)	(0.169)	(0.389)	(0.045)
2012-2014 × treated BRT/Line 1 × Male	-0.026	-0.196	-0.217	-0.039
	(0.034)	(0.162)	(0.297)	(0.030)
2015-2017 × treated BRT/Line 1 × Male	-0.013	-0.106	-0.308	-0.049
	(0.036)	(0.169)	(0.287)	(0.030)
2010-2011 × treated BRT/Line 1 × (Female - Male)	0.070*	0.464**	0.046	-0.001
	(0.040)	(0.201)	(0.237)	(0.022)
2012-2014 × treated BRT/Line 1 × (Female - Male)	0.066**	0.467***	-0.033	0.017
	(0.028)	(0.136)	(0.173)	(0.028)
2015-2017 × treated BRT/Line 1 × (Female - Male)	0.094***	0.583***	0.098	0.035
	(0.028)	(0.139)	(0.146)	(0.027)
District-Year Fixed Effects	YES	YES	YES	YES
Controls (linear and interacted with Female)	YES	YES	YES	YES
Observations	26,668	26,668	26,668	26,668
Number of districts	32	32	32	32

Note: Standard errors in parentheses, clustered at the district level. *** p<0.01, ** p<0.05, * p<0.10.

Table 6. Tests of parallel trends assumption

Coefficient	Employment	Unconditional on employment		Job quality index		Public transport expenditure		Education	
		IHS(Earnings)	IHS(Earnings/hours)	Index value	Index value > 0	Expenditure > 0	IHS(Expenditure)	Years	High school or more
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
2009 × treated BRT/Line 1 x Female	-0.034	-0.181	-0.074	0.180	-0.014	-0.028	-0.178	0.114	-0.018
	(0.034)	(0.249)	(0.128)	(0.152)	(0.028)	(0.036)	(0.226)	(0.373)	(0.041)
2009 × treated BRT/Line 1 × Male	-0.035	-0.215	-0.032	0.045	-0.031	-0.080	-0.420	0.150	0.022
	(0.033)	(0.257)	(0.113)	(0.194)	(0.041)	(0.050)	(0.280)	(0.401)	(0.046)
District-Year Fixed Effects	YES	YES	YES	YES	YES	YES	YES	YES	YES
Controls (linear and interacted with Female)	YES	YES	YES	YES	YES	YES	YES	YES	YES
Observations	4,932	4,932	4,932	4,932	4,932	4,932	4,932	4,932	4,932
Number of districts	25	25	25	25	25	25	25	25	25

Note: Standard errors in parentheses, clustered at the district level. *** p<0.01, ** p<0.05, * p<0.10. The regressions use only data from 2007 to 2009. See notes for Tables 3 and 4 for details on the definition of the outcomes in columns (2) to (5).

Table 7. Treatment effect heterogeneity: BRT v. Line 1

Coefficient	Employment	Unconditional on employment		Job quality index		Public transport expenditure		Education	
		IHS(Earnings)	IHS(Earnings/hours)	Index value	Index value > 0	Expenditure > 0	IHS(Expenditure)	Years	High school or more
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
2010-2011 × BRT × Female	0.072**	0.429**	0.186**	-0.134	-0.024	-0.026	-0.006	-0.382	-0.045
	(0.034)	(0.202)	(0.091)	(0.155)	(0.040)	(0.033)	(0.172)	(0.485)	(0.061)
2012-2014 × BRT × Female	0.071	0.431	0.088	-0.290**	-0.050	0.024	0.162	-0.035	0.011
	(0.044)	(0.324)	(0.096)	(0.108)	(0.039)	(0.050)	(0.212)	(0.309)	(0.036)
2015-2017 × BRT × Female	0.098***	0.699**	0.217*	-0.201	-0.018	0.078	0.380	-0.222	0.006
	(0.035)	(0.278)	(0.113)	(0.152)	(0.038)	(0.054)	(0.244)	(0.292)	(0.040)
2010-2011 × Line 1 × Female	0.046**	0.327**	0.125*	-0.034	-0.022	0.009	0.087	-0.229	-0.033
	(0.021)	(0.151)	(0.069)	(0.112)	(0.028)	(0.022)	(0.128)	(0.324)	(0.040)
2012-2014 × Line 1 × Female	0.081***	0.547***	0.142**	-0.007	0.000	0.043	0.300*	-0.382	-0.039
	(0.021)	(0.147)	(0.061)	(0.115)	(0.024)	(0.032)	(0.158)	(0.263)	(0.024)
2015-2017 × Line 1 × Female	0.103***	0.786***	0.244***	0.104	0.038	0.079***	0.506***	-0.246	-0.029
	(0.026)	(0.190)	(0.057)	(0.169)	(0.034)	(0.029)	(0.168)	(0.367)	(0.039)
2010-2011 × BRT × Male	0.042	0.166	0.066	-0.463*	-0.070	-0.117**	-0.706***	-0.541	-0.044
	(0.031)	(0.176)	(0.099)	(0.251)	(0.057)	(0.052)	(0.224)	(0.509)	(0.061)
2012-2014 × BRT × Male	0.010	-0.063	-0.058	-0.482***	-0.093*	-0.066	-0.446**	-0.356	-0.043
	(0.036)	(0.262)	(0.103)	(0.123)	(0.049)	(0.049)	(0.215)	(0.392)	(0.050)
2015-2017 × BRT × Male	0.016	0.063	0.021	-0.603***	-0.088***	-0.054	-0.401*	-0.701**	-0.076
	(0.022)	(0.187)	(0.108)	(0.137)	(0.027)	(0.047)	(0.201)	(0.262)	(0.048)
2010-2011 × Line 1 × Male	0.009	-0.139	-0.155*	-0.167	-0.050	-0.051	-0.248*	-0.223	-0.034
	(0.032)	(0.250)	(0.080)	(0.182)	(0.030)	(0.031)	(0.141)	(0.380)	(0.043)
2012-2014 × Line 1 × Male	-0.001	-0.239	-0.239***	-0.245**	-0.073***	-0.011	-0.097	-0.157	-0.036
	(0.030)	(0.237)	(0.082)	(0.101)	(0.026)	(0.028)	(0.129)	(0.270)	(0.023)
2015-2017 × Line 1 × Male	0.036*	0.145	-0.022	-0.004	-0.020	0.004	0.023	-0.120	-0.035
	(0.021)	(0.165)	(0.052)	(0.135)	(0.020)	(0.030)	(0.135)	(0.350)	(0.030)
2010-2011 × BRT × (Female - Male)	0.030	0.263	0.121	0.328	0.046	0.091*	0.701**	0.159	-0.002
	(0.042)	(0.316)	(0.155)	(0.199)	(0.063)	(0.052)	(0.290)	(0.251)	(0.028)
2012-2014 × BRT × (Female - Male)	0.061	0.493	0.146	0.192	0.043	0.090**	0.608***	0.321	0.054
	(0.037)	(0.310)	(0.150)	(0.144)	(0.049)	(0.034)	(0.143)	(0.256)	(0.041)
2015-2017 × BRT × (Female - Male)	0.082*	0.636*	0.196	0.402**	0.070*	0.132***	0.781***	0.479**	0.082*
	(0.041)	(0.338)	(0.154)	(0.162)	(0.041)	(0.035)	(0.175)	(0.214)	(0.042)
2010-2011 × Line 1 × (Female - Male)	0.036	0.466*	0.280**	0.134	0.028	0.059	0.335	-0.007	0.001
	(0.032)	(0.271)	(0.107)	(0.189)	(0.043)	(0.045)	(0.214)	(0.273)	(0.026)
2012-2014 × Line 1 × (Female - Male)	0.081***	0.787***	0.381***	0.238*	0.073**	0.054*	0.397**	-0.225	-0.003
	(0.028)	(0.243)	(0.111)	(0.129)	(0.034)	(0.031)	(0.150)	(0.139)	(0.023)
2015-2017 × Line 1 × (Female - Male)	0.066**	0.641**	0.267***	0.108	0.059	0.075**	0.482**	-0.126	0.007
	(0.030)	(0.244)	(0.083)	(0.138)	(0.037)	(0.036)	(0.178)	(0.145)	(0.025)
District-Year Fixed Effects	YES	YES	YES	YES	YES	YES	YES	YES	YES
Controls (linear and interacted with Female)	YES	YES	YES	YES	YES	YES	YES	YES	YES
Observations	26,668	26,668	26,668	26,668	26,668	26,668	26,668	26,668	26,668
Number of districts	32	32	32	32	32	32	32	32	32

Note: Standard errors in parentheses, clustered at the district level. *** p<0.01, ** p<0.05, * p<0.10.

Table 8. Treatment effect heterogeneity: distance to closest line

Coefficient	Employment	Unconditional on employment		Job quality index		Public transport expenditure		Education	
		IHS(Earnings)	IHS(Earnings/hours)	Index value	Index value > 0	Expenditure > 0	IHS(Expenditure)	Years	High school or more
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
2010-2011 × (0 - 1 km) × Female	0.059**	0.393**	0.134*	-0.022	-0.006	0.005	0.084	-0.265	-0.024
	(0.022)	(0.153)	(0.068)	(0.102)	(0.026)	(0.019)	(0.114)	(0.288)	(0.039)
2012-2014 × (0 - 1 km) × Female	0.076***	0.503***	0.122**	-0.042	-0.001	0.038	0.273*	-0.253	-0.019
	(0.018)	(0.135)	(0.050)	(0.136)	(0.029)	(0.030)	(0.154)	(0.235)	(0.024)
2015-2017 × (0 - 1 km) × Female	0.104***	0.769***	0.232***	0.041	0.032	0.071**	0.434***	-0.222	-0.014
	(0.024)	(0.187)	(0.067)	(0.156)	(0.033)	(0.027)	(0.158)	(0.249)	(0.029)
2010-2011 × (1 - 1.5 km) × Female	0.049	0.340	0.187*	-0.029	-0.018	0.020	0.192	-0.230	-0.008
	(0.032)	(0.262)	(0.103)	(0.142)	(0.042)	(0.025)	(0.146)	(0.150)	(0.034)
2012-2014 × (1 - 1.5 km) × Female	0.056**	0.324**	0.088	-0.104	-0.006	0.017	0.157	-0.644***	-0.037
	(0.021)	(0.155)	(0.074)	(0.151)	(0.037)	(0.028)	(0.166)	(0.227)	(0.030)
2015-2017 × (1 - 1.5 km) × Female	0.069**	0.465**	0.201***	-0.035	0.012	0.042	0.249	-0.334	-0.006
	(0.026)	(0.186)	(0.068)	(0.124)	(0.029)	(0.028)	(0.167)	(0.242)	(0.025)
2010-2011 × (0 - 1 km) × Male	0.026	0.005	-0.086	-0.224	-0.041	-0.063*	-0.376**	-0.345	-0.025
	(0.025)	(0.195)	(0.071)	(0.181)	(0.034)	(0.032)	(0.171)	(0.358)	(0.041)
2012-2014 × (0 - 1 km) × Male	0.003	-0.175	-0.171**	-0.252**	-0.062**	-0.026	-0.184	-0.243	-0.037
	(0.025)	(0.191)	(0.071)	(0.111)	(0.027)	(0.032)	(0.155)	(0.296)	(0.029)
2015-2017 × (0 - 1 km) × Male	0.030*	0.120	-0.014	-0.170	-0.029	-0.021	-0.137	-0.340	-0.049
	(0.016)	(0.132)	(0.056)	(0.156)	(0.022)	(0.035)	(0.165)	(0.290)	(0.029)
2010-2011 × (1 - 1.5 km) × Male	0.019	-0.020	-0.069	-0.264	-0.014	-0.023	-0.094	-0.264	0.009
	(0.024)	(0.195)	(0.081)	(0.160)	(0.053)	(0.037)	(0.207)	(0.222)	(0.030)
2012-2014 × (1 - 1.5 km) × Male	0.001	-0.150	-0.162*	-0.320**	-0.018	-0.021	-0.089	-0.362	-0.038
	(0.024)	(0.189)	(0.094)	(0.148)	(0.035)	(0.034)	(0.181)	(0.275)	(0.024)
2015-2017 × (1 - 1.5 km) × Male	0.031	0.173	0.029	0.037	0.039	-0.003	0.010	-0.090	-0.014
	(0.021)	(0.171)	(0.075)	(0.150)	(0.030)	(0.035)	(0.160)	(0.276)	(0.031)
2010-2011 × (0 - 1 km) × (Female - Male)	0.033	0.388	0.220**	0.202	0.035	0.069*	0.460**	0.080	0.000
	(0.032)	(0.255)	(0.106)	(0.183)	(0.046)	(0.040)	(0.202)	(0.238)	(0.021)
2012-2014 × (0 - 1 km) × (Female - Male)	0.073***	0.678***	0.293***	0.210*	0.061*	0.064**	0.457***	-0.010	0.017
	(0.025)	(0.223)	(0.100)	(0.119)	(0.034)	(0.028)	(0.135)	(0.177)	(0.028)
2015-2017 × (0 - 1 km) × (Female - Male)	0.073**	0.649**	0.246**	0.211*	0.061*	0.092***	0.572***	0.118	0.035
	(0.029)	(0.245)	(0.098)	(0.111)	(0.033)	(0.028)	(0.139)	(0.149)	(0.028)
2010-2011 × (1 - 1.5 km) × (Female - Male)	0.030	0.360	0.256*	0.235	-0.004	0.043	0.285	0.034	-0.016
	(0.043)	(0.355)	(0.137)	(0.189)	(0.044)	(0.050)	(0.256)	(0.285)	(0.027)
2012-2014 × (1 - 1.5 km) × (Female - Male)	0.055	0.475	0.250**	0.216	0.012	0.038	0.246	-0.283	0.001
	(0.034)	(0.284)	(0.121)	(0.181)	(0.041)	(0.042)	(0.215)	(0.208)	(0.024)
2015-2017 × (1 - 1.5 km) × (Female - Male)	0.038	0.292	0.172	-0.072	-0.027	0.046	0.239	-0.245	0.008
	(0.037)	(0.301)	(0.117)	(0.176)	(0.047)	(0.037)	(0.194)	(0.228)	(0.027)
District-Year Fixed Effects	YES	YES	YES	YES	YES	YES	YES	YES	YES
Controls (linear and interacted with Female)	YES	YES	YES	YES	YES	YES	YES	YES	YES
Observations	34,105	34,105	34,105	34,105	34,105	34,105	34,105	34,105	34,105
Number of districts	32	32	32	32	32	32	32	32	32

Note: Standard errors in parentheses, clustered at the district level. *** p<0.01, ** p<0.05, * p<0.10.

Appendix

Table A1. Robustness: main outcomes after imposing overlap

Coefficient	Employment	Unconditional on employment		Job quality index		Public transport expenditure		Education	
		IHS(Earnings)	IHS(Earnings/hours)	Index value	Index value > 0	Expenditure > 0	IHS(Expenditure)	Years	High school or more
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
2010-2011 × treated BRT/Line 1 × Female	0.034*	0.215	0.046	-0.064	-0.027	0.017	0.066	-0.287	-0.036
	(0.018)	(0.136)	(0.061)	(0.091)	(0.026)	(0.030)	(0.116)	(0.373)	(0.045)
2012-2014 × treated BRT/Line 1 × Female	0.065***	0.406**	0.053	-0.110	-0.021	0.029	0.263	-0.306	-0.039*
	(0.022)	(0.159)	(0.054)	(0.113)	(0.021)	(0.045)	(0.174)	(0.230)	(0.023)
2015-2017 × treated BRT/Line 1 × Female	0.091***	0.708***	0.212***	0.055	0.020	0.063	0.421**	-0.098	-0.010
	(0.027)	(0.198)	(0.061)	(0.128)	(0.026)	(0.052)	(0.197)	(0.217)	(0.030)
2010-2011 × treated BRT/Line 1 × Male	0.013	-0.106	-0.139*	-0.254	-0.050	-0.080*	-0.411**	-0.273	-0.025
	(0.028)	(0.217)	(0.073)	(0.190)	(0.037)	(0.040)	(0.194)	(0.427)	(0.046)
2012-2014 × treated BRT/Line 1 × Male	-0.002	-0.218	-0.195**	-0.219**	-0.055**	-0.034	-0.220	-0.087	-0.031
	(0.027)	(0.225)	(0.083)	(0.105)	(0.023)	(0.041)	(0.180)	(0.326)	(0.026)
2015-2017 × treated BRT/Line 1 × Male	0.015	0.036	-0.014	-0.071	-0.031	-0.027	-0.180	-0.199	-0.044
	(0.020)	(0.160)	(0.080)	(0.140)	(0.023)	(0.041)	(0.193)	(0.269)	(0.031)
2010-2011 × treated BRT/Line 1 × (Female -	0.021	0.321	0.185*	0.190	0.024	0.070	0.477**	-0.013	-0.011
	(0.031)	(0.254)	(0.106)	(0.167)	(0.039)	(0.045)	(0.223)	(0.277)	(0.027)
2012-2014 × treated BRT/Line 1 × (Female -	0.067**	0.624**	0.247*	0.108	0.034	0.068**	0.482***	-0.218	-0.009
	(0.032)	(0.277)	(0.121)	(0.134)	(0.035)	(0.028)	(0.128)	(0.208)	(0.029)
2015-2017 × treated BRT/Line 1 × (Female -	0.076**	0.672***	0.226**	0.126	0.051	0.098***	0.601***	0.101	0.035
	(0.029)	(0.243)	(0.101)	(0.138)	(0.038)	(0.029)	(0.153)	(0.157)	(0.025)
Conglomerate Fixed Effects	YES	YES	YES	YES	YES	YES	YES	YES	YES
Controls (linear and interacted with Female)	YES	YES	YES	YES	YES	YES	YES	YES	YES
Observations	21,546	21,546	21,546	21,546	21,546	21,546	21,546	21,546	21,546
Number of conglomerates	31	31	31	31	31	31	31	31	31

Note: Standard errors in parentheses, clustered at the conglomerate level. *** p<0.01, ** p<0.05, * p<0.10.