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Transport Division, Office of Strategic Planning and Development Effectiveness, IDB Invest

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A Rapid Road to Employment?
The Impacts of a Bus Rapid Transit System in Lima*

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Abstract

Despite the growing interest in and proliferation of Bus Rapid Transit (BRT) systems around the world, their causal impacts on labor market outcomes remain unexplored. Reduced travel times for those who live near BRT stations or near feeder lines, may increase access to a wider array of job opportunities, potentially leading to increased rates of employment, access to higher quality (or formal) jobs, and increased labor hours and earnings. This paper assesses the effects of the *Metropolitano*, the BRT system in Lima (Peru), on individual-level job market outcomes. We rely on a difference-in-differences empirical strategy, based on comparing individuals who live close to the BRT system with a comparison group that lives farther from the system, before and after the system started to operate. We find large impacts on employment, hours worked and labor earnings for those individuals close to the BRT stations, but not for those who live close to the feeder lines. Despite the potential to connect poor populations, we find no evidence of impacts for populations living in lower income areas.

Keywords: Bus Rapid Transit; employment; impact evaluation

JEL Codes: J01; J21; O12; R40

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1. Introduction

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 (Atlantic Council, 2014). Such rapid urban growth has led to increased value of centrally located land and has pushed lower income populations to move to the outskirts of cities in search of affordable housing. As urban planning mechanisms tend to be fragmented and characterized by a general lack of comprehensive policy frameworks, urban peripheral growth tends to be sprawling, informal, and lacking in adequate transport infrastructure services. This, in turn, tends to increase both monetary and time cost of transportation for the poor, and exacerbates the already low level of access to jobs and other economic opportunities among the poor (Carruthers, Dick, and Saurkar, 2005).

Poor populations are also more dependent on slower modes of transport such as public transit and walking for a large share of their trips. Data from CAF (2009, 2011) shows that in the largest 15 metropolitan areas in Latin America there is an unequal distribution of travel times across social groups. While bus users spend on average 59 minutes per trip, car users in the region spend on average 25 minutes per trip. Travel expenditures as a share of income are also relevant and can consume 30% or more of daily wages of the poor in Latin American cities, adding to the already-high travel time costs (Kaltheier, 2002; Vasconcellos, 2001). Consequently, the poor in urban areas of developing countries tend to sacrifice trips; the majority of the poor make on average between one-fifth and one-third fewer trips per capita than the non-poor (Gakenheimer, 1999). These costs have negative implications for both job search, access, and general social inclusion in economic development[1].

Bus rapid transit (BRT) systems are an increasingly popular approach to cost-effectively improve urban transport systems. They often transport as many passengers as most conventional light rail systems at a fraction of the cost. They also compare well with heavy rail systems, except under circumstances of very high passenger demand exceeding 50,000 passengers per hour per direction (Rodriguez and Mojica, 2008). BRT investments also often seek to include poor and

[1] The notion of social exclusion related to transport contends that insufficient accessibility can lead to a limited participation in the economic, social, and political opportunities offered by cities (Burchardt et al., 1999; Church et al., 2000; Lucas et al., 2011). Lucas (2011) refers to transport-related social exclusion as the social implications of lack of adequate access to opportunities by virtue of poor transport, which can impair both individual and societal development and prevent socially vulnerable individuals to contribute to, and benefit from, economic growth.

socially vulnerable groups who depend on public transit, into the mobility and access benefits of the system. Recent data indicates that at least 52 cities in Latin America have implemented BRT systems, reaching approximately 19 million passengers per day (Global BRT Data, 2018). While the mobility and environmental benefits of BRT investments have been well documented (EMBARQ, 2018), the extent to which the poor and vulnerable groups are included in these benefits is a growing area of research. Lowered travel times to reach destinations within a city, enabled by BRT investments, are theorized to improve accessibility to job markets, thereby increasing the likelihood of employment, access to better quality jobs, and increased income.

Despite the growing interest in and proliferation of BRT systems around the world, their causal impacts on employment effects remain unexplored. This paper assesses the effects of the *Metropolitano*, Lima's BRT system, on individual-level employment status, job formality, hours worked, and labor income using multiple cross-sections of Peru´s annual household-level survey. We hypothesize that reduced travel times for those who live near BRT stations or near feeder lines, may increase access to a wider array of job opportunities, potentially leading to increased rates of employment, access to higher quality (or formal) jobs, and labor earnings. In addition, as lower income populations often need to travel longer distances to reach employment opportunities, we may observe differential impacts on individuals living in low socio-economic status areas that were benefited by BRT stations and feeder lines.

The empirical strategy exploits a difference-in-differences (DID) approach that compares individuals before and after the introduction of the BRT living in treatment (close to the BRT system) and control areas (living further away). We distinguish impacts between areas that are close to the BRT trunk line versus areas close to the feeder lines that serve to connect lower income neighborhoods with the BRT trunk line. Our findings indicate that, on average, the individuals living in the trunk areas derive labor market benefits, with positive impacts on their employment rate, labor hours and monthly labor income. Analyses of compositional changes in the education levels of the household head suggest that our results are not driven by compositional changes in the socio-economic characteristics of individuals living in the treatment areas. The results are robust to computing impacts within the subsample of households that live in treatment and control areas that were as similar as possible in the baseline (i.e., areas that satisfy the overlap condition that pre-treatment observable variables are similar across treatment and comparison areas).

In most cases BRTs have been built in corridors with high public transport demand, which might indicate that extremes of the line, where feeders are located, might exhibit larger impacts, as the other areas were already very connected. However, our results failed to support that hypothesis, as we do not find impacts on households living in feeder areas. In addition, we do not find any differential impacts for lower SES areas. The results in this paper are of value for the justification of urban transport projects aimed at improving mobility and accessibility to employment opportunities by public transit users, as they provide further evidence on the positive impacts of BRT investments.

This paper is structured as follows. The next section summarizes the related literature highlighting the main contributions of this study. Section 3 and 4 present background information about the metropolitan area of Lima and details on the BRT project, respectively. Section 5 details the different sources of information used in the analysis and section 6 presents the empirical strategy. Section 7 presents the main results and section 8 concludes with a discussion and policy implications arising from this work.

2. Related Literature

The literature on urban and labor economics poses two main theories on the role of transport accessibility on employment outcomes. First, spatial segregation of low-income minorities from skill-appropriate job centers decreases the affordability of job searches and commutes, and thus the available range of job opportunities increasing their unemployment rates (Kain,1968). In addition, the reservation wage at which a person is willing to supply labor increases with transport costs; therefore, higher transport costs are likely to limit the geographic radius of job opportunities and job search, particularly for low wage workers (Patacchini and Zenou, 2005).

Several complexities emerge in the empirical identification of employment or other impacts caused by transport investments. First, transport investment placement decisions are non-random and often related to economic considerations, such as travel demand and connectivity, that are frequently correlated with the economic outcomes of interest. These considerations may result in benefits going to populations that were already better connected, that had higher rates of employed, or higher income, resulting in two-way causal directions. Moreover, measured benefits may be the result of compositional changes brought about by mobility and location dynamic changes where new populations, with distinct characteristics, move into and possibly displace the original populations in the project area.

In the case of employment, few studies have rigorously estimated the causal impacts of urban transit investments on employment outcomes and most available studies come from developed countries (Yañez-Pagans et al., 2018). While some studies in developing countries have estimated changes in access to employment opportunities from BRT systems, in terms of ease of access to jobs (Yanez et al, 2018; Bocarejo and Oviedo, 2012; Bocarejo, Portilla and Meléndez, 2016; Hidalgo and Yepes, 2005), no studies to date have empirically estimated the causal effects of BRT systems on employment considering all the components of this system as a whole. This means taking into account the different characteristics of trunk and feeder line components and the fact that they reach low income populations and could have differential impacts across income levels. A related study (Martinez et al., 2018a) looks at the overall impacts of urban transport systems investments in Lima (i.e., including both a metro line and the BRT trunk), on employment outcomes finding large effects for women, which could be attributed to the greater security women feel while traveling in these improved systems.

In this section we summarize the available evidence on employment effects arising from urban transport investments, considering multiple types of transport systems, such as BRT, subways, and elevated rails, among others. We concentrate on the literature that tackles causality.[2] Cervero and Landis (1997) analyze employment changes due to the introduction of the Bay Area Rapid Transit System (BART) (including heavy rail and subway). They look at a window of 20 years after the opening of the system and compare changes between a treatment group, conformed by census tracks with BART stations, versus a control group of census tracks without BART stations but in BART-served counties. Their findings indicate that job growth has been consistently higher around BART areas, but concentrated in downtown San Francisco. Holzer et al. (2003) conduct a longitudinal survey of firms immediately before and one year after the expansion of a BART line opened. Treatment groups were defined as all firms within 6 miles of a station and controls were

[2] There is a strand of the literature that is based on descriptive, correlation or before-and-after analyses, without addressing causality. Among those studies, are of interest to highlight the following. Sanchez (1999) shows that for poor black communities in Portland-Oregon and Atlanta-Georgia, unemployment is higher for those who live more than 400 meters away from a public transit stop. Sanchez et al. (2004) find transit access to be negatively correlated to the probability of a household being on government assistance for several US cities. Bollinger and Ihlanfeldt (1997) analyze the construction of rail infrastructure in the Atlanta region and find no discernible effect on total employment or population growth in station areas, but a positive effect in employment growth in regional node stations, particularly government employment. Guthrie (2016), compares the before and after job changes around dedicated BRT corridors, arterial BRT (in which buses operate primarily in mixed traffic), and in light-rail transit (LRT) corridors in 15 regions of the United States, finding that job growth is largest near downtown stations, with increases in white-collar and high-wage employment, higher in corridors/lines that have higher street density and that arterial BRT stations were associated with significantly less job growth than otherwise similar LRT stations (suggesting that fixed infrastructure might matter). Nelson (2017) shows growth in jobs at different distances of transport systems in the US. For Latin America, Oviedo (2017) finds that workers living close to Bogota's *Transmilenio* stations have a lower probability of being informally employed.

defined as those between 6 and 12 miles. Their conclusions point to an overall increase of 8% in the demand of Latino workers and no increases in the hiring rates of African Americans.

More recently, Tyndall (2017) estimates the impact of an exogenous shock to the metro system of New York (R train), caused by flooding from hurricane Sandy, on access to employment. The paper estimates a DID regression in which the treatment group is composed by people above 16 years old reported to be in the labor force and living in neighborhoods adjacent to the line that shut down in the year 2013 because of the hurricane. The control group is composed by a comparable set of individuals that live in areas not affected by closures. Findings show that living next to the R train during the shutdown resulted in an overall 1.4 percentage increase in the probability of being unemployed and that impacts are lower for individuals who had access to a vehicle (0.7 percentage points) and much higher for those who were transit dependent (2.2 percentage points).

As mentioned before, we have not identified causal studies looking at the employment impacts brought solely by BRT systems and considering the impacts of the components of the system.

3. The Metropolitan Area of Lima

Lima, the capital of Peru, is one of the fastest growing urban areas in the LAC region.[3] Between 2007 and 2012 Lima's population increased by 11% and its population of slightly above 9.9 million represents about one-third of the population of the country. Approximately, 42% of the extreme poor and 19% of the poor population lived in peripheral areas of Lima, defined as all areas at least 9 km from the city center, in 2007 (Scholl, et al, 2016). These low-income populations tend to live in the northern and southern cones, while high-income populations are concentrated in the central and south-central areas of the city. The distribution of socio-economic groups also reflects the historic development patterns of Lima, where new rural migrants typically settled in the urban periphery while the middle-class and elites moved to the City Center (Sabatini, 2003).[4]

In 2016, 54% of Lima's working age individuals were engaged in informal employment (CEPLAN, 2016). Most small employers in Lima, which are more likely to contract informal workers, are distributed somewhat evenly throughout the city, while larger employers, with higher shares of formal jobs, are concentrated along some of the main transportation links in the city (Oviedo, et

[3] The metropolitan area includes the urban population of the provinces of Lima and Callao.

[4] Throughout the paper when we refer to socio-economic status (SES) categories we use the 2007 Population Census classification of areas in five strata: A: high income; B: high-middle income; C: low-middle income; D: poor; E: extreme poor.

al, 2018). According to data from Peru's 2008 National Economic Census, over half (54%) of jobs are concentrated in centrally-located areas of middle and upper socio-economic status (SES); therefore, we hypothesize that lower income populations would need to travel longer distances to reach these employment opportunities, particularly those in the formal sector.

Lower-income groups in Lima have also lower per capita vehicle ownership rates and make a large share of their daily trips in traditional buses-56% for the poor and 55% for the extreme poor followed by those on foot—28% of trips by the poor and 35% of trips among the extreme poor.[5] (JICA, 2013). In addition, Lima is characterized by an oversupply and large informality in the public transit sector that has led to poor service quality as well as high levels of traffic accidents and air pollution. According to Bielich (2009), approximately 30% of public transit services were considered informal (or unregulated). As a result, poor populations in Lima incur in longer average commute times, reaching up to two hours in each direction (IDB, 2014). Overall, the poor quality of the public transit service together with the large commuting time disproportionally affect poor households potentially reducing their employment opportunities.

4. Lima´s BRT Project Background

The *Metropolitano*, Lima's BRT, is the first line of a larger system planned for the city. Consisting of a BRT corridor connecting the lower income neighborhoods in the northern and southern cones of Lima with the financial district, major universities, and the historic downtown, it was also one of the first mass public transit system proposed for Lima. With 28.6 km of segregated busway, 35 stations, and a central transfer, it includes feeder routes that extend up to 14 kilometers from the terminals connecting with the surrounding and primarily low-income neighborhoods in the north and south cones. Serving one of the highest-demand corridors in the city, it offers late night and weekend service as well as express and super express services between high demand stations (IDB, 2015).

The implementation of the system was gradual due to construction delays, lower than expected initial demand, as well as institutional and political challenges. It opened in mid-2010 with only 22% of the planned articulated buses and five of the feeder routes in operation, and with unfinished infrastructure (Protransporte, 2014). One year later, in mid-2011, although the

[5] Such as Combis, Colectivos, Omnibus and Microbuses. The types of informal and traditional collective transport vehicles range in size and service characteristics (e.g. a combi is an informal mini-bus, while an omnibus is a larger bus with capacity to carry 90 passengers or more).

northern section of the trunk line was completed, only 64% of the trunk line fleet was operating. In addition, key reforms that impacted service quality and demand, such as the reorganization of existing bus routes and removing direct competitors from the corridor were significantly delayed.

In the first year of operation, ridership was substantially below the forecasted just under 200,000 passengers, compared to 713,000 per day initially projected, and only the southern portion of the trunk infrastructure was complete. In an effort to increase trunk-line demand from the feeder areas, the tariff was restructured in late 2012, as it was not competitively priced with competing informal modes.[6] After this change, the agency reported an increase in ridership among users coming from the feeder areas traveling to the central areas of the city. By 2014, the system was nearly fully operational, with the full fleet of 300 articulated buses operating, 8 trunk-line services, and 222 feeder buses serving 20 feeder routes (13 in the north and 7 in the south). 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 of which approximately 450,000 were trunk users and 230,000 feeder users. 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, 2016).

Ridership by low income groups has been somewhat lower than expected. According to the study by Scholl, et al. (2016), the system has attained its goal of having 60% of its riders from low-middle, poor, and extreme-poor socio-economic status (SES) areas.[7] Although only 43% of the 60% were found to be of poor or extreme poor SES (strata D or E), these groups are more likely to use the BRT (instead of traditional modes) for longer trips and for work or school purposes.

[6] Initially, fares were 1.5 soles (US$0.56 at prevailing exchange rates) on the trunk line, and an additional 0.80 soles (US$0.30 at prevailing rates) for riding the feeders. The price of the feeder was not competitively priced since most users could use a minibus that would charge 0.5 soles (US$0.19 at prevailing exchange rates) for short distances, enough to reach the terminal and transfer to the trunk line. The price of the trunk line was low given the travel times savings from the dedicated infrastructure. The new tariff was thus integrated to cost no more than 2 soles for a trunk and feeder ride, allowing a reduction of the integrated fee (main feeder fee) of 30 cents (US$0.11 at prevailing exchange rates).

[7] The poor who live within one kilometer of the system use the traditional public transit system at higher rates. For example, roughly half (54%) of public transit users who were from low-middle and below SES strata use the BRT system at least once a week, while rates of usage are much lower among the extreme poor, with 57% of the extreme poor not having used the BRT at all in the previous week. Affordability and lack of coverage to extremely poor areas were found as barriers to using the system for these populations.

5. Data

We investigate the effects of the BRT on employment outcomes utilizing cross-sectional time series data from both before and after the implementation of the BRT and exploiting individual-level data on employment, income, and other demographic characteristics from the National Household Survey on Living Conditions and Poverty (ENAHO, original Spanish acronym) for the period 2007-2017.[8] The ENAHO surveys approximately 3,000 households and 15,000 persons per year in the Lima metropolitan area and provides the geographic coordinates in the centroid of the city block of surveyed households.

Employment and quality of employment outcomes are analyzed for individuals age 18 to 64. We define employed individuals as those who report working in the week prior to their interview and report positive earnings. We follow the INEI's methodology (INEI, 2012) for defining informal employment. Informal workers are defined as: i) unpaid family workers in firms with less than five employees; ii) independent workers in the informal sector (running small, non-registered private sector firms); and iii) dependent workers who work in non-registered (with the tax authority) private sector firms, or whose employers do not contribute to the pension system. Based on this definition we create an indicator variable formal (INEI definition), which is our main indicator of job quality. In addition, we generate several other quality of employment indicators including dummy variables for whether the person is (i) working in a formal firm (identified alternatively as firms registered with the tax authority, that carry accounting books, or with more than five employees); and (ii) whether the person has formal employment based on benefits (contributes to social security or is under a formal contract).

We analyze labor market effects on the intensive margin by using as outcome variables total hours worked in the last week and real monthly income (in both cases adding the values for primary and secondary occupations when needed). Usually, to obtain elasticities, the logarithm of these variables is used as dependent variable. However, as we include all individuals 18 years old and above in the regressions, independent of whether they worked the prior week, many values are equal to zero. As the logarithm of zero is undefined, instead of using logarithms we apply the inverse hyperbolic sine (IHS) transformation, which is defined at zero, and allows the

[8] The ENAHO, administered by Peru's National Institute of Statistics and Information (INEI, original Spanish acronym), is a continuous survey that generates quarterly indicators for levels of poverty, wellbeing, and living conditions of households distributed in both rural and urban areas in the country.

same interpretation as a logarithm in a regression framework, and we refer to it as *IHS* in our results.[9]

We combine the geocoded ENAHO survey data with other sources of information to construct baseline neighborhood characteristics. In particular, we obtain the number of economic establishments, share of non-tradeable activities, share of high skill employers, labor productivity and number of jobs using conglomerate-level[10] data from the Economic Census. We use data from the 2007 National Population Census to characterize socio-economically each conglomerate in the Lima metropolitan area, obtaining conglomerate-level averages of the following household variables: a wealth index constructed as the first principal component of a series of household assets and services,[11] number of household members; and household head age. We also calculate for each conglomerate: percentage of female-headed households; percentage of men; percentage of individuals over 15 years of age with at least high school education; percentage of indigenous population; percentage of households with access to sanitary services; and percentage of apartments. Finally, the 2004 Origin-Destination (OD) Survey, for the metropolitan area of Lima and Callao (JICA, 2005), was used to create indicators of accessibility, including average travel time of work trips, and the number of bus routes in a 500 meters radius at the Traffic Analysis Zones (TAZ)[12] level.

6. Empirical Strategy

To estimate the impacts of the introduction of the BRT on individual level employment outcomes we use a difference-in-differences (DID) approach, comparing individuals before and after the introduction of the BRT living in treatment and control areas. We identify individuals living in treatment or control areas by using the geographic coordinates (centroid of the city block) for each household surveyed in the ENAHO, calculating the Euclidian distances of the household to the: i) closest BRT station and ii) closest BRT feeder line. This allows defining areas of influence of

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[9] 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.

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

[11] 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.

[12] 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).

the BRT, as the treatment areas, and areas less likely to be influenced by the BRT as the control areas.

Treatment areas are defined as those within 1.5 km of the BRT system. This cutoff is based upon the distribution of walk times to access the system, according to the 2011 Lima urban mobility OD survey, which indicates that 99% of BRT users in Lima walk 20 minutes or less to reach the system[13], and considering the standard convention of an average walk speed of 5km/h (Levine and Norenzayan, 1999). Specifically, we define two types of treatment areas, depending on the component of the system being evaluated. That is, areas within 1.5 km of the trunk line, and areas within 1.5 km of the feeder lines.[14] Even though the trunk and feeders are designed to operate as a system (with time transfers and integrated tariffs), our analysis concentrates on each of them separately because the two components of the system have distinct operational characteristics and services quality. The trunk service operates on a segregated highway, has an off-board payment system and offers other features to accelerate wait and travel speeds. In contrast, the feeder service operates in mixed traffic, has an on-board payment system, and has no signal prioritization. Thus, wait times and slower in-vehicle travel times differentiate the two components of the BRT system. This means that while an individual living in the feeder area, may have increased accessibility to the center due to the lowered cost to access the trunk line, absent the service, monetary and travel time costs are still higher (per km) than for an individual living within walking distance of a trunk station.

To select areas that can serve as controls for the treated areas, we identify areas not or less affected by the introduction of the BRT. For this, we leave a buffer of 500 meters between 1.5 km and 2 km of distance to the BRT, to account for the very small number of cases showing some individuals walking to the BRT from further distances than 1.5 km, in the 2011 OD survey. We set as control areas those between 2 km and 6 km from the BRT. Given that Line 1 of the metro in Lima runs parallel and relatively closely to the BRT trunk, we drop from the sample those individuals living up to 1.5 km from the Metro Line 1 light rail. Figure 1 shows, in blue for the trunk line and in light blue for feeder lines, the treatment areas, and in red and yellow (trunk and feeder lines respectively) the control areas. As we perform analyses for the trunk line separately from

[13] The survey indicates that 99% of passengers walk no more than 20 minutes and 90% walk 12 minutes or less to reach the BRT system.

[14] Since we do not have georeferenced data on feeder stops, we calculate the shortest distance to a feeder line. Given that feeder stops may be spaced 500 m apart, this may lead to an underestimation of the actual Euclidian distance to the stop.

those for the feeder lines, while the treatment area of influence can be only for trunk or feeder (individuals who fall under both are assigned to trunk[15]), the control areas could be used for either analysis, if they are within the boundaries imposed in the analysis.

We estimate for each component of the BRT system (where s refers to the system component being analyzed, i.e. trunk line or feeder lines) a DID equation of the form:

$$Y_{sit} = \alpha_s + \gamma_s P_{st} + \delta_s T_{si} + \beta_s P_{st} T_{si} + \theta_s X_{sit} + \eta_{sd} + \varepsilon_{sit} \quad (1)$$

where Y_{sit} is a labor market outcome (employment status, job formality, job quality indicators, hours worked, labor income) of working-age (ages 18-64) individual *i* in time *t* for analysis s; P_{st} is a dummy variable equal to 1 for time periods after the BRT introduction; T_{si} is a dummy variable equal to 1 if individual *i* lives in the area of influence of component s of the BRT system and zero otherwise; X_{sit} is a vector of individual- and household-level covariates for individual *i* in time *t*; η_{sd} represents district fixed effects, to control for potential time-invariant unobserved heterogeneity at the district level (which is the level at which many planning decisions, including transport, are made); and ε_{sit} represents error terms.[16] The covariates included in X_{sit} are age, gender, dummy for married or cohabitating, dummy for single parent household, dummy for female-headed household, years of education of the household head, dummy for indigenous language spoken by the household head, number of household members, number of children under the age of 6 in the household, household dependency rate, and distance to Metro Line 1. The coefficient of interest in (1) is β_s, which represents the effect of component s of the BRT on labor market outcome Y.

Since the BRT system operation and ridership evolved significantly in the first years after opening, with a very slow ramp up since its official opening in 2010, it is interesting to understand the timing of the effects of the BRT system components. Thus, we also estimate equations similar to (1) that allow for time heterogeneity in effects:

$$Y_{sit} = \alpha_s + \sum_k \gamma_{sk} P_{skt} + \delta_s T_{si} + \sum_k \beta_{sk} P_{skt} T_{si} + \theta_s X_{sit} + \eta_{sd} + \varepsilon_{sit} \quad (2)$$

[15] Where the Euclidian distance to a feeder line and a BRT station are equal or close, we define a household as in the trunk line area of influence if the distance to the trunk station is equal to the distance to a feeder line or equal to the distance to the feeder line plus 500 m, since we assume that riders will prefer to walk 500 m than to wait for a feeder service, with longer wait times, and slower in vehicle travel times.

[16] In all regressions, we cluster the standard errors by conglomerate. This allows for arbitrary correlation of the errors among individuals living in the same conglomerate, both contemporaneously and across time.

where the *k* dummies P_{skt} are equal to 1 for different sub-periods after the introduction of the BRT (2010-2011, 2012-2014, 2015-2017) and zero otherwise, and β_{sk} are the coefficients of interest, measuring the effects of the BRT component s in each sub-period *k*.

We also explore whether there are heterogeneous effects by the conglomerate predominant SES prior to the introduction of the BRT. For this, we characterize conglomerates according to the classification by SES of each of its city blocks in the 2007 Population Census and generate a *low SES* dummy for those conglomerates with majority of blocks with low or low-middle SES classification. This allows estimating the following models capturing potential SES heterogeneity:

$$Y_{sit} = \alpha_s + \gamma_s P_{st} + \delta_s T_{si} + \pi_s E_{si} + \beta_s P_{st} T_{si} + \tau_s P_{st} E_{si} + \tau_s T_{si} E_{si} + \lambda_s P_{st} T_{si} E_{si} + \theta_s X_{sit} + \eta_{sd} + \varepsilon_{sit} \qquad (3)$$

$$Y_{sit} = \alpha_s + \sum_k \gamma_{sk} P_{skt} + \delta_s T_{si} + \pi_s E_{si} + \sum_k \beta_{sk} P_{skt} T_{si} + \sum_k \tau_{sk} P_{skt} E_{si} + \tau_s T_{si} E_{si} + \sum_k \lambda_{sk} P_{skt} T_{si} E_{si} + \theta_s X_{sit} + \eta_{sd} + \varepsilon_{sit} \qquad (4)$$

where E_{si} is the *low* SES dummy, and everything else is defined in the same way as in (1) and (2). In equations (3) and (4), respectively, we are interested now not only in the coefficients β_s and β_{sk}, but also in coefficients λ_s and λ_{sk}. While the β coefficients now capture the impacts on the conglomerates that are not *low SES*, the sum of the corresponding β and λ coefficients identify the effect of the component s of the BRT on individuals living in conglomerates with majority *low* SES blocks in 2007.[17].

Finally, there is the concern that the covariates included in a linear way in the equations may not be enough to properly account for differences in observable characteristics at baseline between treatment and control conglomerates. To address any potential bias that could be generated by comparing conglomerates that are not comparable, as a robustness check, we select in a first stage the comparable conglomerates, and then re-estimate the equations only using the selected conglomerates. 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 (i.e. the groups indicated in Figure 1). We then estimate at the

[17] As one of the potential effects of the BRT could be to cause a change in the SES composition of the conglomerates, it is important that the classification of conglomerates by SES relies on data prior to the construction of the BRT.

conglomerate-level, propensity score models for the probability of being a treated conglomerate.[18] The propensity score models are estimated separately for trunk and feeder lines, and for each of these analyses we impose that there is *overlap* 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).[19]

7. Results

In this section we first present the descriptive statistics of the outcomes and covariates used in our estimations. We then discuss the main results obtained from the DID regressions, making a distinction between impacts observed for the trunk line area versus those for the feeder areas, and report results on the heterogeneity analyses across different socio-economic status areas. In addition, we report the results of the parallel trend tests. In the Appendix we present the robustness results imposing overlap in the distributions of the propensity score for the treatment and control conglomerates, as explained above.

Table 1, Panel A, presents summary statistics for the outcome variables showing an overall good balance between treatment and control groups in the period prior to the BRT opening (2007-2009). Approximately, 70% of individuals in our sample report being employed, but less than 30% had a formal job according to INEI's definition in the 2007-2009 period. Panel A also highlights differences between trunk and feeder households, consistent with our empirical strategy of disaggregating our analyses of the two areas. A larger percentage of households living around trunk areas were employed in formal jobs and had higher levels of education compared to households living around feeder areas in the pre-BRT period.

[18] 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..

[19] 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). The values are very close to 0.10, the rule of thumb suggested by Crump et al. (2009).

Panel B in Table 1 presents summary statistics for individual and household-level characteristics in the baseline period. Again, we observe significant differences in characteristics between the influence areas around the trunk line and feeder lines. The individuals in the trunk areas are more educated (both the head and the average member), are less likely to be indigenous, are less likely to have children under age 6, are more likely to be single, and they have a lower dependency rate, which suggests the presence of young professionals in these areas. Panel B also shows the descriptive statistics for control and treatment groups at baseline before and after imposing the overlap condition. The overlap condition, as explained in the prior section, is derived from propensity score regressions at the conglomerate level. We measure variable-by-variable differences with a standardized difference in means.[20] Figures in bold indicate that the standardized difference between treated and controls is larger than 0.10. Imposing overlap reduces the differences for only a few of the covariates, particularly for distance to line 1, for the trunk line, and marital status and single parent household for the feeders.

A key advantage of DID models is that they allow for systematic differences between the treatment and comparison groups, provided these differences are not diverging over time. However, while it is not necessary for the covariates to be similar in levels between treated and control individuals, a large dissimilarity in the means at the baseline weakens the ex-ante assumption of parallel trends between the two groups upon which these models are based. To reduce this concern, we run a parallel trends test using data from the pre-BRT opening years as it will be explained later. In addition, a slight improvement in comparability is attained with the overlap for the feeders' sample, however, at a cost of large losses in statistical power. Twenty-two percent of the treated individuals for the trunk analysis and 17% of the feeder line observations are dropped due to not satisfying the overlap condition. For the control groups, the percentage of observations dropped are 43% and 28%, respectively, although the larger proportions of conglomerates dropped in the control areas is expected, given that they are more heterogeneous areas.

Turning to the analysis of the results from estimating the DID models specified in equations (1) to (4), in all cases, the regressions include the full set of individual and household-level covariates discussed in the prior section, as well as district fixed effects. Standard errors are clustered at the

[20] The standardized (mean) difference is a measure of distance between two group means. It is often used as a balance measure of individual covariates before and after propensity score matching. As it is standardized, comparison across variables on different scales is possible. It is defined as $\Delta_{ct} = \frac{\mu_t - \mu_c}{\sqrt{\sigma_t^2 + \sigma_c^2/2}}$ (Rosembaum and Rubin, 1985)

conglomerate level. All the tables follow the same structure, with each column representing the regressions using a different outcome, and the top panel presenting the trunk line results and the bottom panel presenting the feeder lines results. We report only the estimated coefficients of interest ($\hat{\beta}$) in most cases (the exception being Tables 6 and 7, see below), in the interest of space.[21] All tables show the specification in equation (1), where the post period is defined as 2010 to 2017, and equation (2) for the sub periods 2010-2011, 2012-2014 and 2015-2017, except for Tables 6 and 7 that are based on equations (3) and (4), for the same periods.

Table 2 displays the estimated impact on labor market outcomes. We find large positive and statistically significant effects for employment, hours, and earnings for individuals living near the trunk line. Column 1 shows coefficients for estimated impacts on employment. Employment increases, on average, by 3.9 percentage points in the entire post period 2010 to 2017. When we look at differential impacts by subperiod, we see impacts of 3.8 percentage points in the period 2010-11, 3.5 percentage points for 2012-2014, growing to 4.3 percentage points in the 2015-2017 period for the trunk treatment areas. For the feeders, although the coefficients are positive for the employment outcome, they are small and statistically insignificant.

Columns 2 and 3 of Table 2 display impacts on the IHS of hours and earnings. As their units are equivalent to a logarithmic transformation, the coefficients can be interpreted as percentage changes.[22] Hours worked are estimated to increase by 19% on average in the post period along the trunkline area and earnings by 32% for the post period (2010-2017). The largest increases in hours worked are observed in the first period (2010-2011), 24% increase, tapering off to 18% increases for the latter two periods, 2012-2014, and 2015-2017. Earnings increase by 30% between 2010-2011, 29% between 2012-2014, and 37%, in latter period, between 2015-2017. For the feeders, the coefficient for hours worked indicates an increase of 8.1% percentage point increase for the post period, marginally significant, and a statistically significant 12.4% increase for the 2010-2011 period. The two latter periods appear as not statistically significant, 9.1% for

[21] The full results for all regressions can be made available by the authors upon request.

[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 0.32 the effect is calculated as exp (0.32)-1=0.38. 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.

2012-2014 and 4.9% for 2015-2017.The coefficients on earnings are all relatively small and not statistically significant for the feeder lines.

Table 3 presents the results for formal employment, as defined by INEI, and formality characteristics of the firms (keeps accounting books, is registered, or has more than five employees) and the benefits of the employees (contributes to social security or has a formal contract). For these outcomes we do not find statistically significant effects, in any of the outcomes, suggesting that the BRT has no impacts on formal employment or access to higher quality jobs.

The labor market effects identified in Table 2 could be driven by compositional changes in the characteristics of the individuals living in areas closer to the BRT system, rather than by improvements in labor outcomes for those living in those areas at baseline. To test this hypothesis, in Table 4 we estimate models similar to those in equations (1) and (2) but using as dependent variables years of education and a dummy for whether the individual has high school level education or more. We use education to test for compositional changes as this is an outcome that should barely change over time for adults. Thus, any change in education levels would suggest that population of a different education level is moving to live in areas closer to the BRT system. The results show that educational levels have not changed differentially for the trunk or feeder treatment areas between the pre and post-BRT periods when compared to control areas. This implies that we do not observe differential compositional changes between the treated and control areas, at least as measured by education.

As mentioned before, when running DID regressions it is important to test whether the parallel trends identifying assumption holds. If the treated and control groups were not following parallel trends prior to the BRT opening, then it would not be advisable to use the observed outcomes post-treatment for the controls as a valid counterfactual for the post-treatment outcomes for the treated group. Exploiting the fact that we have three years of pre-treatment (i.e. pre-BRT) data, we run DID regressions using only the pre-treatment years 2007-2009 and estimate a DID coefficient assuming that the year 2009 was the treatment year. This is similar to a placebo test. If the treated and control individuals are following parallel trends in the outcomes, then we would expect the “treatment effect” associated to the year 2009 to be zero. We test this in Table 5, and find that the regressions *cannot* reject the hypothesis that the dependent variables were following parallel trends in the pre-BRT period, both for the trunk and the feeder areas. We also include compositional changes and one of the formality outcomes reported in Table 3, with similar results, confirming that overall our empirical strategy is sound.

In Table 6 and 7 we present the results for the main outcomes of interest disaggregated by socio-economic status for trunk and feeder lines, respectively. As explained before, we do this by classifying conglomerates as low SES when a majority of the blocks in that conglomerate were deemed as low SES by the INEI according to the 2007 population census data. This allows estimating the models specified in equation (3) and (4), using a low SES dummy as interaction term. In both Tables 6 and 7 we present the estimated treatment effects, which are the corresponding $\hat{\beta}$ coefficients in the case of the medium and high SES conglomerates (Panel B), or the corresponding $\hat{\beta} + \hat{\lambda}$ sum of coefficients in the case of the low SES conglomerates (Panel A).

The results for the trunkline, presented in Table 6, show that the impacts reported earlier, for the entire sample, arise mostly from the medium and high SES conglomerates. This is explained by the fact that we have a very small number of low SES households in the trunk sample —only 10% of the individuals within the treated trunk area and 33% of those in the control trunk area live in conglomerates classified as low SES in 2007. For this very small number of individuals living in low SES conglomerates in the trunk treatment area we do observe quite large, although only marginally significant, positive impacts on employment, earnings and formality (with no statistically significant difference between the results in Panels A and B). However, as columns (5) and (6) in Table 6 suggest, these impacts seem to be driven by changes in the education composition of the population in these areas. No changes in composition are observed for the medium and high SES.

Table 7 reports the results for the feeder lines, where we have a large number of individuals living in low SES conglomerates (close to 47%). In this case, we find no statistically significant impacts for populations in either lower or higher income neighborhoods and no evidence of compositional changes. This is consistent with the prior results for the feeder lines (discussed in Tables 2 and 3) and imply that, despite the expectation that the BRT feeders had the potential to connect poor populations to labor opportunities, we cannot find any evidence of these impacts for populations living in lower socio-economic status areas.

Finally, note that in Appendix Table A1 we re-estimate the models presented in Table 2, Table 3 (for INEI's formal employment definition) and Table 4, after imposing the overlap condition. As explained above, imposing overlap implies that a large proportion of the observations in the sample are dropped, with its corresponding decrease in power. We find that even though some coefficients lose some significance, all the prior results are maintained. This indicates that our results are robust and not driven by differences in observed (pre-BRT) characteristics of the treatment and control conglomerates.

8. Discussion and Conclusion

This paper studies the impacts of the introduction of the *Metropolitano*, the first BRT system in Lima, on labor market outcomes. We consider both changes in the extensive margin, measured by effects on the rate of employment, as well as changes in the intensive margin considering impacts on hours worked and earnings. Given that the BRT connects lower income neighborhoods in the north and south of Lima with the city center, where most formal and higher-paid jobs are located, the study also measures effects on access to formal employment.

The empirical strategy follows a difference-in-differences (DID) approach that involves comparing changes in employment outcomes over time between individuals living in areas closer to the BRT trunk or to feeder lines (within 1.5 km) versus those living farther away from this system (between 2 and 6 km). Multiple cross-sections from the Peruvian National Household Survey are used for the analysis, including pre and post-BRT periods. We conduct robustness checks based on obtaining a subsample of individuals that are as similar as possible across conglomerate-level characteristics at baseline and test that the parallel trends assumption, underlying the DID strategy, holds.

Our results indicate that there are large and significant effects on the employment rate, hours worked and monthly labor income, particularly for those individuals living within 1.5 Km distance from the trunkline. In the post period 2010 to 2017, employment rate increases by 3.9 percentage points, hours worked increased by 19% and monthly income by 32%. These effects materialize early in the implementation of the system and continue growing over the study period. For individuals in the feeder areas we find no effects on employment or earnings, and only marginally significant effects on hours worked. The findings on employment outcomes do not seem to be driven by compositional changes, particularly as measured by changes in the levels of education of the individuals living in treatment and control areas. When looking at changes in the quality of employment, we find no evidence of increases in formality rates either for trunk or feeder areas. Parallel pre-BRT trends for treatment and control groups suggest that the identifying assumptions of the DID model are valid and robustness checks including overlap considerations confirm the results.

As BRT investments often seek to include poor and socially vulnerable groups, who more heavily depend on public transit, we also explore whether there are differential effects for individuals living in lower income neighborhoods at the baseline. Results do not show any evidence that individuals in lower socio-economic areas around the feeders experienced positive and differential impacts from others. This seems to suggest that although the provision of feeders and an integrated tariff structure in the design of BRT systems may play important roles in the promotion of social inclusion and poverty reduction, additional and complementary policies and interventions in other sectors might be needed to help materialize positive labor market impacts for these populations.

Within the heterogeneity analysis conducted by socioeconomic status, it is worth highlighting the finding that there are the significant changes observed in the composition of the population in low income neighborhoods around the trunkline. No other changes in composition were observed in feeder areas overall and in medium and high SES conglomerates around the trunkline. These changes in composition are consistent with the hypothesis that urban transport investments may increase the value of centrally located land thus pushing poor populations to the outskirts of the city. Work in progress, also for the case of Lima, seems to confirm that there are important land-use changes and increases in prices around BRT areas (Martinez et al., 2018b).

A key policy question to be explored in the future is the duality in labor market impacts between the trunk and feeder lines. For example, future research could explore the role of the integrated tariff and targeted fare subsidies for lower SES groups in improving access to jobs. In addition, it would be important to study the effects of operational enhancements, such as improving physical coverage of the system by strengthening feeder routes and increasing frequency during late night or off-peak hours, which could be relevant in providing access to employment in occupations involving night or part-time work. Even though this study does not provide answers to all these additional questions, policy makers and urban transport planners should benefit from our findings, as they establish that the BRT trunk line is key for improving labor market outcomes of its users and provide evidence on benefits that should be considered when deciding BRT investments.

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Figure 1. BRT Trunk and Feeder Lines: Treatment and Control Areas

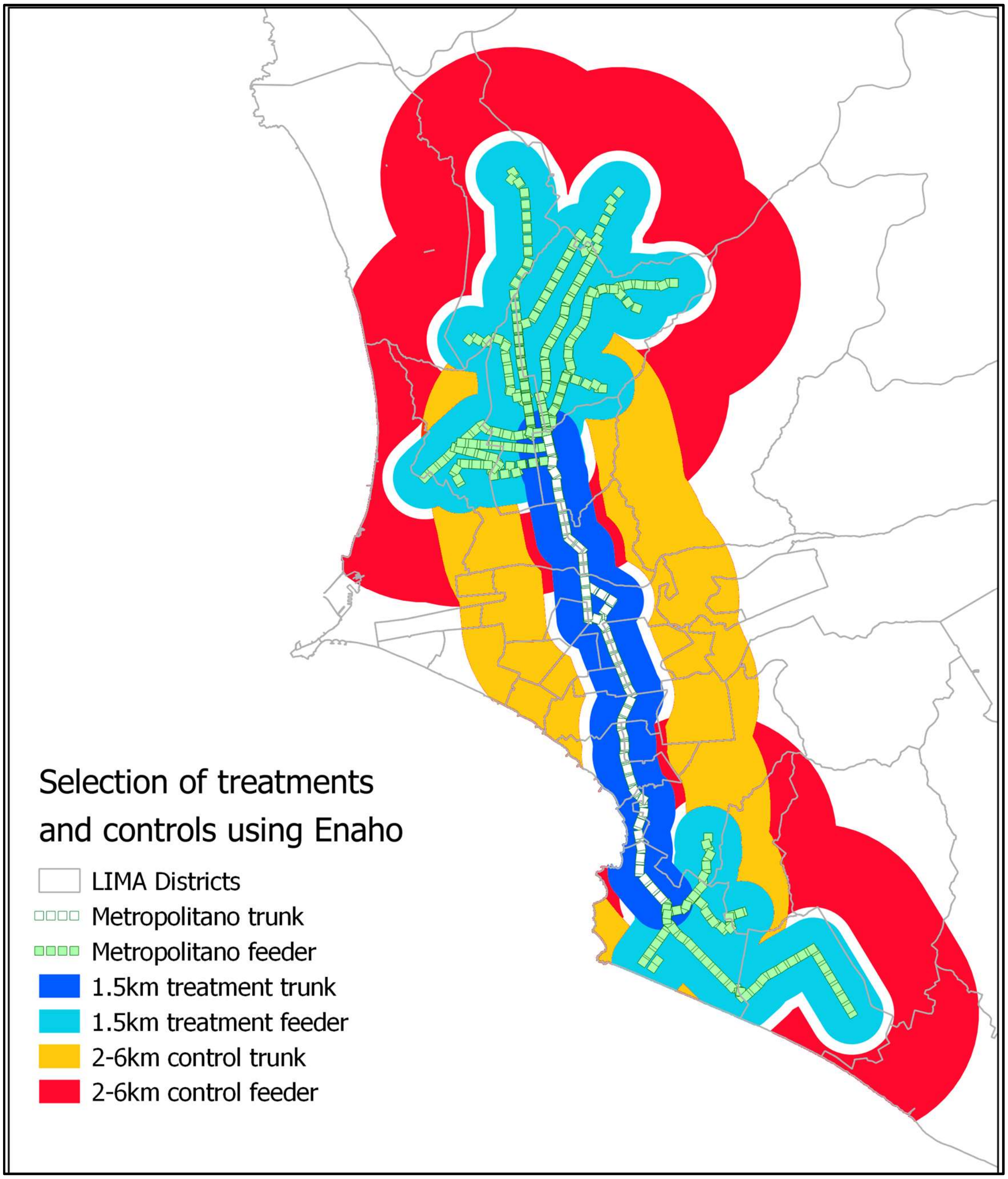

Table 1. Descriptive statistics outcomes and covariates

Panel A. Outcomes

	BRT Trunk				BRT Feeders			
	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 outcome								
Employment	0.73	0.72	0.70	0.73	0.73	0.72	0.71	0.72
Weekly hours worked	34.7	32.1	32.4	31.9	36.4	33.3	33.9	33.0
Monthly earnings (Soles 2017)	1,381	1,627	1,307	1,708	1,005	1,194	1,008	1,251
Job quality Outcomes								
Formal employment (INEI definition)	0.28	0.36	0.28	0.37	0.22	0.29	0.24	0.32
Firm keeps accounting books	0.32	0.36	0.31	0.37	0.27	0.32	0.27	0.32
Firm is registered	0.27	0.42	0.28	0.43	0.22	0.37	0.22	0.37
Firm has more than 5 employees	0.36	0.40	0.37	0.39	0.32	0.37	0.32	0.36
Employee contributes to social security	0.35	0.44	0.36	0.44	0.28	0.37	0.29	0.37
Employee has a formal contract	0.30	0.37	0.30	0.36	0.25	0.31	0.25	0.31
Composition outcomes								
Years of education	11.8	12.4	12.1	12.6	10.5	11.0	11.2	11.7
High school education level or more	0.79	0.85	0.83	0.88	0.67	0.75	0.76	0.81
Observations	2,118	8,806	1,610	7,403	2,715	11,357	3,518	11,756

Panel B. Covariates balance in 2007-2009

	BRT Trunk				BRT Feeders			
	Before overlap		After overlap		Before overlap		After overlap	
	Controls	Treated	Controls	Treated	Controls	Treated	Controls	Treated
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Age	37.0	38.2	37.2	38.3	36.3	37.2	36.5	37.1
Female	0.54	0.54	0.54	0.54	0.52	0.52	0.52	0.52
Indigenous ethnicity	**0.08**	**0.06**	**0.08**	**0.05**	**0.13**	**0.10**	**0.12**	**0.11**
Children under 6 years old in the household	0.44	0.39	0.41	0.33	0.53	0.45	0.49	0.48
Single parent household	**0.08**	**0.05**	**0.07**	**0.05**	**0.07**	**0.06**	0.07	0.07
Married or cohabiting with partner	**0.53**	**0.47**	**0.52**	**0.47**	**0.58**	**0.55**	0.55	0.55
Number of household members	4.81	4.58	4.58	4.45	5.14	4.98	5.23	5.00
Years of education of the household head	11.3	11.8	11.6	11.9	9.7	10.5	9.8	10.2
Household head is female	**0.22**	**0.27**	**0.22**	**0.27**	**0.22**	**0.20**	**0.23**	**0.20**
Dependency rate	0.36	0.35	0.35	0.34	0.41	0.40	0.39	0.40
Distance to Line 1 station	**6.12**	**3.83**	5.46	4.12	8.75	6.49	7.33	6.60
Observations	2,118	1,610	1,213	1,262	2,715	3,518	1,964	2,922

Note: Figures in bold in Panel B indicate that the standarized difference between treated and controls is larger than 0.10.

Table 2. Impacts on Employment Outcomes

Panel A. BRT trunk

Coefficient	**Employment**	**IHS(Hours)**	**IHS(Earnings)**
	(1)	**(2)**	**(3)**
(a) 2010-2017 x treated BRT trunk	0.039***	0.190***	0.318***
	(0.012)	(0.061)	(0.095)
(b) 2010-2011 x treated BRT trunk	0.038**	0.237***	0.297**
	(0.016)	(0.081)	(0.132)
(b) 2012-2014 x treated BRT trunk	0.035***	0.184***	0.269**
	(0.013)	(0.067)	(0.107)
(b) 2015-2017 x treated BRT trunk	0.043***	0.178**	0.368***
	(0.014)	(0.074)	(0.115)
Observations	19,937	19,937	19,937

Panel B. BRT feeders

Coefficient	**Employment**	**IHS(Hours)**	**IHS(Earnings)**
	(1)	**(2)**	**(3)**
(a) 2010-2017 x treated BRT feeder	0.006	0.081*	0.039
	(0.010)	(0.048)	(0.074)
(b) 2010-2011 x treated BRT feeder	0.013	0.124**	0.125
	(0.013)	(0.060)	(0.096)
(b) 2012-2014 x treated BRT feeder	0.005	0.091	0.016
	(0.012)	(0.055)	(0.087)
(b) 2015-2017 x treated BRT feeder	0.004	0.049	0.035
	(0.012)	(0.057)	(0.089)
Observations	29,346	29,346	29,346

Notes:
(a) DID coefficient from regressions using one post-BRT period
(b) DID coefficients from regressions dividing the post-BRT period in three sub-periods
Standard errors in parentheses, clustered at the conglomerate level, *** p<0.01, ** p<0.05, * p<0.1
IHS() refers to the inverse hyperbolic sine transformation

Table 3. Impacts on Job Quality Outcomes

Panel A. BRT trunk

Coefficient	Formal (INEI definition)	Formality based on firm characteristics: Keeps accounting books	Formality based on firm characteristics: Registered	Formality based on firm characteristics: More than five employees	Formality based on employee benefits: Contributes to social security	Formality based on employee benefits: Has a formal contract
	(1)	(2)	(3)	(4)	(5)	(6)
(a) 2010-2017 x treated BRT trunk	0.011	0.020	-0.004	-0.016	0.002	0.007
	(0.019)	(0.019)	(0.020)	(0.019)	(0.021)	(0.019)
(b) 2010-2011 x treated BRT trunk	-0.016	0.012	-0.018	-0.033	-0.039	-0.020
	(0.027)	(0.024)	(0.025)	(0.025)	(0.030)	(0.027)
(b) 2012-2014 x treated BRT trunk	0.012	0.015	-0.007	-0.020	0.010	0.013
	(0.022)	(0.021)	(0.022)	(0.022)	(0.023)	(0.022)
(b) 2015-2017 x treated BRT trunk	0.022	0.026	0.005	-0.006	0.011	0.012
	(0.022)	(0.022)	(0.022)	(0.021)	(0.022)	(0.022)
Observations	19,937	19,937	19,937	19,937	19,937	19,937

Panel B. BRT feeders

Coefficient	Formal (INEI definition)	Formality based on firm characteristics: Keeps accounting books	Formality based on firm characteristics: Registered	Formality based on firm characteristics: More than five employees	Formality based on employee benefits: Contributes to social security	Formality based on employee benefits: Has a formal contract
	(1)	(2)	(3)	(4)	(5)	(6)
(a) 2010-2017 x treated BRT feeder	0.009	-0.004	0.002	-0.013	-0.010	-0.003
	(0.014)	(0.015)	(0.016)	(0.014)	(0.014)	(0.015)
(b) 2010-2011 x treated BRT feeder	0.026*	0.022	0.023	0.016	-0.009	0.017
	(0.015)	(0.018)	(0.018)	(0.017)	(0.018)	(0.018)
(b) 2012-2014 x treated BRT feeder	-0.008	-0.014	-0.009	-0.030*	-0.015	-0.019
	(0.016)	(0.019)	(0.018)	(0.017)	(0.017)	(0.017)
(b) 2015-2017 x treated BRT feeder	0.026	0.000	0.020	-0.008	-0.003	0.009
	(0.017)	(0.018)	(0.018)	(0.017)	(0.017)	(0.017)
Observations	29,346	29,346	29,346	29,346	29,346	29,346

Notes:
(a) DID coefficient from regressions using one post-BRT period; (b) DID coefficients from regressions dividing the post-BRT period in three sub-periods
Standard errors in parentheses, clustered at the conglomerate level, *** p<0.01, ** p<0.05, * p<0.1

Table 4. Composition Effects

Panel A. BRT trunk

Coefficient	**Years of education**	**High school education level or more**
	(1)	**(2)**
(a) 2010-2017 x treated BRT trunk	0.098	0.005
	(0.151)	(0.017)
(b) 2010-2011 x treated BRT trunk	0.151	0.002
	(0.173)	(0.021)
(b) 2012-2014 x treated BRT trunk	0.130	0.013
	(0.166)	(0.019)
(b) 2015-2017 x treated BRT trunk	0.053	-0.001
	(0.169)	(0.019)
Observations	19,937	19,937

Panel B. BRT feeders

Coefficient	**Years of education**	**High school education level or more**
	(1)	**(2)**
(a) 2010-2017 x treated BRT feeder	0.045	-0.012
	(0.107)	(0.015)
(b) 2010-2011 x treated BRT feeder	0.196	0.003
	(0.125)	(0.018)
(b) 2012-2014 x treated BRT feeder	0.044	-0.009
	(0.119)	(0.016)
(b) 2015-2017 x treated BRT feeder	0.008	-0.016
	(0.129)	(0.018)
Observations	29,346	29,346

Notes:
(a) DID coefficient from regressions using one post-BRT period
(b) DID coefficients from regressions dividing the post-BRT period in three sub-periods
Standard errors in parentheses, clustered at the conglomerate level, *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 5. Tests of Parallel Trends Assumption

Panel A. BRT trunk

Coefficient	Employment	Formal (INEI definition)	IHS(Hours)	IHS(Earnings)	Years of education	High school education level or more
	(1)	(2)	(3)	(4)	(5)	(6)
(a) Post placebo x treated BRT trunk	0.013	0.019	0.164*	0.092	-0.012	-0.008
	(0.022)	(0.034)	(0.099)	(0.183)	(0.208)	(0.025)
Observations	3,728	3,728	3,728	3,728	3,728	3,728

Panel B. BRT feeders

Coefficient	Employment	Formal (INEI definition)	IHS(Hours)	IHS(Earnings)	Years of education	High school education level or more
	(1)	(2)	(3)	(4)	(5)	(6)
(a) Post placebo x treated BRT feeder	-0.013	-0.014	-0.098	-0.098	-0.028	-0.015
	(0.017)	(0.023)	(0.075)	(0.129)	(0.149)	(0.021)
Observations	6,233	6,233	6,233	6,233	6,233	6,233

Notes:
(a) DID coefficient from regressions using 2009 as (placebo) treatment year. The regressions use only data from 2007 to 2009.
Standard errors in parentheses, clustered at the conglomerate level, *** p<0.01, ** p<0.05, * p<0.1

Table 6. Treatment Heterogeneity: Low SES v. Medium and High SES - Trunk Line

Panel A. Low SES

Coefficient	Employment	Formal (INEI definition)	IHS(Hours)	IHS(Earnings)	Years of education	High school education level or more
	(1)	(2)	(3)	(4)	(5)	(6)
(a) 2010-2017 x treated BRT feeder	0.053*	0.052*	0.165	0.494*	0.627***	0.123***
	(0.030)	(0.029)	(0.159)	(0.297)	(0.218)	(0.025)
(b) 2010-2011 x treated BRT feeder	-0.004	0.063	-0.096	0.112	1.262***	0.108***
	(0.033)	(0.044)	(0.146)	(0.290)	(0.230)	(0.037)
(b) 2012-2014 x treated BRT feeder	0.063*	0.060	0.254	0.551	0.663**	0.157***
	(0.038)	(0.037)	(0.167)	(0.335)	(0.301)	(0.035)
(b) 2015-2017 x treated BRT feeder	0.064*	0.037	0.166	0.557*	0.319	0.085**
	(0.037)	(0.046)	(0.197)	(0.336)	(0.284)	(0.036)
Observations	19,937	19,937	19,937	19,937	19,937	19,937

Panel B. Medium and High SES

Coefficient	Employment	Formal INEI	IHS(Hours)	IHS(Earnings)	Years of education	High school education level or more
	(1)	(2)	(3)	(4)	(5)	(6)
(a) 2010-2017 x treated BRT feeder	0.039***	0.003	0.168**	0.294***	0.027	-0.009
	(0.014)	(0.021)	(0.073)	(0.111)	(0.172)	(0.017)
(b) 2010-2011 x treated BRT feeder	0.047**	-0.015	0.270***	0.340**	-0.081	-0.025
	(0.021)	(0.030)	(0.101)	(0.165)	(0.199)	(0.019)
(b) 2012-2014 x treated BRT feeder	0.035**	-0.003	0.151*	0.242*	0.043	-0.011
	(0.016)	(0.024)	(0.080)	(0.128)	(0.190)	(0.019)
(b) 2015-2017 x treated BRT feeder	0.039**	0.020	0.147*	0.328**	0.072	0.001
	(0.017)	(0.023)	(0.084)	(0.132)	(0.183)	(0.019)
Observations	19,937	19,937	19,937	19,937	19,937	19,937

Notes:
(a) DID impacts from regressions using one post-BRT period
(b) DID impacts from regressions dividing the post-BRT period in three sub-periods
Standard errors in parentheses, clustered at the conglomerate level, *** p<0.01, ** p<0.05, * p<0.1
IHS() refers to the inverse hyperbolic sine transformation

Table 7. Treatment Heterogeneity: Low SES v. Medium and High SES - Feeder Lines

Panel A. Low SES

Coefficient	**Employment**	**Formal (INEI definition)**	**IHS(Hours)**	**IHS(Earnings)**	**Years of education**	**High school education level or more**
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
(a) 2010-2017 x treated BRT feeder	-0.002	0.021	0.036	-0.009	0.144	-0.001
	(0.013)	(0.019)	(0.064)	(0.095)	(0.136)	(0.022)
(b) 2010-2011 x treated BRT feeder	0.001	0.020	0.063	0.000	0.205	-0.002
	(0.017)	(0.022)	(0.081)	(0.125)	(0.175)	(0.029)
(b) 2012-2014 x treated BRT feeder	-0.002	0.006	0.057	-0.009	0.095	-0.001
	(0.015)	(0.022)	(0.075)	(0.111)	(0.156)	(0.023)
(b) 2015-2017 x treated BRT feeder	-0.003	0.035	0.002	-0.017	0.155	-0.003
	(0.015)	(0.022)	(0.073)	(0.109)	(0.156)	(0.025)
Observations	29,346	29,346	29,346	29,346	29,346	29,346

Panel B. Medium and High SES

Coefficient	**Employment**	**Formal INEI**	**IHS(Hours)**	**IHS(Earnings)**	**Years of education**	**High school education level or more**
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
(a) 2010-2017 x treated BRT feeder	0.003	0.001	0.060	0.023	0.076	-0.000
	(0.019)	(0.023)	(0.085)	(0.146)	(0.183)	(0.021)
(b) 2010-2011 x treated BRT feeder	0.029	0.074***	0.203	0.339	0.225	0.006
	(0.028)	(0.027)	(0.133)	(0.215)	(0.189)	(0.024)
(b) 2012-2014 x treated BRT feeder	0.006	-0.013	0.093	0.025	0.147	0.003
	(0.020)	(0.027)	(0.090)	(0.162)	(0.211)	(0.024)
(b) 2015-2017 x treated BRT feeder	-0.007	0.021	-0.008	-0.013	0.061	0.004
	(0.022)	(0.027)	(0.102)	(0.174)	(0.207)	(0.024)
Observations	29,346	29,346	29,346	29,346	29,346	29,346

Notes:
(a) DID impacts from regressions using one post-BRT period
(b) DID impacts from regressions dividing the post-BRT period in three sub-periods
Standard errors in parentheses, clustered at the conglomerate level, *** $p<0.01$, ** $p<0.05$, * $p<0.1$
IHS() refers to the inverse hyperbolic sine transformation

Appendix Table A1. Robustness: Main Outcomes After Imposing Overlap

Panel A. BRT trunk

Coefficient	Employment	Formal (INEI definition)	IHS(Hours)	IHS(Earnings)	Years of education	High school education level or more
	(1)	(2)	(3)	(4)	(5)	(6)
(a) 2010-2017 x treated BRT trunk	0.037**	0.007	0.176**	0.259**	0.150	0.011
	(0.014)	(0.023)	(0.077)	(0.115)	(0.185)	(0.019)
(b) 2010-2011 x treated BRT trunk	0.033*	0.002	0.209**	0.221	0.314	0.014
	(0.019)	(0.031)	(0.099)	(0.158)	(0.212)	(0.024)
(b) 2012-2014 x treated BRT trunk	0.032*	0.003	0.177**	0.207	0.122	0.015
	(0.017)	(0.026)	(0.085)	(0.135)	(0.202)	(0.022)
(b) 2015-2017 x treated BRT trunk	0.043**	0.023	0.162*	0.338**	0.155	0.011
	(0.017)	(0.026)	(0.089)	(0.141)	(0.202)	(0.021)
Observations	13,406	13,406	13,406	13,406	13,406	13,406

Panel B. BRT feeders

Coefficient	Employment	Formal INEI	IHS(Hours)	IHS(Earnings)	Years of education	High school education level or more
	(1)	(2)	(3)	(4)	(5)	(6)
(a) 2010-2017 x treated BRT feeder	0.004	0.009	0.052	0.016	0.127	0.007
	(0.011)	(0.015)	(0.052)	(0.083)	(0.116)	(0.016)
(b) 2010-2011 x treated BRT feeder	0.014	0.033*	0.124*	0.129	0.293**	0.016
	(0.015)	(0.017)	(0.068)	(0.107)	(0.142)	(0.021)
(b) 2012-2014 x treated BRT feeder	0.003	-0.009	0.073	-0.000	0.056	0.003
	(0.013)	(0.018)	(0.060)	(0.097)	(0.133)	(0.017)
(b) 2015-2017 x treated BRT feeder	-0.000	0.027	-0.005	-0.002	0.159	0.013
	(0.013)	(0.019)	(0.064)	(0.102)	(0.136)	(0.018)
Observations	22,982	22,982	22,982	22,982	22,982	22,982

Notes:
(a) DID coefficient from regressions using one post-BRT period
(b) DID coefficients from regressions dividing the post-BRT period in three sub-periods
Standard errors in parentheses, clustered at the conglomerate level, *** p<0.01, ** p<0.05, * p<0.1
IHS() refers to the inverse hyperbolic sine transformation