TRR
JOURNAL OF THE TRANSPORTATION RESEARCH BOARD

*Research Article*

Transportation Research Record
1–13

DOI: 10.1177/03611981211029650
journals.sagepub.com/home/trr
SAGE

# Impacts of Light Rail Transit on Labor Participation and Housing Affordability in the U.S.: Longitudinal Analysis Using Propensity Score Matching

**Keuntae Kim[1], Keunhyun Park[2], and Arthur C. Nelson[3]**

**Abstract**

Planners and planning scholars have debated the effects of public transit on changes in various employment outcomes. However, few studies have tried to understand how public transit affects employment changes in a community while accounting for housing costs at the same time. As an update to and methodological advance on early studies, this study aims to measure light rail transit (LRT) systems' impacts on the change in labor participation and housing affordability. This study uses the decennial Census and 5-year American Community Survey (ACS) data at the block group level and conducts propensity score matching in 12 selected LRT systems across the U.S. opened between 2000 and 2010. By comparing growth rates of the average weeks worked and the median gross rent between treatment and control groups, the results show that an introduction of an LRT station increases the average weeks worked—a measure of labor participation—while not raising the median gross rent. Further analysis also shows that the increased average weeks worked after operation of LRT systems is a result of an increase in the percentage of full-time and year-round workers and a decrease in the proportion of part-time and part-year workers. Ultimately, the findings provide planners and policymakers with a better understanding of the effects of LRT systems on the economic stability of urban communities.

The suburbanization of housing and jobs in the U.S. metropolitan areas has been mentioned as an explanation for many problematic planning trends. Problematic trends include longer work trips, an increase in automobile trip demand, lack of workers in the suburbs, and unemployment in the inner city (*1*, *2*). For low-income and minority populations, the uneven shift of jobs and housing from the city core to suburbs has limited their access to stable job opportunities and affordable housing units because neither can they afford housing costs in suburban areas nor do they have an automobile to commute to a workplace or meet their travel demands (*3*, *4*). To fill these gaps, transportation planning and policies have focused on providing low-income workers and disadvantaged neighborhoods with access to jobs through multiple travel modes, especially constructing new fixed-guideway transit systems or extending existing transit routes. Since the 1990s, the rapid growth of public transit development projects has catalyzed enhancement of accessibility to diverse economic opportunities (*5*). Empirical research has also shown that better accessibility to various types of public transit systems or routes can significantly influence changes in household income and the duration of employment, which in turn leads to having better economic outcomes for a community in the long term.

In the context of urban planning history in the U.S., fixed-guideway public transit development as a catalyst for better economic outcomes and housing affordability is not new. Providing diverse public transportation choices for better economic outcomes has been adopted along with the civil rights movement for achieving transportation equity throughout urbanized areas. After the outbreak of riots and demonstrations in Los Angeles in the 1960s, the McCone Commission report in 1965

[1]Department of City and Metropolitan Planning, University of Utah, Salt Lake City, UT
[2]Department of Landscape Architecture and Environmental Planning, Utah State University, Logan, UT
[3]College of Architecture, Planning and Landscape Architecture, University of Arizona, Tucson, AZ

**Corresponding Author:**
Keuntae Kim, keuntae.kim@utah.edu

argued that inadequate provision of public transportation systems was one of the reasons for the high rate of unemployment among African American communities (*6*). Since this report, subsequent legislative acts—from the Intermodal Surface Transportation Efficiency Act (ISTEA) in 1991 to the Fixing America's Surface Transportation (FAST) Act in 2015—have acknowledged the importance of providing long-term investment in transportation infrastructure planning for workforce development of low-income populations, which leads to an increase in labor participation as a result of making diverse and full-time job opportunities available by public transit (*7*, *8*). These legislative efforts have considered public transit development as a catalyst for overcoming the spatial mismatch between residence and workplace of low-income and minority workers who have limited mobility options and seek to secure more stable and full-time jobs, to create stable economic conditions for them.

Housing affordability is another economic outcome affected by the proximity of fixed-guideway public transit stops or routes. Empirical studies have identified that the added values of residential property and rent price tend to be higher close to the transit station and get lower as the distance from transit station increases, worsening housing affordability for existing low-income residents who live near transit stops (*9*, *10*). Using microlevel and time-series public transit trip data, recent studies have extended discussions over the relationships between proximity to transit stops and residential property values into an analysis of public transit impacts on overall neighborhood change—such as transit-induced gentrification (*11*, *12*), socioeconomic inequality in communities of color or disadvantaged neighborhoods (*13*, *14*), the uneven distribution of poverty and neighborhood/racial/ethnicity segregation (*15*), and public health and physical activity related to active transportation modes (*16*). While fixed-guideway transit development aims to improve job access for low-income and minority populations in disadvantaged neighborhoods, housing affordability close to a transit station is low. Lack of housing affordability near an LRT station forces existing low-income households to move out to other neighborhoods with poor access to public transit, and thus less diverse and stable employment. It is one of the dilemmas that planners and policymakers face when considering the socioeconomic impacts of public transit systems.

Nevertheless, there has been little research that analyzes the effects of access to public transit on employment and housing affordability together. Using cross-sectional regression analysis, the relationships among transit access, the level of employment, and housing affordability have been mixed. Some argue that affordable transportation options lower the transportation cost burden for low-income households while giving them access to more opportunities (*17*, *18*). Others argue that improved location efficiencies because of transit access are passed onto both households and businesses, which causes a geographical imbalance between affordable housing locations and jobs and makes it hard for low-income households to maintain their housing near transit stops despite the reduction in transportation costs (*19*, *20*). In particular, recent literature using microdata of affordable housing locations near frequent transit networks shows the great variance of housing affordability as a function of the distance from the nearest transit stops, depending on differences in urban form and development patterns (*21*). Therefore, considering the recent popularity and benefits of LRT throughout the U.S., it is necessary to find more refined and up-to-date evidence on the relationship between access to public transit and changes in employment level and housing affordability through longitudinal data analysis and research design. Changes in the level of employment can be measured by the change in the duration of labor participation per week and the proportions of full-time workers and part-time workers. A percentage change can examine the housing affordability change in gross rent because renters are more vulnerable to a housing price increase than owners.

Longitudinal data analyses of employment and housing affordability allow planners and decision-makers to identify a causal path from public transit development to employment change in neighborhoods. If changes in labor participation and housing affordability vary between neighborhoods with and without access to public transit, it stands to reason that public transit development may influence the economic condition of the neighborhoods over time. Especially if labor participation increases and housing affordability does not change (or even better if it increases), it will show that residents in neighborhoods near light rail transit (LRT) stations will benefit from the increased job opportunities. In this case, public transit development can work as a positive sign of improving physical conditions for economic stability.

Using longitudinal data of employment and housing affordability data, this study aims to examine how public transit development—in particular, LRT introduction to metropolitan areas—affects labor participation and housing affordability in surrounding neighborhoods over time. Our analysis will control for demographic and economic characteristics of neighborhoods using propensity score matching (PSM). As an advancement to the literature on this subject, PSM will be used to match LRT block groups (the treatment group) with non-LRT block groups (the control group). A total of 260 LRT stations on 12 routes, which began operation between 2000 and 2010, are cases in this study.

This article is organized as follows. The literature section presents the current literature about spatial mismatch and the impacts of public transit on employment and housing affordability. The method section which follows contains an explanation of the longitudinal datasets used in this study, and goes on to explain the statistical method (PSM) employed to analyze the impacts of proximity to LRT stations on changes in labor participation and housing affordability, showing how to select the control Census block group using PSM. After describing the crossover patterns of changes in labor participation and housing affordability around LRT stations, this article ends with a conclusion that summarizes the causal effects of public transit development on employment and housing affordability identified by PSM in this study.

## Literature Review

One critical function of public transit is to increase location efficiency by connecting workers to job opportunities. Kain (*22*) argued that the spatial mismatch of affordable housing and employment was worsened by poor access to affordable transportation options. A subsequent study by Kain (*23*) confirmed that improving access to suburban employment centers by fixed-guideway public transit played a significant role in reducing job disparity and housing market discrimination problems for low-income and minority households. Ihlanfeldt and Sjoquist (*24*) summarized factors confirming the spatial mismatch hypotheses—such as a difference in commuting behaviors among racial groups, job accessibility measured by the distance between residences and workplaces, and a difference in the labor market outcome (i.e., household earnings) between the central city and suburban residents.

From the transportation equity standpoint, previous studies have focused on examining the economic benefits of public transportation development on employment outcomes for low-income households or minority populations (*25–27*). However, the results of these studies have been somewhat mixed depending on the types of transportation, different transportation measures, and employment outcome used for analysis (*28*). For example, assuming that bus services are the most affordable transportation option connected to most employment centers within an urban area, some studies argued that low-income neighborhoods with good access to bus stops or higher bus stop density were more likely to provide their residents with better access to diverse job opportunities because of higher concentration of low-income households near bus stops rather than rail transit routes (*20*, *29*). On the other hand, other studies argued that there were no significant associations between bus services and employment outcome, especially for low-income and black households with a single mother as a head of household (*30*). Sanchez (*31*) analyzed the effects of public transit services on labor participation in Atlanta and Portland and found the presence of public transit like LRT (e.g., MAX Light Rail in Portland) and heavy rail (e.g., MARTA in Atlanta) has a positive impact on the increase in average labor participation. However, his later study examined the effects of public transit access on the employment rates of welfare recipients, but no significant relationships were identified (*32*). Using cross-sectional research designs, these earlier studies did not explore change or variations in employment outcomes before and after transit development or control for endogeneity because it was difficult to figure out whether transit access affected employment or changes in employment outcomes led to transit development for better accessibility to jobs (*20*).

Studies about analyzing the effects of LRT on employment outcomes began to emerge in the transportation planning literature when many light transit systems were constructed between 2000 and 2010 in the U.S. metropolitan areas. Compared with bus services examined in the previous studies, most studies on LRT access and employment suggest a positive relationship between proximity to LRT stations and employment outcomes but still point to mixed results. A case study of Portland, Oregon, and Dallas, Texas by Noland et al. (*33*) examined the relationships between LRT proximity and new firm birth. Using the National Establishment Time-Series (NETS) data from 1991 to 2008, their study found the clustering of new firms near LRT stations, but new firm births are not always correlated with proximity to light rail transit. Schuetz (*34*) analyzed the effects of newly open rail transit stations on neighborhood retail activity in four metropolitan statistical areas (MSAs) in California and also found weak evidence of links between openings of new rail transit stations and increases in retail employment for suburban neighborhood areas. Some studies, however, find a positive association between new businesses and proximity to LRT stations, which confirms findings in the previous studies (*5*, *35*, *36*). A case study of Charlotte, North Carolina by Canales et al. (*37*) shows mixed results on LRT access and jobs. It finds no significant increase in employment level in neighborhoods with good access to LRT stations but mentions that the transit line increases accessibility to areas with higher percentages of high-wage industries.

There have been numerous literature review studies that analyze the effects of LRT systems on housing affordability, but as with the relationships between transit access and jobs, the results are quite mixed (*10*, *38–40*). For low-income households and minority populations, the introduction of transit systems to their neighborhoods has both merits and demerits. Improved access to their job accessibility and economic activities

increases the likelihood of getting high-quality and stable jobs to maintain their housing. On the other hand, transit access can also bring development pressures to their neighborhoods, including increased property values and new high-end residential developments that cause gentrification and neighborhood displacement.

Using hedonic price modeling, earlier studies on transit access and housing affordability compared property values located within a certain radius of a catchment area (i.e., 0.5 mi) with those outside that catchment area and found price premiums for housing within a certain radius of a light rail station—0.25 to 0.5 mi (*9*, *41*, *42*). A case study of housing premiums near LRT in Charlotte, North Carolina, by Billings (*43*) found that single-family home values increased by 4% within a 1-mi buffer of an LRT station. In the case of Salt Lake County, Utah, Petheram et al. (*9*) examined the relationship between LRT and rental apartment building values and found that a positive relationship between the distance from an LRT station and rental apartment building values was identified up to 1.25 mi away. Another case study of Buffalo, New York, conducted hedonic pricing models to measure a change in housing property values near LRT stations and found 2% to 5% premium effects of median home values within a 0.25-mi radius of a light rail station. Meta-analysis studies of rail transit access in relation to land and property values synthesized previous studies. They suggested that the overall effect of proximity of LRT on land and property values seemed to be positive. Still, its magnitudes could vary depending on each MSA's economic and housing market characteristics (*44*, *45*). Using microdata of housing locations or parcel-level land value data, recent studies aim to understand the causal pathways to transit-induced gentrification in terms of housing and property value change (*11*, *12*, *46–48*) or the spatial patterns of housing eviction filing data (*49*, *50*).

In sum, although a few longitudinal studies have been published, the research to date on transit access, employment outcomes, and housing affordability in terms of change in housing price values still complicates the interpretations of the results because of its cross-sectional data analysis, endogeneity, and varying magnitudes of LRT effects ranging from negative to positive. This gap gives researchers a chance to find more evidence for spatial mismatch of employment and labor participation in relation to public transit development, which is the main objective of this study.

## Methodology

### Data and Variables

Data for exposure and outcome variables in this study come from the 2000 and 2010 decennial Census data at the block group level. For the average hours worked and rental housing price data in 2010, this study uses the 5-year 2008–2012 American Community Survey (ACS) estimate data because it generally reflects demographic and socioeconomic conditions in its mid year—that is, the year 2010. For the point locations of each LRT station, the General Transit Feed Specification (GTFS) data by Google are used. To match with the decennial Census data, only LRT stations built between 2000 and 2010 are selected. Based on these selection criteria, 260 stations out of 552 LRT stations in operation within 12 metropolitan areas as of 2021 are selected (Table 1). LRT stations for the selected 12 LRT routes are located in 19 counties.

**Table 1.** A List of 12 Light Rail Transit (LRT) Routes, Host Counties, and the Number of Stations Selected

| LRT route name | Metropolitan area where LRT passes | Number of LRT stations (as of 2021) | Number of selected stations (opened between 2000 and 2010) |
|---|---|---|---|
| LYNX Blue and Gold Lines | Charlotte, North Carolina | 43 | 15 |
| Dallas Area Rapid Transit (DART) | Dallas, Texas | 65 | 19 |
| Denver Regional Transportation District (RTD) | Denver, Colorado | 74 | 23 |
| METRORail | Houston, Texas | 39 | 16 |
| METRO Light Rail Blue and Green Lines | Minneapolis, Minnesota | 37 | 19 |
| Valley Metro Rail | Phoenix, Arizona | 38 | 32 |
| Metropolitan Area Express (MAX) LRT | Portland, Oregon | 94 | 37 |
| Sacramento Regional Transportation (RT) Light Rail | Sacramento, California | 54 | 17 |
| TRAX | Salt Lake City, Utah | 50 | 28 |
| SPRINTER | San Diego, California | 15 | 15 |
| Link LRT (Line 1 and Line T) | Seattle, Washington | 22 | 18 |
| River Line LRT | Camden, New Jersey | 21 | 21 |
| Total | | 552 | 260 |

To avoid compatibility issues between the 2000 and 2010 Census block group boundaries, we use data normalized for the 2010 boundary by GeoLytics. The 2010 decennial Census and ACS data and the 2010 TIGER/Line files are collected from the National Historical Geographical Information System (NHGIS) database. All Census data are combined to the block group GIS shapefiles of each host county where LRT stations are located before implementing the PSM process. Table 1 shows a list of LRT routes, region names, and the numbers of total LRT stations and selected stations for this study.

The outcome variables include the percentage of changes in labor participation and housing affordability measures. From the decennial Census and ACS data, four variables are used as labor participation measures—the average weeks worked and percentage changes in the number of workers based on employment level. Based on the work status in the previous 12 months by usual hours worked per week in the Census data, three categorical variables are drawn to identify employment status changes within each Census block group. According to the Bureau of Labor Statistic (BLS), percentage changes in employment status are calculated based on three categories: the full-time and year-round workers who worked over 35 h per week and remained employed for over 50 weeks in the previous year; part-time and full-year-round workers who worked less than 34 h per week but stay employed for over 50 weeks in the previous year; the part-time and part-year workers who used to work for less than 34 h per week and remained employed for less than 49 weeks in the earlier year. Given that low-wage workers and low-income households are more sensitive to the change in rental housing costs for their settlement than to the housing price, we use the percentage change in the median gross rent between 2000 and 2010 to test whether rent housing is still affordable while the level of labor participation changes over time.

Table 2 shows all variables used in this study. The treatment variable in PSM is a binary variable of whether a block group falls within a 0.5-mi buffer of an LRT station. The 0.5-mi buffer is determined based on the maximum walking distance people can feel comfortable walking to their destination. A few studies in transportation planning confirmed the 0.5-mi buffer for public transit's desirable catchment area (*51*, *52*). Also, this study includes a list of demographic and employment variables at the Census block group level. They are used as observational covariates in PSM, which will be explained in the next section.

## *Propensity Score Matching Method*

To examine how each outcome variable changes over time for a given treatment assignment, we believe that propensity score matching (PSM) is appropriate. As one of the quasi-experimental designs, PSM allows researchers to overcome the non-random assignment of treatment to evaluate outcome variables (*53*, *54*). Propensity scores in this study are estimated as the conditional probability of having access to an LRT station as a specific treatment, given a vector of observed covariates—demographic and employment characteristics of each Census block group. Based on confounding covariates' values, individuals in the treatment group (i.e., LRT block groups) are likely to differ systematically from those in the control group (i.e., non-LRT block groups). Statistically, this generates a biased estimate of the treatment effect. However, it is impossible to select a control group with the same characteristics as the treatment group for a true experiment in planning practice and research. It suggests that a quasi-experimental approach like PSM is more reasonable to explore the relationship between the treatment and the outcome variables by mimicking the randomized experimental design (*53*, *55*, *56*).

The propensity score for matching purposes can be better calculated when we include as many variables as possible that serve as confounders for independent and dependent variables. Also, other predictors of the outcome variable can be included in PSM to reduce the variance of treatment estimates, although they are not related to treatment and do not affect the reduction of selection bias (*55*). In this study, 14 confounding covariates and three outcome predictors based on the 2000 decennial Census data are used in PSM to select a control group similar to the treatment group. Figure 1 shows the relationships among the treatment, covariates, and outcome variables for the PSM. The PSM was implemented in R 3.4.2 using the *MatchIt* package. A caliper length of 0.03 is used for matching, meaning that for a treatment observation, we use a match in control observations whose propensity scores are within 0.03 of the score of the treatment observation (*55*, *56*).

In PSM, nearest neighbor matching is used to select the control groups. The control group in this study consists of block groups having no access to LRT in both 2000 and 2010, while the treatment group has LRT access in 2010 but not in 2000. The total number of Census block groups within 19 host counties is 16,303, but because of missing observation values occurring at complete random, 673 block group data are removed from our analysis. Unfortunately, these 673 block group data also include 15 block group data that fall within a 0.5-mi buffer of an LRT station, so the final treatment group—LRT block groups—includes 1,048 block groups. Using the one-to-one match, another 1,048 Census block groups are selected as the control group so that we can get 1,048 block group comparison pairs. Maps in Figure 2 visualize how the control Census block groups—non-LRT block groups—corresponding to the

**Table 2.** Variables Description and Data Source

| Variable | Definition | Source |
|---|---|---|
| Dependent variables | | |
| Percentage change in the average weeks worked | The percentage change in the average weeks worked of workers (adults more than 25 years old who are employed) in the previous years (1999 for 2000 and 2009 for 2010) | Census 2000<br>ACS 2008–2012 |
| Difference in the share of stable workers (full-time/year-round) | The difference in a share of the number of workers within a block group who worked for 50–52 weeks and over 35 hours per week in the previous years (1999 for the year 2000 and 2009 for the year 2010) | Census 2000<br>ACS 2008–2012 |
| Difference in the share of semi-stable workers (part-time/year-round) | The difference in a share of the number of workers who worked for 50–52 weeks and less than 35 hours per week in the previous years (1999 for the year 2000 and 2009 for the year 2010) | Census 2000<br>ACS 2008–2012 |
| Difference in the share of unstable workers (part-time/part-year-round) | The difference in a share of the number of workers who worked for less than 50 weeks and less than 35 hours per week in the previous years (1999 for the year 2000 and 2009 for the year 2010) | Census 2000<br>ACS 2008–2012 |
| Percentage change in the median gross rent | The percentage change in the median gross rent for the rent-occupied housing units in a block group between 2000 and 2010 | Census 2000<br>ACS 2008–2012 |
| Independent variables | | |
| LRT access dummy | 1 = if a block group falls within a 0.5-mi buffer of an LRT station<br>0 = if a block group is located outside a 0.5-mi buffer of an LRT station | General Transit Feed Specification (GTFS) |
| Total jobs | The total number of jobs within a block group in 2002 (2004 for Arizona) | LEHD 2002 |
| Total population | The total number of people | Census 2000 |
| Median household income | Median household income | Census 2000 |
| Non-white population | The number of non-white population | Census 2000 |
| Total housing units | The total number of housing units | Census 2000 |
| Population with a bachelor's degree or higher | The number of population (25 years and over) who have at least a bachelor's degree | Census 2000 |
| Block group size | The area of a Census block group (acres) | TIGER 2010 |
| Unemployment rate | The unemployment rate | Census 2000 |
| Employment mix index | The employment mix (or entropy) based on the 5-tier employment categories based in turn on the formulae of the EPA's Smart Location Database (2013) | LEHD 2002 |
| Average commuting time | The average commuting time (minutes) of workers | Census 2000 |
| Host county | Host counties where LRT stations are located (a categorical variable) | TIGER/LINE + 2010 |

*Note*: LRT = light rail transit; ACS = American Community Survey; LEHD = Longditudinal Employer-Household Dynamics; EPA = U.S. Environmental Protection Agency.

treatment group—LRT block groups—are selected from the 19 counties in this study.

Finally, after selecting the block group pairs based on propensity score estimation, this study conducts a *t*-test to examine whether the treatment Census block groups' characteristics are systematically different from those of the control block groups selected from the PSM. Also, using the matching block group data, the average treatment effects (ATEs), the observed differences, and the ratio between treatment and control block groups for labor participation and rent-occupied housing cost variables are calculated to examine the more direct effects of public transit. All of these analysis results will be summarized in the next section.

It should be noted that PSM is not without limitations. PSM works only when all confounding factors are included in the analysis. As changes in employment stability and the rental market are complex, it is nearly impossible to include all relevant variables in the matching process. The risk of not controlling all confounding factors is that the effect of having a new LRT station on the outcome variables—employment stability and rental price change—might be under- or over-estimated. Thus, in this study, we assume that we included all available factors to explain the phenomena but still call for a careful interpretation of the findings.

## Results

### *Difference-of-Means Test Using PSM*

Before measuring the true impact of LRT on employment level and housing affordability, it is important to examine if PSM works well for Census block group

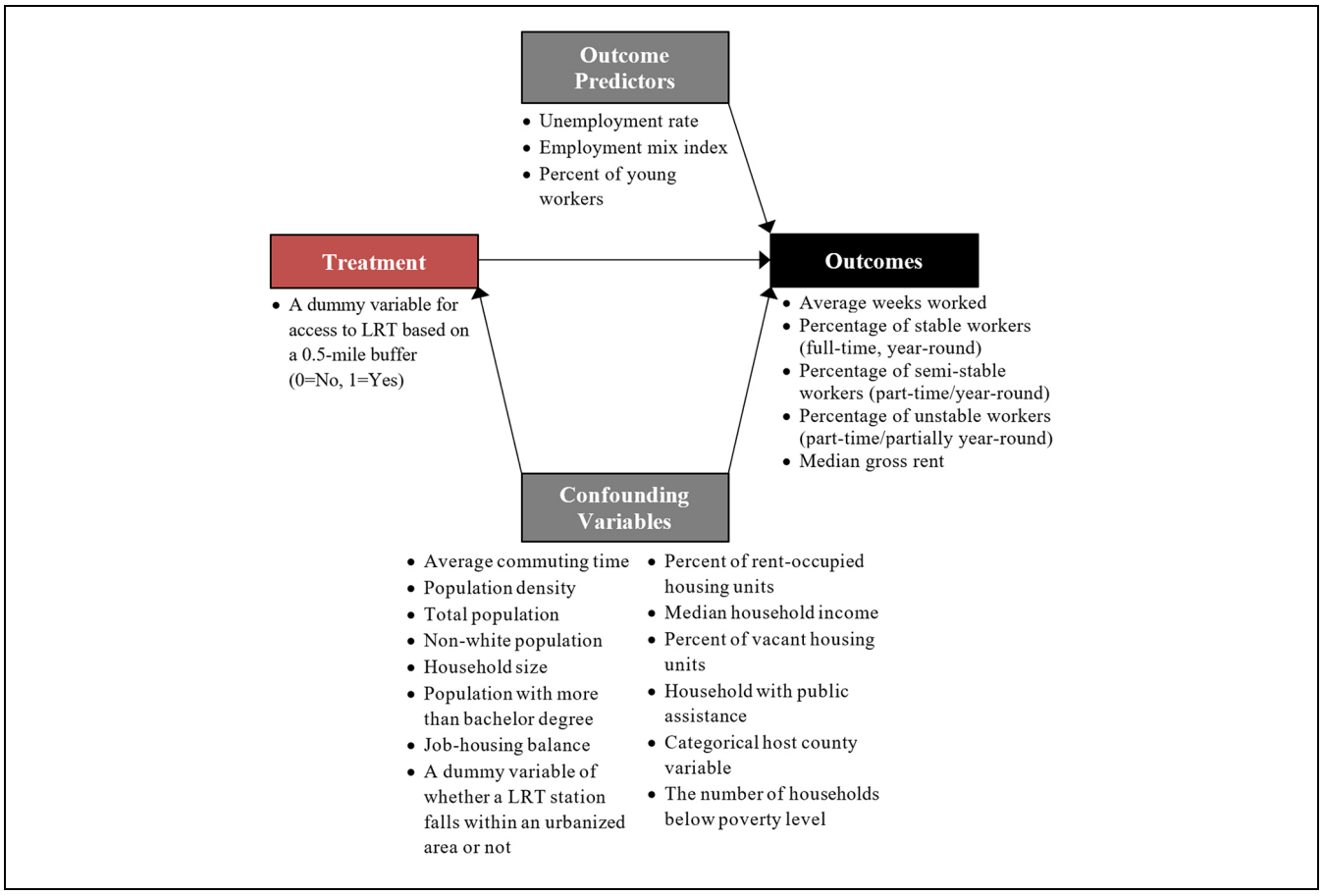


**Figure 1.** A diagram of relationships among variables in the propensity score matching in this study.
*Note*: All data come from the 2000 decennial Census data to determine the control group—Census block groups that have similar demographic, physical, and socioeconomic characteristics of the treatment Census block groups except for proximity to a light rail transit (LRT) station.

matching. Table 3 shows the differences in block group characteristics with *t*-tests before and after matching. The original LRT block groups are significantly different from non-LRT block groups in most covariates except total housing units and block size. Census block groups that fall within a 0.5-mi buffer of the nearest LRT station built between 2000 and 2010 have more jobs, fewer residents, less median household income, more non-white population, fewer educated people, higher unemployment rate, and less commuting time in 2000 (or 2002 for Longitudinal Employer-Household Dynamics (LEHD) variables). After PSM, *t*-test results for matched samples show that attributes of treatment and control neighborhood groups based on access to LRT stations do not differ in most covariates except for total jobs at the 0.05 significance level. This result shows that the PSM performed well.

## *Estimating the True Impacts of LRT on Employment Level*

The ultimate goal of PSM is to compute the more direct impact of the treatment—the presence of LRT in this study—on the outcome, that is, changes in average hours worked per week, percentage of full- and part-time workers, and median gross rent. Once the matching is complete, we calculate the ATEs, the observed differences, and the ratio between them on the four outcome variables. As an example of median gross rent, the observed difference is the median gross rent of LRT block groups minus that of no-LRT block groups in the original sample. The ATE measures the differences in mean outcomes of interest based on the matched samples assigned to the treatment and control groups.

Table 4 shows the results of the true impact of LRT on dependent variables. After matching (i.e., controlling for confounders), block groups with LRT opened between 2000 and 2010 show a significantly higher increase in both labor participation and housing cost variables. The average weeks worked of non-LRT block groups in the matched sample increased by 2.4% between 2000 and 2010. The ATE/control ratio is 0.43, which indicates that after accounting for the influence of confounding effects, the percentage increase of average weeks worked is 43% higher in the LRT neighborhoods

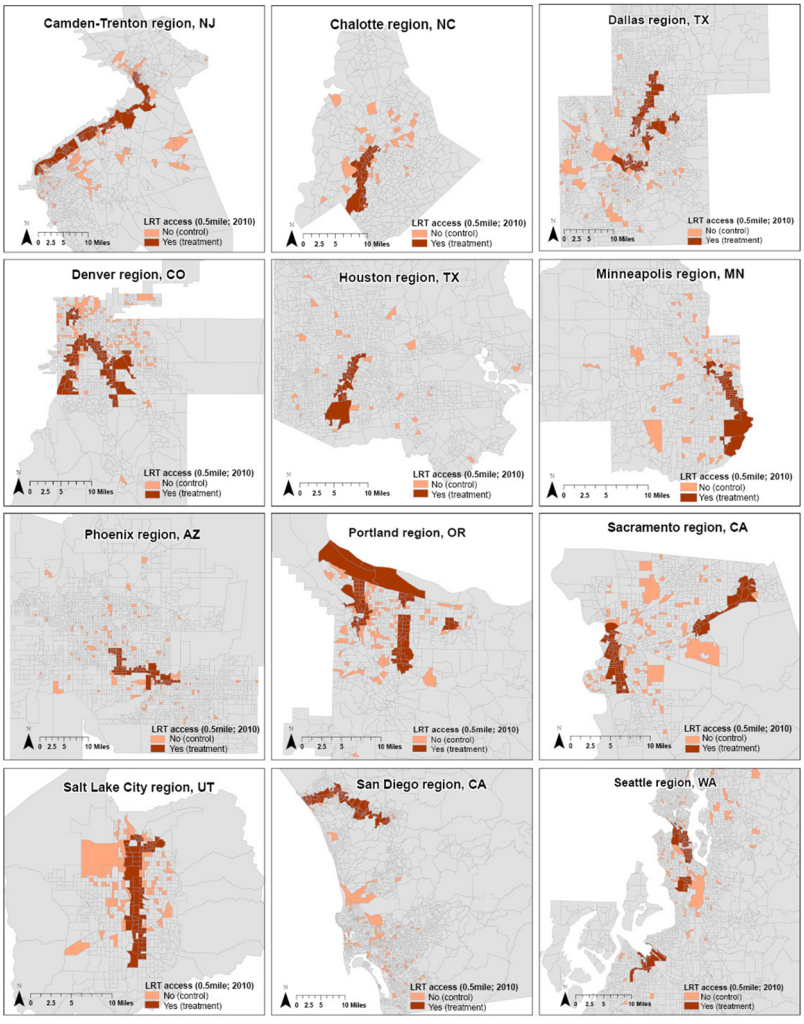


**Figure 2.** Matched samples after propensity score matching in 12 regions.

than in its counterparts. Likewise, the matched sample shows a significant increase ($p < .01$) in the percentage of full-time, year-round workers in LRT-accessible block groups.

The percentage of full-time, year-round workers of non-LRT block groups in the matched sample increased by 4.17% between 2000 and 2010. The ratio of the ATE led by the presence of LRTs against the control block group is 0.39, which means that after accounting for the influence of confounding effects, the percentage increase of average weeks worked is 39% higher in the LRT neighborhoods than in its counterparts. The percentage of part-time, part-year workers of non-LRT block groups increased by 0.69% between 2000 and 2010, while that for LRT block groups decreased by 0.09%, showing a crossover pattern. That difference is statistically significant at $p < .05$ level. The percentage change of part-time, year-round workers is not statistically different between the two matched groups.

Additionally, the median gross rent change was 3.87% higher in LRT block groups (46.87% increase) than in no-LRT counterparts (43% increase), but the difference is not statistically significant ($p > .05$). That is, if a randomly-selected block group came to have an LRT station access within 0.5 mi, we might not expect an increase in gross rent higher than other block groups without such an LRT system. The ratio of the ATE led by the presence of LRTs against the control block group is -0.09, showing that after accounting for the influence of confounding effects, the percentage increase of median gross rent was 9% higher in the LRT neighborhoods than in the no-LRT neighborhoods.

Figure 3 visualizes a longitudinal change in all outcome variables of labor participation and housing costs

**Table 3.** Mean Differences[1] of Observed Covariates between Treatment Block Groups (Having Access to a Light Rail Transit (LRT) Station within a 0.5-mi Buffer) and Control Block Groups (Having no Access to an LRT Station within a 0.5-mi Buffer) in Unmatched and Matched Samples

| | Before matching | | | After matching | | |
|---|---|---|---|---|---|---|
| Variables | No LRT ($n$ = 14,582) | LRT ($n$ = 1,048) | Mean difference[2] | No LRT ($n$ = 1,048) | LRT ($n$ = 1,048) | Mean difference[1] |
| Population density | 8.7 | 10.9 | 2.2*** | 10.6 | 10.9 | 0.3 |
| Total population | 1361.1 | 1282.1 | −79.0*** | 1282.3 | 1282.1 | −0.2 |
| Median household income | 53127.7 | 39931.6 | −13196.2*** | 40147.2 | 39931.6 | −215.7 |
| Non-white population | 399.4 | 466.5 | 67.1*** | 478.7 | 466.5 | −12.2 |
| % vacant housing units | 5.5 | 7.3 | 1.8*** | 7.4 | 7.3 | −0.1 |
| Household size | 2.7 | 2.4 | −0.3*** | 2.5 | 2.4 | −0.0 |
| % households with public assistance | 3.0 | 5.0 | 2.0*** | 5.1 | 5.0 | −0.1 |
| % families below the poverty level | 8.3 | 12.9 | 4.6*** | 12.9 | 12.9 | 0.0 |
| Job–housing balance | 1.8 | 13.0 | 11.2*** | 7.2 | 13.0 | 5.8 |
| Population with bachelor's degree or higher | 29.9 | 28.0 | −1.9*** | 27.3 | 28.0 | 0.6 |
| % renter-occupied housing units | 33.0 | 50.1 | 17.1*** | 48.7 | 50.1 | 1.3 |
| % young workers | 29.8 | 28.6 | −1.1*** | 28.3 | 28.6 | 0.3 |
| Unemployment rate (%) | 6.0 | 7.9 | 1.9*** | 8.2 | 7.9 | −0.2 |
| Employment mix index (2002) | 0.7 | 0.7 | 0.0** | 0.7 | 0.7 | 0.0 |
| Average commuting time (min) | 28.3 | 25.1 | −3.2*** | 25.0 | 25.1 | 0.1 |

[1]The $t$-test results in the table are drawn from the independent $t$-test.
[2]***$p < .01$, **$p < .05$, *$p < .1$.

**Table 4.** Differences[1] in Outcome Variables between Light Rail Transit (LRT) and no-LRT Block Groups ($n$ = 1,048 pairs)

| Outcomes | Observed difference (original sample)[2] | ATE (difference after matching) | Mean of control group | ATE/control ratio |
|---|---|---|---|---|
| Labor participation | | | | |
| Average weeks worked (% change) | 1.32*** | 1.03** | 2.40 | 0.43 |
| Full-time, year-round workers (over 35 h/wk & 50–52 wks/yr; %$p$ difference) (%) | 1.22*** | 1.62*** | 4.17 | 0.39 |
| Part-time, year-round workers (less 35 h/wk & 50–52 wks/yr; %$p$ difference) (%) | −1.65*** | −0.62 | −8.94 | 0.07 |
| Part-time & part-year workers (less 35 h/wk & less 50 wks/yr; %$p$ difference) (%) | −0.34 | −0.78** | 0.69% | −1.13 |
| Housing cost | | | | |
| Median gross rent (% change) | 11.13*** | 3.87 | 43.00 | 0.09 |

*Note*: ATE = average treatment effects; h/wk = hours per week; wks/yr = weeks per year. The differences are calculated as LRT group value minus non-LRT group value.
[1]The $t$-test results in the table are drawn from the independent $t$-test.
[2]***$p < .01$, **$p < .05$, *$p < .1$.

for 1,048 LRT block groups and the other 1,048 matched non-LRT block groups. In Figure 3*a*, the average number of weeks worked, a proxy variable of labor participation, was lower in the LRT group than the non-LRT group in 2000, but it inverted as the average weeks worked is higher (about 0.23 weeks) in LRT block groups than non-LRT block groups in 2010. This crossover pattern shows strong evidence of the effectiveness of the treatment—development of light rail transit—on labor participation.

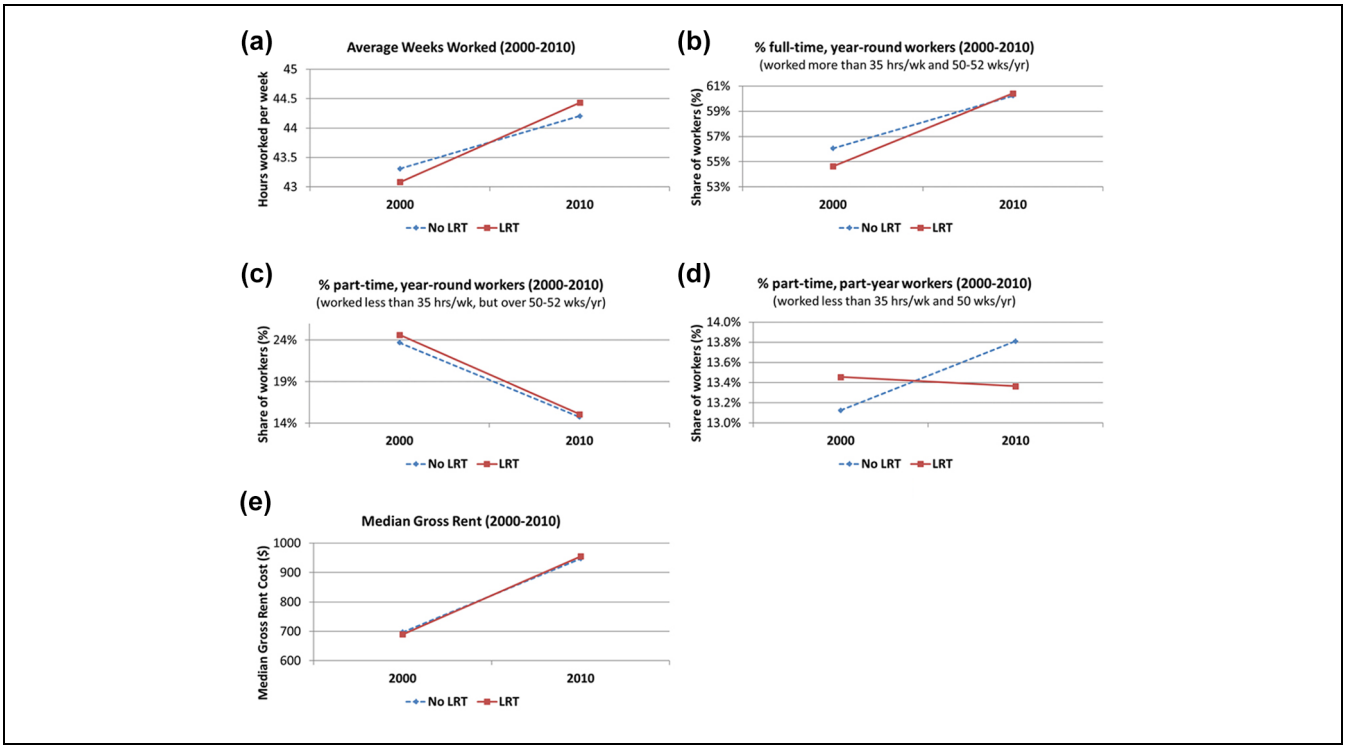


**Figure 3.** Changes in labor participation and rental housing affordability in matched samples between 2000 and 2010.
*Note*: LRT = light rail transit.

The percentage of full-time and year-round workers is another proxy variable of stable workers. In Figure 3*b*, the PSM result shows that the percentage of full-time and year-round workers increased in Census block groups with access to LRT by 5.8%, which is a higher percentage growth rate compared with control Census block groups without access to LRT (4.2% increase). The higher percentage growth rate of stable workers in the Census block group with access to LRT plays a role in narrowing the gap of labor participation level against the control Census block groups without access to LRT. In contrast, the percentage of unstable workers, measured as the percentage of part-time/year-round or part-time/part-year workers, decreased more in LRT block groups than in those without access to LRT. Figures 3*b* to 3*d* suggest that the development of LRT may affect employment stability.

Finally, Figure 3*e* shows changes in rent for the renter-occupied housing before and after LRT was built between 2000 and 2010. The median gross rent was slightly lower in the LRT group than in the matched no-LRT group in 2000, but the trend line inverted in 2010, which shows that the median gross rent amount is higher (approximately $7.5 per month) in LRT block groups than in no-LRT block groups in 2010. This crossover trend seems to confirm findings in the past literature on the premium pricing effects on residential properties, but our analysis shows that this difference is not statistically significant when using the longitudinal data of the median gross rent between 2000 and 2010.

## Conclusions

This study investigates the effects of public transit on the change in the level of employment status and housing affordability by using the longitudinal data of 2000 and 2010. A higher level of employment stability and lower rental price provide residents with better economic stability. This study selects 12 LRT routes as case sites. PSM is used to select control block groups (no LRT access) corresponding to each treatment block group (new LRT station built between 2000 and 2010). Using the PSM analysis is a methodological advance on previous studies. As far as we know, this study is one of only a few studies that apply PSM techniques to longitudinal data analysis of neighborhood change. Our findings imply causal relationships between public transit development and changes in labor participation and rental housing affordability of areas near the transit route.

Through PSM and difference-of-means tests, this study suggests that good access to public transit improves the employment level, such as the duration of jobs and the percentage of stable workers, while not deteriorating housing affordability. Block groups within a 0.5-mi

buffer of an LRT station had lower average weeks worked than the control groups in 2000, but in 2010, they showed more average weeks worked than control block groups without access to light rail transit. Controlling for potential confounding factors, this crossover pattern of outcomes indicates the clear causal relationship between public transit and employment. Also, as we see in Table 4 and Figure 3, further analysis shows that the increase in the average weeks worked is associated with an increase in the number of stable workers and a decrease in the number of unstable workers. Contrary to our expectation, the number of semi-stable and unstable workers is not linked with LRT access. Albeit a not-statistically-significant difference, this study shows the crossover pattern of median gross rent, meaning the premium effect of LRT on housing rent price and, thus, a weak negative impact on the possibility of existing residents staying in their place.

Although this study finds that good access to LRT leads to better economic stability over time, several caveats also exist. First, the aggregated Census block group data used in this study are proxy values. Because of data availability, we cannot collect the change in employment level over time at the individual household level. Some studies, such as Yi (*57*), use household-level employment status data to measure the impact of LRT on employment status, but the availability of these individual household level data is quite limited. This study chooses 12 different regions with LRT systems to get better generalizability. Second, because there are only two-time-period Census data available for analysis, this study had to select LRT stations for each route that opened between 2000 and 2010. However, since the year 2010, many LRT routes have been further extended. With more recent data, further analysis may include all up-to-date LRT stations and investigate a stronger causal path between access to LRT and economic stability over time. The PSM, a methodological approach of this study, can be further applied in other contexts (e.g., different countries, different time periods) to validate and theorize the various influences of public transit on the surrounding communities.

In sum, this study suggests that public transit development in an urban area may help workers have better access to stable employment opportunities while not losing the current level of housing affordability and thus staying in place. These two factors can play a vital role in enhancing the possibility of maintaining existing low-income households in their residence so that they can take advantage of the benefits of better accessibility to their jobs via public transit. From a broader sense, our findings imply that public transit development may encourage community empowerment over time. Of course, public transit is not a complete cure at all. Without appropriate interventions—such as minimum construction of housing units with low rental prices or median values for housing affordability and transit-oriented development (TODs)—it often induces gentrification and displacement (*11*, *12*). However, using longitudinal employment and housing data and PSM analysis, this study defies the contention that public transit development may be harmful for unemployed or low-income population in a neighborhood and suggests that although there may be a struggle in implementing better quality public transit services, efforts to improve public transit service should be continued.

## Author Contributions

The authors confirm contributions to the paper as follows: Study conception and design: K. Kim, K. Park, A. C. Nelson; literature review: K. Kim; data collection: K. Kim, K. Park; analysis and interpretation of results: K. Park, K. Kim; draft manuscript preparation: K. Kim, K. Park, A.C. Nelson. All authors reviewed the results and approved the final version of the manuscript.

## Declaration of Conflicting Interests

The author(s) declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

## Funding

The author(s) received no financial support for the research, authorship, and/or publication of this article.

## ORCID iDs

Keuntae Kim https://orcid.org/0000-0002-5877-1348
Keunhyun Park https://orcid.org/0000-0001-5055-7833
Arthur C. Nelson https://orcid.org/0000-0003-2578-3884

## Data Accessibility Statement

Data used in this research are provided by the U.S. Census Bureau and Google. Data are publicly available for research purposes via their websites.

## References

1. De Vise, P. The Suburbanization of Jobs and Minority Employment. *Economic Geography*, Vol. 52, No. 4, 1976, pp. 348–362.
2. Mills, E. S., and R. Price. Metropolitan Suburbanization and Central City Problems. *Journal of Urban Economics*, Vol. 15, No. 1, 1984, pp. 1–17. https://doi.org/10.1016/0094-1190(84)90019-6.
3. Giuliano, G. Low Income, Public Transit, and Mobility. *Transportation Research Record: Journal of the Transportation Research Board*, 2005. 1927: 63–70.

4. Fan, Y., A. Guthrie, and D. Levinson. Impact of Light-Rail Implementation on Labor Market Accessibility. *Journal of Transport and Land Use*, Vol. 5, No. 3, 2012, pp. 28–39.
5. Sanchez, T. W. The Connection Between Public Transit and Employment. *Journal of the American Planning Association*, Vol. 65, No. 3, 1999, pp. 284–296. https://doi.org/10.1080/01944369908976058.
6. National Advisory Commission on Civil Disorders. *Report of the National Advisory Commission on Civil Disorders: Summary of Report*. Government Printing Office, 1968.
7. Sanchez, T. *The Right to Transportation: Moving to Equity*. Routledge, New York, NY, 2018.
8. Program History. U.S. Department of Transportation. https://www.transportation.gov/utc/program-history. Accessed March 7, 2021.
9. Petheram, S. J., A. C. Nelson, M. Miller, and R. Ewing. Use of the Real Estate Market to Establish Light Rail Station Catchment Areas. *Transportation Research Record: Journal of the Transportation Research Board*, 2013. 2357: 95–99.
10. Bartholomew, K., and R. Ewing. Hedonic Price Effects of Pedestrian- and Transit-Oriented Development. *Journal of Planning Literature*, Vol. 26, No. 1, 2011, pp. 18–34. https://doi.org/10.1177/0885412210386540.
11. Padeiro, M., A. Louro, and N. M. da Costa. Transit-Oriented Development and Gentrification: A Systematic Review. *Transport Reviews*, Vol. 39, No. 6, 2019, pp. 733–754. https://doi.org/10.1080/01441647.2019.1649316.
12. Baker, D. M., and B. Lee. How Does Light Rail Transit (LRT) Impact Gentrification? Evidence from Fourteen US Urbanized Areas. *Journal of Planning Education and Research*, Vol. 39, No. 1, 2019, pp. 35–49. https://doi.org/10.1177/0739456X17713619.
13. Yeganeh, A. J., R. P. Hall, A. R. Pearce, and S. Hankey. A Social Equity Analysis of the U.S. Public Transportation System Based on Job Accessibility. *Journal of Transport and Land Use*, Vol. 11, No. 1, 2018, pp. 1039–1056.
14. Lyons, T., and D. Choi. Transit Economic Equity Index: Developing a Comprehensive Measure of Transit Service Equity. *Transportation Research Record: Journal of the Transportation Research Board*, 2021. 2675: 288–300.
15. Wang, K., and M. Woo. The Relationship between Transit Rich Neighborhoods and Transit Ridership: Evidence from the Decentralization of Poverty. *Applied Geography*, Vol. 86, 2017, pp. 183–196. https://doi.org/10.1016/j.apgeog.2017.07.004.
16. Xiao, Y., and M. Watson. Guidance on Conducting a Systematic Literature Review. *Journal of Planning Education and Research*, Vol. 39, No. 1, 2019, pp. 93–112. https://doi.org/10.1177/0739456X17723971.
17. Sanchez, T. W. *Addressing the Impact of Housing for Virginia's Economy*. Virginia Coalition of Housing and Economic Development Researchers, 2017.
18. Luckey, K. S. Affordable for Whom? Introducing an Improved Measure for Assessing Impacts of Transportation Decisions on Housing Affordability for Households with Limited Means. *Research in Transportation Business and Management*, Vol. 29, 2018, pp. 37–49. https://doi.org/10.1016/j.rtbm.2018.04.003.
19. Sanchez, T. W. A Transit Access Analysis of TANF Recipients in Portland, Oregon. *Journal of Public Transportation*, Vol. 2, No. 4, 1999, pp. 61–73.
20. Pasha, O., C. Wyczalkowski, D. Sohrabian, and I. Lendel. Transit Effects on Poverty, Employment, and Rent in Cuyahoga County, Ohio. *Transport Policy*, Vol. 88, 2020, pp. 33–41. https://doi.org/10.1016/j.tranpol.2020.01.013.
21. Kramer, A. The Unaffordable City: Housing and Transit in North American Cities. *Cities*, Vol. 83, 2018, pp. 1–10. https://doi.org/10.1016/j.cities.2018.05.013.
22. Kain, J. F. Housing Segregation, Negro Employment, and Metropolitan Decentralization. *The Quarterly Journal of Economics*, Vol. 82, No. 2, 1968, pp. 175–197.
23. Kain, J. F. The Spatial Mismatch Hypothesis: Three Decades Later. *Housing Policy Debate*, Vol. 3, No. 2, 1992, pp. 371–460. https://doi.org/10.1080/10511482.1992.9521100.
24. Ihlanfeldt, K. R., and D. L. Sjoquist. The Spatial Mismatch Hypothesis: A Review of Recent Studies and Their Implications for Welfare Reform. *Housing Policy Debate*, Vol. 9, No. 4, 1998, pp. 849–892. https://doi.org/10.1080/10511482.1998.9521321.
25. Glaeser, E. L., M. E. Kahn, and J. Rappaport. Why Do the Poor Live in Cities? The Role of Public Transportation. *Journal of Urban Economics*, Vol. 63, No. 1, 2008, pp. 1–24. https://doi.org/10.1016/j.jue.2006.12.004.
26. Welch, T. F. Equity in Transport: The Distribution of Transit Access and Connectivity among Affordable Housing Units. *Transport Policy*, Vol. 30, 2013, pp. 283–293. https://doi.org/10.1016/j.tranpol.2013.09.020.
27. Pathak, R., C. K. Wyczalkowski, and X. Huang. Public Transit Access and the Changing Spatial Distribution of Poverty. *Regional Science and Urban Economics*, Vol. 66, 2017, pp. 198–212. https://doi.org/10.1016/j.regsciurbeco.2017.07.002.
28. Bastiaanssen, J., D. Johnson, and K. Lucas. Does Transport Help People to Gain Employment? A Systematic Review and Meta-Analysis of the Empirical Evidence. *Transport Reviews*, Vol. 40, No. 5, 2020, pp. 607–628. https://doi.org/10.1080/01441647.2020.1747569.
29. Barton, M. S., and J. Gibbons. A Stop Too Far: How Does Public Transportation Concentration Influence Neighbourhood Median Household Income? *Urban Studies*, Vol. 54, No. 2, 2017, pp. 538–554. https://doi.org/10.1177/0042098015593462.
30. Lichtenwalter, S., G. Koeske, and E. Sales. Examining Transportation and Employment Outcomes Evidence for Moving beyond the Bus Pass. *Journal of Poverty*, Vol. 10, No. 1, 2006, pp. 93–115. https://doi.org/10.1300/J134v10n01_05.
31. Sanchez, T. W. The Connection between Public Transit and Employment: The Cases of Portland and Atlanta. *Journal of the American Planning Association*, Vol. 65, No. 3, 1999, pp. 284–296. https://doi.org/10.1080/01944369908976058.
32. Sanchez, T. W., Q. Shen, and Z.-R. Peng. Transit Mobility, Jobs Access and Low-Income Labour Participation in

US Metropolitan Areas. *Urban Studies*, Vol. 41, No. 7, 2004, pp. 1313–1331. https://doi.org/10.1080/0042098042000214815.

33. Noland, R. B., D. G. Chatman, and N. J. Klein. *Transit Access and the Agglomeration of New Firms: A Case Study of Portland and Dallas*. MNTRC Report 12-15. Mineta National Transit Research Consortium, San José, CA, 2014.
34. Schuetz, J. Do Rail Transit Stations Encourage Neighbourhood Retail Activity? *Urban Studies*, Vol. 52, No. 14, 2015, pp. 2699–2723. https://doi.org/10.1177/0042098014549128.
35. Credit, K. Transit-Oriented Economic Development: The Impact of Light Rail on New Business Starts in the Phoenix, AZ Region, USA. *Urban Studies*, Vol. 55, No. 13, 2018, pp. 2838–2862. https://doi.org/10.1177/0042098017724119.
36. Blumenberg, E., and G. Pierce. Automobile Ownership and Travel by the Poor. *Transportation Research Record: Journal of the Transportation Research Board*, 2012. 2320: 28–36.
37. Canales, K. L., I. Nilsson, and E. Delmelle. Do Light Rail Transit Investments Increase Employment Opportunities? The Case of Charlotte, North Carolina. *Regional Science Policy & Practice*, Vol. 11, No. 1, 2019, pp. 189–202. https://doi.org/10.1111/rsp3.12184.
38. Cervero, R., C. Ferrell, and S. Murphy. *Transit-Oriented Development and Joint Development in the United States: A Literature Review*. TCRP Research Results Digest No. 52, Transportation Research Board, Washington, D.C., 2002.
39. Renne, J., and R. Ewing. *Transit-Oriented Development: An Examination of America's Transit Precincts in 2000 & 2010*. Report. UNOTI Publications, 2013.
40. Stokenberga, A. Does Bus Rapid Transit Influence Urban Land Development and Property Values: A Review of the Literature. *Transport Reviews*, Vol. 34, No. 3, 2014, pp. 276–296. https://doi.org/10.1080/01441647.2014.902404.
41. Cervero, R., and M. Duncan. Transit's Value-Added Effects: Light and Commuter Rail Services and Commercial Land Values. *Transportation Research Record: Journal of the Transportation Research Board*, 2002. 1805: 8–15.
42. Nelson, A. C. Transit and Real Estate Rents. *Transportation Research Record: Journal of the Transportation Research Board*, 2017. 2651: 22–30.
43. Billings, S. B. Estimating the Value of a New Transit Option. *Regional Science and Urban Economics*, Vol. 41, No. 6, 2011, pp. 525–536. https://doi.org/10.1016/j.regsciurbeco.2011.03.013.
44. Mohammad, S. I., D. J. Graham, P. C. Melo, and R. J. Anderson. A Meta-Analysis of the Impact of Rail Projects on Land and Property Values. *Transportation Research Part A: Policy and Practice*, Vol. 50, 2013, pp. 158–170. https://doi.org/10.1016/j.tra.2013.01.013.
45. Higgins, C. D., and P. S. Kanaroglou. Forty Years of Modelling Rapid Transit's Land Value Uplift in North America: Moving beyond the Tip of the Iceberg. *Transport Reviews*, Vol. 36, No. 5, 2016, pp. 610–634. https://doi.org/10.1080/01441647.2016.1174748.
46. Bardaka, E., M. S. Delgado, and R. J. G. M. Florax. Causal Identification of Transit-Induced Gentrification and Spatial Spillover Effects: The Case of the Denver Light Rail. *Journal of Transport Geography*, Vol. 71, 2018, pp. 15–31. https://doi.org/10.1016/j.jtrangeo.2018.06.025.
47. Tehrani, S. O., S. J. Wu, and J. D. Roberts. The Color of Health: Residential Segregation, Light Rail Transit Developments, and Gentrification in the United States. *International Journal of Environmental Research and Public Health*, Vol. 16, No. 19, 2019, p. 3683. https://doi.org/10.3390/ijerph16193683.
48. Dong, H. Rail-Transit-Induced Gentrification and the Affordability Paradox of TOD. *Journal of Transport Geography*, Vol. 63, 2017, pp. 1–10. https://doi.org/10.1016/j.jtrangeo.2017.07.001.
49. Delmelle, E. C., I. Nilsson, and A. Bryant. Investigating Transit-Induced Displacement Using Eviction Data. *Housing Policy Debate*, Vol. 31, No. 2, 2021, pp. 326–341. https://doi.org/10.1080/10511482.2020.1815071.
50. Kim, K., I. Garcia, and S. Brewer. Spatial Relationship between Eviction Filings, Neighborhood Characteristics, and Proximity to the Central Business District: A Case Study of Salt Lake County, Utah. *Housing Policy Debate*, 2021, pp. 1–26. https://doi.org/10.1080/10511482.2020.1838598.
51. Guerra, E., R. Cervero, and D. Tischler. Half-Mile Circle. *Transportation Research Record: Journal of the Transportation Research Board*, 2012. 2276: 101–109.
52. Andersen, J. L. E., and A. Landex. GIS-Based Approaches to Catchment Area Analyses of Mass Transit. *Proceedings of the ESRI Users Group Conference*, 2009.
53. Oakes, J. M., and P. J. Johnson. Propensity Score Matching for Social Epidemiology. *Methods in Social Epidemiology*, Vol. 1, 2006, pp. 370–393.
54. Rosenbaum, P. R., and D. B. Rubin. Reducing Bias in Observational Studies Using Subclassification on the Propensity Score. *Journal of the American Statistical Association*, Vol. 79, No. 387, 1984, pp. 516–524. https://doi.org/10.1080/01621459.1984.10478078.
55. Leite, W. *Practical Propensity Score Methods Using R*. SAGE Publications, Thousands Oaks, CA, 2016.
56. Olmos, A., and P. Govindasamy. A Practical Guide for Using Propensity Score Weighting in R. Practical Assessment, Research, and Evaluation, Vol. 20, No. 1, 2015, p. 13. https://doi.org/10.7275/JJTM-R398.
57. Yi, C. Impact of Public Transit on Employment Status. *Transportation Research Record: Journal of the Transportation Research Board*, 2006. 1986: 137–144.