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On the link between rail transit and spatial income segregation

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ABSTRACT

The link between transportation infrastructure and income segregation has long been recognized in the literature, but has received renewed attention with the increased investment in rail transit in US cities. In this paper, we examine the impacts of rail transit investments on neighborhood income diversity and metropolitan income segregation. For the neighborhood-level analysis, we apply a difference-in-difference approach combined with propensity score matching in 11 metropolitan areas that invested in rail transit between 2000 and 2005. We then estimate the effect of changes in rail transit access on income segregation across the 50 largest metropolitan areas in the US between 1990 and 2010. We find no statistical evidence that rail transit investments spur changes in neighborhood income diversity when compared to similar neighborhoods elsewhere in the city. Similarly, we find no significant impact of new or expanded rail transit lines on metropolitan wide income segregation.

1. Introduction

Residential segregation by income has increased across most major metropolitan areas in the United States every decade since 1970 (Fry & Taylor, 2012, p. 26; Reardon & Bischoff, 2011; Reardon et al., 2015, 2018; Watson, 2009). These increases have been driven by a rising share of individuals and households living in neighborhoods that are majority lower or upper-income, and a declining share of those in more moderate or mixed-income neighborhoods (Fry & Taylor, 2012, p. 26). These trends are concerning given the wealth of literature that documents the detrimental effects that long-term exposure to neighborhood poverty has on a host of individual outcomes including poorer academic achievement, adversary health outcomes, and a reduced chance of experiencing upward social mobility, among others (Chetty et al., 2014; Do & Finch, 2008; Evans & Schamberg, 2009).

Increases in income segregation have occurred alongside rising levels of income inequality; as the income gap between the richest and poorest residents has widened, so too have their spatial separation (Reardon & Bischoff, 2011; Watson, 2009). While income inequality is a significant predictor of spatial segregation, it is not the sole explanatory factor (Reardon et al., 2018). Research on other underlying causes of the growing separation of households by income has received far less attention than research on racial segregation or inequality, though these concepts are intertwined (Glasmeier & Farrigan, 2007). In particular, the role of metropolitan-wide policies in shaping the geography of income segregation are not well understood (Lens, 2017). The purpose of this article is to examine how one such policy, the implementation of a new rail transit system, contributes to income segregation at the neighborhood and metropolitan scale for multiple cities across the United States.

The past two decades have been characterized by a 'rail renaissance' in cities across the United States in an effort to both encourage transit use and as an urban redevelopment or branding strategy (Baker & Lee, 2019; Ferbrache & Knowles, 2017; Nilsson & Delmelle, 2018). One contention accompanying these large-scale public investments is the perception that cities compromise the potential social benefits of increasing accessibility to a transit-dependent population by favoring economic development possibilities (Revington, 2015). The idea that transit may spur gentrification and displacement has garnered a body of literature examining this paradox (Bardaka, Delgado, & Florax, 2018; Nilsson & Delmelle, 2018; Dong, 2017; Padeiro et al., 2019; Rayle, 2015). The evidence to date suggests that transit may play some role in accelerating gentrification, but the effects vary considerably by geographic context (Padeiro et al., 2019).

In this article, we expand this line of research to draw a conceptual link between new transit investments and income segregation at both the neighborhood and metropolitan scale. We hypothesize that new rail transit investments, which are not placed uniformly across a city, contribute to uneven development patterns that give rise to increasing levels of income segregation. Areas surrounding new stations attract new developments, re-shape surrounding land values and alter residential mobility patterns into and out of nearby neighborhoods. Those

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with greater financial resources are attracted to these newly developed areas and those priced out seek housing in a more restrictive housing market causing concentrations of poverty to deepen as wealth accumulates along the new transit line. We test our hypothesis and conceptual framework in a study of income segregation at the neighborhood scale in 11 US metropolitan areas (MSAs) that invested in rail transit between 2000 and 2005. We employ a difference-in-differences modeling approach combined with propensity score matching to identify a plausible set of control neighborhoods in each city. The use of proper counterfactuals in prior transit-neighborhood change studies was identified as a shortcoming in the existing body of research, and a possible contributor to the variation in results across studies (Padeiro et al., 2019). Second, to understand how transit investments may reshape the broader metropolitan income segregation landscape, we estimate the effect of changes in rail transit access on an index of income segregation across the 50 largest MSAs in the United States between 1990 and 2010. Overall, this article contributes to our understanding of how large public investments may or may not contribute to the exacerbation of unequal landscapes of opportunity in a systematic manner across multiple US cities and from a multi-scalar perspective.

2. Related literature

Income segregation can be explained as an outcome of interactions between individual and structural factors operating at multiple spatial scales (Bailey et al., 2017; Glasmeier & Farrigan, 2007). Individual preferences for certain types of housing, locations within the urban environment, and associated amenities combined with the monetary ability to realize these preferences create the supply and demand mechanisms that serve to sort residents according to income (Tiebout, 1956). Individuals have also shown a strong tendency to live in neighborhoods comprised of residents like themselves (Shelling, 1971). Structural considerations help explain significant socioeconomic differences across urban spaces including characteristics of the local economy that may exacerbate spatial inequalities (Watson, 2009); historical patterns of racial discrimination and disinvestment (Glasmeier & Farrigan, 2007); and uneven development spurred by public investments, for example (Zuk et al., 2018).

At the metropolitan scale, empirical research has identified city-wide characteristics that offer some explanation for higher or lower levels of income segregation including an MSA's size and growth rate. Segregation is higher in larger metropolitan areas with fast growing populations (Florida & Mellander, 2018; Watson, 2009), in denser cities (Florida & Mellander, 2018), but also in sprawling more decentralized urban areas including those with density restrictions (Lens & Monkkonen, 2016). We next outline our conceptual framework explaining how a public investment such as transit may contribute to income segregation.

2.1. Conceptual framework

Our conceptual framework for understanding the relationship between a new public investment such as transit and income segregation is summarized in Fig. 1. Public transit is expected to spur changes in land values and rents given the longstanding role that accessibility plays in shaping urban land price gradients (Alonso, 1964; Mills, 1967; Muth, 1969). New transit-oriented developments around stations offer additional amenities beyond accessibility that are expected to generate increased local demand (Bartholomew & Ewing, 2011). The literature is generally in agreement that new rail transit stations lead to some price capitalization effects, but the magnitude varies depending on local and metropolitan contexts – strong economic and population growth, proximity to other amenities, center city locations and walk-and-ride stations all appear to strengthen this relationship (Bowes & Ihlandfeldt, 2001; Hamidi et al., 2016; Higgins & Kanaroglou, 2018). These latter considerations reinforce recent reinvestigations onto the declining importance of commuting costs and accessibility versus proximity to the

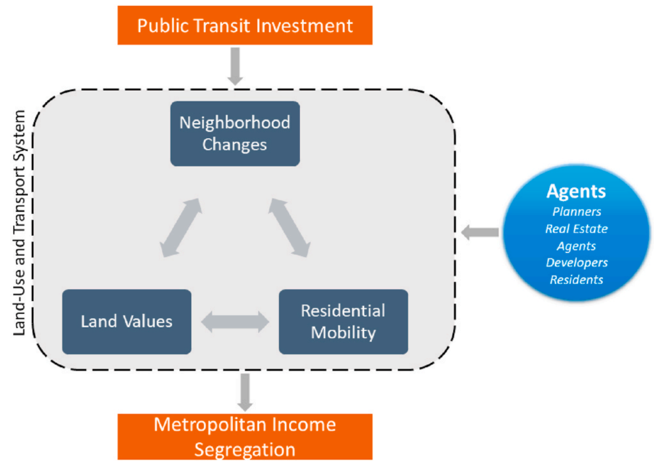

Fig. 1. Conceptual framework on link between rail transit investments and income segregation.

central city in explaining residential sorting (Bogin et al., 2019; Couture & Handbury, 2017). Traditional land price gradients are undergoing a reversal across many North American cities.

Changes in land values have the potential to alter who moves into and out of nearby locations – rising property values and rents may lead to an influx of more affluent residents and a disproportionate out-migration of lower-income residents. This relationship forms the crux of the transit-induced displacement hypothesis (Rayle, 2015; Zuk et al., 2018). The empirical evidence on residential movements is rather limited, but two studies that examine residential mobility using the Panel Study on Income Dynamics across the United States (Delmelle & Nilsson, 2020) and property tax records in Los Angeles (Rodnyansky, 2018), respectively, find no evidence that lower-income residents have heightened out mobility rates in new transit neighborhoods. Using housing mortgage data for the city of Charlotte, North Carolina, Delmelle et al. (2020) uncover a significant shift in the racial profile of mortgage applicants in new transit neighborhoods in Charlotte, North Carolina, but not in their income profile. This relationship was most pronounced in neighborhoods accompanied by other attractive amenities such as walkability, proximity to the center city and previously gentrified neighborhoods.

The aggregate result of these residential movements are changes to a neighborhood's socioeconomic composition. There has been a recent flurry of literature addressing the extent to which new transit stations lead to gentrification or other forms of neighborhood changes. Mirroring the price capitalization literature, the bulk of this more recent work has found changes to be highly context dependent, and not necessarily the norm (Bardaka et al., 2018; Dong, 2017; Kahn, 2007; Nilsson & Delmelle, 2018; Padeiro et al., 2019). Walk-and-ride stations and neighborhoods located in faster grower urban areas are more likely to undergo gentrification-type changes (Kahn, 2007; Baker & Lee, 2019; Nilsson & Delmelle, 2018; Pollack et al., 2010). In an analysis of neighborhood income change in Dallas, (Heilmann (2018)) finds that while overall, access to transit led to increases in neighborhood-scale incomes, this relationship was strongest for neighborhoods that were initially more well-off. Poorer neighborhoods saw either no or negative income changes. Some of the variations in findings from these studies have been attributed to a lack of consistent research design and a failure to use a quasi-experimental approach to control for broader metropolitan trends (Padeiro et al., 2019).

The outer circle in our diagram represents exogenous agents who influence this process in a way that changes are not expected to be uninform across or within all metropolitan areas. These agents can aid in producing gentrification by encouraging the movement of capital into previously disinvested parts of the city (Revington, 2015) or by advertising access to transit as a luxury amenity in certain neighborhoods, for example (Delmelle et al., 2020).

While in the short run, at the neighborhood level, the arrival of more affluent residents can result in increased neighborhood diversity with a mix of higher- and lower income households sharing space. In the long run, the neighborhood could potentially become less diverse if higher-income households replace long-term lower-income residents (Freeman, 2009). Such changes at the neighborhood level could influence city level spatial patterns of income segregation. If rail transit investments lead to a reduced number of neighborhoods with affordable housing, it could contribute to increased concentration of poverty in a few neighborhoods. However, if it results in the dispersion of higher-income residents into a greater number of neighborhoods, reducing the number of affluent neighborhoods, it could contribute to less segregation. Therefore, studying transit's impact on segregation calls for an investigation at both a neighborhood and metropolitan scale.

3. Data and methodology

For this study, we use data from the Longitudinal Tract Database (LTDB) (Logan et al., 2014), the US Census Bureau (Census, 2019a, 2019b, 2019c), and IPUMS (Manson et al., 2019) adjusted to 2010 census tract boundaries using LTDB crosswalks.[1] The LTDB and IPUMS provide census data at different geographic scales that has been integrated across time and space which allows us to study changes in various socioeconomic and demographic variables over time. The main source for the neighborhood (tract-level) analysis is the LTDB which has been complemented with variables from IPUMS National Historical Geographic Information System (NHGIS) while the variables for the MSA-level analysis mainly come from IPUMS NHGIS, complemented with more recent data from the US Census Bureau. Metropolitan Statistical Areas (MSAs) also change boundaries over time with counties added or removed from the MSA. We use 2010 urbanized area and MSA boundary definitions from the US Census. However, an issue in studying urban income segregation using MSAs, is that they can be very large and include upwards of 30 counties (e.g., Atlanta), many which are primarily rural. MSAs are based on commuting flows, not necessarily migration patterns, so if rail transit is implemented in the urban core, it is unlikely that this would significantly affect residential sorting in fourth order neighboring, rural counties. Therefore, we restrict our analysis to the counties within the MSA that contain at least 5% of the urbanized area[2] of the urban core. Fig. 2 illustrates this, using the MSAs of Atlanta, Birmingham, Charlotte, and Nashville as examples, showing which counties were included and excluded from the analysis.

To assess difference in trends before and after opening, we need to observe at least three time stamps. As racial classifications in the decennial census changed after 1970 and there is a lack of available of high-resolution population data prior to 1990, our first time period of observation is 1990. To study pre- and post-trends, we only include MSAs that opened a rail transit line between 2000 and 2005 in the neighborhood level analysis. These will have 2000 as their pre-period and 2010 as their post-period. This limits heterogeneity in the time period between the pre-year and implementation, and between the implementation and post-year. Given that no heavy rail line opened in the US during this time period, we only examine the effects of light rail transit. The resulting 11 MSAs with light rail lines that opened between 2000 and 2005 are shown in Table 1. For the MSA-level analysis of income segregation, we use the 50 most populous MSAs in the US as of the 2010 Census (including the 11 listed in Table 1). Station data comes from the Center for Transit-Oriented Development (CTOD) and has been verified and supplemented by the authors.

To study income segregation over time and between metropolitan areas, ordinal measures that consider the rank ordering of incomes are recommended as they separate segregation from inflation and changes in income inequality over time (Reardon & Bischoff, 2011). Ordinal measures necessitate the construction of income categories. We use definitions described in the Home Mortgage Disclosure Act (HMDA) and Community Reinvestment Act (CRA) to classify families into low, moderate, middle, and upper income (e-CFR – Electronic Code of Federal Regulations, 2019). Low-income households are those whose income is less than 50% of the MSA median household income. Moderate-income households are those with an income of at least 50% and less than 80%, middle-income at least 80% and less than 120%, and finally, upper-income means that the household income is 120% or more of MSA median household income. Census data on number of households by 15 income categories (ranging from less than $10,000 to more than $150,000) for 1990, 2000 and 2010 comes from IPUMS (Manson et al., 2019) and were converted to 2010 census tract boundaries using the crosswalks from the LTDB website. We chose the income categories provided in the census data that come closest to matching the HMDA and CRA income categories. Using the HMDA/CRA classification has the advantage of making the classification both time and MSA specific since it is relative to the individual MSA income levels (and proximate cost of living) at each time stamp.

To measure neighborhood diversity and metropolitan level income segregation, we follow Freeman (2009) who suggests the use of metrics where: (1) higher and lower values indicate greater and lower diversity, and (2) neighborhood income diversity can be used to construct an MSA-level measure of income segregation. Therefore, to measure neighborhood income diversity we use the index of ordinal variation (Kvålseth, 1995) which satisfies these criteria and is calculated as follows:

$$H_i = \frac{1}{k-1} \sum_{k=1}^{k-1} 4c_k(1-c_k) \tag{1}$$

where k is the number of ordinal categories or levels (four in our case, following the HMDA/CRA classification) and c_k is the cumulative proportion of the total number of households at level k or lower. The index measures the average deviation of each level when there is no variation (i.e., when the cumulative proportion each equals 0 or 1). It reaches its maximum value of 1 when the number of households in a tract is evenly split between the highest- and lowest-ranked income categories and its minimum when households is divided among all the income categories. For example, a neighborhood with its households weighted towards low- and upper-income households will receive a higher value and be considered more diverse than a neighborhood with predominately moderate- and middle-income households.

Following Freeman's (2009) and Reardon and Bischoff's (2011) approach, we use the information theory index to measure income segregation at the MSA-level. This index measures the extent to which the average neighborhood-level entropies deviate from the maximum entropy for the entire MSA (Theil, 1972) and is calculated as follows:

$$H_s = \sum_{i=1}^{n} \frac{w_i(H_m - H_i)}{WH_m} \tag{2}$$

where H_i is the neighborhood-level entropy and H_m is the MSA-level entropy, w_i is the number of households at the neighborhood-level and W is the total number of households in the MSA. The information index is the weighted average of the proportional difference between the neighborhood-level entropies and the MSA-level entropy (Freeman, 2009). It ranges from 0 to 1 where a score of zero indicates that the income composition of every neighborhood mirrors that of the entire MSA. A score of 1 indicates that only one group is present in each

[1] https://s4.ad.brown.edu/projects/diversity/Researcher/LTDB1.htm.

[2] Definition of urbanized area which is used by the Office of Management and Budget to define MSAs: https://www.census.gov/programs-surveys/geography/guidance/geo-areas/urban-rural/2010-urban-rural.html https://www.nal.usda.gov/ric/what-is-rural.

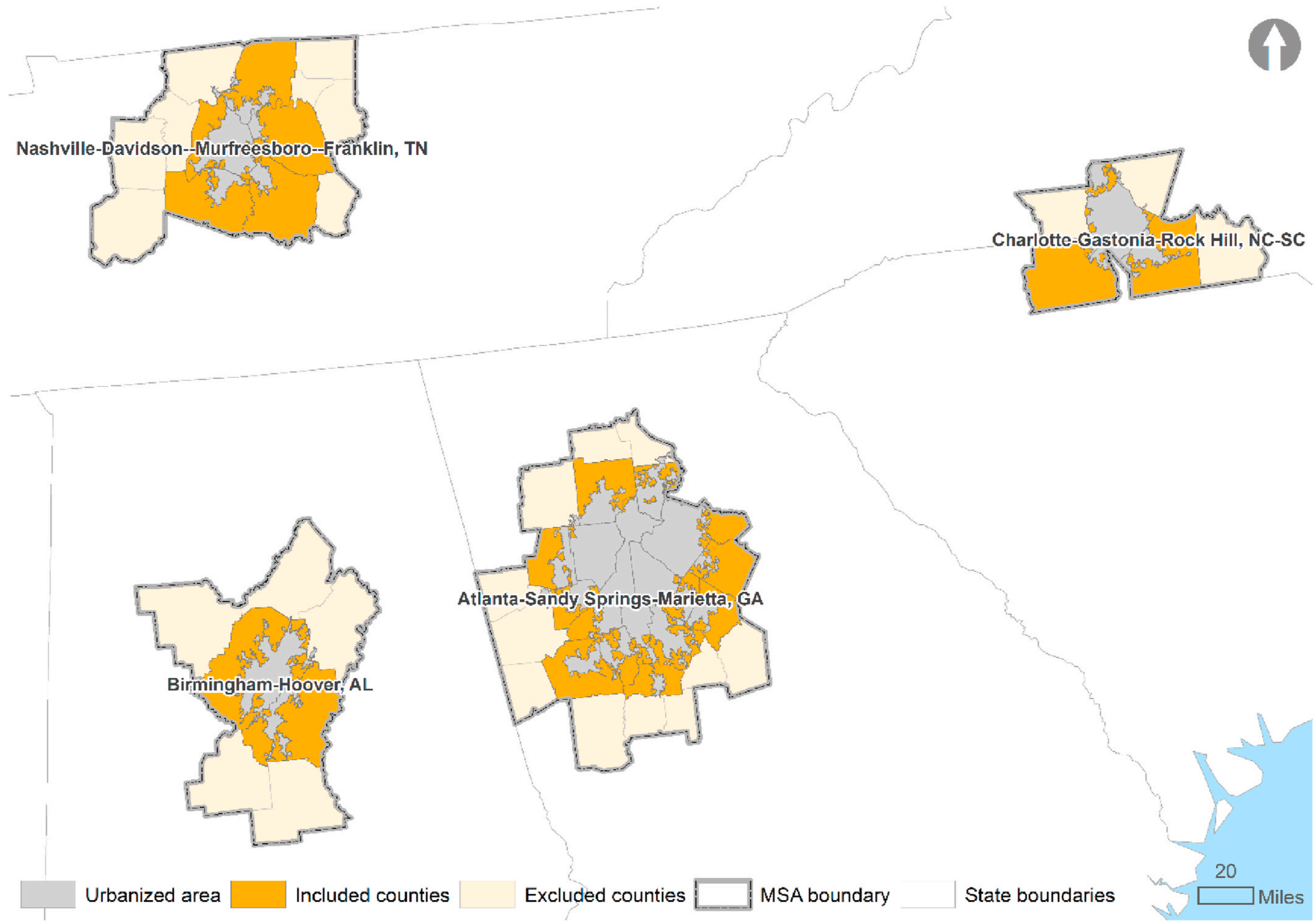

Fig. 2. Example of delineation of urban core counties of MSAs.

Table 1
MSAs and rail lines included in the neighborhood level analysis.

MSA	Lines	Year(s) of opening	City's first rail transit line?
Dallas DART	Red (extension)	2000–2002	No
Denver RTD	C	2002	No
Houston METRORail	Red	2004	Yes
Los Angeles Metro Rail	Gold/L	2003	No
Minneapolis Metro	Blue	2004	Yes
Philadelphia NJ Transit Rail	Riverline Light Rail	2004	No
Portland MAX (TriMet)	Yellow	2004	No
Salt Lake City TRAX	Red	2001	No
San Diego Trolley	Green	2005	No
Santa Clara VTA Light Rail (San Jose)	Tasman East, Capitol, Vasona	2001–2004, 2005	No
St. Louis MetroLink/ Metro	Blue	2001–2003	No

neighborhood (or stated differently, when there is no income variation in any neighborhood).

3.1. Empirical models

To estimate the difference in neighborhood diversity between transit (treatment) and control neighborhoods, we combine propensity score matching (PSM) and difference-in-differences estimations. Difference-in-differences is a method used for assessing causal inference of a treatment on an outcome. It compares changes in an outcome over time between a population that has received the treatment (in our case a rail transit station) and a population that has not (the comparison or control group). Comparing neighborhoods that received and did not receive a rail transit station can be difficult if there are unobserved reasons for why some neighborhoods received the investment and others did not, causing bias in the estimated effect (Gertler et al., 2011). Since the assignment of which neighborhoods receive rail transit stations is not random, we utilize PSM to find control (or comparison) neighborhoods that are similar to and have a similar probability of receiving a rail transit station, but that did not. PSM for findings suitable controls in analyses of causal inference in the social and health sciences where randomized experiments are difficult have been widely applied (Daw & Hatfield, 2018; Dong, 2017; Gertler et al., 2011; Thoemmes & Kim, 2011; Pathak et al., 2017).

While both methods have risks for bias, the risk can be reduced by combining them, offsetting the limitations of a single method and increasing the robustness of the results (Gertler et al., 2011). While PSM can achieve balance on observed covariates, meaning subjects in the treatment and control group are similar in terms of observable characteristics except for the treatment (Thoemmes & Kim, 2011), it cannot account for unobserved characteristics. Using matched difference-in-difference accounts for unobserved characteristics that are constant across time (Gertler et al., 2011). However, there are also risks of inducing bias by using matching in difference-in-difference analyses, particularly when matching on pre-treatment period levels of the outcome variable or on time-varying covariates with low serial correlation (Daw & Hatfield, 2018).

"Treated" neighborhoods in this study are identified as census tracts that intersect a 0.25-mile buffer of a rail transit station. The census tract is the smallest geographic unit for which data is consistently recorded since 1980 and for which we can account for changes in boundaries over time, necessitating their use as a proxy for a neighborhood. The use of a quarter mile buffer is simply a means of selecting those census tracts in closest proximity to the transit station. Since census tracts can be fairly large, the treatment areas are likely to extend beyond the 0.25 to 0.5-mile distance usually assumed as the distance people are willing to walk to a transit stop. However, research suggest that transit-oriented planning areas should be extended up to one mile (Ko & Cao, 2013; Nelson et al., 2015; Petheram et al., 2014). While direct economic benefits around rail transit stations in the form of new developments may occur in the immediate proximity around a station, secondary, indirect effects including property value increases stemming from spatial proximity to both the station and new developments around it are expected to occur beyond this immediate area. Research on price capitalization of new transit stations has shown positive impacts to occur a mile or more from new stations (Billings, 2011; Bowes & Ihlandfeldt, 2001; Debrezion et al., 2007). So, while census tracts are imperfect neighborhood proxies, based on our conceptual framework linking new transit stations with rising property values rents and subsequent changes in the income profile of residents, we expect impacts on sorting and consequently segregation to be felt beyond the immediate area surrounding a station.

To minimize potential bias in the PSM procedure used to find suitable control neighborhoods, we do not include the outcome variable itself. We do include time-variant characteristics in the matching procedure as the literature as shown that neighborhoods characteristics are typically slow to change (Nilsson & Delmelle, 2018; Wei & Knox, 2014). We therefore expect these to have strong serial correlation, further reducing the risk of inducing bias in our estimates. Our time-variant variables include population density, percent Black, Hispanic, and Asian, percent with a Bachelor's degree or more, percent manufacturing employees, percent unemployed, percent in poverty, percent female headed households, percent owner-occupied housing units, percent multi-family units, median home value, median rent, and percent of structures less than 10 and more than 30 years old (following Pathak et al. (2017)). These come from the 2000 Census, the decade before opening. In addition, we include the following time-invariant characteristics: the county in which the tract is located in to account for variations in local government programs and amenities, and the distance from the city center.

We apply stepwise logistic regressions to each MSA to identify the strongest predictors of treatment from the above to include in the estimation of propensity scores. While all MSAs have some common determinants in which neighborhoods are most likely receive a station (e.g., distance to CBD and population density), there are local variations in terms of racial make-up, new construction versus older housing stock, etc. Models for each city are therefore slightly different to accommodate for local conditions in finding the most suitable controls. Tracts intersecting a one-mile buffer of an existing or future rail transit station are not included in the matching process. We apply an optimal matching algorithm with a 1:1 matching ratio (one control per treatment) by MSA to find a possible set of controls for each group of treatment neighborhoods within each MSA.[3] We assess the balance of covariates between the treatment and control group through both numerical and graphical summaries following Ho et al. (2011).

After finding a suitable control group, we estimate the following difference-in-difference model through ordinary least squares (OLS):

$$DIV_{it} = \alpha + \beta_1 Treat_i + \beta_2 Post_t + \beta_3 Treat_i \times Post_t + \boldsymbol{\beta}' \boldsymbol{X}_{it} + \varepsilon_{it} \tag{3}$$

Where i indexes the neighborhood and t the Census year. DIV_{it} is the neighborhood diversity index measuring ordinal variation across income groups described in previous section. $Treat_i$ and $Post_t$ control for initial between group differences and time period differences, respectively. $\boldsymbol{X}_{it}$ is a vector of controls including MSA level fixed effects, distance to the CBD, share of multi-family units and owner-occupied housing in year 2000. Our difference-in-difference estimator, β_3 is given by the interaction between $Treat_i$ and $Post_t$ and is our coefficient of interest. It measures whether neighborhoods near transit experienced significantly higher or lower levels of neighborhood diversity after the opening of the station compared to the control group.

Since many of the 50 MSAs included in our MSA-level analysis already had some rail transit lines before 1990, we cannot estimate a DID model at the MSA level. Therefore, we estimate the effect of changes in rail transit access on income segregation using the following fixed effects model:

$$SEG_{it} = \beta_1 TA_{it} + \beta_2 G_{it} + \boldsymbol{\beta}' \boldsymbol{Z}_{it} + \alpha_i + \gamma_t + u_{it} \tag{4}$$

where i indexes the MSA and t the Census year. SEG_{it} is the information theory index measuring (un)evenness in among income groups, in MSA i at year t. TA_{it} is a proxy for the level of rail transit access in MSA i in decade t measured as the proportion of the population living in neighborhoods with access to light or heavy rail transit. This is calculated as the population in census blocks that intersect a ½ mile buffer, divided it by the total population in the MSA, by decade. The variable G_{it} is a measure of income inequality measured with the Gini Index.[4] $\boldsymbol{Z}_{it}$ is a vector of controls including metropolitan demographic, housing, and labor market characteristics (Reardon & Bischoff, 2011).[5] Finally, we include MSA (α_i) and decade (γ_t) fixed effects.

4. Results

To examine the balance between our treatment and control group, we calculate the difference in means in several neighborhood

[3] Common practice is to use nearest neighbor matching, a "greedy" algorithm, where the closest control match for each treated unit is chosen one at a time. While these algorithms minimize the distance within each matched pair, it does not minimize the total distance within matched pairs. "Optimal" matching algorithms on the other hand finds the matched samples with the smallest average absolute distance across all matched pairs. While greedy and optimal matching approaches generally choose the same set of controls for the overall matched samples, optimal matching is sometimes noticeably (or at least marginally) better in producing closely matched pairs (Ho et al., 2011; Gu & Rosenbaum, 1993).

[4] The Gini index is a standard summary measure of income inequality. It is based on the difference between the observed cumulative income distribution of a region and the notion of a perfectly equal income distribution. The index ranges from 0, indicating perfect equality (where every group receives an equal share), to 1, indicating perfect inequality (where only one group receives all income). Our estimates come from the Census Bureau at the county level and averaged across included counties by MSA (Census, 2019a, 2019b).

[5] These include MSA-level: white population (%), older than 65 and younger than 18-years old (%), with at least a high-school diploma (%), foreign born (%), manufacturing sector employment (%), finance, insurance, and real estate employment (%), unemployment rate, in-migration rate (per 1000 people), new construction proxied by new building permits (per 1000 people), and female-headed households with children under 18 years old (%).

characteristics in 2000, the pre-period. This is done by MSA and the full sample with results for the latter presented in Table 2.[6] Overall, the differences between the treatment and control group are small[7] with some distinctions in distance to the city center (0.3 miles on average), percent owner-occupied housing in the treatment neighborhoods (close to 6 percent points more in the control neighborhoods) and percent multi-family housing units (approximately 7 percentage point difference). While the assumption of the difference-in-differences method does not require pre-treatment conditions to be the same for the results to be valid, we control for such differences in our estimations.

Next, we examine whether there are obvious violations of the parallel trend assumption of the difference-in-differences estimator. To be valid, the control group must exhibit a similar trend to the treatment group in the pre-treatment period (in this case 1990 to 2000) to serve as a counterfactual (Gertler et al., 2011). Means of the dependent variable in 1990, 2000, and 2010 are plotted by MSA in Fig. 3 and for the full sample in Fig. 6. These provide visual confirmation that the trends between the treatment and controls are similar in the pre-treatment period, indicated by the vertical dashed line.

The graphs in Fig. 3 display similar trends in the mean of the dependent variable, H_i (neighborhood diversity), between the treatment and control group prior to 2000 for all MSAs. The divergence in trends between 2000 and 2010 varies by MSA and underscores the importance of controlling for the MSA in both the PSM and in the difference-in-difference estimations. From these graphs, we can discern several distinctions between MSAs in their treatment and control trends. For instance, Denver, Minneapolis, and Portland show an overall increase in neighborhood income diversity from 1990 to 2000, but after 2000, diversity in treatment neighborhoods continued to rise while it declined or remained stagnant in control neighborhoods.

Table 2
Difference in means between treatment and control group in 2000.

	Mean (sd)		
	Treatment	Control	Difference
Population density	2.61 (2.13)	2.62 (2.02)	0.01
Distance to CBD (miles)	1.72 (1.51)	2.02 (1.84)	−0.3
Black (%)	14.15 (18.16)	14.49 (22.68)	−0.34
Hispanic (%)	21.80 (21.95)	21.52 (23.07)	0.38
Asian (%)	10.72 (15.03)	10.54 (14.25)	0.18
Manufacturing employment (%)	12.50 (8.86)	12.57 (7.91)	−0.07
Unemployment (%)	7.19 (6.01)	6.46 (4.63)	0.73
Bachelor's degree or more (%)	29.79 (18.58)	29.84 (19.01)	−0.05
Poverty (%)	16.22 (11.73)	14.52 (10.73)	1.70
Female-headed households (%)	8.82 (6.79)	8.98 (7.01)	−0.16
Owner-occupied housing (%)	43.26 (24.52)	48.93 (24.60)	−5.67
Multi-family units (%)	46.56 (29.35)	39.19 (27.84)	7.37
Median home value ($1000)	171.58 (116.55)	173.00 (119.29)	−1.42
Median rent ($)	663.37 (245.86)	678.24 (265.75)	−14.87
Structures > 30 years old (%)	59.74 (26.76)	59.02 (29.16)	0.72
Structures < 10 years old (%)	67.34 (13.40)	65.50 (13.26)	1.84
N	239	239	

Houston, Philadelphia, and San Diego also saw an increase in income diversity during the pre-treatment period, followed by a decline for both groups post-2000. Treatment neighborhoods in San Diego saw a more rapid decline than in the control group. In Dallas and St. Louis, diversity remained stagnant between 1990 and 2000, but underwent a decline in both groups after 2000. Los Angeles stands out with a decline in the pre-treatment period, but an increase post-treatment. Overall, the rate of increase in income diversity between 2000 and 2010 appears greater in the rail transit neighborhoods than in the control neighborhoods.

To understand what is driving changes in neighborhood diversity, Fig. 4 shows the change in distribution of income classes for each MSA. We grouped the moderate- and middle-income classes in this figure to get a better sense of how the low- and upper-income classes have changed over time. From the figure, we observe two contrasting trends: a decrease in low-income and increase in upper-income residents in the case of Houston, Los Angeles, Philadelphia and Portland or an increase in low-income and decrease in upper-income residents in Dallas, San Diego and St. Louis. San Jose's treatment neighborhoods also saw an increase in the share of low-income residents, but the upper-income segment remained stable. Treatment neighborhoods in Minneapolis and, to a lesser extent, Salt Lake City experienced an increase in higher-income residents, but the share of low-income residents remained the same between 2000 and 2010. Denver saw an increase in moderate-middle income classes alongside a shrinking share of lower- and upper-income residents. Across all MSAs, changes in shares are strikingly small as is evidenced by the narrow range of the y-axis in Figs. 3 and 6.

Three examples illustrating both changes in diversity and income are shown for the cases of San Diego, Portland, and Minneapolis in Fig. 5. In the maps, neighborhoods falling in the upper right quadrat of the legend have undergone increases in diversity coupled with rising incomes. Neighborhoods that increased in diversity, but whose share of high-income households did not increase fall in the upper right quadrat. Conversely, those with low increases in diversity, but high increases in high-income household shares are on the bottom right quadrat. The case of San Diego indicates that census tracts along the light rail corridor largely did not see significant increases in high-incomes, and most had low increases in income diversity as well. The exception are three tracts towards the west of the corridor that show high changes in diversity coupled with low increases in income; these are likely driving the results displayed in Fig. 4 that indicated a slight decline in upper income levels and rises in lower income level groups. Portland and Minneapolis highlight an opposite spatial pattern along the rail corridor with rising shares of high income levels along most tracts. More tracts in Minneapolis show a combined rising income and diversity pattern compared to Portland where tracts are split between rising income and either rising or declining diversity. Overall, these three examples again emphasize the heterogeneity that occurs both within and between metropolitan areas.

When we aggregate the MSA treatment and control samples into one combined sample, both the mean levels and trends in H_i are very similar between 1990 and 2000 (Fig. 6). The divergence in trends post-2000 show both groups experienced a decline in income diversity, but the rate of decline was slightly lower in the treatment group. As expected from Fig. 3, once averaging out across all MSAs, the changes across time periods are quite small (in the second or third decimal-digit, see y-axis in Fig. 4).

To analyze these trends in a more systematic fashion, we estimate the difference-in-difference model both in a reduced form, without additional neighborhood controls, and its full form as described in Equation (3). The results are reported in Table 3. The reduced form model shows no significant change in income diversity following the opening of a rail transit station as indicated by our difference-in-difference estimator, the coefficient of *Treatment* × *Post*, controlling for initial differences between the treatment and control group, time period differences, and MSA-level unobservables. The coefficients for the Treatment and Post

[6] While it is common to perform *t*-test on the difference in means, performing hypothesis testing to assess balance between treatment and control samples is highly misleading and should not be used to assess balance as demonstrated by Imai et al. (2008).

[7] This result hold by MSA as well which is how the treatment and control was originally constructed. The balance between the treatment and control sample was further assessed using graphical output such as histograms and jitter plots. Due to space limitations we do not include them in the paper but they are available from the authors upon request.

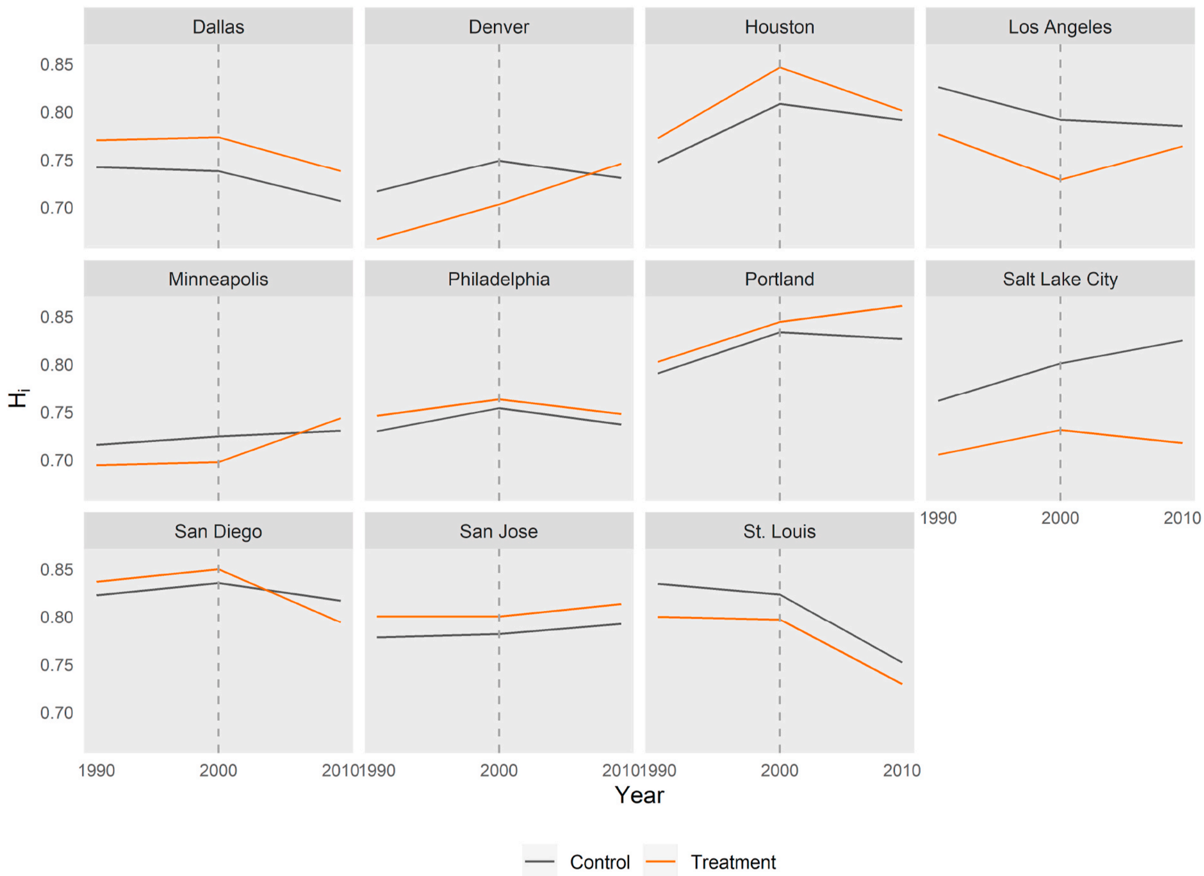

Fig. 3. Treatment vs. control trends by MSA.

variables verify the trend in Fig. 6 with lower levels of diversity in the treatment neighborhoods in the pre-period (2000) and a reduction in diversity in both groups in the post-period (2010). After controlling for other neighborhood characteristics which we saw had some more distinctive differences in Table 2 including distance to the city center and the share of owner-occupied and multi-family housing, the sign of the difference-in-difference estimator does not change but the magnitude is reduced. It remains insignificantly different from the trend in the control neighborhoods.

Given differences found by MSA in Fig. 3, we run Model 2 by MSA without MSA fixed effects. Results of interest are shown in Table 4. While the signs of the estimated coefficient for the difference-in-difference estimator varies across cities, none of them are statistically significant. Whether it was the MSA's first rail transit line (Houston and Minneapolis) or not does not appear to make a difference in the results.

To test the robustness of the model we estimated the model with an alternative specification of the dependent variable based on a more disaggregate set of income categories. For this specification, we used seven income categories based on quintiles ranging from households with incomes less than 20% of the MSA median household to those with incomes of more than 120% of MSA median household income. Model test statistics and estimated coefficients (magnitude, sign and significance) of variables of interest as well as other explanatory variables remain qualitatively the same.[8] All but the sign and significance of the distance to downtown variable in Model 2, Table 3 which becomes significant at the 5% level and negative with a magnitude of 0.004. This would suggest neighborhood income diversity is lower towards the city center.

As a final robustness check, we run the full model specification for the full sample on varying definitions of what is considered a rail transit (or treatment) tract, beyond our original definition of intersecting a 0.25-mile Euclidean buffer around the station. The different definitions include tracts that intersect a station's 0.25 and 0.50 network service area and tracts where at least 25%, 50% or 75% of the total tract area is covered by the 0.5-mile service area. These results are presented in Table 5 and indicate no qualitative change in the interpretation of the results from the original model specification in Table 3.

In summary, based on all the results pertaining to income diversity at the neighborhood level, we find no statistical evidence that rail transit investments spur changes in neighborhood income diversity when compared to similar neighborhoods elsewhere in the city.

We now turn to the MSA-level results on urban income segregation for the 50 largest MSAs in Table 6. With respect to our variable of interest, the block level population within a half mile of a transit station, as a share of the total population, we again find no statistically significant results.[9]

As for the remaining control variables, we find that the share of white and foreign-born residents in an MSA reduces income segregation – this could be explained by greater homogeneity in income diversity between

[8] Full regression results from these models are available from the authors on request.

[9] Several robustness checks on the model were performed including without MSA and year fixed effects, share of Black instead of share of White population, and checks for multicollinearity between variables. Results remain qualitatively the same. The model in Table 6 was chosen based on model performance indicators and tests. There is a risk of overfitting in the current model. However, given robustness in results, we choose to keep the fixed effects in order to not bias estimated coefficients of other variables through MSA or time unobservables. Models without MSA and year fixed effects has R^2s of 0.40.

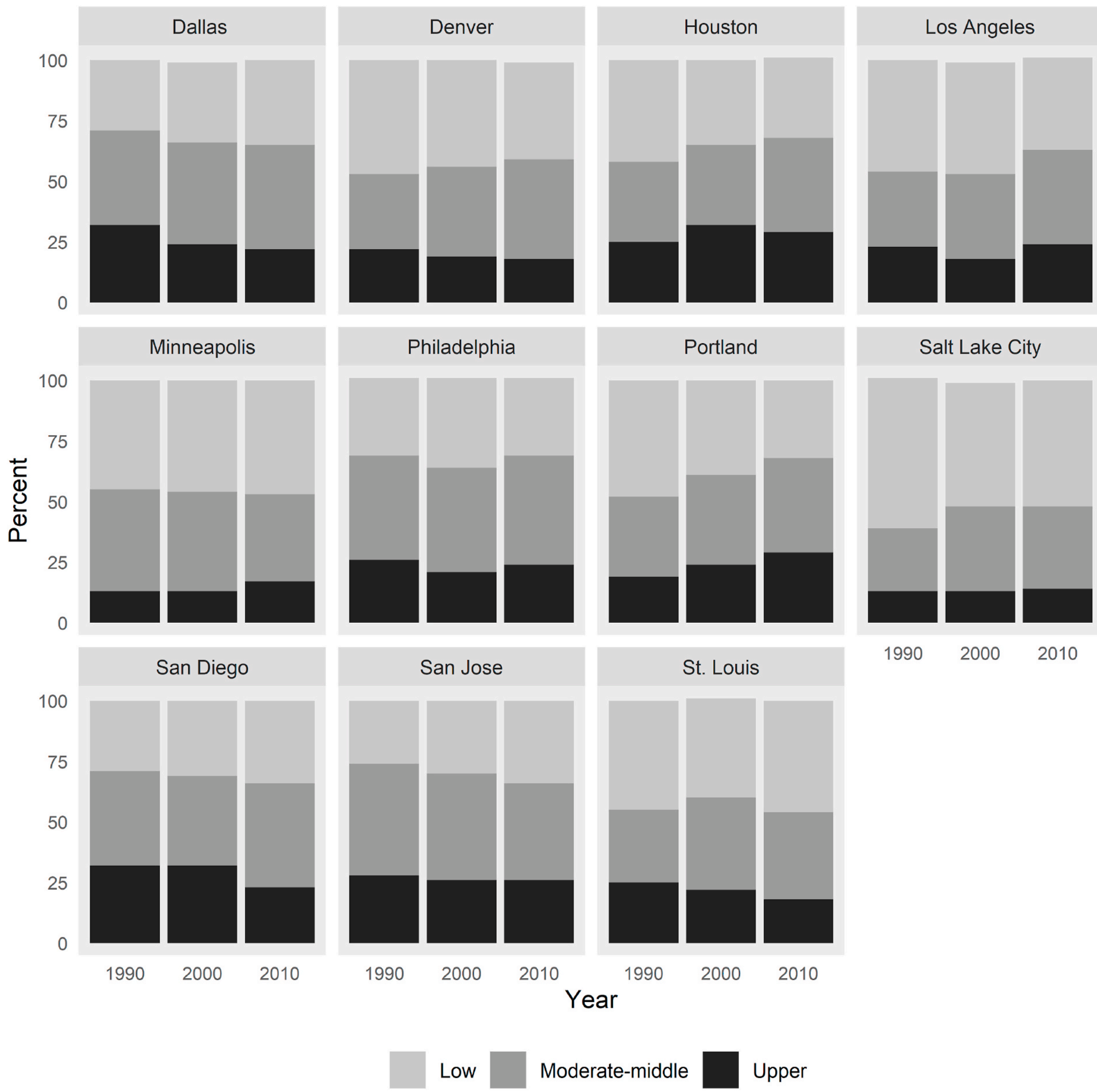

Fig. 4. Distribution of income classes in treatment group by MSA.

neighborhoods in less racially diverse cities. Cities with a large share of children (18 years or younger) and new construction (proxied by building permits) are associated with higher levels of income segregation. These results may be explained by the literature's emphasis on the role of school quality on sorting and the impact of growing housing markets on increases in income segregation (Friedman, 2017).

We estimated this model as well with a dependent variable constructed from the set of seven income categories based on quintiles, as explained earlier. The results remain robust with no significant changes to model test statistic or sign, magnitude, or significance of the estimated coefficients.[10]

5. Concluding remarks

This paper contributes to the literature by studying the effect of transit investments on neighborhood income diversity and subsequent metropolitan-level urban income segregation. Using a case study of 11 MSAs that implemented a new light rail transit line between 2000 and 2005, we find no statistical evidence that proximity to new stations spurred significantly different changes in nearby neighborhood income diversity, compared to similar neighborhoods elsewhere in the city. Overall, the changes in shares of different income groups between 1990, 2000, and 2010 in new transit neighborhoods were strikingly small across the 11 MSAs studied. Consistent with these results, we then found no significant impact of accessibility to rail transit stations on metropolitan-wide income segregation in the 50 largest MSAs in the United States. Instead, we find that income segregation is positively associated with the share of children in the population and growing housing markets.

These findings contribute to the current literature on the relationship between rail transit investments and income segregation by more closely investigating changes in share of different income groups in transit neighborhoods compared to those occurring in similar neighborhoods. This approach has some advantages over those that rely on median income to study neighborhood changes given the significant heterogeneity both within and across cities that may mask the nuances of what is

[10] Full regression results from these models are available from the authors on request.

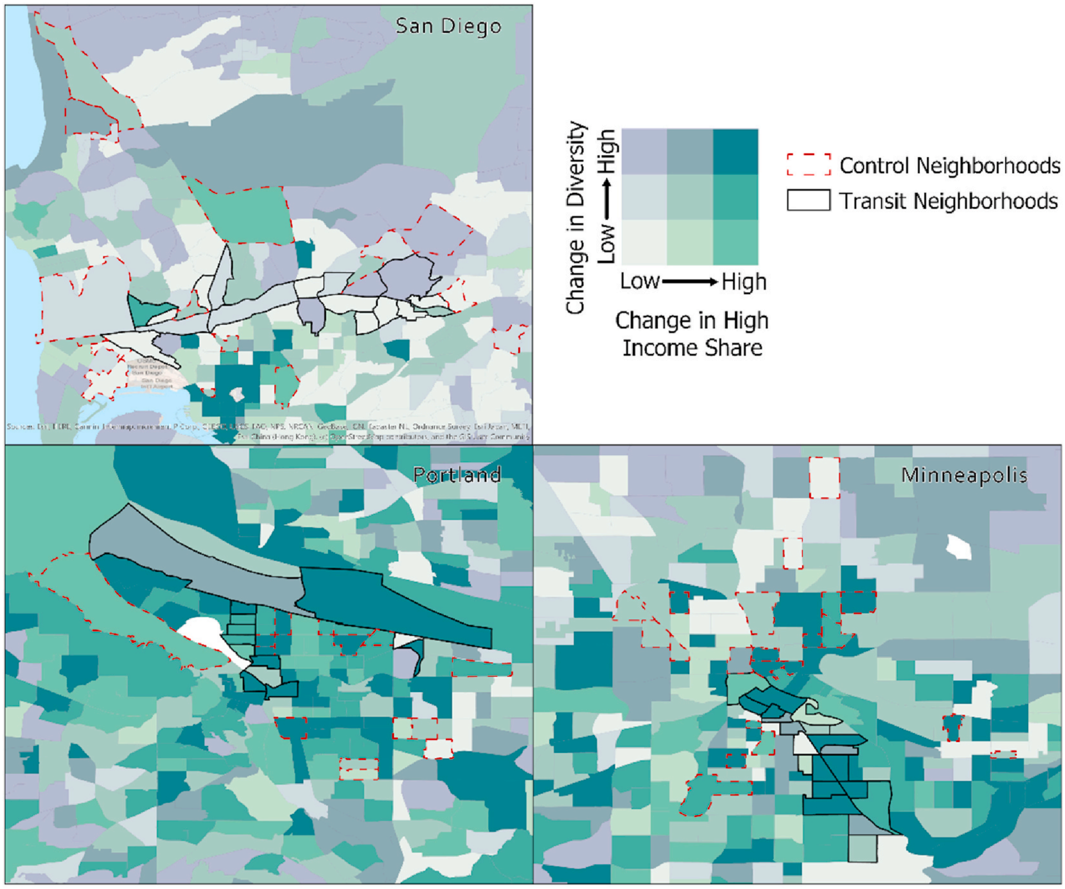

Fig. 5. Changes in neighborhood diversity and income 1980–2000 in San Diego, Portland, and Minneapolis (breaks for changes in high income shares are: <0.05; 0.09; 0.90 and for change in diversity are: <-0.04; 0.02; 0.85).

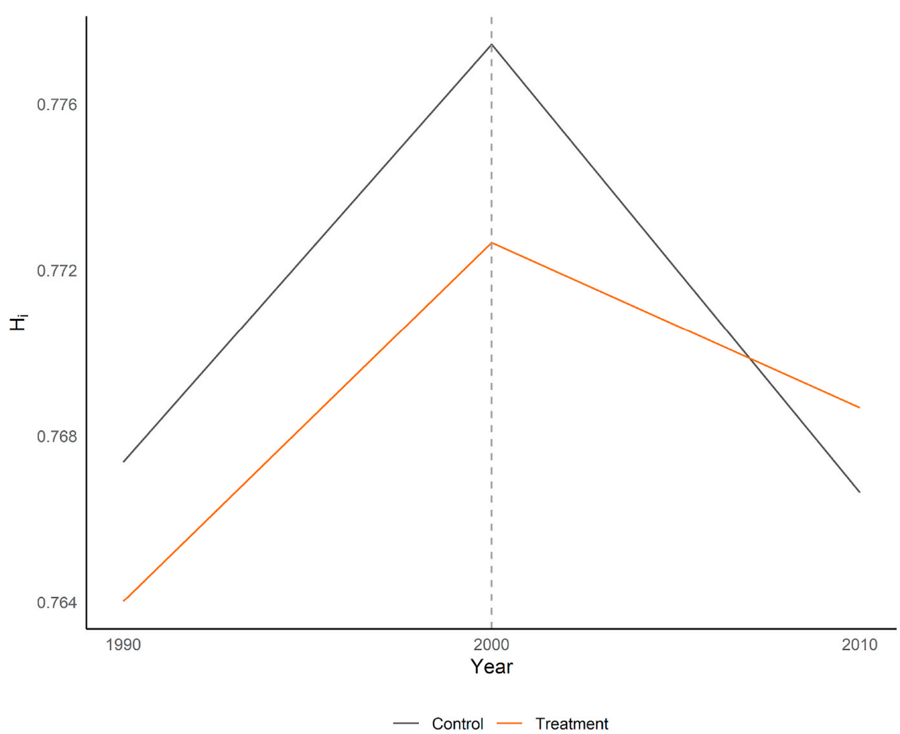

Fig. 6. Treatment vs. control trends combined for all MSAs.

Table 3
Difference-in-differences estimations for the full sample.

	Model 1	Model 2
Treatment × Post	0.008	0.002
Treatment	−0.005	0.002
Post	−0.012	−0.006
Owner occupied housing (%)		0.004***
Multi-family housing (%)		0.002***
Distance to city center (miles)		0.001
MSA fixed effects	Yes	Yes
N	934	934
R^2	0.09	0.25

***, **, * indicates significance at the 1%, 5% and 10% significance level.

Table 4
Difference-in-differences estimations by MSA.

	Treatment × Post	Treatment	Post	N	R^2
Dallas	−0.001	0.024	−0.034	140	0.21
Denver	0.042	−0.008	−0.004	61	0.27
Houston	−0.032	0.009	−0.034	66	0.36
Los Angeles	0.037	−0.057**	−0.015	121	0.46
Minneapolis	0.006	−0.018	0.053	87	0.58
Philadelphia	0.000	0.009	−0.006	105	0.54
Portland	0.021	0.021	−0.001	55	0.17
Salt Lake City	−0.041	−0.111**	0.027	44	0.32
San Diego	−0.037	0.013	−0.022	68	0.10
San Jose	0.003	0.020	0.010	136	0.03
St. Louis	0.013	−0.019	−0.070*	51	0.34

***, **, * indicates significance at the 1%, 5% and 10% significance level.

Table 5
Robustness checks.

	Intersect service area		Percent of tract covered by ½ mile service area		
	¼ mile	½ mile	25%	50%	75%
Treatment × Post	0.009	0.002	0.012	−0.008	0.027
Treatment	−0.003	−0.008	0.012	0.029	0.031
Post	−0.011	−0.007	−0.006	0.030	0.005
Owner occupied housing (%)	0.004***	0.004***	0.006***	0.006***	0.005***
Multi-family housing (%)	0.002***	0.002***	0.003***	0.003***	0.002***
Distance to city center (miles)	0.004	0.008***	0.022***	0.002	−0.003
MSA fixed effects	Yes	Yes	Yes	Yes	Yes
N	986	1320	557	302	166
R^2	0.17	0.21	0.45	0.38	0.30

***, **, * indicates significance at the 1%, 5% and 10% significance level.

Table 6
MSA-level model of income segregation.

	Income segregation
Population within ½ mile of a transit station (%)	−0.0012
White (%)	−0.0017***
18 years or younger (%)	0.0041***
65 years or older (%)	−0.0007
At least a high school diploma or GED (%)	−0.0012
Foreign born (%)	−0.0030***
Manufacturing employment (%)	−0.0002
Finance, insurance and real estate employment (%)	0.0023
In-migration (per 1000 people)	−0.0000
Female-headed households (%)	0.0049*
Building permits (per 1000)	0.0009***
Gini index of income inequality	−0.0167
MSA fixed effects	Yes
Year fixed effects	Yes
N	149
R^2	0.94

***, **, * indicates significance at the 1%, 5% and 10% significance level.

driving changes. This is a sentiment emphasized in Heilmann's (2018) analysis of income changes along Dallas' transit corridor where neighborhood changes were found to be contingent upon their initial income composition – rising in already wealthy neighborhoods and declining in poorer ones. We too uncover divergent trends both between and within MSAs, rendering generalizable statements on the role of transit on shaping income segregation nearly impossible. According to our analysis, the net impact of transit alone on neighborhood income profiles and metropolitan segregation trends are minimal. This is consistent with the evidence emerging in the literature that has attempted to quantify the transit-induced gentrification and displacement hypothesis at both the neighborhood and individual scale. Thus far, there is some evidence that new transit investments in already wealthy neighborhoods, combined with other attractive amenity may lead to some observable sorting changes (Delmelle et al., 2020; Heilmann, 2018; Nilsson & Delmelle, 2020). However, this outcome is more of an exception rather than the norm, as we have demonstrated in this analysis. This is not to say that no changes are felt in neighborhoods where we have found insignificant results – there may be less quantifiable changes as new developments are placed in the immediate vicinity of a station including feelings of a loss of place or exclusion from the planning process that studies such as these cannot account for (Atkinson, 2015; Elliott-Cooper et al., 2019). This challenge is not unique to the transit literature of course as gentrification studies more broadly have grappled with conflicting findings between qualitative and quantitative analyses (Brown-Saracino, 2017; Newman & Wyly, 2006). However, it does underscore the need for complementary analyses on the experiences of residents in neighborhoods where we have found no significant effects.

The analysis performed in this paper is subject to limitations. Census tract are rather large, and though we performed robustness checks to include only tracts that were largely covered by a half-mile walking-service area, it is certainly plausible that changes are very localized and overlooked by this unit of analysis. Our regression analysis examines averages, meaning that local variations across neighborhoods are not reported. There may be instances where changes are a significant problem that are masked in the overall results.

CRediT authorship contribution statement

Isabelle Nilsson: Conceptualization, Methodology, Formal analysis, Investigation, Writing - original draft, Writing - review & editing, Visualization, Funding acquisition. **Elizabeth C. Delmelle:** Conceptualization, Methodology, Formal analysis, Investigation, Writing - original draft, Writing - review & editing, Visualization, Funding acquisition.

Declaration of competing interest

The authors declared no potential conflict of interest with respect to the research, authorship, and/or publication of this article.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.apgeog.2020.102364.

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