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The local labour market effects of light rail transit

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ABSTRACT

Many US cities have made large investments in light rail transit in order to improve commuting networks. I analyse the labour market effects of light rail in four US metros. I propose a new instrumental variable to overcome endogeneity in transit station location, enabling causal identification of neighbourhood effects. Light rail stations are found to drastically improve employment outcomes in the surrounding neighbourhood. To incorporate endogenous sorting by workers, I estimate a structural neighbourhood choice model. Light rail systems tend to raise rents in accessible locations, displacing lower skilled workers to isolated neighbourhoods, which reduces aggregate metropolitan employment in equilibrium.

1. Introduction

US cities have made significant investments in Light Rail Transit (LRT) in recent years. A common justification for LRT is that transit infrastructure will improve urban commuting networks by providing spatial connections between workers and jobs. I test the contention that LRT improves labour market outcomes. First, I estimate the neighbourhood level effects of LRT stations. I introduce a new instrumental variable that establishes orthogonality between station location and pretreatment local economic conditions. I find that gaining a LRT station increases the local employment rate. Second, I estimate a structural neighbourhood choice model to uncover the mechanisms that generate neighbourhood employment changes and estimate aggregate effects. The analysis spans four US cities over the 2000–2015 period.

LRT has become a popular form of transit due to low construction costs relative to subway systems and large perceived economic benefits. LRT systems are typically built along existing roads, removing the need for expensive tunnelling or elevated infrastructure. While LRT shares road space with vehicles and pedestrians, portions of routes are given traffic priority, enabling faster speeds and fewer delays than experienced by buses. In contrast to bus transit, the need for rails, an overhead power source and station platforms ensures that LRT represents a long term local investment.

Transit is not allocated randomly within a city, but is directed toward neighbourhoods with specific characteristics. Comparing the economic outcomes of areas with transit to those without will not provide causal estimates of project impacts due to the effect of differing pretreatment conditions and economic trends. An inclination among transportation planners to extend light rail to the airport provides a natural experiment that introduces an element of randomness to station location. Neighbourhoods between downtown and the airport were much more likely to receive a LRT station than similar neighbourhoods located elsewhere in the metro. I exploit a preference for airport connections to estimate local effects. The endogeneity of transit location is a well known issue from prior literature (Baum-Snow and Kahn, 2000; Holzer et al., 2003; Ihlanfeldt and Sjoquist, 1998). For example, affluent neighbourhoods have been found to resist rail infrastructure due to concerns that transit may lead to a rise in local crime (Kahn, 2007). After correcting for endogenous transit allocation, I find LRT stations generate large improvements in *neighbourhood level* employment outcomes.

Using neighbourhood change estimates as model inputs, I propose and estimate a structural neighbourhood choice model and conclude that LRT systems fail to raise *aggregate metropolitan* employment. In addition to facilitating commutes, LRT stations are valuable local consumption amenities that increase demand for local housing, raising rents. LRT is typically built in accessible, central locations. As a result, low skilled workers are displaced from central locations by rising prices. As employment status is more elastic among the low skilled, the mechanism leads to an aggregate decrease in metropolitan employment. LRT may, counterintuitively, exacerbate the spatial isolation of low skilled workers

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through a process of household displacement. The ability of local amenities to drive up land values and alter a neighbourhood's composition is a familiar mechanism from literature on place based urban policies (Hanson, 2009; Kline, 2010; Kline and Moretti, 2014). This mechanism has been known to undermine spatially targeted policies. I show that the same mechanism is relevant to LRT projects. Structural estimation results show that LRT stations represent a valuable local amenity. I also find LRT is effective at raising aggregate transit use, as it appeals to higher skilled workers who would be unlikely to take other forms of public transit while low skilled workers remain captive transit users.

Poor spatial access to job opportunities can hinder employment outcomes due to high commuting costs (Kain, 1968). Numerous studies have expanded upon the *spatial mismatch* hypothesis to explain heterogeneity in urban labour market outcomes and particularly to explain the lagging outcomes of racial minorities and youth (Andersson et al., 2018; Gobillon et al., 2007; Holzer et al., 2003; Sanchez et al., 2004; Stoll, 1999; Tyndall, 2017). Past research has found that unemployed and poor workers tend to live in places that are isolated from relevant job opportunities. However, the literature has not shown conclusively whether the relationship between accessibility and employment is the result of unemployed workers self-selecting into isolated neighbourhoods, or if there is a causal effect of neighbourhood connectivity on individual employment outcomes. If the effect is causal, transit infrastructure expansion may raise equilibrium employment by reducing spatial isolation.

There is strong evidence that proximity to transit is an important consideration in household location choice (Glaeser et al., 2008). LeRoy and Sonstelie (1983) provided a dynamic model of transportation induced urban change. Wasmer and Zenou (2002, 2006) propose a general urban commuting model that leads to unemployed workers voluntarily occupying inaccessible areas due to infrequent travel. I extend the intuition of these models by incorporating a polycentric city, which generates more complex patterns of neighbourhood sorting.

Some prominent papers have directly analysed local effects of rail stations (Baum-Snow and Kahn, 2000; Kahn, 2007). Results pointed towards localized increases in home values and increased transit use. Few studies have attempted to estimate the neighbourhood effects of LRT stations specifically. Cao and Schoner (2014) studied ridership effects of LRT in Minneapolis. Residents moving towards new transit were found to be less likely to use LRT than the original residents, suggesting a gentrification effect. Heilmann (2018) found evidence of rising incomes in Dallas neighbourhoods that gained a rail station. Contrastingly, Delmelle and Nilsson (2018) analyzed rail projects across the US and found little evidence that stations cause displacement among low income residents. Recent work by Severen (2018) investigates the effect of LRT construction in Los Angeles, finding that LRT has a positive effect on labour supply. The literature provides limited guidance on the overall effects of LRT systems on labour markets, which is striking given the rapid propagation of such systems in the US.

I contribute to the literature in a number of ways. First, I provide policy relevant estimates of the labour market effects of LRT. Second, I supply a new instrumental variable for endogenous station location. Third, I add to the discrete neighbourhood choice literature by developing a structural sorting model that includes preference parameters for transit.

The paper will proceed as follows. Section 2 summarizes the LRT projects under analysis. Section 3 introduces data sources. Section 4 estimates the neighbourhood effects of new LRT stations. Section 5 proposes and estimates a structural neighbourhood choice model and Section 6 concludes.

2. Light rail investment in four US cities

LRT has become a popular transportation and economic development strategy across the US. Between 2000 and 2015 the number of LRT stations in the US grew by 56% (Fig. 1). The empirics of this study will focus on four metropolitan areas: Minneapolis, Minnesota; Portland, Oregon; Salt Lake City, Utah; and Seattle, Washington. These four metropolitan areas are unique within the US in that they all completed new LRT lines over the period of study that included a station at the main metropolitan airport. I exclude metros that do not meet this narrow definition. For example, Los Angeles expanded its LRT system significantly over the study period but did not complete an airport connection. Denver expanded its LRT system but elected to connect the airport through its commuter rail network. Phoenix expanded its LRT system but implemented a monorail connection to the airport. The choice to limit analysis to four metros simplifies data collection and model estimation, but caution should be used when generalizing results to other locations.

Between 2000 and 2015, Salt Lake City constructed 40 new LRT stations, Minneapolis constructed 37, Portland constructed 34 and Seattle constructed 19. These substantial increases in infrastructure produce a significant number of treatment observations. Minneapolis and Seattle had no LRT stations prior to 2000, while Portland and Salt Lake City had already completed a portion of their systems. The metros range in population from 1.2 million (Salt Lake City) to 3.7 million (Seattle). Table 1 displays metropolitan level characteristics as contrasted with the full sample of US metropolitan residents. The median household income of the four metros is comparable to the US urban population as a whole.

Public transit comprises only a small share of total commutes in these metros. Seattle had the highest rate in 2015, with 9.6% of commuters using public transit. Salt Lake City had the lowest public transit mode share in the sample at 3.7%. Across the entire metropolitan population of the US, 5.9% of workers commuted by public transit in 2015. The sample of metros is therefore fairly representative of typical transit uptake among US metropolitan populations. Public transit mode share increased in all four metros during the 2000–2015 period. Seattle experienced the largest increase, expanding public transit mode share among commuters by 45%. While overall transit use is small, populations who depend on public transit are more likely to be on the margin of the labour market (Sanchez, 1999; Sanchez et al., 2004), suggesting the transit expansions may have had significant labour market effects by expanding opportunities among those dependent on transit.

3. Data

Empirical analysis will rely on US Census data products, housing price data, detailed commuter flow information and a matrix of Google navigation trip level data. I use census tract level data from the 2000 US Decennial Census as well as the 2017 American Community Survey (ACS), five-year estimates. Census data from 2000 are crosswalked to boundaries consistent with the 2017 ACS by using the Missouri Census Data Center's Geographic Correspondence Engine. Metropolitan areas will be bounded according to 2015 Bureau of Labor Statistics Core Based Statistical Areas (CBSAs). Census microdata on worker characteristics will be used in structural estimation to provide joint distributions of worker income and demographic characteristics. Worker microdata is taken from the 2000 US Census Integrated Public Use Microdata Sample (IPUMS). All income and price variables are inflation adjusted to 2015 dollars.

In addition to census data on home prices I make use of the US Federal Housing Finance Agency (FHFA) Annual House Price Index (HPI). FHFA HPI estimates are derived from a repeat sales index constructed from multiple public and proprietary data sources on home sales and are reported at the census tract level. A description of the HPI methodology can be found in Bogin et al. (2016).

Job flow data is obtained from the Longitudinal Employer-Household Dynamics, Origin-Destination Employment Statistics (LODES) data products. LODES provides linked workplace and residence data that include a matrix of commute flows at the census block level, which I collapse to the tract level. LODES data coverage extends to 95% of wage and salaried employment nationally (Graham et al., 2014). Omitted workers include self-employed individuals and US mil-

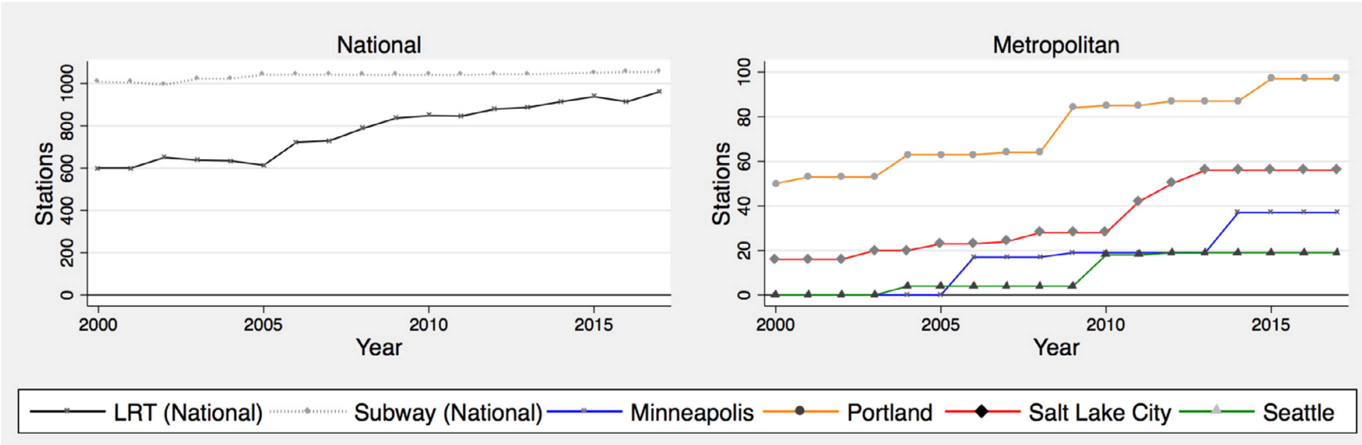


Fig. 1. The Proliferation of LRT Stations. Station counts were obtained from the annual American Public Transportation Association Fact Book. Between 2000 and 2015, the number of LRT stations in the US grew by 56% while the number of heavy rail subway stations grew by 4%.

Table 1
Summary Statistics, Metropolitan Areas.

	Minneapolis	Portland	Salt Lake City	Seattle	All US Metros
Metro Population (2015)	3,526,149	2,382,037	1,170,057	3,735,216	.
Median Household Income (2015)	71,735	64,938	66,089	75,276	73,191
Public Transit Mode Share (2000)	4.4%	5.5%	3.3%	6.6%	5.4%
Public Transit Mode Share (2015)	4.7%	6.5%	3.7%	9.6%	5.9%
LRT Stations (2000)	0	53	16	0	601
LRT Stations (2015)	37	87	56	19	938

Average characteristics of the four metros analyzed are shown, as compared with the average characteristics of all US metropolitan residents. Data is from the 2000 Census and 2017 5-year American Community Survey.

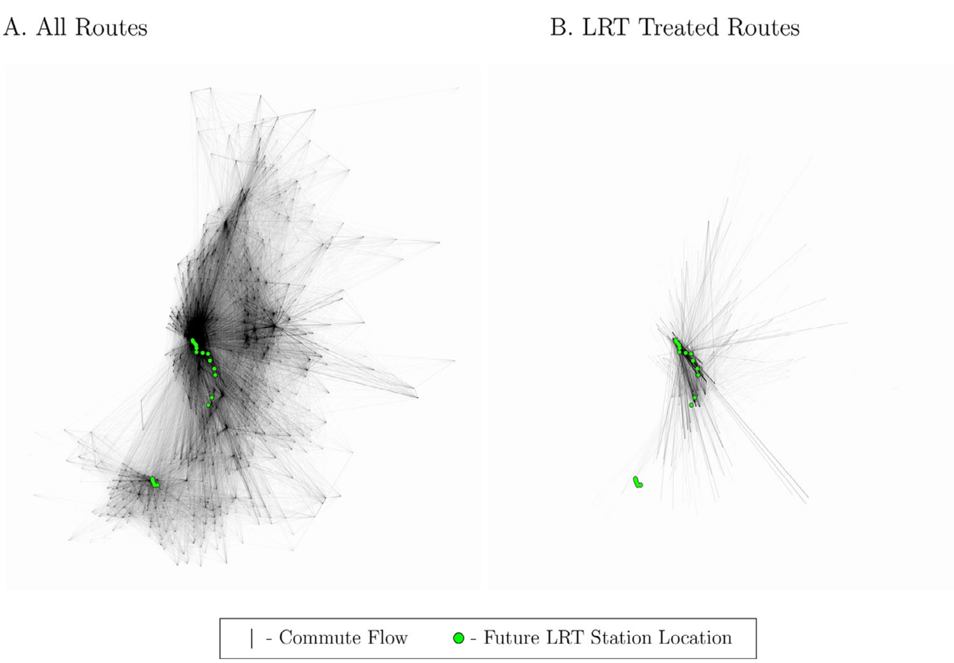


Fig. 2. Pre-treatment Commute Flows, Seattle. Heavier lines indicate more popular commutes. Panel A displays all commutes. Panel B displays only those commutes where new LRT infrastructure will be part of the fastest public transit route between the two points in the post treatment period. While only Seattle is shown, similar data is used for the other three metros.

itary personnel (Graham et al., 2014). I use 2002 data as an indication of pre-treatment commute flows. Data from 2000 are not available from LODES. As an illustration of the data, Fig. 2A maps every 2002 commute in Seattle included in the LODES data. LODES does not include interstate commuters, so analysis will exclude areas that are outside of the principal city's state. To confirm that interstate commuting is relatively rare, I use the 2011–2015 5-Year ACS Commuting Flows data, which estimates commuting flows and includes interstate commuters. In the Seattle metro 0.7% of workers who live in the metro work outside of their home state (Washington). The figure is 0.9% for Salt Lake City, 2.6% for Minneapolis and 7.9% for Portland, which is located close to the Oregon-Washington border. Across the four metros, 2.9% of workers are omitted from the analysis because they cross state lines.

I model the transportation network by constructing a matrix of urban commute times. Internet based route planning services, such as Google

Maps, publicly disseminate travel instructions and estimates of travel duration. To approximate the commute options faced by urban travelers I automate a process to collect Google travel estimates within my sample of metros. Specifically, I use the Google Maps Application Programming Interface (API) to scrape data on relevant trips. I construct a full matrix of potential tract to tract commute routes for each metro, resulting in 1,412,602 origin-destination pairs. Data scraping was executed between September, 2017 and March, 2018. The API provides travel instructions for both driving and public transit for an 8 am departure on a Wednesday. The resulting data set provides the precise travel time and distance for any possible commute executed through the network, with granularity at the census tract level. I impose the assumption that all trips start and end at the population weighted centroid of the tracts. The data collection method allows travel time and distance estimates for all routes, including those not actually used by commuters. Collecting data on the full matrix will be important in the discrete choice methodology, by allowing worker home and work location choice to be informed by the full set of possible travel costs. I collect driving instructions for all routes. Google will return public transit instructions if the trip can be completed with less than one hour of walking. 32% of routes do not have public transit connections because there is no route that involves less than an hour of walking. In Appendix A I show that straight line distances are a poor proxy for public transit trip characteristics. The use of Google routing data provides a much more realistic matrix of travel times than would be possible using traditional commute flow data sets alone.

I further process the Google data to identify all trips that make use of new LRT infrastructure. I first compile a list containing the name of every LRT station built between 2000 and 2015, as it is identified within the Google API. Using step-by-step navigation instructions for public transit trips, a text search program identifies all of the origin-destination pairs that make use of the new LRT infrastructure. Fig. 2B displays all populated commute flows in Seattle that would make use of LRT infrastructure in the post treatment period if the commuter used public transit, according to the route suggested by the Google API. Modeling the network shock induced by LRT expansions is enabled by identifying all cells in the commute matrix that were subject to the shock.

4. Neighbourhood effects of LRT

4.1. Methodology

I estimate the local neighbourhood effects of LRT by comparing places that gained a LRT station to a control group. I consider a census tract to be "treated" by LRT if a new station was built within one km of the tract's population weighted centroid, between the pre and post treatment periods (2000–2015). There are 102 treated tracts identified across the four metros. 38 are in Minneapolis, 22 are in Salt Lake City, 22 are in Seattle and 20 are in Portland. To isolate a valid control group, a number of tracts are dropped from analysis. Tracts with a population weighted centroid within one kilometre of the central business district (CBD) or the airport are dropped, where CBD location is proxied by city hall. CBD and airport tracts may be on economic trajectories that are unique to the rest of the metro. Any tract with a population weighted centroid within one km of a LRT station prior to 2000 is also omitted from analysis in order to ignore network effects that may impact these tracts. For example, Fesselmeyer and Liu (2018) finds significant network effects in the case of an expansion of the Singapore rail system. Additionally, all untreated tracts that are within three km of a new station are omitted to avoid tracts that were partially treated by local spillovers. The resulting data set contains 1924 tracts. The location of LRT stations, treated tracts and omitted tracts are shown in Fig. 3.

Eq. (1) presents the general regression approach.

$$\Delta Y_i = \beta_0 + \beta_1 \mathrm{LRT}_i + \Gamma X_i + \Theta_{m(i)} + \varepsilon_i \tag{1}$$

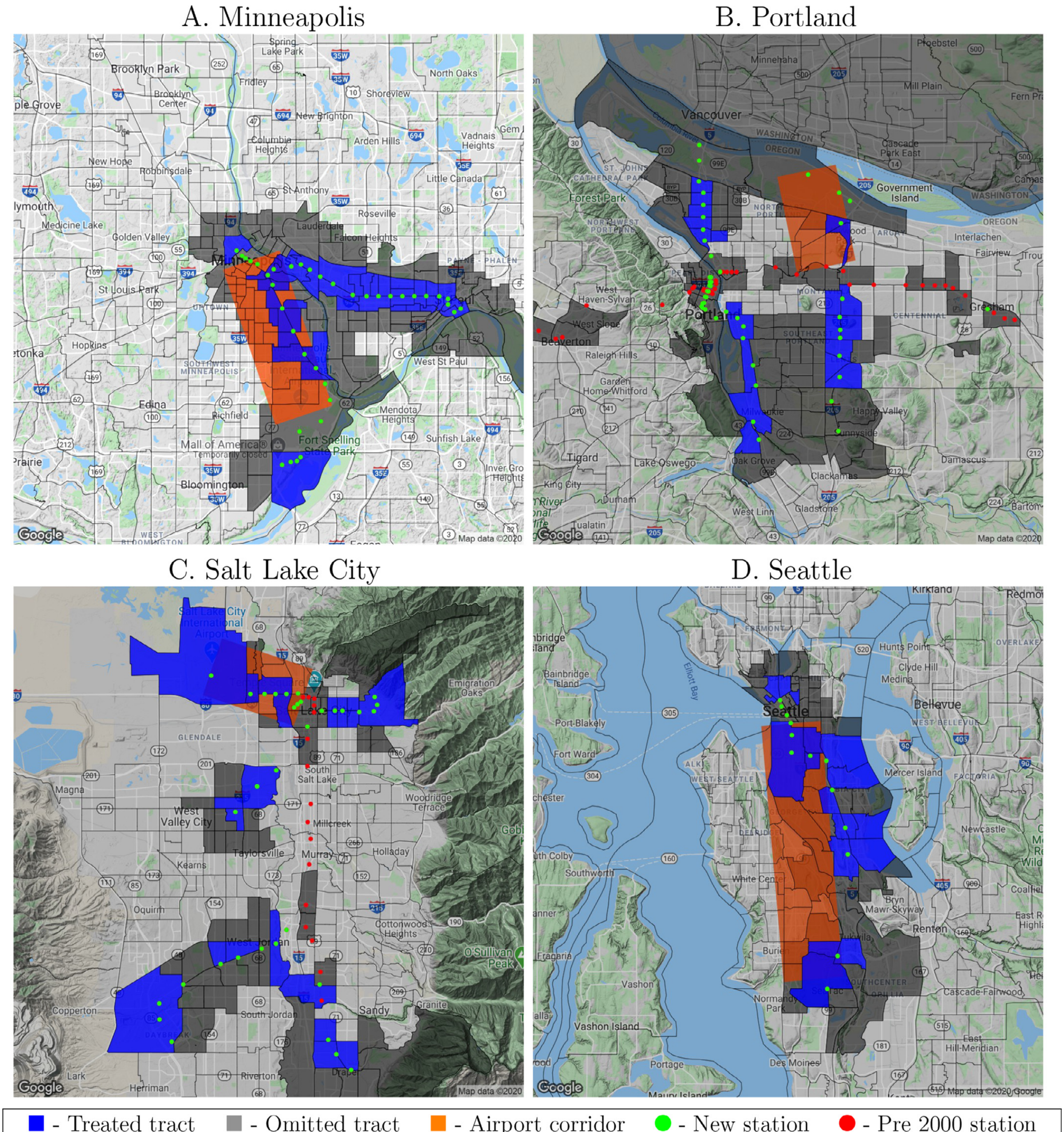
ΔY_i is the change in a neighbourhood characteristic between 2000 and 2015. LRT_i is a dummy variable that takes a value of one if the tract is treated with LRT. X_i is a vector of spatial control variables, including distance to city hall and distance to the airport. $\Theta_{m(i)}$ captures CBSA fixed effects. i indexes tract and m indexes metropolitan area.

OLS results are expected to be biased due to the endogenous placement of rail stations relative to local economic trends (Ihlanfeldt and Sjoquist, 1998). To identify a causal relationship, researchers have equipped past empirical investigations with exogenous network shocks. Holzer et al. (2003) focused on reverse commuters, whose behaviour is potentially orthogonal to subway planning decisions that focus on commutes towards downtown. Tyndall (2017) made use of station closures triggered by a hurricane event as an exogenous shock to the New York City subway system. Analogous endogenous placement issues for the case of road infrastructure have been addressed in Baum-Snow and Kahn (2000), Baum-Snow et al. (2017) and Baum-Snow (2019). I propose a new instrument for deriving random variation in LRT placement: straight lines connecting the CBD to the metro's primary airport.

Consider the ideal randomized experiment to identify the effect of a LRT station on neighbourhood outcomes. Among a set of neighbourhoods, a lottery determines which subset of tracts gain LRT stations. After treatment is applied, any differences in outcomes observed between the treated and control neighbourhoods would be attributed to the causal effect of LRT. This is true because the mechanism that assigned treatment status is orthogonal to pretreatment characteristics. The proposed instrument aims to capture a case of analogous random allocation.

In 1975, of the 25 largest US metros, only Boston and Cleveland had a direct rail link from the CBD to the largest metropolitan airport. By 2017, 16 of the largest 25 metros had an airport link. Fig. 4 plots this progression. The economic development motivation for constructing rail links from city centres to airports is based on very little economic literature. Case studies have generally been unable to provide compelling arguments in favour of such projects (Stubbs and Jegede, 1998; Widmer and Hidber, 2000). Contrastingly, the political motivations for constructing such "mega-projects" appear to be strong (Altshuler and Luberoff, 2004). The origins of these large rail projects are often attributed to state or regional governments who are promoting broad economic development goals and are unlikely to be apprised of, or motivated by, differences in neighbourhood level transit demand. As such, tracts treated by LRT *by virtue* of their location relative to the airport can be assumed to have local economic trends that are orthogonal to the mechanism assigning treatment status. I assume an exclusion restriction wherein changes to local economic conditions are unaffected by being en route to the airport except through differential LRT allocation. The assumption is imposed after controlling directly for distance to the airport and distance to the CBD, which eliminates spatial trends that could be caused by downtown or airport proximity. Redding and Turner (2015) provided a discussion of instruments in the urban economics literature that rely on the incidental connection of spatial units located between important economic nodes. Implementations of this approach have included Chandra and Thompson (2000) and Faber (2014). The proposed instrument relies on a similar logic.

The airport corridor instrument is viable because it is unlikely to affect the local labour market through alternative mechanisms, whereas instruments suggested in past literature have a less plausible exclusion restriction. A potential alternative instrument for transit infrastructure location could be the location of historic transit right of ways. Brooks and Lutz (2019) provided a detailed discussion regarding why such an instrument may not be valid. The authors provided evidence that the location of historic streetcar routes in Los Angeles have had long lasting effects on neighbourhoods, even half a century after streetcars were removed from roadways. The result suggests that historic transit infrastructure placement is not exogenous to current neighbourhood conditions or trends. Differences between planned transit routes and the routes actually constructed may provide a source of exogeneity for station location in some cases (for example Heilmann, 2018), though the standardization of such an instrument, particularly across multiple



All treatment tracts are identified above. Tracts omitted from the sample are shown in grey. The instrumental variable will rely in the location of the airport corridors, identified above.

Fig. 3. LRT Treated Tracts and Instrumental Variable.

cities, is difficult as route plans typically go through many iterations of proposal and revisions. Instruments based on local employment shares (i.e. Bartik et al., 1991 type instruments) would not solve the spatial endogeneity issue of station location.

I instrument the LRT dummy variable in Eq. (1) with a dummy variable for being within the “airport corridor.” A tract is considered to be in the airport corridor if its centroid is within two km of a straight line drawn between the airport and the pre 2000 station that is closest to the airport, creating a corridor that is four km wide. If there is no pre 2000 station (Seattle and Minneapolis) then city hall is used. Airport corridors are mapped in Fig. 3. First stage regression results are shown in Table 2. Being located within the airport corridor increases the probability of receiving a LRT station by 55.0 percentage points. The corridor variable alone explains 14.8% of the variation in station assignment. First stage

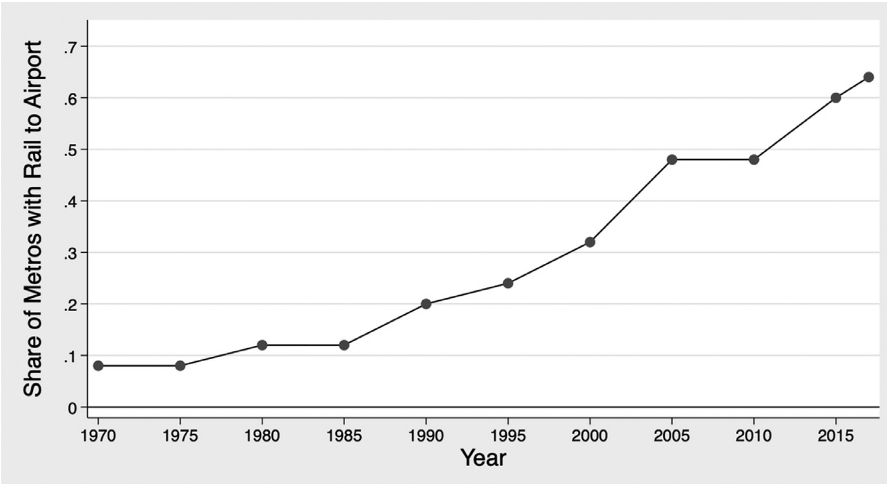


Fig. 4. Expansion of Airport Rail Service, 25 Largest Metros. The share of large US metros with a rail link from downtown to the largest airport has increased rapidly. The composition of the largest 25 metros is allowed to change through time according to US Census population estimates.

Table 2
First Stage Results, Predicting Station Locations.

Variable	
Airport Corridor (dummy)	0.550**
	(.076)
Distance to city hall control?	Y
Distance to airport control?	Y
CBSA fixed effects?	Y
R^2	0.176
Cragg-Donald Wald F statistic	284.77

Significance levels: $*$: 5% $**$: 1%. N = 1,924. Robust standard errors in parenthesis. The outcome variable is a dummy variable for LRT treatment status.

results demonstrate that the instrument is a strong predictor of LRT station location over the period of study. Standard weak instrument tests strongly reject the proposition that the instrument is weak.[1]

The four km wide corridor is selected because it maximizes the explanatory power of the first stage. However, results were estimated using corridors ranging from two to eight km and results changed very little. Corridors wider than eight km experience weak instrument issues.

I use robust standard errors throughout the analysis. I have repeated analysis with standard errors clustered at the CBSA level and find results that are very simlar. I follow the advice of Imbens and Kolesar (2016) as well as Angrist and Pischke (2008) and do not cluster standard errors due to the small number of clusters.

4.2. Neighbourhood change results

Neighbourhood change results are summarized in Table 3. Initially, a naive OLS approach is used to estimate the effect of LRT stations on neighbourhood characteristics (Eq. (1)). Table 3 also provides IV results, where treatment status (LRT_i) is instrumented with a binary variable for being within the airport corridor. The partial effects of control variables are excluded from the table. In general, a local LRT station is found to significantly improve local employment outcomes. The below summary of results will focus on the IV specification. A comparison of IV and OLS results suggests that rail infrastructure was directed towards neighbourhoods with economic trends that were below average. Because distance to the airport and city center are controlled for directly, the causes of the different economic trends must be orthogonal to effects of proximity to these locations.[2] Potentially this bias is related to transportation infrastructure being directed to neighbourhoods that lack the political and economic clout to resist construction.

I first consider IV estimates that do not control for local demographic changes, allowing estimates to correspond to the full effect of a new LRT station on the average outcomes within a neighbourhood. Labour market outcomes in treated tracts had a strong positive response to the introduction of LRT (Table 3). The local employment rate among adults rose by a large and highly significant 12.3 percentage points, relative to a 2000 treatment tract average of 62.1%. Correspondingly, the share of the local adult population participating in the workforce rose by 10.2 percentage points and the local unemployment rate fell by 5.4 percentage points. A portion of the positive labour market effects could in theory be attributable to public transit providing access to new labour market opportunities for the local population. However, the drastic shift in labour market outcomes may be the result of a large change in the characteristics of the local workforce. When regressions are run with the inclusion of neighborhood demographic control variables (Table 3), I find the magnitude of employment, labour force participation and unemployment effects are reduced by roughly 30%, consistent with sorting contributing to the local increases.

Viewed as a place-based urban renewal policy, LRT appears to be a powerful tool to advance average local labour market outcomes. The local employment effects I find are larger than those typically reported in evaluations of government run place based economic development policies such as Empowerment Zones and Enterprise Zones (Ham et al., 2011; Neumark and Kolko, 2010).

Policy makers may be interested in LRT as a means to increase the use of public transit and decrease reliance on privately owned vehicles in treated neighbourhoods. The partial effect of gaining a local station on the transportation mode share of local commuters is shown in Table 3. There is no evidence that a local LRT station led to an increase in the share of the local workforce commuting by public transit, relative to control tracts. IV as well as OLS estimates find no significant local effect

[1] The Cragg-Donald Wald F Statistic is estimated as 284.8, strongly rejecting the null hypothesis that the model is weakly identified. The Cragg-Donald Wald F statistic relies on the assumption that errors are independent and identically distributed (i.i.d.). If errors were not i.i.d. the Kleibergen-Paap Wald F statistic would be robust. The Kleibergen-Paap Wald F statistic is estimated as 52.1, also strongly rejecting the null hypothesis of weak model identification.

[2] The effect of airport proximity could vary through time. I run an alternative specification where I control for the 2000–2015 change in number of commercial takeoffs originating from the metro's airport as reported by the Federal Aviation Administration, interacted with a tract's distance to the airport. The control should absorb time varying airport amenity effects, such as noise pollution. When including the control I find results that are essentially identical to the main specification.

Table 3
Neighbourhood Change Results.

	Δ Employment			Δ Labour Force			Δ Unemployment		
	Local Labour Market Changes								
	Δ Employment Rate			Δ Labour Force Participation Rate			Δ Unemployment Rate		
	OLS	IV	IV	OLS	IV	IV	OLS	IV	IV
Gained LRT Station	0.043**	0.123**	0.078**	0.034**	0.102**	0.065**	0.026**	0.054**	0.047**
	(0.010)	(0.023)	(0.020)	(0.009)	(0.023)	(0.031)	(0.004)	(0.012)	(0.013)
Demographic controls?	N	N	Y	N	N	Y	N	N	Y
Mean 2000 Value (treated obs)		.621			.675			.081	
	Local Transportation Changes								
	Δ Public Transit Mode Share			Δ Private Vehicle Mode Share			Δ Private Vehicle Access Rate		
	OLS	IV	IV	OLS	IV	IV	OLS	IV	IV
Gained LRT Station	0.005	0.020	0.012	0.009	0.002	0.001	0.027**	0.038*	0.021
	(0.007)	(0.019)	(0.022)	(0.009)	(0.022)	(0.023)	(0.008)	(0.015)	(0.015)
Demographic controls?	N	N	Y	N	N	Y	N	N	Y
Mean 2000 Value (treated obs)		0.132			0.738			79.994	
				Local Demographic Changes					
	Δ Log Home Value			Δ Repeat Sales Index			Δ Log Housing Units		
	OLS	IV		OLS	IV		OLS	IV	
Gained LRT Station	0.134**	0.198*		10.449**	16.652**		0.125**	0.305*	
	(.031)	(.077)		(3.671)	(9.633)		(.040)	(.134)	
Demographic controls?	N	N		N	N		N	N	
Mean 2000 Value (treated obs)	12.181			100			7.269		
	Δ White Pop. Share			Δ College Degree			Δ Log Median Income		
	OLS	IV		OLS	IV		OLS	IV	
Gained LRT Station	0.063**	0.110**		0.042**	0.077**		0.054	0.163*	
	(.012)	(.035)		(.011)	(.030)		(.029)	(.077)	
Demographic controls?	N	N		N	N		N	N	
Mean 2000 value (treated obs)	0.632			0.246			10.731		

Significance levels: ∗ : 5% ∗∗ : 1%. N = 1,924. Robust standard errors in parenthesis. All regressions include control variables for CBSA fixed effects, the distance to city hall and distance to the airport. The additional demographic control variables include changes in white population share, Black population share, Asian population share, Hispanic population share, share of adults with a high school diploma, share of adults with a college degree, share of adults with a graduate degree, share of population between 18 and 35, and share of population over 65. The Δ Repeat Sales Index estimates are executed on a reduced sample (1,809 tracts) due to missing observations in the FHFA data.

on either public transit mode share or private vehicle mode share. While all four cities reported increased public transit use across the study period, the effect appears not to be caused by the direct neighbourhood effects of LRT stations. Results of IV regressions also indicate that a local LRT station causes the share of individuals who report having access to a private vehicle in the average treatment tract to increase from 80.0% to 83.8%, providing complementary evidence that the arrival of a LRT station does not lead to a local reduction in private vehicle use. Comparison of IV estimates with and without demographic control variables suggests that the local demographics of treated neighborhoods are shifting towards populations who are less likely to use public transit for commuting and more likely to own a private vehicle, though the addition of control variables does not change these estimates significantly.

It is informative to jointly consider the employment effects and public transit use effects. LRT stations drastically improve average local labour market outcomes while simultaneously generating no increase in local transit commuting, relative to control tracts. The results suggest that neighbourhood employment effects are not due to transit providing new job accessibility opportunities for commuters. A mechanism of neighbourhood sorting where residents with better employment prospects move to LRT tracts endogenously is more consistent with the results.

If LRT is increasing the demand for housing in a neighbourhood there should be an observable increase in local prices. Prior research has generally found transit amenities have a positive effect on local home values. Kahn (2007) found new "walk-and-ride" transit stations increased average local home values by 5.4%, 10 years after station construction. I use two separate data sources on home values and both results suggest a large increase in home values caused by LRT stations. Using US census and ACS figures on tract level mean home values I estimate a local LRT station increases the average local home value by 21.9%. LRT station construction may cause a change in the quality of local housing due to local redevelopment. The tract level FHFA HPI is used to control for changes in housing characteristics. Using this repeat sales index, LRT stations are found to cause a 16.7% increase in local housing values.

LRT allocation is often accompanied by local real estate development and reductions in zoning restrictions (Atkinson-Palombo, 2010). This reality will be important for structural estimation as the introduction of LRT may increase demand for a neighbourhood, but may simultaneously increase the supply of housing in that neighbourhood. Relative to control tracts, tracts that received LRT saw an average increase in local housing stock of 35.7%, over the 15 year period. The result suggests that cities followed an approach of Transit Oriented Development (TOD), directing new housing towards transit stations. New housing is likely to be of a higher quality than the older stock, potentially contributing to gentrification and raising local housing demand.

In addition to increasing the stock of housing, development adjacent to stations could include an increase in firms, which may represent amenities to local residents. When studying the Phoenix LRT system Credit (2018) found large local increases in business formation around new stations, including significant increases in service and retail firms.

LRT may also represent an amenity through its provision of access to leisure activities near other stations in the network. While a local

LRT station does not appear to induce an increase in local transit commuting, it may accommodate trips for leisure activities. Within the four metropolitan areas studied only 44% of public transit trips are commuting trips and among trips by rail only 50% are for commuting.[3] Cao and Schoner (2014) used survey data for Minneapolis and found that those who moved towards a new LRT station became significantly more likely to use transit for leisure trips, but were no more likely to use transit for commuting. LRT stations provide access to consumption amenities that may be particularly valuable to higher income households such as shopping centers, the airport and stadiums. For example, the stadiums of all 12 men's major league sports teams in the four metros are directly accessible from a LRT station. Access to consumption amenities provides a mechanism that could cause higher socioeconomic workers to cluster around LRT stations, even if they do not use these systems for commuting.

After initial increases in the level of neighbourhood amenities, neighbourhood conditions may continue to improve due to endogenous neighbourhood change. The rising socioeconomic status of incoming residents may itself attract additional high socioeconomic households.

If LRT is causing high socioeconomic status residents to move into the neighbourhood there may be an observable change in average local demographics. I first test for an effect of LRT on shifts in racial composition. I find that LRT led to an increase in the local white population share of 11.0 percentage points (Table 3). I also test for an effect on local education rates and find that the share of the local population with a college degree increased by 7.7 percentage points. Both of these results provide evidence of LRT induced neighbourhood gentrification. I also test for an effect on changes in local income, though such a change could be due to sorting or a change in the labour market outcomes of original residents. I find median incomes increased by a significant 17.7%.

While I am able to control for the effect of observable demographic changes on labor market and commuting outcomes, unobserved sorting may also exist. As noted in prior works (LeRoy and Sonstelie, 1983; Wasmer and Zenou, 2002; 2006), workers are likely to sort on employment status itself. Even with identical demographics, a worker who is employed or searching for employment is more likely to locate in an area of high labour market access. Employed workers may also wish to locate closer to consumption amenities given their higher spending relative to the unemployed. Without the ability to observe the location decisions of individuals through time, it is not possible to directly decompose neighbourhood changes into sorting effects and individual behaviour effects.

The level of neighbourhood change generated by stations may be a function of the time elapsed since the station was completed, due to neighbourhood development and worker sorting proceeding over time. In Appendix B I test for differential neighbourhood change effects based on the time elapsed since station construction. I find evidence of larger demographic shifts in tracts where the station has existed for more time.

Within the sample studied, LRT stations appear to have profoundly changed the neighbourhoods in which they are located, most notably by drastically improving average local employment outcomes. Simultaneously, LRT stations appear to generate no increase in the share of local residents using public transit and dramatic changes in local demographics, with a shift towards higher socioeconomic status residents. Taken together, this evidence suggests that the apparent labour market effects of LRT are largely due to endogenous household sorting rather than a mobility induced expansion in labour market opportunities. The subsequent section will directly model the process of neighbourhood choice to better understand the distribution of LRT effects across income groups and estimate the aggregate impact of LRT construction on the metropolitan wide labour market.

[3] National Household Travel Survey, pooled data from 2001, 2009 and 2017 surveys.

5. Urban structural estimation

5.1. Modelling neighbourhood choice

I rely on the above estimated causal neighbourhood effects to estimate a structural neighbourhood choice model. I estimate the model to precisely match IV estimates from the prior section. By assigning workers a utility function, the observed changes in the LRT system can be reconciled with observed neighbourhood impacts through the decisions of individual workers. The model will yield parameters that govern worker preferences for LRT. Preference parameters will enable counterfactual analysis, facilitating estimation of aggregate LRT effects and how the impacts of LRT are spread across income groups. The microfounded model overcomes the issue of endogenous sorting by modelling worker choice explicitly.

The practice of estimating structural neighbourhood choice models is becoming increasingly popular due to advances in methodology and the ubiquity of computational power. Structural estimation provides an important advantage in its ability to recover the parameter estimates that account for complex and endogenous choice. In regards to the current research question, the ability of new rail infrastructure to advance neighbourhood development is of general interest. However, a more fundamental question is how these investments affect individual behaviour and aggregate outcomes.

The contributions of Alonso (1964), Muth (1969), Mills (1967) and Fujita and Ogawa (1982) provide a basis for modeling urban spatial structure. From this early work it was clear that the rational decisions of utility maximizing agents who face different commuting costs give rise to spatial heterogeneity in the characteristics of residents.

Anas (1981) provided an early application of logit choice modeling for household location and transportation mode choice, making use of the discrete choice framework of McFadden (1973). Epple and Sieg (1999) pioneered an estimation methodology for structural neighbourhood choice models. The focus of Epple and Sieg (1999) as well as Bayer and McMillan (2012) was primarily on reconciling observed data with the predictions of Tiebout (1956). Bayer et al. (2004) further developed a framework of discrete neighbourhood choice. Past applications have included modeling the impacts of air quality improvement (Sieg et al., 2004), the study of parental schooling decisions and neighbourhood choice (Bayer et al., 2007; Ferreyra, 2007) as well as estimating agglomeration economies (Ahlfeldt et al., 2015). The common challenge shared by these papers is to estimate the benefits of a spatially delineated amenity in the presence of sorting. Recent applications to transportation amenities are found in Severen (2018) (LRT in Los Angeles), Tsivanidis (2018) (bus rapid transit in Bogota, Columbia) and Craig (2019) (public transit expansion in Vancouver, Canada).

The basic equation structure of the model will build upon Epple and Sieg (1999). I make use of the model extensions introduced in Bayer et al. (2004) as well as Bayer and McMillan (2012), which allow for a worker's choice to depend explicitly on commuting costs. I further extend the choice function to allow workers to simultaneously make decisions on home location, work location and commuting mode. I also incorporate explicit parameters for pecuniary transportation costs, non-pecuniary transportation costs and the local amenity effect of rail stations.

5.2. Workers

Modeling worker choice will take the following general form. The utility of a worker is represented by a Cobb-Douglas style function (Eq. (2)).

$$U_{ijkv} = (\rho_j(C - c_{ijkv}))^{\gamma} H^{(1-\gamma)} \xi_{ijkv} \tag{2}$$

Workers derive utility from numeraire consumption (C) and the consumption of generic units of housing (H). Workers lose consumption utility from non-pecuniary commuting costs (c_{ijkv}). The share of income a worker spends on housing is set by $1-\gamma$. i indexes the worker, j indexes home tract, k indexes work tract and v indexes a transportation mode. In addition to the effect on commute times, the presence of a local LRT station may improve utility through its ability to enhance numeraire consumption. LRT may allow workers to consume a wider variety of local goods and services due to their improved mobility or through enjoyment of local economic development or neighbourhood change adjacent to stations. ρ_j takes a value of one if no LRT station was built in the tract. If a LRT station was built in the tract ρ_j is a uniform consumption multiplier that will be endogenously determined. A Type 1 extreme value distributed error term (ξ_{ijkv}) captures a worker's idiosyncratic preferences over home location, work location and mode choice. All workers are renters and pay rent to a landlord outside of the local economy.

The non-pecuniary cost of commuting (Eq. (3)) is calculated according to the time duration of the trip (τ_{jkv}) multiplied by the worker's wage and a value of time constant (ζ_v). ζ_v is indexed by travel mode to allow for the possibility that distaste for travel with a private vehicle, bus or LRT may be different. I use the term bus to denote all commutes that do not include a private vehicle or new LRT. Routes that use new LRT infrastructure are classified as a LRT route even if the trip requires some amount of bus travel to complete. As I do not model the possibility that workers walk, cycle or take alternative modes, any commute that does not use a private vehicle will be considered as public transportation for the purpose of this section.

$$c_{ijkv} = \zeta_v w_{ik} \tau_{jkv} \tag{3}$$

Pecuniary commuting costs vary according to the home location, work location, and mode choice. Use of a private vehicle carries a flat rental fee (r) and a per km use fee (g), such that the pecuniary cost of commuting (θ) by private vehicle is $r + gd_{jkv}$. d_{jkv} is the trip distance (km) between locations j and k. In estimation, d_{jkv} will be taken from Google routing data and corresponds to the actual road distance covered. The worker can forgo renting a car and instead incur a flat pecuniary commuting cost equal to the cost of a monthly transit pass (t), such that $\theta_{jkv} = t$.

Utility maximization is subject to a budget constraint (Eq. (4)). Workers sell their labour in a competitive market and receive a wage (w_{ik}). Wages may differ across space (tracts) in equilibrium. p^H_j is the location specific price of a unit of housing. θ_{jkv} captures money spent on commuting. There is no saving, and workers exhaust their budget constraint.

$$w_{ik} = Hp^H_j + C + \theta_{jkv} \tag{4}$$

Workers make the following choices simultaneously:

(1) the location of the home tract

(2) the location of the work tract

(3) whether to rent a private vehicle

I assume that workers can consume as much or as little housing as they prefer, implying that zoning restrictions do not prevent the construction of very small or very large units. Because housing quantity is dictated as a share of income by the Cobb-Douglas utility function and income is determined by the choice of work location, workers do not explicitly choose a quantity of housing, rather the quantity is uniquely determined by the other choices. Pecuniary relocation costs within a metro are assumed to be zero. I assume a closed city, where workers must stay within their current metro. Each worker makes their location decisions independently, meaning I abstract away from multi-worker households. This simplification is necessary to solve the model while preserving the mechanisms of interest.

Eqs. (2) and (4) result in an indirect utility function which governs worker choice (Eq. (5)).

$$V_{ijkv} = (w_{ik} - c_{ijkv} - \theta_{jkv})\gamma^{\gamma}\rho^{\gamma}\, \frac{1-\gamma}{p^H_j}^{1-\gamma} \xi_{ijk} \tag{5}$$

There are two types of workers who are not employed. First, a worker may intentionally forgo employment rather than selecting a work location if the choice is utility maximizing. Second, workers who choose to work experience an *ex post* probability of frictional unemployment, equal to F. Some workers may therefore choose to pay for a central housing location that provides a less costly commute, but find themselves unemployed and not incurring any commuting costs. Unemployed workers receive a set government transfer (η), earn zero employment income, select a null work location ($k = \emptyset$), select a null commute mode ($v = \emptyset$) and pay no commuting costs ($\theta = 0,\ c = 0$). The importance of frictional unemployment in spatial models has been highlighted in Chapelle et al. (2020). Workers internalize the possibility of frictional unemployment by calculating the weighted sum of utility when employed and when jobless, with weights corresponding to the probability of frictional unemployment. Eq. (6) captures the weighted indirect utility function calculated by each worker, accounting for frictional unemployment. In equilibrium, every worker selects the home, work, and mode that maximizes Ψ_{ijkv}.

$$\Psi_{ijkv} = (1-F)V_{ijkv} + FV_{ij\emptyset\emptyset} \tag{6}$$

5.3. Firms

Every tract possesses a representative firm, located at its centroid. Firms exist in a competitive market, possess constant returns to scale production technology, have access to a perfectly elastic external capital market and earn zero profits. In such an environment, firms will be willing to expand to hire as many workers as are willing to accept employment at a persistent, zero profit wage level.

If workers need to complete a costly commute to reach a firm, the firm will need to set wages relatively higher to attract workers. If the introduction of LRT reduces commuting costs for some workers, the location will experience an increase in the supply of labour. In practice, local employment expansion could occur from firms expanding, or new firms forming locally.[4] In the context of the model, all employment growth is captured by expansion of the representative firm. Locations that do not benefit from LRT become less competitive and experience pressure to endogenously shrink relative to more accessible locations.

In the pretreatment period, the number of workers employed by each firm (tract) is set according to observed LODES data from the year 2002. Firms (tracts) will raise or lower wages through a firm specific linear wage multiplier (a_k) to attract exactly the number of workers needed to match the pretreatment period data. After the introduction of the LRT system, firms may endogenously hire more or fewer workers at the persistent wage rate. Aggregate employment in the metro may rise or fall endogenously in response to LRT.

a_k is matched to pretreatment data meaning that any local effects that motivated the spatial distribution of employment will be captured in a_k. For example, agglomeration economies may cause some locations to be relatively more productive. Locations with high agglomeration economies will therefore have a relatively high value of a_k, as firms will be willing to pay higher wages to attract more workers. I assume that agglomeration economies and any spatial wage premiums across tracts are held constant across the study period. Because the original distribution of firms across space is known, I do not explicitly model agglomeration economies, rather a_k acts as a location fixed effect that captures the relative productivity of a tract.

5.4. Estimation method

Neighbourhood causal effects estimated in Section 4 will be reconciled within the structural model. This methodology compels structural estimation to be grounded in observable effects, diminishing the reliance of results on imposed functional form assumptions, which is a

[4] Credit (2018) estimated firm effects for the Phoenix, Arizona LRT system, finding a large increase in firm formation adjacent to new LRT stations.

common concern for structural estimation models. Relying on IV estimates, LRT caused the share of local workers commuting by private vehicle in treated tracts to increase slightly by 0.2 percentage points, while the local employment rate rose by 12.3 percentage points. Both of these neighbourhood changes are the effect of LRT on treated tracts relative to control tracts, where the treatment and control tracts are those defined in the IV analysis. Tracts excluded from the IV analysis are included in the structural model, but are not used to match neighbourhood change moments. The share of workers commuting by private vehicle in the pretreatment period was 87.2%. The structural model will be solved to precisely match this moment in the data as well as the two neighbourhood change moments noted above. I do not force the model to match the other IV estimates. I select these three moments as they can be directly mapped to parameters in the structural equations, while enabling the system to be solved for worker preference parameters related to transit. The model relies on pretreatment tract conditions and these neighbourhood change results as inputs.

Microdata is used to construct a distribution of potential labour income (ω_i), which is an estimate of what each worker would expect to earn if they were employed. The valuation of an individual's labour is determined by estimating a Mincer equation on a vector of observed worker characteristics among employed workers (Eq. (7)).

$$\ln(\omega_i) = \beta_0 + \beta_1 X_i + \epsilon_i \tag{7}$$

X_i is a vector of individual characteristics including age, age squared and dummy variables for educational attainment (high school, college, graduate school), race and ethnicity (black, white, Hispanic, Asian), gender, and home metro. Every worker is assigned a potential income (ω_i) that is calculated based on their characteristics and the partial effects estimated in Eq. (7). Potential income is a measure of worker skill, as valued by employers. To simplify estimation I divide the population of each metro into potential income terciles, so that each metro's population is divided equally into low skill, medium skill and high skill workers. Workers within metro terciles are identical and earn the mean potential wage within their metro tercile when employed. The actual wage earned by a worker (w_i) is equal to potential wage (ω_i) multiplied by a tract specific multiplier (a_k), as shown in Eq. (8).

$$w_{ik} = \omega_i a_k \tag{8}$$

The model being estimated departs from the prior literature by including heterogeneous workers. Because workers are heterogeneous, I must parameterize the magnitude of the idiosyncratic error term to pin down the extent to which worker's choices are determined by their idiosyncratic preferences. The error term (ξ_{ijkv}) is scaled linearly, where the magnitude is set to generate income heterogeneity across neighbourhoods that matches a moment in the data. Specifically, I match the standard deviation of log household income across neighbourhoods in the pretreatment period. The level of neighbourhood income heterogeneity is monotonically decreasing in the magnitude of the idiosyncratic error term. I identify the unique magnitude of idiosyncratic preference that generates the level of income segregation in the data.

One parameter will be taken directly from prior literature; the value of time for car commuting (ζ_{car}). Significant prior research has attempted to estimate the value of time for private vehicle commuting. Estimation will proceed by using the estimated value from Small et al. (2005). Using data from drivers in the Los Angeles area Small et al. (2005) estimated the parameter to be 0.93. This suggests workers would be willing to undertake an additional hour of private vehicle commuting if they were compensated by a cash transfer equal to 93% of one hour's wages. Exogenously imposed structural parameters are summarized in Table 4.

Eq. (2) implies that workers spend a constant fraction of income on housing ($1-\gamma$). Davis and Ortalo-Magné (2011) provided estimates of this parameter across US metros. The central estimate of Davis and Ortalo-Magné (2011) shows metropolitan households spend 24% of income on housing ($\gamma = 0.76$). Estimation will rely on microdata of reported rent expenditure and income. According to 2000 microdata from the four metros, the mean share of income spent on rent is 24.0%, precisely matching the national estimate reported in Davis and Ortalo-Magné (2011). The average masks heterogeneity across income groups in the four metros. For the lowest earning tercile workers report spending 31.7% of income on rent on average, the middle tercile spends 20.6% while the highest tercile spends 14.4%. Estimation will proceed by setting each worker's γ to match the average value for their tercile. Workers without a job are assumed to spend the same fraction of income on housing as done by the lowest skill tercile.

Monthly pecuniary transport costs are generally observable. r is assumed to be \$471 which is an industry estimate of monthly fixed vehicle costs (American Automobile Association, 2007). g is assumed to be \$3.96 per km of commuting, which is derived from the industry estimate of variable vehicle costs (gas and maintenance), scaled up with the assumption that workers complete 22 round trip commutes per month (American Automobile Association, 2007). The pecuniary cost of public transit (t) is parametrized as the price of a monthly transit pass in the relevant CBSA. t ranges from a low of \$83.75 in Salt Lake City to a high of \$110 in Minneapolis.

In the main specification I set the probability a worker experiences frictional unemployment (F) to 4.9%, to match the Bureau of Labor Statistics' estimate of the long term rate of natural unemployment over the study period. However, I can test alternative assumptions regarding F. For example, frictional unemployment could vary spatially, with workers located in different tracts being more or less likely to experience frictional unemployment. I reestimate the model under several alternative assumptions regarding F. I estimate the model while assuming zero frictional unemployment, frictional unemployment that is increasing with distance from the city center (as suggested in Wasmer and Zenou (2002, 2006) and Zenou (2009)), unemployment that is matched to average neighborhood levels according to observed ACS data, and rates that are matched to Census data in the pre-treatment period but are allowed to move endogenously in response to changing neighborhood demand. Details of these alternative specifications are provided in Appendix C. Across all of these alternative assumptions I find that the model results are nearly unchanged, providing evidence that modeling assumptions concerning F are not driving results.

The model's pre and post treatment periods are differentiated in that a subset of tracts gain LRT stations and a subset of commute routes receive a shock due to new LRT service. LRT may reduce transit times or improve the experience of riders relative to the bus in terms of reliability, comfort, or diminished social stigma. The introduction of LRT along a route will represent a change to both the value of time while traveling (ζ) and the commute time (τ) simultaneously, but does not affect the pecuniary cost of commuting (θ). I do not uniquely identify the changes in ζ and τ caused by converting a route from bus to LRT. However, because the ζ and τ enter Eq. (3) in the same way, I can apply the shock as a combined effect on both ζ and τ. I multiply non-pecuniary commuting costs (c) by a parameter λ, such that for a particular individual and route $c_{\text{LRT}} = \lambda c_{\text{bus}}$. A value of λ less than one indicates the trip is less costly on LRT than it was on bus. λ is uniquely identified in the model solution. For routes that do not gain LRT, I assume the transit commute costs are identical in the pre and post treatment periods.

In addition to modeling the transit network shock, I rely on IV estimates of housing expansion and increase the relative share of available housing units in LRT treated tracts by 37.8%. As a robustness check, I rerun the model while assuming zero endogenous housing growth. Results do not change significantly, suggesting results are driven by LRT changes rather than spatial changes to housing allocation.

Calculating the probability that a particular worker will select a particular home, work, mode combination is enabled by the assumed extreme value distributed idiosyncratic errors, which results in the following multinomial logit probability function, where P_{ijkv} is the probability of worker i selecting a specific home location, work location and vehicle rental decision (Eq. (9)). Upper bar notation indicates the maximum

Table 4
Exogenously Imposed Structural Parameters.

Symbol	Value	Source	Description
ζ_{car}	0.93	Small et al. (2005)	Time value as share of wage rate, private vehicle
g	3.96	American Automobile Association (2007)	Variable vehicle cost per commute km per month ($)
r	471	American Automobile Association (2007)	Monthly rental fee for a vehicle ($)
$t^{Minneapolis}$	110	Local transit information	Metro specific monthly transit pass ($)
$t^{Portland}$	100	" "	" "
$t^{Seattle}$	99	" "	" "
$t^{Salt\ Lake\ City}$	83.75	" "	" "
η	500	.	Out of labour force monthly income ($)
F	0.049	Bureau of Labor Statistics	Frictional unemployment probability

The table indicates all parameters that were exogenously imposed on the structural model.

Table 5
Structural Model Solution Parameters.

Symbol	Value	Description
ζ_{bus}	1.30	Time value as share of wage rate, bus transit
γ	0.75	Non-pecuniary commute cost multiplier, LRT relative to bus transit
ρ_j	1.25	Amenity value of transit (ratio of consumption utility in LRT tract to non LRT tract)

Solving the model yields the three transit amenity parameters.

value in the set.

$$P_{ijkv} = \frac{e^{\Psi_{ijkv}}}{\sum_1^{\bar{j}} \sum_1^{\bar{k}} \sum_0^{\bar{v}} e^{\Psi_{ijkv}}} \tag{9}$$

Computationally, local rents, local wages, and structural parameters ($\zeta_{bus}, \lambda, \rho_j$) are solved through iteration using contraction mapping, until the system reaches an equilibrium wherein every tract contains the share of employees and residents dictated by the LODES data in the pretreatment period. The three structural parameters are identified by restricting the possible equilibriums to generate the three observed moments in the data; the neighbourhood change IV estimates of private vehicle mode share (+ 0.2 percentage points) and the employment rate (+ 12.3 percentage points) as well as the private vehicle mode share in the pretreatment period (87.2%). While all tracts in the CBSAs are included in the model, I match moments based only on the subset of tracts used in the neighbourhood level analysis. An equilibrium is further defined by a Nash equilibrium where the decision of every worker is optimal, taking into account the decision of all other workers. The uniqueness of the equilibrium follows naturally from Brouwer's fixed-point theorem. A proof of equilibrium uniqueness for this class of model can be found in Bayer and Timmins (2005). The uniqueness of the current model solution is clear as the decision of each worker only affects other workers through home prices and local wages and not through endogenous neighbourhood amenity characteristics. Intuitively, neighbourhood rents and wages must be at a level that exactly attract the correct number of residents and employees. *Ceteris paribus*, the share of workers using public transit decreases monotonically with ζ_{bus}, the change in local transit commuting in tracts gaining LRT decreases monotonically in λ and the increase in the local employment rate in tracts gaining LRT increases monotonically in ρ_j. Therefore, there is a unique set of parameters that map to the neighbourhood change moments.

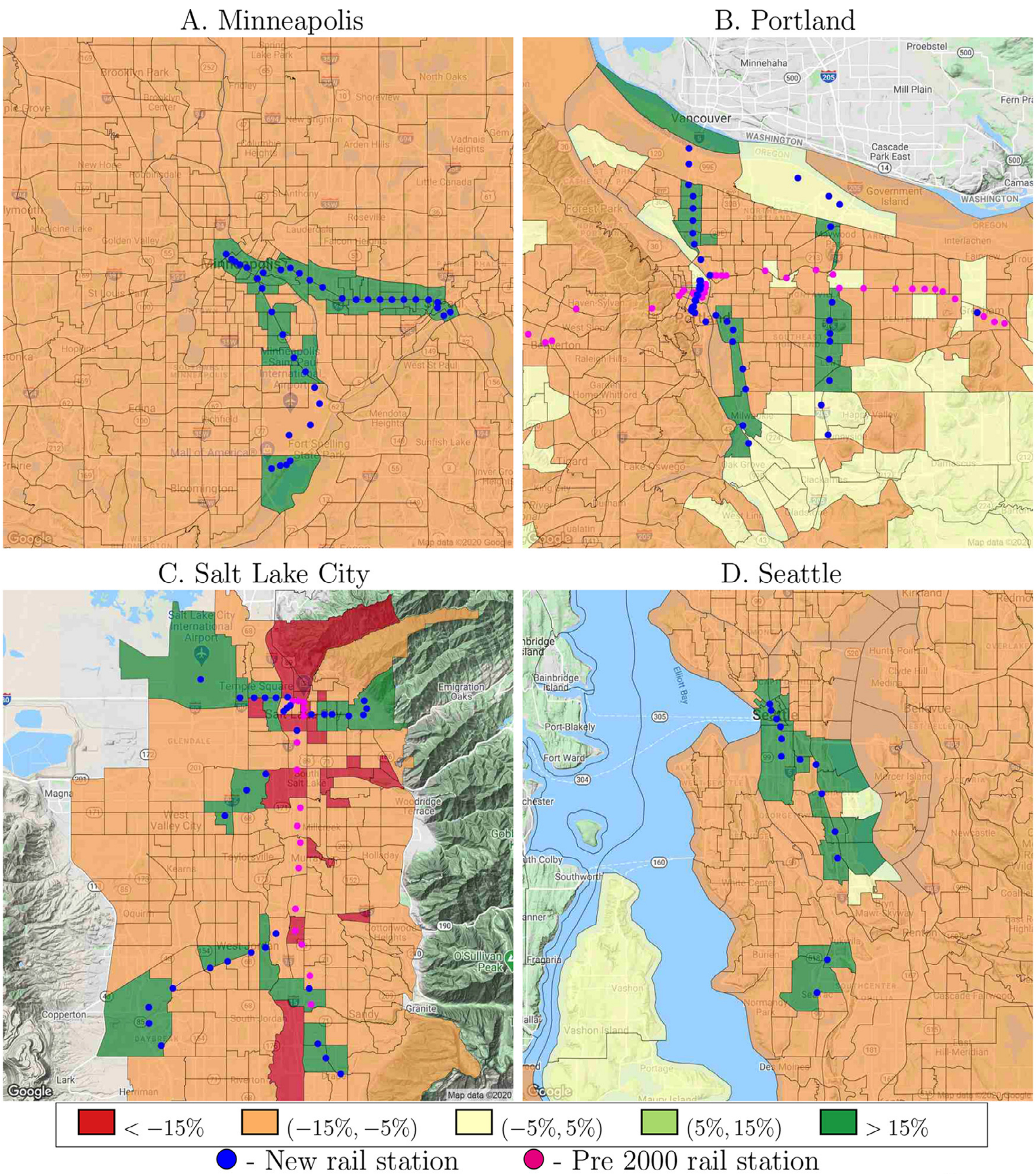
5.5. Results

Solving the model yields the desired preference parameters (Table 5). The time value parameter for bus commuting (ζ_{bus}) is found to be 1.30, substantially higher than the imposed time value of private vehicle commuting (0.93). This parameter aligns with the perception that bus travel is unpleasant relative to private vehicle travel, particularly due to uncertainty in trip duration (Kou et al., 2017; Tyndall, 2018). Workers would be willing to undertake an additional hour of car commuting if they were compensated with 93% of one hours wage, but would require 130% of one hours wage to undertake an additional hour of bus commuting. The difference in non-pecuniary costs of bus and LRT is the result of the combined effect of LRT being faster as well as potentially more pleasant to ride, captured by the parameter λ. The model is solved when λ is equal to 0.75. The interpretation of the parameter is that when a transit route is converted from bus to one including LRT, the non-pecuniary costs of commuting fall by 25%, on average. If LRT is both faster and more pleasant to ride than the bus, then some share of this cost reduction is due to time saving and some is due to increased comfort.

The model also recovers the average amenity preference for living in a tract with a LRT station. The value of ρ for tracts with a LRT station is estimated as 1.25. ρ suggests that numeraire consumption provides 25% more utility per dollar when the household is located in a LRT tract relative to a tract without a LRT station. The result indicates that there is a substantial positive amenity value of a local LRT station. The parameter captures not only consumption mobility benefits, such as access to leisure amenities through the LRT network, but also changing neighbourhood characteristics related to the local development and gentrification effects of the stations. Modelling LRT as a local amenity that improves consumption provides a mechanism that raises local employment and socioeconomic outcomes without raising transit commuting mode share.

An advantage of the discrete neighbourhood choice model is that it can predict counterfactual neighbourhood changes across the entire metro. Figs. 5 and 6 show spatial predictions of the model for local rents and employment. A clear prediction of the model is an increase in rent per unit of housing consumption in neighbourhoods gaining a LRT station (Fig. 5). The valuation of LRT as a local amenity is capitalized in the price of local housing. While it is plausible that neighbourhoods that contained LRT stations in the pretreatment period would benefit from the new stations through network effects, I find no evidence of substantial neighbourhood change in these tracts. The effects appear to be dominated by localized amenity effects adjacent to new stations.

Fig. 6 maps the changing local employment rates across the metros caused by LRT. The pattern shows large employment rate increases at new stations and reductions in the employment rate in outlying areas. Proximity to a LRT station is more attractive to employed workers for two reasons. First, they are potentially able to reduce commuting costs by using LRT. Second, the amenity effect of a local station enters the model as a multiplier of numeraire consumption, and employed workers have higher numeraire consumption. High consumption is



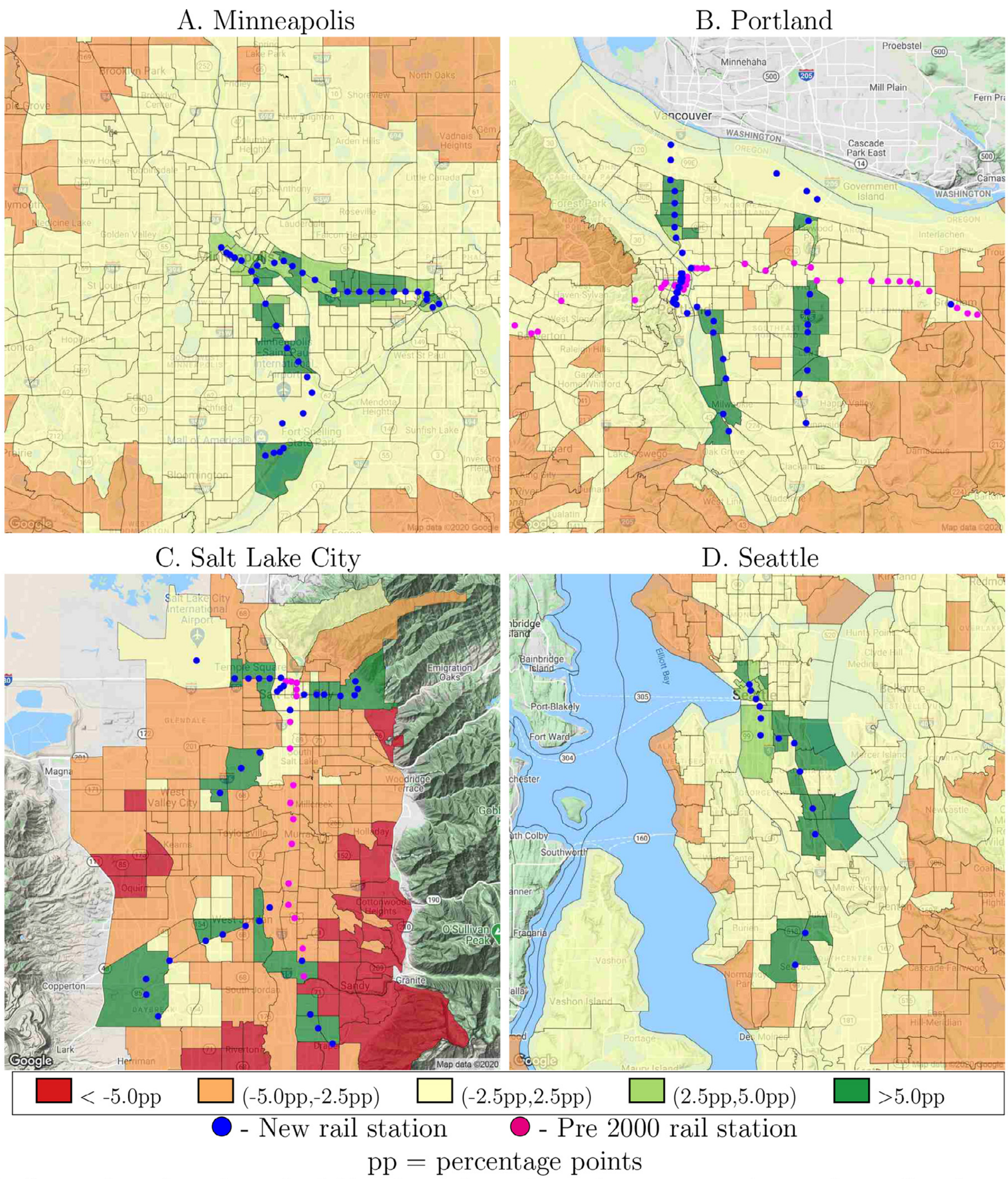
The figures show the estimated neighbourhood change in rent per generic unit of housing (Δp_j^H) that can be attributed to the LRT stations constructed between 2000 and 2015, according to results of the structural estimation model.

Fig. 5. Structural Results, Change in Rent per Generic Unit of Housing.

complimentary to living near a LRT station as it allows for greater consumption variety locally, and at leisure amenities along the LRT network. Lower skilled workers who would have located in the central city without LRT are repelled by the high housing prices in LRT neighbourhoods and are more likely to locate towards the edges of the metro area.

I find that the spatial distribution of transit commuters is essentially unchanged by the introduction of LRT. The high skilled workers who move towards the treated neighbourhoods are inherently less likely to use public transit. However, this potential reduction in use is tempered by the increase in transit quality in LRT tracts. Low skilled workers moving to the urban periphery are more likely to use public transit than high skilled workers but are moving to areas of low transit quality. The net effect of these forces is that heterogeneity in transit use across neighbourhoods changes very little as a result of LRT.

Fig. 7 presents the average aggregate metropolitan effects of LRT. I scale results to correspond to the predicted average effect of constructing 10 new LRT stations in a metro. I find that every 10 LRT stations increase the aggregate rate of public transit commuting by 0.27 percentage points (Fig. 7A). This result is consistent with the null neighbourhood effects because the impact is not concentrated in the tracts that gain LRT but is spread relatively uniformly across the metro due to sorting and heterogeneous preferences. I find that the lowest tercile of earners increases public transit mode share by 0.14 percentage points, while the highest tercile increases mode share by 0.44 percentage points.

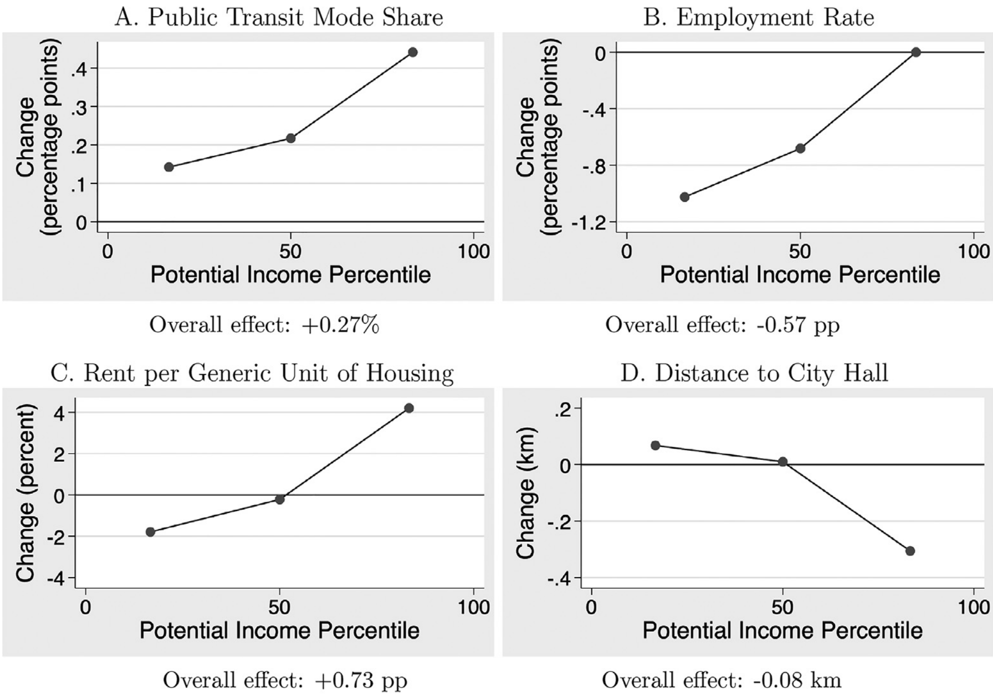


The figures show the estimated neighbourhood change in employment rates that can be attributed to the LRT stations constructed between 2000 and 2015, according to results of the structural estimation model.

Fig. 6. Structural Results, Change in Employment Rate.

Attempts by planners to expand urban public transit use often consider “captive” and “choice” riders (Krizek and El-Geneidy, 2007). The former have public transit as their only option, while the latter only choose public transit if it provides better service than their alternative (private vehicle). High housing prices near LRT stations repel captive users and attract choice users. LRT may be an effective method to raise aggregate metropolitan transit use because the mode choice elasticity of choice riders is higher and they sort towards high quality transit. However, the process degrades the spatial access of captive transit riders, undermining the progressivity of transit investment.

Fig. 7B graphs the effect of 10 LRT stations on the metropolitan employment rate. Overall, the introduction of LRT is estimated to *reduce* metro employment. The share of workers who are employed falls by 0.57 percentage points, from a baseline of 69.9%. While reduced transit times encourage employment, increased rents in accessible neighbourhoods cause the displacement of low skilled workers to low access areas. The negative aggregate effect is caused by differences in employment elasticity across skill groups. Low skilled workers are more likely to be on the margin of employment and labour force participation and therefore have an elastic labour supply. The higher skilled workers who move into the central locations -encouraged by the potential consumption benefits of LRT- are very likely to be employed with or without the new LRT infrastructure. I find LRT exacerbates spatial mismatch through the gentrification of accessible areas.



Results are scaled to represent the effect of 10 LRT stations in a metro of average size (1.25 million workers).

Fig. 7. Structural Results, Distribution Across Potential Income (ω_i) Terciles.

LRT stations have little influence on commuting mode choice, but as local amenities, stations alter residential location incentives substantially. It may be more informative to consider LRT stations as primarily a location specific consumption amenity rather than a commuting network improvement. The gentrification effects of the amenity alters the spatial distribution of high and low skilled labour in a way that lowers aggregate employment and this effect appears to outweigh any employment expansion caused by commuting network improvements.

The results of this section demonstrate that if the consumption amenity effects of public transit are sufficiently large, the consequent sorting may completely eliminate intended labour supply increases. I estimate that the employment rate among the lowest tercile falls by 1.03 percentage points due to the construction of 10 LRT stations, while the employment rate among the highest tercile is essentially unchanged. The result is surprising, given new transit is often built with the explicit goal of improving labour market accessibility and outcomes for lower skilled groups.

Fig. 7 C displays how the rent paid per generic unit of housing (p_j^H) changes across income terciles. Higher earning workers end up paying more per unit of housing due to LRT because they preferentially move towards the high rent LRT neighbourhoods. Lower earning workers see a reduction in rent per unit of housing as they become more likely to locate towards low rent peripheral areas. The mechanism mirrors modern accounts of higher skilled groups returning to denser urban locations due to consumption preferences (Couture and Handbury, 2017). This monocentric sorting can be demonstrated directly by estimating the change in distance to the CBD experienced across terciles. Fig. 7D charts this change. I estimate that every 10 LRT stations cause the lowest earning tercile to live, on average, 68 m farther from the CBD (as proxied by city hall) than they otherwise would have, while the highest earning tercile lives 306 m closer, on average. The distance to city hall effect is not mean zero because housing stock is expanded in LRT treated tracts, which are centrally located.

The impact of LRT construction at the metropolitan level is relatively consistent across the four metros. Table 6 shows the full effects of the LRT projects, without normalizing for number of stations constructed. LRT had a positive effect on transit mode share across all metros, with the increase ranging from 0.58 percentage points (Minneapolis and Seattle) to 1.98 percentage points (Salt Lake City). LRT also decreased the employment rate in each city, with effects ranging from 1.76 percentage points (Salt Lake City) to 1.39 percentage points (Portland).

Table 6
Aggregate Changes by Metro.

Metropolitan Area	Stations Constructed	Public Transit Mode Share (percentage points)	Employment Rate (percentage points)
Minneapolis	37	+ 0.58	1.70
Portland	34	+ 0.90	1.39
Salt Lake City	40	+ 1.98	1.76
Seattle	19	+ 0.58	1.56

The table shows the estimated effect of the LRT interventions in each city between 2000 and 2015 on aggregate metropolitan outcomes, according to structural model estimates. Effects are not normalized for the number of stations constructed.

The impacts of a new station will depend on its location within the metro and the location of other stations. I only recover average effects of new stations, which may mask heterogeneous effects across station locations. In particular, a system concentrated in the city center will have more pronounced sorting effects than one that extends more uniformly across a metro.

6. Conclusion

Between 2000 and 2015, an average of 22 new LRT stations opened per year in the US. The potentially significant economic consequences of this large infrastructure investment has received relatively little economic study. I test whether LRT has significantly affected urban labour markets across four US metros. I find strong evidence that LRT improves *neighbourhood level* employment outcomes but reduces *aggregate metropolitan* employment.

I provide a structural model that can capture the complexities of neighbourhood sorting that result from new transit amenities. Model results provide a nuanced understanding of the mechanisms that relate LRT to local labour markets. LRT improves transit networks but sharply increases the demand for transit accessible areas. Lower earning residents are more likely to directly consume the commuting benefits of public transit, but are also more likely to be displaced by local rent increases. I find that LRT causes a reduction in overall metropolitan employment, as the local gentrification caused by LRT stations causes workers on the margin of the labour force to locate in areas that are not transit accessible, exacerbating worker isolation. The effect is driven by the relatively high employment elasticity among low skilled workers. The result is counterintuitive, given that public transit projects are often constructed with the explicit intention of improving labour market access for economically vulnerable populations.

LRT's role in improving commuting networks has an unambiguously positive effect on employment by reducing travel costs. However, the role of LRT stations as centrally located urban amenities has a negative effect on employment by driving up home values in the urban core, causing workers with higher labour supply elasticity to move to areas of lower spatial connectivity. Overall, I find the negative employment effects brought on by the local amenity effect dominates the positive employment effect of the commuting network improvements.

The mechanisms described in this paper provide some explanation for efforts to resist LRT projects. For example, the second phase of LRT construction in Minneapolis faced significant resistance from local populations along the planned route who were concerned that the gentrification induced by LRT may be sufficiently harmful to completely offset mobility benefits.[5] Resistance included a lawsuit filed by the National Association for the Advancement of Colored People that aimed to halt the project. This paper aimed to provide some description of the complicated economic impacts of LRT on urban residents. I do find that local home price increases undercut the mobility benefits that would otherwise flow to low earning workers through LRT. High quality bus service, such as Bus Rapid Transit, could potentially provide similar mobility improvements to LRT without inducing the same level of gentrification, yielding a more progressive distribution of benefits and blunting unintended negative employment effects.

Given that high earning workers are able to capture significant benefits from LRT, even though transit commuting among high earners is extremely low, provides a partial explanation as to why LRT projects are proliferating rapidly while bus transit systems have not undergone similar expansions over this time period. Higher earning households may wield outsized control over public policy. These households would support using public funds for LRT transit over bus because LRT directs significant consumption benefits towards higher earning households.

Current analysis is limited by a lack of longitudinal worker microdata. Tracking an individual's response to new transit infrastructure through time would allow for the relevant discrete choice effects to be estimated directly. The absence of such data necessitates innovative approaches to modelling worker choice and the introduction of novel instruments.

Credit author Statment

The Local Labour Market Effects of Light Rail Transit (YJUEC-D-20-00040R1) Journal of Urban Economics.

This is a single authored manuscript. I completed all components of the project.

Appendix A

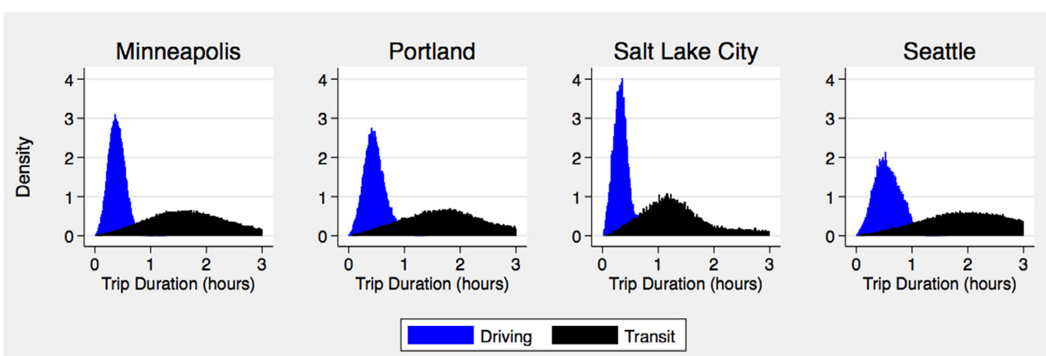


Fig. A1. Distribution of Google API Generated Trip Times. The figure displays the distribution of travel times for both driving and public transit commuting for the full matrix of home and work locations. Across the four metros, 66% of public transit commutes take over 90 min and 43% take over 2 h. Only 0.6% of drive times exceed 90 min.

[5] *The Train Line That Brought the Twin Cities Back Together*, by E. Trickey, Politico Magazine, March 16, 2017.

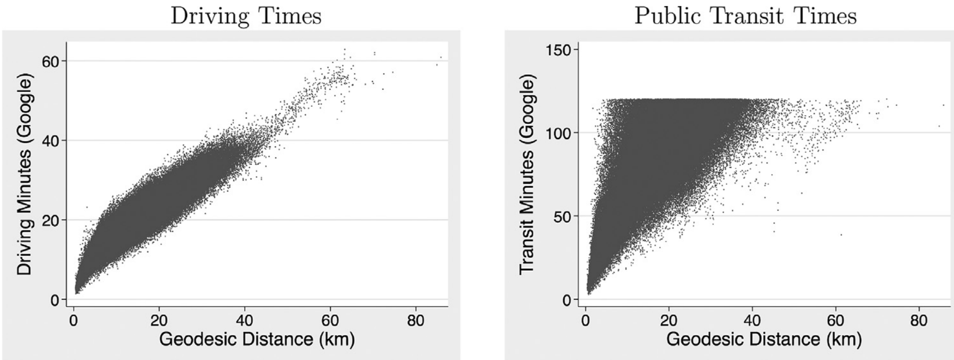


Fig. A2. Correlation Between Google Travel Times and Geodesic Distance. Each dot represents one potential commute. The figure includes every commute route that can be completed by both driving and public transit (*N*=944,085). Constructing the full commuting matrices required extensive data collection. A more easily constructed alternative to the Google API trip data would be to use a matrix of straight line travel distances and assume that these correlate with actual trip times. Analysis reveals that straight line distances may be a reasonable proxy for drive times, but are a poor proxy for public transit durations. The circuity of a public transit commute is often high, as transit infrastructure funnels travellers along indirect routes. Across the 944,085 origin-destination pairs that are connected through public transit, straight line distance can explain 89% of the variation in private vehicle trip duration, but only 38% of the variation in public transit trip duration.

Appendix B

The main neighbourhood change results, shown in Table 3, corresponded to the average neighbourhood change between 2000 and 2015 experienced by tracts that gained a LRT station during that period. Potentially, the level of neighbourhood change caused by a station will depend on the time elapsed since the station was built. In this appendix I provide evidence regarding how the neighbourhood effects change with time. Table B1 includes main Table 3 results, compared with alternative specifications that account for how long a station has been present in the neighbourhood.

Table B1, shows main OLS estimates (column 1) juxtaposed with three alternative OLS specifications (columns 2–4). Column 2 regresses the neighbourhood change variables against a variable for the number of years since the station was built. Column 3 uses a log transformed version of the station duration variable. The log version captures the possibility that the effect of stations on neighbourhoods might diminish through time as the neighbourhood converges towards a new equilibrium. Column 4 includes both the level effect of gaining a station and the linear duration effect simultaneously.

Using time elapsed measurements rather than a dummy variable for gaining a station does not add explanatory power to the model,

Table B1
Neighborhood Changes per Year of LRT Exposure.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
				Δ Employment Rate			
	OLS	OLS	OLS	OLS	IV	IV	IV
Gained LRT Station	0.043**			0.037*	0.123**		
	(0.010)			(0.015)	(0.023)		
Years with LRT Station		0.005**		0.001		0.015**	
		(0.001)		(0.002)		(0.003)	
Log(Years with LRT Station + 1)			0.022**				0.057**
			(0.005)				(0.012)
R^2	0.089	0.083	0.087	0.089	.	.	.
				Δ Private Vehicle Mode Share			
	OLS	OLS	OLS	OLS	IV	IV	IV
Gained LRT Station	0.009			0.005	0.002		
	(0.009)			(0.014)	(0.022)		
Years with LRT Station		.002		.002		0.0003	
		(0.001)		(0.002)		(0.003)	
Log(Years with LRT Station + 1)			.006				0.001
			(0.005)				(0.010)
R^2	0.121	0.123	0.122	0.123	.	.	.
				Δ White Population Share			
	OLS	OLS	OLS	OLS	IV	IV	IV
Gained LRT Station	0.063**			0.042**	0.110**		
	(0.012)			(0.016)	(0.035)		
Years with LRT Station		0.008**		0.004		0.013**	
		(0.002)		(0.002)		(0.004)	
Log(Years with LRT Station + 1)			0.035**				0.051**
			(0.007)				(0.016)
R^2	0.133	0.131	0.134	0.135	.	.	.
				Δ College Degree			
	OLS	OLS	OLS	OLS	IV	IV	IV
Gained LRT Station	0.042**			0.004	0.077**		
	(0.011)			(0.015)	(0.030)		
Years with LRT Station		0.007**		0.007**		0.009*	
		(0.002)		(0.002)		(0.004)	
Log(Years with LRT Station + 1)			0.028**				0.036**
			(0.006)				(0.014)
R^2	0.097	0.106	0.104	0.106	.	.	.

Significance levels: ∗ : 5% ∗∗ : 1%. N = 1,924. Robust standard errors in parenthesis. All regressions include CBSA fixed effects and controls for distance to city hall and distance to airport, consistent with Eq. 1.

Table C1
Comparing Model Results Under Alternative Assumptions of Frictional Unemployment (F).

	(1) Main	(2) F=0	(3) F Varies by Distance	(4) F Matched to ACS	(5) F Varies with Housing Price
ζ_{bus}	1.30	1.30	1.36	1.30	1.30
γ	0.75	0.74	0.71	0.75	0.76
ρ_j	1.25	1.26	1.31	1.25	1.24
Δ Public transit mode share*	+ 0.27	+ 0.28	+ 0.29	+ 0.27	+ 0.24
Δ Employment rate*	0.57	0.58	0.78	0.56	0.52

Results from the main structural model are shown in column 1. Column 2 assumes all workers experience a 0% chance of frictional unemployment. Column 3 assumes frictional unemployment increases linearly with distance from the city center. Column 4 matches the value of F in each tract to ACS data and column 5 matches the value of F in each tract to Census data in the pretreatment period, but allows F to move endogenously with housing demand in the post-treatment period. *Represents the average estimated effect of 10 new LRT stations, consistent with Fig. 7.

suggesting the use of the dummy variable is picking up much of the meaningful variation. The use of time varying station variables produces estimates that are consistent with main estimates. Including the level effect of a station with the time elapsed since construction variable in the same regression (Column 4) provides some evidence that effects increase with time. For example, I estimate that a tract that gained a station one year ago would see the share of the population with a college education increase by 1.1 percentage points, but a tract that gained a station 10 years ago would have experienced a 7.4 percentage point increase. Among tracts gaining a station, the number of years elapsed ranges from 1 to 14 years, with an average of 5.9 years. The point estimates for white population change also suggest effects are increasing with time.

In columns 5–7 I provide estimates of IV regressions, where the LRT station variable is instrumented by the airport corridor instrument. Coefficient estimates for LRT exposure duration variables provide a similar picture of the effect of gaining a station on overall neighbourhood change. Because I only have a single instrument I cannot estimate the IV model with the level and time varying station effect included simultaneously.

Appendix C

I incorporate frictional unemployment into the structural model by assuming each worker faces an equal probability of becoming unemployed after choosing their home location, work location and transportation mode. I use the average Bureau of Labor Statistics (BLS) estimate of the natural rate of unemployment over this period (4.9%) as a proxy for the probability of frictional unemployment. In this appendix I show results under alternative assumptions regarding the probability of experiencing frictional unemployment.

Table C1 shows the model parameter and aggregate metro change estimates from the main model, compared to alternative assumptions for frictional unemployment. I first reestimate the model under the assumption of zero frictional unemployment (column 2), so that all workers are either employed or voluntarily out of the workforce. I find the main results do not change significantly under this assumption.

Following the results of prior literature, I then assume that workers farther from the city center are more likely to experience frictional unemployment due to higher search costs as a result of spatial isolation from jobs (Wasmer and Zenou, 2002; 2006; Zenou, 2009) or informational limitations from diminished social ties (Zenou, 2013; 2015). I test an extreme assumption regarding the effect of location on frictional unemployment in an effort to bound the effect of spatially heterogeneous frictional unemployment. I calculate each worker's distance to the city center in terms of a percentile out of all of the metro's workers. I then assume that frictional unemployment varies linearly, with the worker closest to the city center experiencing no frictional unemployment, the worker at the 50$^{\text{th}}$ percentile of distance experiencing an average (4.9%) probability of frictional unemployment, and the worker farthest from the city center experiencing twice the average probability (9.8%). The transformation preserves the average rate of frictional unemployment. Workers are aware of the effect of location on frictional unemployment and incorporate the probabilities into their choices. Results of this specification are provided in Table C1, column 3.

The rate of unemployment may also be neighbourhood specific for reasons other than distance to the city center. As an alternative approach to modeling frictional unemployment, I rerun the model so that local unemployment in each census tract is matched to the value of unemployment from the 2010 5-year American Community Survey. I inflate estimates to preserve the overall rate of 4.9%. Workers make their home location decision with the knowledge that their probability of frictional unemployment (F) is impacted by their neighbourhood choice. I provide results from this specification in Table C1, column 4, and again find very little change in the parameters of interest.

In the above specifications F is set exogenously, so that the local value of F is not affected by the introductions of LRT. I note that neighborhoods that experienced an increase in property values over the study period also experienced a decrease in local unemployment. I use the log home value and unemployment rate variables used in Table 3 and run a linear regression of the change in unemployment rate against the change in log home values and CBSA level fixed effects. I standardize the change in home value variable so it has a mean of zero and standard deviation of one, allowing the estimate to be compatible with the structural model. I find that a one standard deviation increase in home value correlates with a 0.15 percentage point decrease in the local unemployment rate. I use this estimate to endogenize the value of F in the post-treatment period. I set F in the pretreatment period to match observed values from the 2000 US Census for each census tract. I then allow the values of F to move endogenously based on the change in housing prices for each tract, as generated in the model. I reestimate the model in this way, report results in Table C1, column 5, and find consistent results.

I find almost no change in the model results across differing assumptions regarding F, shown in Table C1. The consistent results suggest that the particular assumptions regarding F do not drive model results. I do find that allowing frictional unemployment to vary by linear distance leads to a larger estimate of metro employment loss, but this differential effect does not appear when F is matched to real spatial variation in F gathered from Census Bureau data.

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