The Local Labour Market Effects of Light Rail Transit †

Justin Tyndall

justin.tyndall@sauder.ubc.ca
Sauder School of Business,
University of British Columbia

December 10, 2018
Job Market Paper
Link to most recent version

Abstract

US cities have made large investments in light rail transit in recent years. Arguments in favour of light rail construction typically focus on enhancing workers' access to job opportunities. I analyse the labour market effects of light rail construction in four US metropolitan areas between 2000 and 2013. I propose a new instrumental variable to overcome endogeneity in transit station location. An inclination among transportation planners to extend light rail to the airport introduces a source of quasi-random neighbourhood assignment, enabling causal identification of neighbourhood effects. I find that light rail improves local employment outcomes. Local amenities cause workers to sort within a city, meaning that neighbourhood effects could be the result of endogenous sorting. To estimate distributional consequences and welfare effects, I propose and estimate a structural model of neighbourhood choice. The model is estimated with novel Google navigation data. I find that light rail systems fail to raise aggregate metropolitan employment because induced rent increases repel low skilled workers, displacing them to inaccessible locations.

JEL: J20, J60, R13. R23, R40, R58

† Awarded best paper by a graduate student, 2018 Transportation Research Forum.

1 Introduction

US cities have made significant investments in Light Rail Transit (LRT) in recent years, with current annual expenditures exceeding six billion dollars.[1] A common justification for LRT is that transit infrastructure will improve urban commuting networks.[2] 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 employment changes and estimate welfare effects. My analysis spans four US cities over the 2000-2013 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, it 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. I propose a new instrumental variable to estimate the causal effect of LRT stations on neighbourhoods. 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).

[1] American Public Transportation Association, 2017 Public Transportation Fact Book.

[2] For example, the environmental impact assessment for Seattle's LRT system claimed the project would result in, "improved access to employment opportunities" (Sound Transit, 1999). A chief political advocate for the Minneapolis LRT system stated: "We're trying to reconnect people, particularly people with high levels of unemployment, to the job market" (Peter McLaughlin, Hennepin County Commissioner, from *The Train Line That Brought the Twin Cities Back Together*, by E. Trickey, Politico Magazine, March 16, 2017).

After correcting for endogenous transit allocation, I find LRT generates large improvements in *neighbourhood level* employment outcomes.

Using reduced form estimates as model inputs, I estimate a structural neighbourhood choice model and conclude that LRT systems fail to raise *aggregate metropolitan* employment. LRT stations 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 labour force participation 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 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. Taking account of household sorting, I find that the welfare benefits of LRT are positive and exceed typical project costs. Welfare benefits are generated through reductions in the commuting costs of some workers but also through LRT acting as a local amenity that enhances consumption. I also find LRT is effective at raising aggregate transit use, as it appeals to higher income workers who would be unlikely to take other forms of public transit.

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 (Gobillon et al., 2007; Holzer, 1991; Holzer et al., 2003; Immergluck, 1998; 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, expanded access to transit may raise equilibrium employment by reducing spatial isolation.

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.

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 paper addressed empirical identification challenges related to neighbourhood choice models. Otherwise, the literature provides sparse guidance on the overall effects of LRT systems, which is striking given the rapid propagation of such systems in the US.

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, where heterogeneity in worker earning ability gives rise to heterogeneity in transportation mode choice and neighbourhood composition. 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.

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 extend the neighbourhood choice literature by developing a structural sorting model that includes preference parameters for transit.

The study will proceed as follows. Section 2 will summarize 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 providing estimated welfare effects 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 2016 the number of LRT stations in the US grew by 60% (Figure 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 similar in that they all completed substantial LRT construction over the period of study. Minneapolis and Seattle had no LRT stations prior to 2000, while Portland and Salt Lake City had already completed a portion of their systems. Following a popular trend in transportation planning, these four cities all extended rail access to the metro's largest airport. The metros range in population from 1.1 million (Salt Lake City) to 3.6 million (Seattle). Table 1 displays metropolitan level characteristics as contrasted with the full sample of US metropolitan residents. The four selected metros contain residents with higher median household income than the US urban population as a whole.

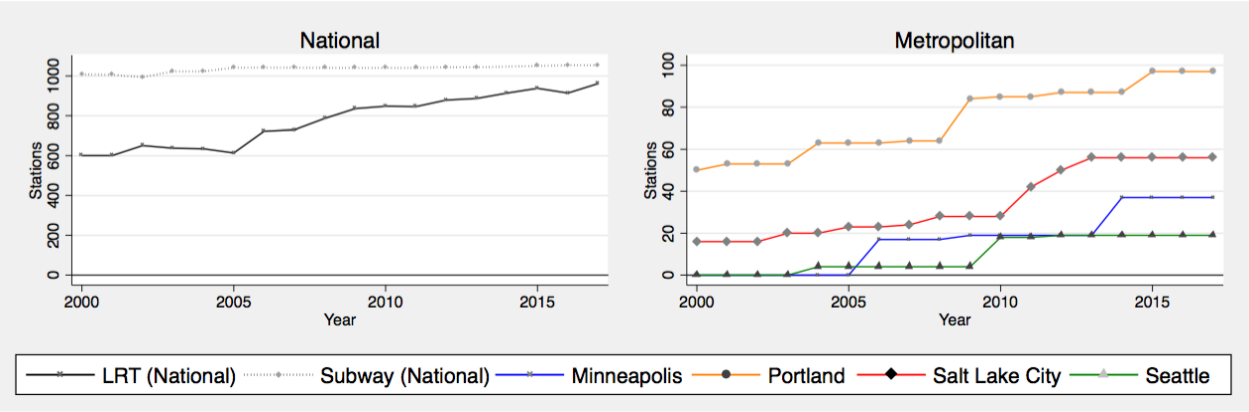


Figure 1: The Proliferation of LRT Stations[3]

Table 1: Summary Statistics, Metropolitan Areas

	Minneapolis	Portland	Salt Lake City	Seattle	All US Metros
Metro Population (2013)	3,458,513	2,312,503	1,141,510	3,609,617	.
Median Household Income (2013)	73,585	63,891	67,808	75,391	54,516
Public Transit Mode Share (2000)	4.4%	5.5%	3.3%	6.6%	4.6%
Public Transit Mode Share (2013)	4.8%	6.1%	3.6%	8.4%	5.1%
LRT Stations (2000)	0	53	16	0	601
LRT Stations (2013)	19	87	56	19	887

Public transit comprises only a small share of total commutes in these metros. Seattle had the highest rate in 2013, with 8.4% of commuters using public transit. Salt Lake City had the lowest public transit mode share in the sample at 3.6%. Across the entire urban population of the US, 5.1% of workers commute by public transit. The sample of cities is therefore fairly representative of transit uptake in a typical US metro. Public transit mode share increased in all four metros during the 2000-2013 period. Seattle experienced the largest increase, expanding public transit mode share among commuters by 27%. 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 transit expansions may have significant labour market effects.

3 Data

I use census tract level data from the 2000 US Decennial Census as well as the 2015 American Community Survey (ACS), five-year estimates. Census data from 2000 are crosswalked to 2010 boundaries using the Missouri Census Data Center's Geographic

[3]Station counts obtained from the annual American Public Transportation Association Fact Book. Between 2000 and 2016, the number of LRT stations in the US grew by 60% while the number of heavy rail subway stations grew by 2%.

Correspondence Engine. Metropolitan areas will be bounded according to 2013 Bureau of Labor Statistics core-based statistical areas. 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 the 2000 US Census Integrated Public Use Microdata Sample (IPUMS). All income and price variables are inflation adjusted to 2013 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 are obtained from the Longitudinal Employer-Household Dynamics, Origin-Destination Employment Statistics (LODES) data products. LODES provides linked workplace and residence data that provide a matrix of commute flows at the census tract level. The data is compiled by the US Census Bureau. LEHD data coverage extends to 95% of wage and salaried employment nationally (Graham et al., 2014). Omitted workers include self-employed individuals and US military personnel (Graham et al., 2014). 2013 data are used for post-treatment commute flows, and 2002 data are used for pre-treatment commute flows. Data from 2000 are not available from LODES.

Empirically identifying the effect of commuting costs requires detailed data on 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 travellers 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 constructed a full matrix of potential tract to tract commute routes for each metro, resulting in 1,412,602 origin-destination pairs. I queried routes through the API for travel instructions for both driving and public transit for an 8 am departure on a Wednesday. The API provided the trip time and distance as estimated by Google's algorithm. 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 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 2013, as it is identified within the API. Using step-by-step navigation instructions for public transit trips, I run a text search program to identify all of the origin-destination pairs that make use of the new LRT infrastructure. Identifying routes

that use new LRT allows for the approximation of a commute matrix from before LRT was constructed. Furthermore, this novel data set allows for the direct estimation of LRT's power to redirect commute flows (section 4.3). Further details on the API generated data are relegated to Appendix A. I find that straight line distances are a poor proxy for public transit trip durations, as public transit trips often follow circuitous routes. 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.

4 Neighbourhood Effects of LRT

4.1 Methodology

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 (2000-2013). There are 70 treatment tracts identified across the four metros. 22 are in Seattle, 18 are in Salt Lake City, 15 are in Minneapolis and 15 are in Portland. To isolate a valid control group, a number of tracts are dropped from analysis. Tracts within one kilometre of the central business district (CBD) or the airport are dropped, where CBD location is proxied by city hall. Any tract that contained or was within one km of a LRT station prior to 2000 is also omitted from analysis. 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.[4] The resulting data set contains 1,974 tracts. The location of new LRT stations and treated tracts are shown in Figure 2.

Equation 1 presents the general regression approach.

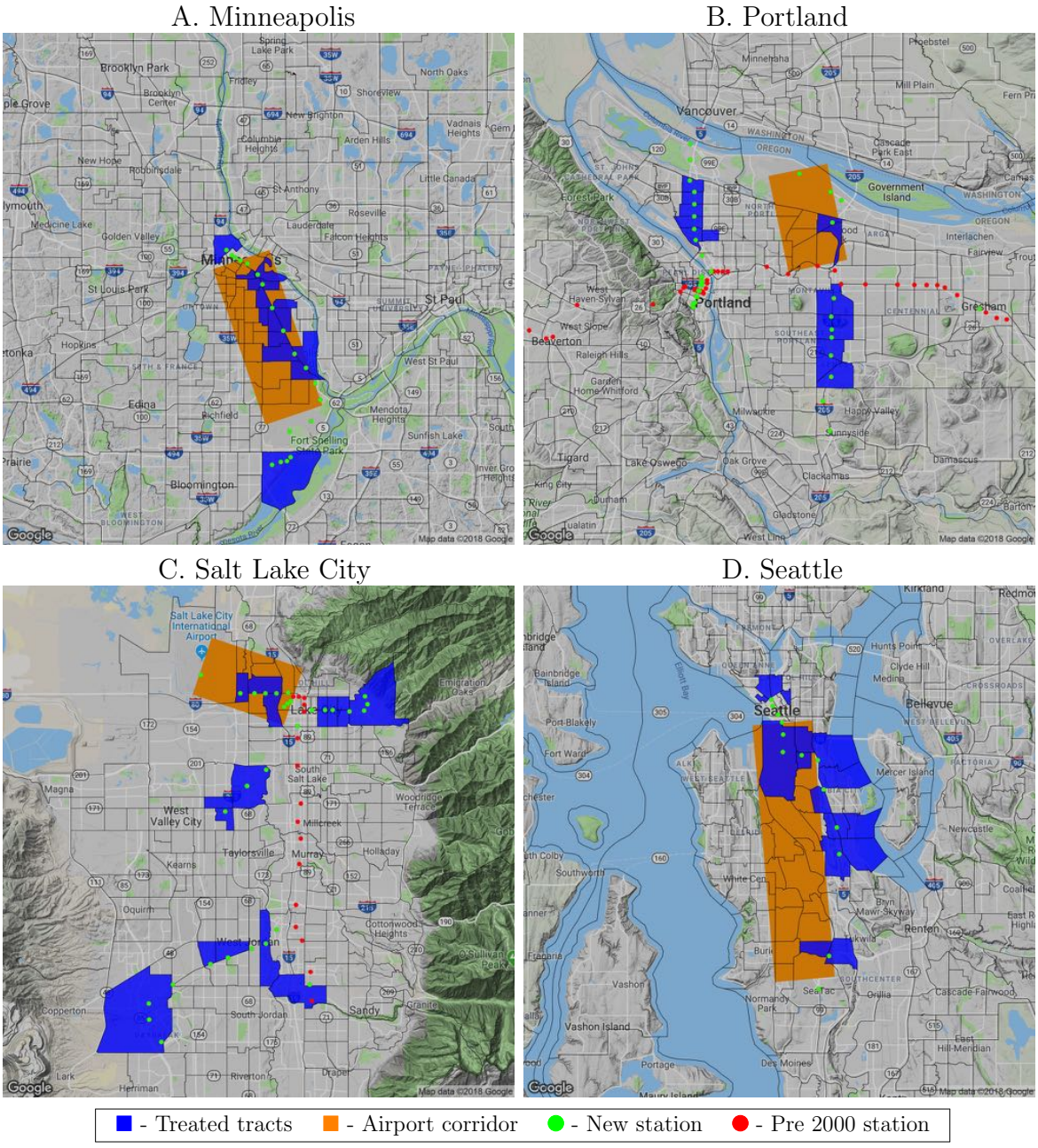
$$\Delta Y_i = \beta_0 + \beta_1 \text{LRT}_i + \Gamma X_i + \Theta_i + \varepsilon_i \tag{1}$$

ΔY_i is the change in a neighbourhood characteristic between 2000 and 2013. 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 control variables. The list of control variables comprising X can be found below Table 3. Control variables are drawn from 2000 and 1990 values to control for differences in both levels and trends. Θ_i captures CBSA fixed effects.

OLS results are expected to be biased due to the endogenous placement of LRT stations relative to local economic trends (Ihlanfeldt and Sjoquist, 1998; Holzer et al., 2003; Tyndall, 2017). To identify a causal relationship, researchers have equipped past empirical

[4]Minneapolis opened a second LRT line in 2014. To avoid potentially confounding partial treatment or anticipation effects, tracts within three km of a 2014 station are also omitted.

Figure 2: LRT Treated Tracts and Instrumental Variable



investigations with exogenous network shocks. Notably, Holzer et al. (2003) analysed an extension of the San Francisco subway system, focussing on firms located along the suburban portion of the extension. A key identifying assumption was that transportation planners never anticipated a local demand for reverse commuting, which would mean the effect of the infrastructure was plausibly exogenous to future job growth among reverse

commuters. The exogeneity is unclear as relevant policy documents called for a "special emphasis on off peak and reverse commute trips" (Bay Area Rapid Transit District, 1987). Tyndall (2017) made use of station closures triggered by a hurricane event as an exogenous shock to the New York City subway system, finding neighbourhoods that lost subway access experienced increased rates of unemployment. 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 was 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, today 16 of the largest 25 metros have such a link. Figure 3 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 for pretreatment observables, including distance to the airport.

I instrument the LRT dummy variable in equation 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 Figure 2. First stage regression results are shown in Table 2. A tract in the

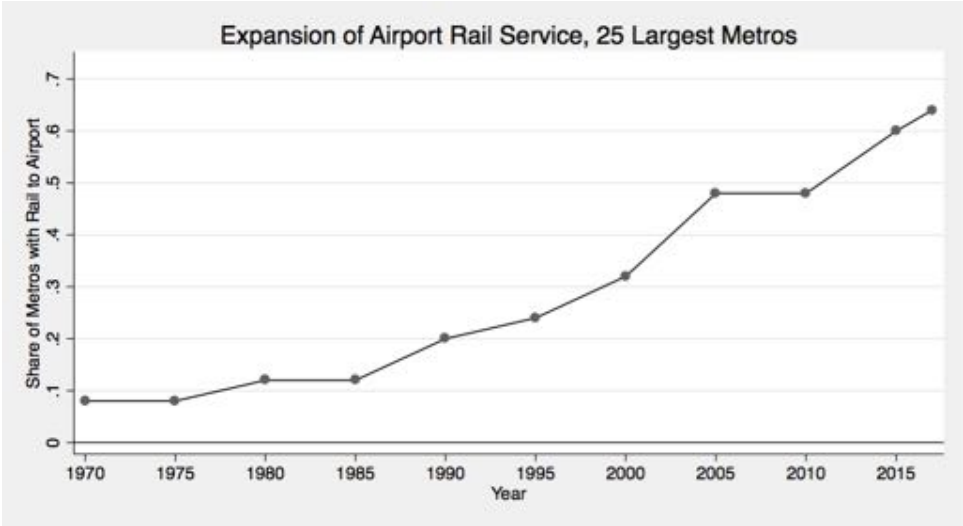


Figure 3: Share of large US metros with a direct rail link from downtown to the largest airport. The composition of the largest 25 metros is allowed to change through time according to US Census population estimates. Additional US cities are currently planning LRT extensions to their airports, including Buffalo, Pittsburgh and Sacramento.

airport corridor is 46.7 percentage points more likely to receive a LRT station relative to a similar tract located outside of the corridor, according to first stage OLS results. The corridor variable alone explains 22.2% of the variation in station assignment probability. First stage 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.

Table 2: First Stage Results, Predicting Station Locations

Variable	
Airport Corridor (dummy)	.467**
	(.079)
Tract level controls?	Y
CBSA fixed effects?	Y
R^2	0.334
Cragg-Donald Wald F statistic	300.12
Kleibergen and Paap Wald F statistic	35.24

Significance levels: $*$: 5% $**$: 1%. N = 1,974. Robust standard errors in parenthesis. See notes under Table 3 for full list of control variables. The outcome variable is a dummy variable for LRT treatment status.

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 (equation 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. All estimates are executed in first differences to focus analysis on changes in neighbourhood characteristics between 2000 and 2013. 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. The IV results will be important to the subsequent structural estimation approach. A comparison of IV and OLS results suggests that rail infrastructure was directed towards neighbourhoods with latent economic trends that were below average. The effect is consistent with the findings of Kahn (2007), wherein transit infrastructure is routed through less affluent neighbourhoods.

Labour market outcomes have a strong positive response to the introduction of LRT (Table 3). The local employment rate among adults rose by a highly significant 8.3 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 6.4 percentage points and the local unemployment rate fell by 4.0 percentage points. A portion of the positive labour market effects may be attributable to public transit providing access to new labour market opportunities for the local population. However, the shift in labour market outcomes may be the result of a large change in the characteristics of the local workforce. A rise in characteristics that are correlated with strong employment outcomes could be considered as evidence of LRT induced gentrification. Additionally, workers may be sorting on employment status itself, as employed workers will value the commuting benefits of LRT (Wasmer and Zenou, 2002, 2006).

Viewed as a place-based 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).

Table 3: Neighbourhood Change Results

	Δ Employment Rate		Δ Labour Force Participation Rate		Δ Unemployment Rate	
	OLS	IV	OLS	IV	OLS	IV
Gained LRT Station	.009	.083**	.006	.064**	-.010	-.040**
	(.008)	(.025)	(.007)	(.024)	(.005)	(.013)
Mean 2000 value (treated obs)	.621		.675		.081	
	Δ Public Transit Mode Share		Δ Private Vehicle Mode Share		Δ Commute Time (min)	
	OLS	IV	OLS	IV	OLS	IV
Gained LRT Station	.018**	.031	-.024*	-.058*	.201	.237
	(.006)	(.016)	(.009)	(.023)	(.364)	(1.042)
Mean 2000 value (treated obs)	.132		.738		22.422	
	Δ Log Home Value		Δ Repeat Sales Index		Δ Log Housing Units	
	OLS	IV	OLS	IV	OLS	IV
Gained LRT Station	-.018	-.016	5.200	16.378	.187**	.320*
	(.031)	(.080)	(2.870)	(9.945)	(.048)	(.148)
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	.005	.039	.015	.026	.020	.106
	(.012)	(.036)	(.010)	(.031)	(.027)	(.070)
Mean 2000 value (treated obs)	.632		.246		10.731	

Significance levels: $*$: 5% $**$: 1%. N = 1,974. Robust standard errors in parenthesis. Control variables include CBSA fixed effects, the distance to city hall, the distance to the airport, as well as the 1990 and 2000 values of the following variables: private vehicle mode share, public transit mode share, white population share, black population share, Asian population share, share of population with a high school diploma, share of population with a college degree, share of population with a graduate degree, employment rate, unemployment rate, median household income, share of population between age 18 to 30, share of population over age 65 and share of local housing units that are detached homes.

Policy makers may be interested in LRT as a means to increase the use of public transit and decrease reliance on privately owned vehicles. The partial effect of gaining a local station on the transportation mode share of local commuters is shown in Table 3. There is only weak evidence that LRT stations increase the share of the local workforce commuting by public transit, relative to control tracts. However, structural estimation will conclude that LRT causes an aggregate increase in public transit use, but the effects are dispersed across the metro (Section 5). A LRT station is found to increase the share of the workforce using public transit by 3.1 percentage points from a baseline of 13.2%. The effect

is statistically insignificant. However, there is strong evidence that the share of the local workforce using private vehicles to commute is reduced. The share using a private vehicle falls by a significant 5.8 percentage points, from a treatment tract average of 73.8%. While a portion of the effect may be attributable to commuters switching from cars to the new LRT option, a portion is potentially due to induced changes in neighbourhood demographics and preferences, brought about by endogenous household sorting. I test for an effect on the share of commuters either walking or biking to work and find a statistically significant increase. Why local LRT would *cause individuals* to walk or bike is not obvious, suggesting mode changes are influenced by changing characteristics of local workers. Redevelopment around LRT stations that include pedestrian and cyclist friendly infrastructure may also contribute to this result. I also find that a local LRT station causes the share of individuals who report having access to a private vehicle to fall from 93.6% to 90.2%, the effect is significant at the 10% level.

It is informative to consider the comparative magnitudes of the employment effects and public transit use effects. If there is no endogenous sorting, new public transit commuters are comprised of employed workers switching modes and workers who were previously not working, securing employment as a result of improved transit. Even if every new public transit commuter had previously been unemployed, the public transit effects are insufficient to explain the employment effects. This suggests that neighbourhood employment effects are largely driven by workers sorting within the metro.

Lower income residents may disproportionately benefit from public transit if they value their time at a low rate or their ability to afford a private vehicle is limited. However, lower income residents may also be more sensitive to local increases in housing costs. 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 find no evidence that LRT raises the *average* local home value. However, this estimate is not adjusted for potentially changing housing size or quality. Of particular concern is that LRT station constructions may be accompanied by the displacement of local single family homes with condominiums, as cities attempt to coordinate transportation and land use policies. 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 16.4% increase in local housing values. The repeat sales estimate is executed on a reduced sample (1,852 tracts rather than 1,974) due to missing observations in the FHFA data. Data constraints render the home value estimates tentative, but the evidence points towards LRT induced home value increases.

I test for an effect of LRT on shifts in racial composition. No statistically significant

effects are found but point estimates suggest that LRT led to an increase in the local white population share of 3.9 percentage points (Table 3). I also test for an effect on local education rates. Similarly, I find no statistically significant shifts, but point estimates suggest a rise in local education levels, including an 11% increase in the share of the local population with a college degree. Both of these results provide some evidence of LRT induced neighbourhood gentrification.

While LRT constructions are often proposed as a means of reducing commute times, I find no evidence that average commute durations are reduced when a tract gains a LRT station (Table 3). Private vehicle commuting is the fastest mode for virtually every route, so reductions in private vehicle commuting lead to longer average commute times. However, monetary commuting costs likely fell due to reduced use of private vehicles.

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 37.7%, over the 13 year period. The result suggests that cities followed an approach of Transit Oriented Development (TOD), directing new housing towards transit stations.

Despite the relatively small sample size available to conduct neighbourhood estimates, LRT has a clear effect on labour market outcomes and commuter mode share at the neighbourhood level. There are two mechanisms that potentially contribute to LRT's effect on neighbourhood labour market outcomes, (1) the beneficial expansion of local individual's access to transit and labour market opportunities and (2) endogenous neighbourhood sorting in response to local transit infrastructure.

Table 4 directly controls for local post-treatment demographic characteristics (race and education) as a way to reduce the statistical effect of neighbourhood sorting. The magnitude of employment effects are reduced by roughly 10% when post-treatment demographics are controlled for. While observable demographics may be controlled for, a more intractable form of sorting may persist. 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, an employed individual has a motivation to locate close to their workplace while a worker without a job lacks this incentive. Without the ability to observe the locational decisions of individuals through time, it is not possible to accurately decompose neighbourhood changes into sorting effects and individual incentive effects. Section 5 will propose and estimate a microfounded structural model that incorporates both mechanisms.

Table 4: Controlling for Post Treatment Demographics

	IV	IV with Post Treatment Controls
Δ Employment Rate	.083**	.074**
	(.025)	(.022)
Δ Labour Force Participation Rate	.064**	.057**
	(.024)	(.021)
Δ Unemployment Rate	-.040**	-.037**
	(.013)	(.012)

Significance levels: $*$: 5% $**$: 1%. N = 1,974. Robust standard errors in parenthesis. Control variables from Table 3 are included. Additionally, the following post treatment controls, calculated as the difference between 2013 and 2000 values, are added: white, black and Asian population shares; and high school, college and graduate education rates.

4.3 Effect of Light Rail on Commute Flows

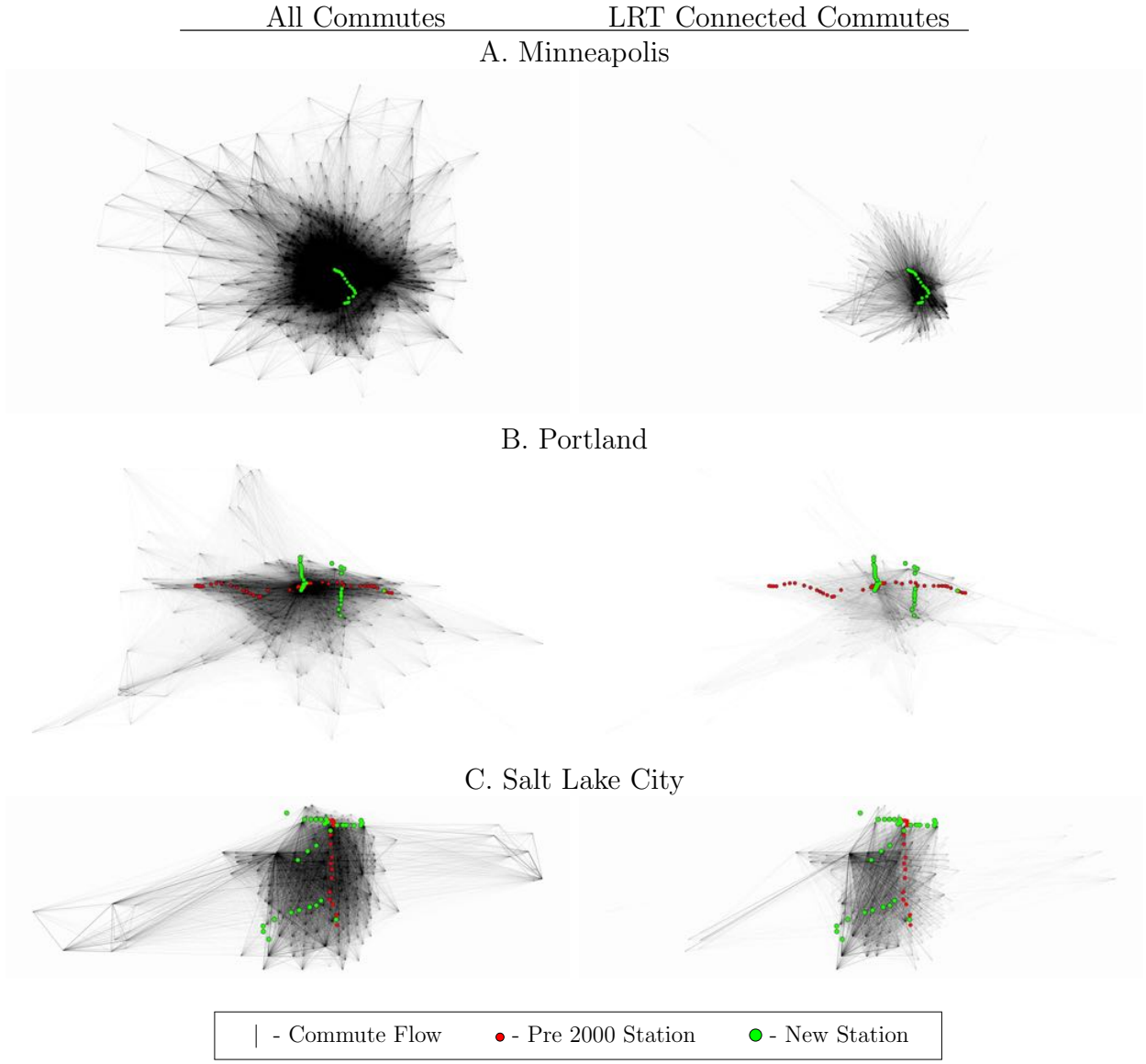
An observed increase in commuting along LRT routes would be an indication that workers are responding to the infrastructure. I find that, once LRT is in place, workers are more likely to execute commutes along routes that directly benefit from LRT. I use Google routing data to identify all home-work pairs for which the fastest transit route involves a segment of newly added LRT infrastructure. Of 1,412,602 possible home-work pairs, 84,063 (6.0%) were connected through new LRT infrastructure. These newly connected home-work pairs cover 6.2% of 2013 jobs. Figure 4 maps 2013 observed commute flows across the four metros. Commute routes that are populated by at least one commuter (according to LEHD LODES data) are captured on the map, with heavier lines indicating more commuters. The left column of Figure 4 displays all commutes in 2013. The right column displays only the commutes that make use of a LRT station added between 2000 and 2013. In Salt Lake City, the large expansion of LRT meant that 26.5% of 2013 commuters had new LRT infrastructure as a component of their quickest transit route. In Portland, 9.8% of commuters became connected through new LRT. Relative to metro size, LRT construction in Minneapolis and Seattle was less expansive. In Minneapolis, 2.4% of commuters were covered by new LRT infrastructure and in Seattle the figure is 2.0%.

$$[\text{LRT Route Share}]_{jt} = \beta_0 + \beta_1[\text{Post LRT}]_{jt} + \Phi_j + \Psi_t + \varepsilon_{jt} \tag{2}$$

LRT Route Share is the share of the tract's employed workers who commute along a route that received new LRT service. j indexes home tract. t indicates year; either 2000 or 2013. Φ is a home census tract fixed effect. Ψ is a year fixed effect. β_1 is the parameter of interest.

I compare the share of commutes executed along LRT treated routes before and after

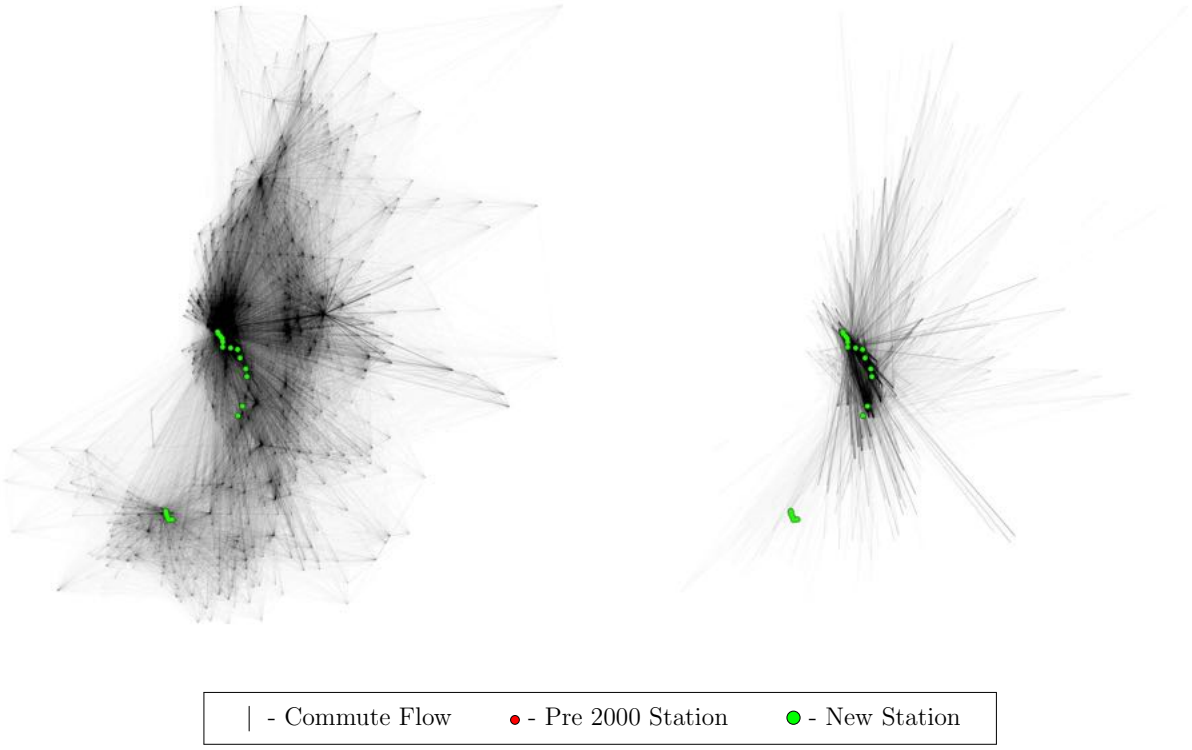
Figure 4: Mapping Commuter Flows



The figure continues on the following page.

the LRT infrastructure was built. A home-work route is considered to be treated if the fastest transit link between home and work, according to Google data, includes a LRT station built between 2000 and 2013. I regress the share of a tract's workers who commute along a LRT treated route against a dummy variable for post treatment status, as shown in equation 2. Fixed effects are included for the tract as well as the year. Table 5, column 1 displays the effect of a LRT connection on the LRT route share. Results show a small but significant increase in the overall share of the local workforce commuting along LRT

D. Seattle



LODES data does not include interstate commutes, therefore the Washington state portion of the Portland metro and the Wisconsin portion of the Minneapolis metro are omitted from this portion of analysis.

serviced routes. In the average tract in 2000, 7.13% of a tract's workers were commuting along a route that would be treated with LRT, in 2013 the fraction had risen to 7.24%. The relatively modest public transit use across the three cities (4.94% of commuters in 2000) is consistent with LRT having only a minor effect on overall commute flows.

Limiting the analysis to populations who are more likely to be reliant on public transit yields results that are significantly larger, suggesting that the role of LRT in choosing where to work and live is more significant to particular groups. Column 2 limits analysis to jobs that pay less than $15,000 annually –capturing part time and low wage employment– and shows an effect 2.6 times higher than the aggregate, with the share of low income jobs traversing LRT treated routes increasing from an average of 6.4% to 6.7%. Column 3 tests for an effect among jobs that pay over $40,000 annually, but finds no effect. Column 4 tests for an effect among workers under 30 years of age. Workers under 30 had a response 2.5 times larger than the overall effect. The strong effect on the commute flows of young people is consistent with prior literature that has found youth to be more sensitive to the spatial

proximity of jobs, for example O'Regan and Quigley (1998). The stronger effect among low income workers is consistent with this group's higher rate of reliance on public transit.

Table 5: Shifts in Commuter Flows Towards LRT Treated Routes

	All Jobs	Low Income	Mid-High Income	Under Age 30
	(1)	(2)	(3)	(4)
Treatment	.0011**	.0029**	-.0005	.0028**
Effect	(.0004)	(.0006)	(.0006)	(.0006)
Home Tract FE?	Y	Y	Y	Y
Year FE?	Y	Y	Y	Y
Mean LRT Route Share, Treated Routes (2000)	.0713	.0642	.0770	.0694

Significance levels: $*$: 5% $**$: 1%. N = 3,592. Robust standard errors in parenthesis. Low income jobs pay below $15,000 annually. Mid-High jobs pay above $15,000 annually.

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. 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. Model results can answer whether LRT is successful at catalysing welfare improving labour market linkages. Preference parameters will also enable counterfactual welfare analysis, facilitating estimation of how the benefits of LRT are spread across skill 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 translate into a distribution of societal welfare changes.

The contributions of Alonso et al. (1964), Muth (1969), Mills (1967) and Fujita and Ogawa (1982) provide a basis for modelling 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.

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. Sieg et al. (2004) applied a neighbourhood choice model to estimate the welfare effects of a change in air quality in southern California, demonstrating that reduced form methods were not able to capture the distribution of welfare effects due to residential sorting. The exploration of parental schooling decisions and neighbourhood choice has become an interesting application for neighbourhood sorting structural models (Bayer et al., 2007; Ferreyra, 2007). Ahlfeldt et al. (2015) implemented a structural approach to investigate agglomeration and amenity forces in an urban environment. Recent applications to transportation amenities are found in Severen (2018) (LRT in Los Angeles) and Tsivanidis (2018) (bus rapid transit in Bogota, Columbia). The common challenge shared by these papers and the current task is to estimate the benefits of a spatially delineated amenity in the presence of sorting.

5.2 Workers

The model of worker choice will take the following general form. The utility of a worker is represented by a Cobb-Douglas style function (equation 3).

$$U_{ijkv} = (\rho_j C)^{\gamma} H^{(1-\gamma)} + \xi_{ijkv} \tag{3}$$

Workers derive utility from numeraire consumption (C) and the consumption of generic units of housing (H). 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 adjacent to stations. Indeed, LRT routes are often oriented to provide access to consumption amenities, for example airports, professional sports venues and retail. 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.

Workers experience iceberg commuting costs. Commuting costs (equation 4) vary according to the particular home-work pair, wage, and mode choice. The cost contains both a pecuniary and non-pecuniary component. 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 $r + gd_{jkv}$. Where d_{jkv} is the trip distance (km) between locations j and k. d_{jkv} is 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 $\theta_{jkv} = t$.

$$c_{ijkv} = \underbrace{\theta_{jkv}}_{\text{pecuniary}} + \underbrace{\zeta_v w_i \tau_{jkv}}_{\text{non-pecuniary}} \tag{4}$$

The non pecuniary cost of commuting 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 in private vehicles, bus and LRT may be different. I use the term bus to denote all public transit trips that do not include new LRT.

Utility maximization is subject to a budget constraint (equation 5).

$$w_i = Hp_j^H + C + c_{ijkv} \tag{5}$$

w_i is worker income, p_j^H is the location specific price of a unit of housing and c_{ijkv} is the transportation cost incurred from commuting. There is no saving, and workers exhaust their budget constraint.

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
Equations 3 and 5 result in an indirect utility function which governs worker choice (equation 6).

$$V_{ijkv} = (w_i - c_{ijkv})\gamma^\gamma \rho_j^\gamma (\frac{1-\gamma}{p_j^H})^{1-\gamma} + \xi_{ijkv} \tag{6}$$

Workers sell their labour in a competitive market. Microdata is used to construct a distribution of potential labour income. I do not observe the market price of labour for individuals who are not employed, so I estimate the full distribution based on observable

characteristics, imputing potential labour income for those not employed. The valuation of an individual's labour is determined by estimating a Mincer equation on a vector of observed demographics among employed workers (equation 7).

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

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 ($w_i^{\text{potential}}$) that is calculated based on their characteristics and the partial effects estimated in equation 7. Potential income is a measure of worker skill, as valued by employers. The wage earned through employment (w_i) is equal to potential wage ($w_i^{\text{potential}}$) multiplied by a tract specific multiplier. Wages may differ across space. Agglomeration economies provides one theoretical source of wage heterogeneity through space. Average wages in a CBSA are matched to data, while spatial wage differentials are endogenous to the model.

In equilibrium, every worker selects the home, work, and mode that maximizes V_{ijkv}. I assume a closed city, where workers must stay within their current metro. A worker can forgo employment, in which case they receive a set government transfer (η), earn zero employment income and pay zero commute costs. Pecuniary relocation costs within a metro are assumed to be zero.

5.3 Firms

Every tract possesses a single 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 the zero profit wage level.

In the pretreatment period, the number of workers employed by each firm (tract) is set according to observed LEHD data from the year 2002. Firms (tracts) will raise or lower wages in order to attract exactly the number of workers for which they have capacity. After the introduction of the LRT system, firms may endogenously hire more or fewer workers, as consistent with profit maximization. A local reduction in commuting costs may increase the number of workers willing to accept employment at the persistent wage rate. Credit (2018) estimated such an effect for the Phoenix, Arizona LRT system, finding a large increase in firm formation adjacent to new LRT stations. Locations that do not

benefit from LRT become less competitive and experience pressure to endogenously shrink. Aggregate employment in the metro may rise or fall endogenously in response to LRT.

5.4 Estimation Method

The 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 common concern for structural estimation models. Within treated LRT tracts, LRT caused the share of local workers commuting by private vehicle to fall by 5.80 percentage points, and the local employment rate to rise by 8.28 percentage points. The share of workers commuting by private vehicle in the pretreatment period was 87.2%. The structural model will be solved to precisely match these three terms.

To enable estimation, 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 car commuting if they were compensated by a cash transfer equal to 93% of one hour's wages.

Equation 3 assumes that workers spend a constant fraction of income on housing $(1-\gamma)$. Davis and Ortalo-Magné (2011) provided evidence that this share is relatively constant across US cities. The central estimate of Davis and Ortalo-Magné (2011) shows households spend 24% of income on housing ($\gamma = .76$). 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 25.6%, consistent with Davis and Ortalo-Magné (2011). The average masks heterogeneity across income groups. At the 10th percentile of the income distribution workers report spending 50.9% of income on rent, while at the 90th percentile the figure is 16.1%. Estimation will proceed by setting each worker's γ to accord with their position on the potential income distribution as estimated in equation 7.

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/km, 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. Structural parameters are summarized in Table 6.

Table 6: Structural Parameters

Symbol	Value	Source	Description
ζ_{car}	0.93	Small et al. (2005)	Time value as share of wage rate, private vehicle
ζ_{bus}	1.34	(estimated within model)	Time value as share of wage rate, bus transit
ζ_{LRT}	1.03	(estimated within model)	Time value as share of wage rate, new LRT transit
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 (\$)
$t^{\text{Minneapolis}}$	110	Local transit information	Metro specific monthly transit pass (\$)
t^{Portland}	100	" "	" "
t^{Seattle}	99	" "	" "
$t^{\text{Salt Lake City}}$	83.75	" "	" "
η	1000	.	Out of labour force monthly income (\$)
ρ_j	1.096	(estimated within model)	Amenity value of transit (ratio of consumption utility in LRT tract to non LRT tract)

The model's pre and post treatment periods are differentiated in that a subset of tracts gain LRT stations and an updated commute time matrix is used to capture the effect of LRT. Additionally, I rely on IV estimates of housing expansion and increase the relative share of available housing units in LRT treated tracts by 37.8%.[5] Changes to the commute time matrix can be estimated with the Google travel data. The pretreatment commute time matrix is adjusted to approximate the state of affairs before the LRT expansions were in place. Pre LRT transit commute times are not observed in the data. The reduction in commute costs that can be attributed to the introduction of LRT is the combined effect of a reduction in travel time and a change in the valuation of time while commuting. LRT may be more desirable than bus service in terms of reliability, comfort, or diminished social stigma. LRT treated commute routes are assumed to experience a reduction in trip duration of 30%. The time value of bus commuting (ζ_{bus}) and LRT commuting (ζ_{LRT}) will be estimated within the model.

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 (equation 8). Upper bar notation indicates the maximum value in the set.

$$P_{ijkv} = \frac{e^{V_{ijkv}}}{\sum_1^{\overline{j}} \sum_1^{\overline{k}} \sum_0^{\overline{v}} e^{V_{ijkv}}} \tag{8}$$

Computationally, local rents, local wages, and structural parameters ($\zeta_{bus}, \zeta_{LRT}, \rho_j$) are

[5] 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.

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 data. The model is identified by restricting the possible equilibriums to generate the observed pretreatment private vehicle mode share of 87.2%, a fall in private vehicle commuting in treatment tracts of 5.80 percentage points and a rise in the local employment rate of 8.28 percentage points. Neighbourhood changes are relative to the control tracts denoted in Section 4. 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 equilibrium prices and wages and not through endogenous neighbourhood amenity characteristics. Intuitively, neighbourhood rents and wages must be at a level that exactly attracts 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 ζ_{LRT} 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 unique moments in the data.

5.5 Results

Solving the model yields the necessary preference parameters. The time value parameter for bus commuting (ζ_{bus}) is found to be 1.34, 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). The value of ζ_{LRT} is estimated as 1.03, suggesting workers consider a unit of time spent on LRT as less costly than riding a bus, but more costly than driving in a private vehicle. According to estimates, a worker earning $20 per hour would be willing to forgo $16.80 to avoid one hour of commuting by bus and $10.60 to avoid one hour of commuting by LRT. These figures are pure time costs, independent of the accompanying monetary costs of transportation.

The model also recovers the average amenity preference for living in a tract with LRT. The value of ρ_j is estimated as 1.096. ρ_j suggests that numeraire consumption provides 9.6% more utility per dollar when the household is located in a LRT tract. 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 shopping and leisure amenities, but also changing neighbourhood characteristics induced by LRT.

It is worth considering why the positive amenity value of local LRT must exist, given the estimated neighbourhood changes. A local LRT station causes more individuals to become employed than it causes to begin commuting by public transit. This is only plausible if LRT increases local employment through a channel unrelated to commuting costs. Modelling LRT as a local amenity that improves consumption provides such a mechanism. The local amenity raises local rents, repelling low skilled workers and workers without employment, pushing up the local employment rate.

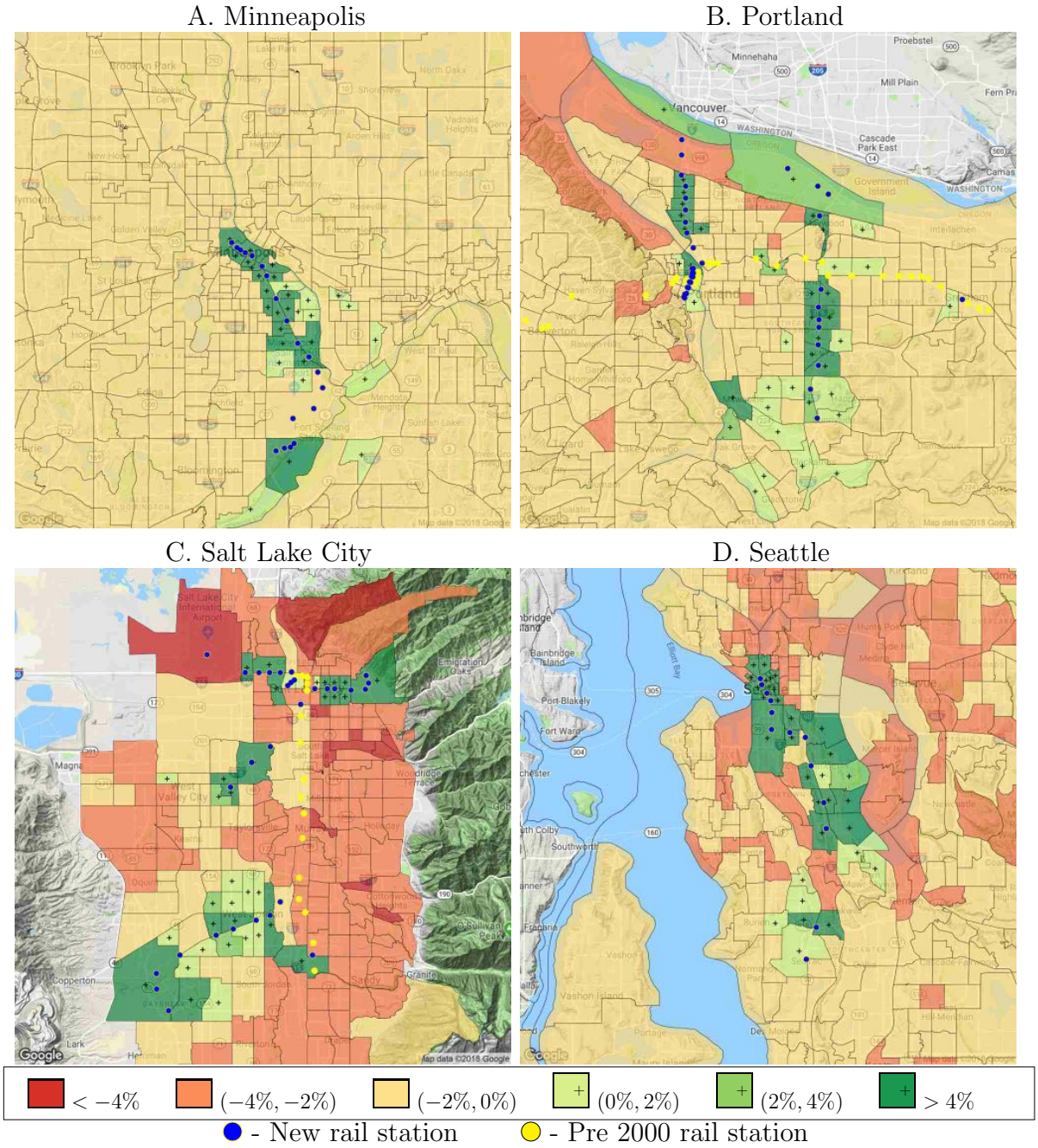
An advantage of the discrete neighbourhood choice model is that it can predict neighbourhood changes across the metro. Figures 5, 6 and 7 show the spatial predictions of the model. A clear prediction of the model is an increase in rent per unit of housing in neighbourhoods gaining access to LRT (Figure 5). The valuation of LRT as a local amenity increases the utility of any worker able to locate in a LRT tract. The commuting benefit of LRT further increases the utility of local employed workers commuting by transit, but has no additional effect on car commuters or those out of the labour force. Given these mechanisms, LRT unambiguously increases demand for a neighbourhood and therefore local rents. Areas not gaining LRT generally experience rent reductions as they become less desirable relative to the areas gaining LRT (Figure 5).

Residing in a LRT tract requires paying higher rents, in part, for the opportunity to reduce commuting costs. Therefore, the benefits of LRT to an individual who is not in the labour force are comparatively low. Figure 6 maps the changes in local employment levels induced by LRT. Employment rates rise in neighbourhoods that gained LRT stations, and fall marginally in other areas.

Figure 7 shows neighbourhood impacts on the share of local workers commuting by public transit. While the average public transit mode share in tracts gaining LRT increased more than other areas, the effect is quite heterogeneous across treatment neighbourhoods. The large increase in local amenities encourages high skilled workers to move towards the treated neighbourhoods, and these workers are less likely to use public transit. Positive public transit effects are spread throughout the metropolitan area, including neighbourhoods very far from the new infrastructure. The broad spatial distribution of mode shift is a result of low skilled, transit dependent populations relocating out of the urban core to avoid local rent increases. The new suburban location of these workers does not enable them to afford a private vehicle, and they remain transit commuters in less transit accessible areas.

Attempts to expand urban public transit use often consider “captive” and “choice”

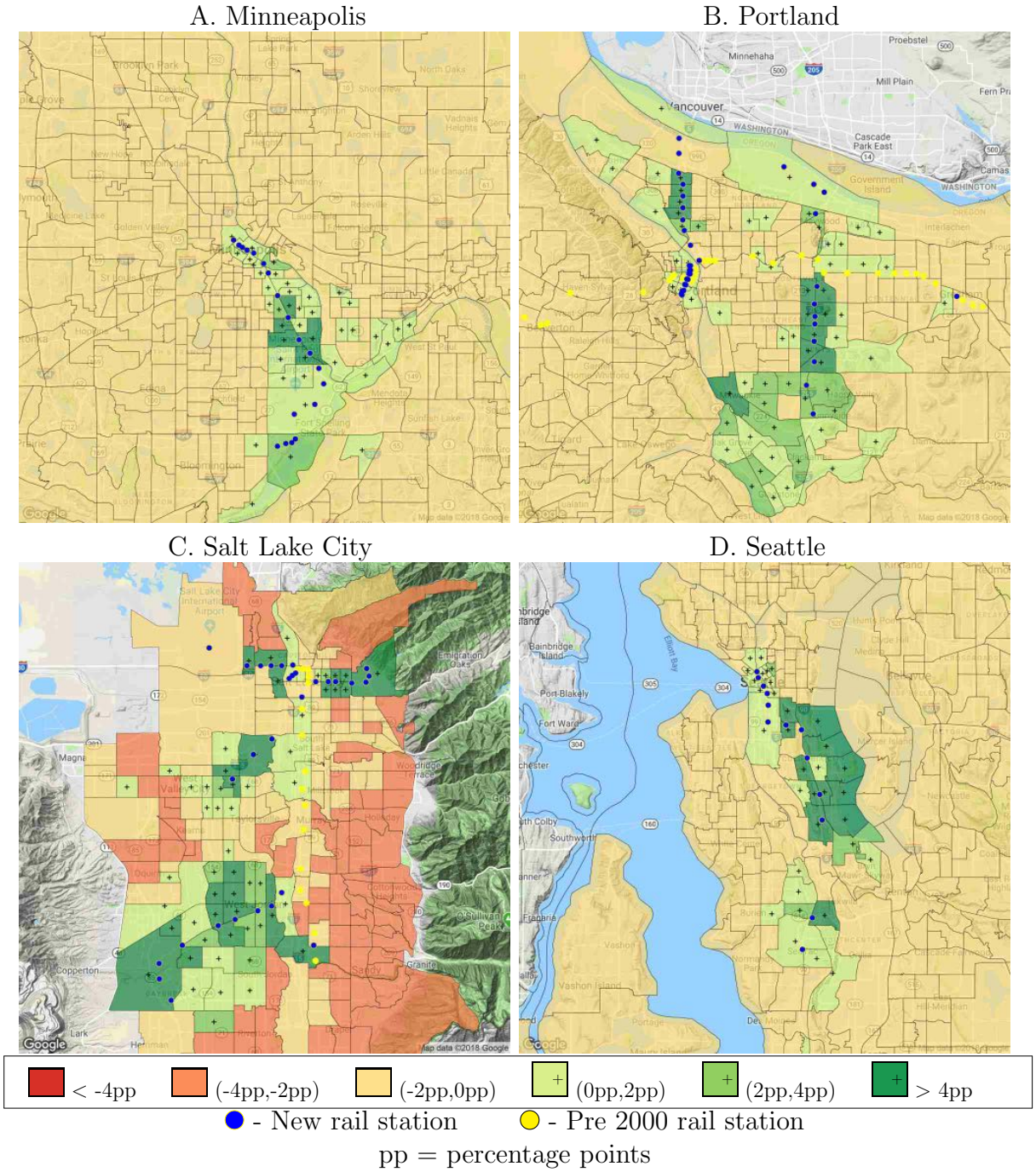
Figure 5: Structural Results, Change in Rent



("+" symbols are redundant with colours, but enable interpretation of figures if viewed in grayscale.)

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). Local amenity effects of LRT stations repel captive users and attract choice users. This 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 the high

Figure 6: Structural Results, Change in Employment Rate

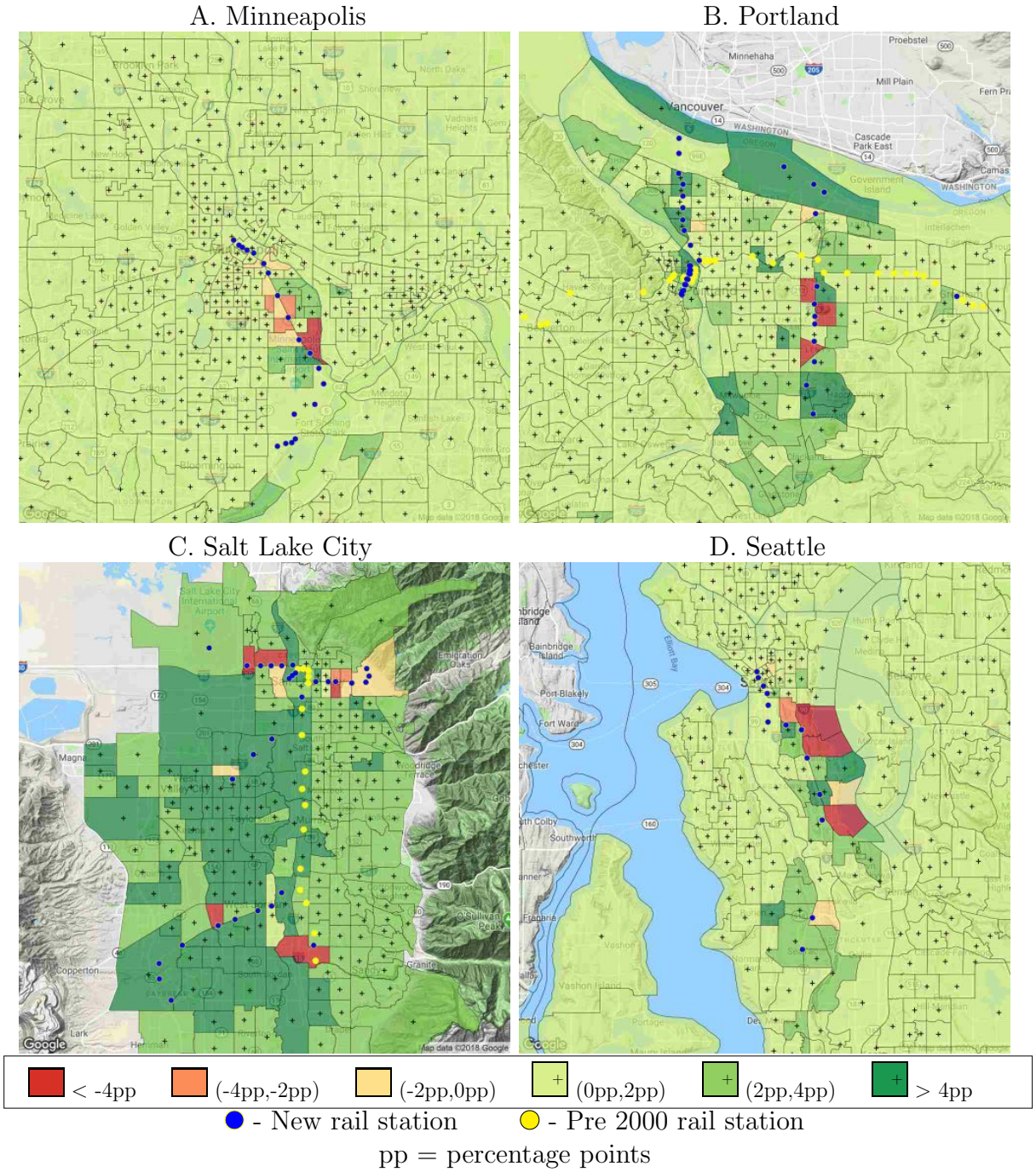


("+" symbols are redundant with colours, but enable interpretation of figures if viewed in grayscale.)

quality transit. However, the process degrades the spatial access of captive transit riders, undermining the progressivity of transit investment.

There is some evidence that neighbourhoods with pre 2000 stations benefit from the new stations constructed elsewhere. Network effects generate this outcome, as

Figure 7: Structural Results, Change in Public Transit Mode Share



("+" symbols are redundant with colours, but enable interpretation of figures if viewed in grayscale.)

neighbourhoods along the LRT extensions become more accessible from other parts of the LRT system. However, the local amenity effects of LRT appear to dominate the network effects, with positive changes much larger in neighbourhoods that actually gained a new station.

The distribution of behavioural and welfare effects across income groups can be recovered from the model and are graphed in Figure 8. I scale results to correspond to the predicted effect of constructing ten new LRT stations within a metro of average size (1.25 million workers). Panel A indicates that the probability of a worker switching to public transit is distributed uniformly across potential income groups. While low skilled workers are generally more willing to take public transit, high skilled workers are more likely to relocate adjacent to the new LRT infrastructure. The two opposing effects result in the new uptake of transit being spread uniformly across groups. Every ten LRT stations are estimated to increase metro wide public transit mode share by 0.43 percentage points (3.4% rise from the 2000 baseline).

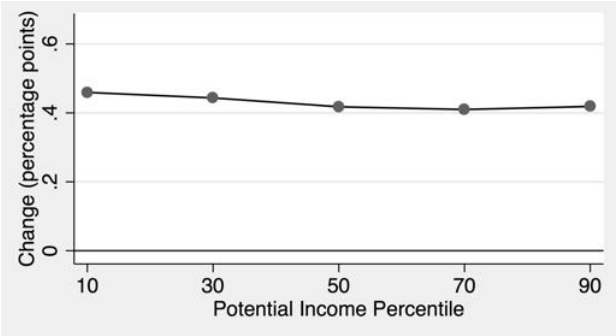
Panel B graphs the effect of ten LRT stations on the employment rate. Overall the introduction of LRT is estimated to marginally *reduce* overall metro employment. The share of workers who are employed falls by one tenth of a percentage point, from a baseline of 69.9%. While reduced transit times may encourage employment, increased rents in accessible neighbourhoods cause the displacement of low skilled workers to low access areas. Low skilled workers are likely to be on the margin of the labour market. 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. The result demonstrates that if the consumption amenity effects of public transit are sufficiently large, the consequent sorting may completely eliminate intended employment increases. The result is counterintuitive, given new transit is often built with the explicit goal of improving labour market accessibility.

The mechanism of displacement is also highlighted by rent effects shown in panel C. Residents with low potential income pay lower rents per unit of housing as a result of LRT infrastructure, while residents with high potential income pay higher rents. This effect is generated by higher income residents moving to more central locations to reap consumption benefits of LRT and low income workers moving out of the central city. The mechanism mirrors modern accounts of higher skilled groups returning to denser urban locations due to consumption preferences (Couture and Handbury, 2017).

Given transit's relatively slow speed relative to private vehicles, the average worker experiences a small increase in commute duration (panel D). The lowest skilled workers see a small reduction in average commute time, as low skill workers who retain their residential location close to LRT stations reap time savings as they switch from bus to LRT. When averaged across the labour force, the effect of the transit infrastructure on average commute duration is negligibly small.

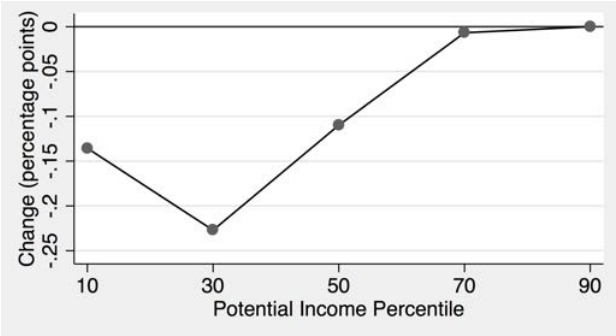
Figure 8: Structural Results, Distribution Across Potential Income ($w_i^{\text{potential}}$) Percentiles

A. Public Transit Mode Share



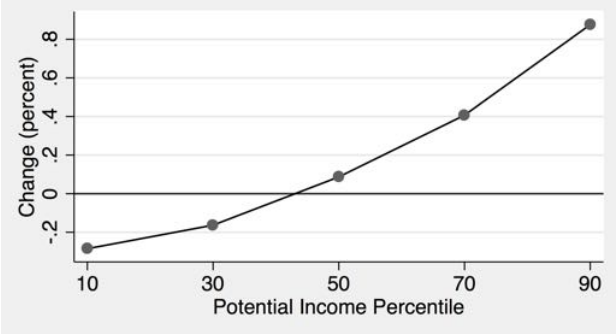
Overall effect: +0.43 pp

B. Employment Rate



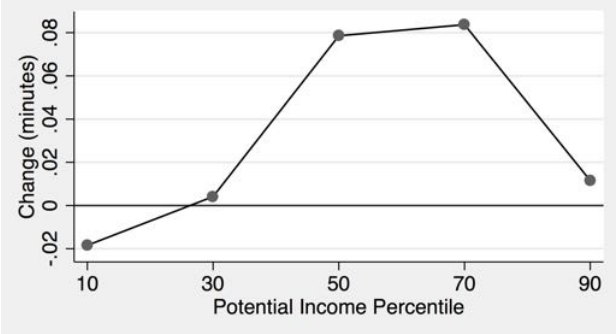
Overall effect: -0.10 pp

C. Rent per Square Foot



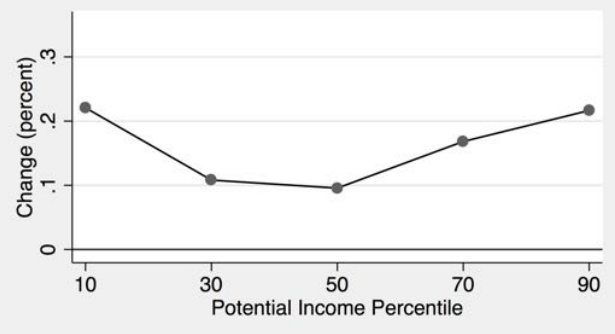
Overall effect: +0.18%

D. Commute Duration



Overall effect: +0.03 minutes

E. Welfare



Overall effect: +0.16%

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

Panel E illustrates the distribution of changes in the deterministic portion of worker utility. Every ten LRT stations increases the average resident's utility by 0.16%. A large share of the welfare gains are derived from the direct consumption amenity benefits of LRT but also through monetary savings from forgone car ownership. Critically, welfare benefits are not generated by increased employment. While LRT may reduce monetary travel costs and raise the enjoyment of travel for those using transit, local rent increases cause sorting that eliminates the potential for increased aggregate employment. All groups are found to experience positive welfare effects, with low and high skill groups capturing the largest benefits. I revisit the implications of these welfare effects in the conclusion.

The ability of LRT to expand transit commuting and increase employment is undercut by sorting. In Appendix B, I propose a complimentary policy regarding transit passes that reduces sorting, limiting these negative impacts.

5.6 Cost Benefit Analysis

I compare the estimated welfare benefits of LRT with typical project costs. The previous section estimated that a hypothetical ten station LRT line would increase the welfare of the metro's average worker by 0.16%. Achieving an equivalent variation through a uniform cash transfer program would require every worker to receive $92.50 annually. The average metro in the sample contains 1.25 million workers, suggesting this cash transfer program would cost $116 million annually in the average sized metro. Assuming an annual discount rate of 5%, the present value of this cash transfer program is equal to $2.32 billion. Therefore, a LRT project in the average sized metro cannot be justified on the basis of worker welfare benefits if project costs exceed $2.32 billion. All figures in this section are in inflation adjusted 2013 dollars.

The cost of building and maintaining LRT varies across metros, but is in many cases below $2.32 billion per 10 stations. The Minneapolis project had capital costs of $880 million,[6] for a line with 19 stations. Annual operational expenses in 2010 were reported to be $27.5 million.[7] Using the same 5% discount rate suggests that the cost of the Minneapolis light rail system in present value terms was $1.43 billion. Scaling the expense down to a hypothetical 10 station system yields costs of $0.75 billion, substantially less than the estimated benefits.

Costs of the Seattle system were higher than Minneapolis. Reported capital costs were $2.40 billion for a 13 station line.[8] The annual 2010 operating budget for the LRT line was

[6] Metro Transit, *Facts About Light-Rail Trains and Construction*, 2010.
[7] MetroTransit, *Blue Line Operations, Financial Results by Calendar Year*, 2013.
[8] The Seattle Times, *Light-rail contract dispute is resolved*, June 23, 2011.

$51.6 million.[9] The present value of these costs under a 5% discount rate is $3.43 billion. Scaling to a hypothetical 10 station line yields costs of $2.64 billion. The Seattle system had costs slightly above the estimated benefits accruing to workers. Seattle may be an outlier in terms of high capital costs, as costs were inflated by the decision to put a downtown portion of the line underground.

I calculate benefits that directly accrue to workers. I do not account for numerous other potential benefits of LRT. In particular, LRT may generate substantial positive environmental benefits. I find strong evidence that LRT reduces the use of private vehicles for commuting, which are a large source of emissions. Benefits accruing to those out of the labour force, such as children and retired persons, are also unaccounted for in the above analysis. The simplified calculation in this section suggests that, in many cases, benefits accruing directly to the workforce may be sufficient to justify LRT project expenditures.

6 Conclusion

Between 2000 and 2017, an average of 20 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.

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 commuting networks but also raises demand for transit accessible areas. Lower skilled residents are more likely to directly consume the mobility benefits of public transit, but are also more likely to be displaced by local rent increases. Overall, I find that LRT causes a modest reduction in overall metropolitan employment, as the local gentrification caused by LRT stations forces workers on the margin of the labour force to locate in areas that are not transit accessible, exacerbating spatial mismatch. The effect is driven by the relatively high employment elasticity among low skilled workers: pushing lower skilled workers out of transit accessible locations can degrade their ability to obtain employment, undoing the accessibility benefits of LRT. The result is counterintuitive, given that public transit projects are often constructed with the explicit intention of improving labour market access for socially vulnerable populations. Despite the effect of sorting, I find that LRT systems provide positive welfare benefits across the metropolitan population. A simplified cost

[9] Sound Transit, *Adopted 2010 Budget*, 2009.

benefit analysis suggests that the welfare benefits of LRT exceed typical project costs.

The mechanisms described in this paper provide some explanation for efforts to resist LRT projects. For example, a second LRT line that was recently constructed 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.[10] 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. While I find LRT creates positive welfare effects, I do find that local home price increases reduce the mobility benefits accruing to workers with lower earning ability. High quality bus transit could potentially provide similar mobility improvements to LRT without inducing the same level of gentrification, potentially yielding a more progressive distribution of benefits. Given that high earning workers are able to capture significant welfare benefits from LRT transit, 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. Rich households may wield outsized control over public policy. These households would support using public money for LRT transit over bus because LRT directs significant consumption benefits towards the rich.

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

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

References

Ahlfeldt, G. M., Redding, S. J., Sturm, D. M., and Wolf, N. (2015). The economics of density: Evidence from the berlin wall. *Econometrica*, 83(6):2127–2189.

Alonso, W. et al. (1964). Location and land use. toward a general theory of land rent. *Location and land use. Toward a general theory of land rent.*

Altshuler, A. A. and Luberoff, D. E. (2004). *Mega-projects: The changing politics of urban public investment*. Brookings Institution Press.

American Automobile Association (2007). Your driving costs.

Angrist, J. D. and Pischke, J.-S. (2008). *Mostly harmless econometrics: An empiricist's companion*. Princeton university press.

Atkinson-Palombo, C. (2010). Comparing the capitalisation benefits of light-rail transit and overlay zoning for single-family houses and condos by neighbourhood type in metropolitan phoenix, arizona. *Urban Studies*, 47(11):2409–2426.

Baum-Snow, N. and Kahn, M. E. (2000). The effects of new public projects to expand urban rail transit. *Journal of Public Economics*, 77(2):241–263.

Bay Area Rapid Transit District (1987). 1987 five year plan, volume 1, operations and service plan.

Bayer, P., Ferreira, F., and McMillan, R. (2007). A unified framework for measuring preferences for schools and neighborhoods. *Journal of political economy*, 115(4):588–638.

Bayer, P. and McMillan, R. (2012). Tiebout sorting and neighborhood stratification. *Journal of Public Economics*, 96(11-12):1129–1143.

Bayer, P., McMillan, R., and Rueben, K. (2004). An equilibrium model of sorting in an urban housing market. Technical report, National Bureau of Economic Research.

Bayer, P. and Timmins, C. (2005). On the equilibrium properties of locational sorting models. *Journal of Urban Economics*, 57(3):462–477.

Bogin, A. N., Doerner, W. M., Larson, W. D., et al. (2016). Missing the mark: House price index accuracy and mortgage credit modeling. Technical report.

Cao, X. J. and Schoner, J. (2014). The influence of light rail transit on transit use: An exploration of station area residents along the hiawatha line in minneapolis. *Transportation Research Part A: Policy and Practice*, 59:134–143.

Couture, V. and Handbury, J. (2017). Urban revival in america, 2000 to 2010. Technical report, National Bureau of Economic Research.

Credit, K. (2018). Transit-oriented economic development: The impact of light rail on new business starts in the Phoenix, Az region, USA. *Urban Studies*, 55(13):2838–2862.

Davis, M. A. and Ortalo-Magné, F. (2011). Household expenditures, wages, rents. *Review of Economic Dynamics*, 14(2):248–261.

Epple, D. and Sieg, H. (1999). Estimating equilibrium models of local jurisdictions. *Journal of political economy*, 107(4):645–681.

Ferreyra, M. M. (2007). Estimating the effects of private school vouchers in multidistrict economies. *The American Economic Review*, 97(3):789–817.

Fujita, M. and Ogawa, H. (1982). Multiple equilibria and structural transition of non-monocentric urban configurations. *Regional science and urban economics*, 12(2):161–196.

Glaeser, E. L., Kahn, M. E., and Rappaport, J. (2008). Why do the poor live in cities? the role of public transportation. *Journal of urban Economics*, 63(1):1–24.

Gobillon, L., Selod, H., and Zenou, Y. (2007). The mechanisms of spatial mismatch. *Urban studies*, 44(12):2401–2427.

Graham, M. R., Kutzbach, M. J., McKenzie, B., et al. (2014). Design comparison of lodes and acs commuting data products. Technical report.

Ham, J. C., Swenson, C., İmrohoroğlu, A., and Song, H. (2011). Government programs can improve local labor markets: Evidence from state enterprise zones, federal empowerment zones and federal enterprise community. *Journal of Public Economics*, 95(7-8):779–797.

Hanson, A. (2009). Local employment, poverty, and property value effects of geographically-targeted tax incentives: an instrumental variables approach. *Regional Science and Urban Economics*, 39(6):721–731.

Holzer, H. J. (1991). The spatial mismatch hypothesis: What has the evidence shown? *Urban Studies*, 28(1):105–122.

Holzer, H. J., Quigley, J. M., and Raphael, S. (2003). Public transit and the spatial distribution of minority employment: Evidence from a natural experiment. *Journal of Policy Analysis and Management*, 22(3):415–441.

Ihlanfeldt, K. R. and Sjoquist, D. L. (1998). The spatial mismatch hypothesis: a review of recent studies and their implications for welfare reform. *Housing policy debate*, 9(4):849–892.

Imbens, G. W. and Kolesar, M. (2016). Robust standard errors in small samples: Some practical advice. *Review of Economics and Statistics*, 98(4):701–712.

Immergluck, D. (1998). Job proximity and the urban employment problem: do suitable nearby jobs improve neighbourhood employment rates? *Urban Studies*, 35(1):7–23.

Kahn, M. E. (2007). Gentrification trends in new transit-oriented communities: Evidence from 14 cities that expanded and built rail transit systems. *Real Estate Economics*, 35(2):155–182.

Kain, J. F. (1968). Housing segregation, negro employment, and metropolitan decentralization. *The Quarterly Journal of Economics*, 82(2):175–197.

Kline, P. (2010). Place based policies, heterogeneity, and agglomeration. *American Economic Review*, 100(2):383–87.

Kline, P. and Moretti, E. (2014). People, places, and public policy: Some simple welfare economics of local economic development programs. *Annu. Rev. Econ.*, 6(1):629–662.

Kou, W., Chen, X., Yu, L., Qi, Y., and Wang, Y. (2017). Urban commuters' valuation of travel time reliability based on stated preference survey: A case study of beijing. *Transportation Research Part A: Policy and Practice*, 95:372–380.

Krizek, K. J. and El-Geneidy, A. (2007). Segmenting preferences and habits of transit users and non-users. *Journal of public transportation*, 10(3):5.

LeRoy, S. F. and Sonstelie, J. (1983). Paradise lost and regained: Transportation innovation, income, and residential location. *Journal of Urban Economics*, 13(1):67–89.

Mills, E. S. (1967). An aggregative model of resource allocation in a metropolitan area. *The American Economic Review*, 57(2):197–210.

Muth, R. F. (1969). Cities and housing; the spatial pattern of urban residential land use.

Neumark, D. and Kolko, J. (2010). Do enterprise zones create jobs? evidence from California's enterprise zone program. *Journal of Urban Economics*, 68(1):1–19.

O'Regan, K. M. and Quigley, J. M. (1998). Where youth live: economic effects of urban space on employment prospects. *Urban Studies*, 35(7):1187–1205.

Sanchez, T. W. (1999). The connection between public transit and employment: the cases of portland and atlanta. *Journal of the American Planning Association*, 65(3):284–296.

Sanchez, T. W., Shen, Q., and Peng, Z.-R. (2004). Transit mobility, jobs access and low-income labour participation in us metropolitan areas. *Urban Studies*, 41(7):1313–1331.

Severen, C. (2018). Commuting, labor, and housing market effects of mass transportation: Welfare and identification.

Sieg, H., Smith, V. K., Banzhaf, H. S., and Walsh, R. (2004). Estimating the general equilibrium benefits of large changes in spatially delineated public goods. *International Economic Review*, 45(4):1047–1077.

Small, K. A., Winston, C., and Yan, J. (2005). Uncovering the distribution of motorists' preferences for travel time and reliability. *Econometrica*, 73(4):1367–1382.

Sound Transit (1999). Central Link Light Rail Transit Project, Seattle, Tukwila and Seatac: Environmental Impact Statement, Volume 1. pages 4–21.

Stoll, M. A. (1999). Spatial job search, spatial mismatch, and the employment and wages of racial and ethnic groups in los angeles. *Journal of Urban Economics*, 46(1):129–155.

Stubbs, J. and Jegede, F. (1998). The integration of rail and air transport in britain. *Journal of transport Geography*, 6(1):53–67.

Tiebout, C. M. (1956). A pure theory of local expenditures. *Journal of political economy*, 64(5):416–424.

Tsivanidis, N. (2018). The aggregate and distributional effects of urban transit infrastructure: Evidence from bogota's transmilenio. *Working Paper, University of Chicago Booth School of Business*.

Tyndall, J. (2017). Waiting for the r train: Public transportation and employment. *Urban Studies*, 54(2):520–537.

Tyndall, J. (2018). Bus quality improvements and local commuter mode share. *Transportation Research Part A: Policy and Practice*, 113:173–183.

Wasmer, E. and Zenou, Y. (2002). Does city structure affect job search and welfare? *Journal of urban Economics*, 51(3):515–541.

Wasmer, E. and Zenou, Y. (2006). Equilibrium search unemployment with explicit spatial frictions. *Labour Economics*, 13(2):143–165.

Widmer, J.-P. and Hidber, C. (2000). Effects of rail stations at airports in europe. *Transportation Research Record: Journal of the Transportation Research Board*, (1703):90–97.

Appendix A

A1. Distribution of Google API Generated Trip Times

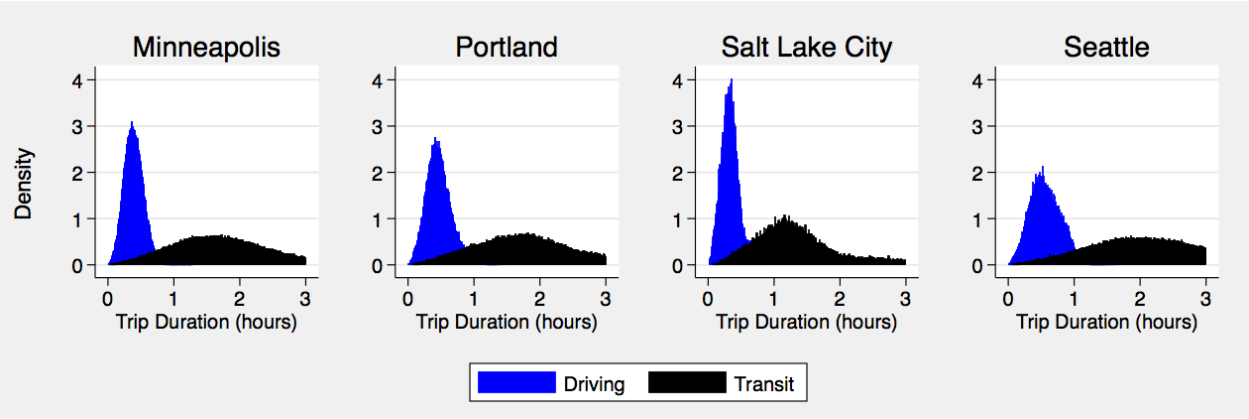
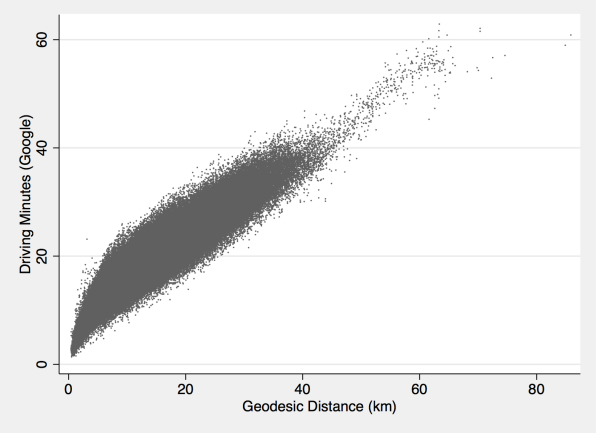


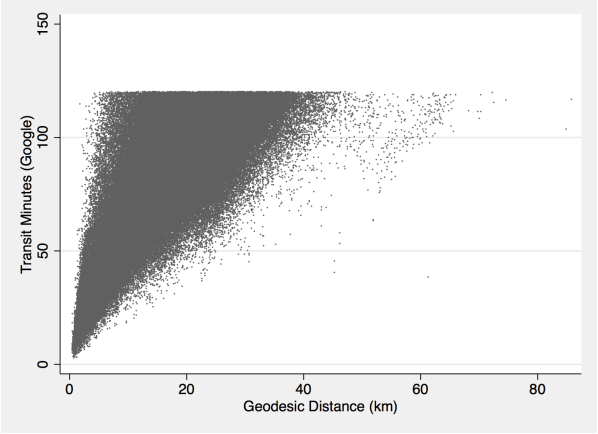
Figure A1 displays the distribution of travel times for both driving and public transit commuting for the full matrix of home and work locations. Across the four metros, 66% of public transit commutes take over 90 minutes and 43% take over 2 hours. Only 0.6% of drive times exceed 90 minutes.

A2. Correlation Between Google Travel Times and Geodesic Distance

Driving Times



Public Transit Times



Each dot represents one potential commute. 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

Policy Extension: Local Transit Pass Requirement

In this appendix I propose a novel policy instrument to increase the societal benefits of LRT. When proposing LRT projects, policy makers normally state the joint objectives of improving labour market outcomes and increasing public transit use. As shown in this paper, LRT induced neighbourhood demand may crowd out the population most likely to use transit for commuting, undercutting benefits.

Consider the following program: the local government imposes a levy on every resident living in a tract that received a new LRT station. The levy is set to be exactly the cost of a local transit pass (t). In exchange, the local government provides a transit pass to every resident who pays the levy. The program essentially mandates the purchase of a transit pass within the neighbourhoods gaining a LRT station. The policy causes LRT neighbourhoods to become less desirable for workers who wish to live in a LRT neighbourhood but commute by private vehicle. Such workers are charged for a transit pass that they do not use.

I rerun the model with the preference parameters identified in the original specification, but apply the new policy in addition to LRT. Figure B1.A displays the combined effect of the policies on public transit mode share. While LRT alone increased transit commuting by .43 percentage points, LRT combined with the mandatory transit pass program increases the share of commuters using transit by .56 percentage points.

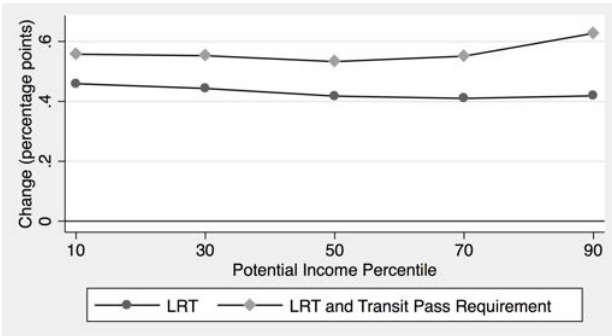
The policy is also effective at reducing the negative aggregate employment effects of LRT. Figure B1.B displays employment effects. Compared to LRT alone, the addition of the local mandatory transit pass program cuts the negative employment effect roughly in half.

The program provides money to the government in two ways. First, a majority of residents in the tracts gaining LRT continue to drive to work, consistent with low overall transit uptake in the metros. These workers pay for transit passes but do not use transit for commuting, transferring revenue to the government. Second, more employed workers means that fewer workers require government transfers. In the model, transfers come from outside of the metropolitan economy, which is consistent with the reality that social welfare programs are mainly supplied by state and federal governments. However, depending on the relationships between levels of government, these savings may also be salient.

If the money raised from unused passes is rebated to local residents through a uniform transfer, welfare effects are approximately the same as without the mandatory transit program (+.16%). If the money saved from reduced transfers to the jobless is also rebated

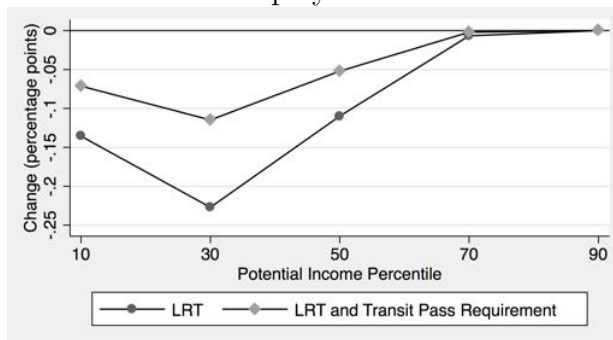
B1. Structural Results, Distribution Across Potential Income ($w_i^{\text{potential}}$) Percentiles

A. Public Transit Mode Share



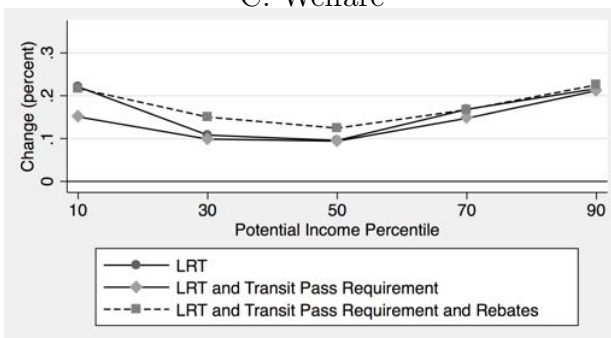
Average Effects
LRT: +0.43 pp
LRT and Transit Pass Requirement: +0.56 pp

B. Employment Rate



Average Effects
LRT: −0.10 pp
LRT and Transit Pass Requirement: −0.05 pp

C. Welfare



Average Effects
LRT: +0.16%
LRT and Transit Pass Requirement: +0.14%
LRT and Transit Pass Requirement and Rebates: +0.18%

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

through a uniform transfer, the welfare gains are higher (+.18%). Figure B1.C graphs welfare effects. When all benefits are considered, the mandatory transit pass program improves the welfare benefits of LRT.

The program is effective because it reduces the appeal of neighbourhoods gaining LRT among rich car users, as they do not stand to gain from the provided transit passes. The mechanism preserves accessible housing for those who do use transit.