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Light Rail Transit Station Area Economic Development and Demographic Outcomes with Post-Pandemic Implications

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LIGHT RAIL STATION AREA ECONOMIC DEVELOPMENT AND DEMOGRAPHIC OUTCOMES WITH POST-PANDEMIC IMPLICATIONS

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LIGHT RAIL STATION AREA ECONOMIC DEVELOPMENT AND DEMOGRAPHIC OUTCOMES WITH POST-PANDEMIC IMPLICATIONS

ABSTRACT

This article is the first comprehensive assessment of the extent to which light rail transit (LRT) station areas attract jobs, people and households, and influence commuting mode choice as well as real estate values. Research is based on 17 LRT systems between the Great Recession of 2007-2009 and the global COVID-19 pandemic of 2020-2023. The study area extends 800 meters (about 0.50-miles) from LRT stations, which comprises less than one percent of the urbanized land area of the counties within which LRT systems operate. During the study period, LRT station areas accounted for about one million new jobs. Yet, those areas lost share of total job growth compared to their counties. On the other hand, LRT station areas added proportionately more people and households than their respective counites. Indeed, overall and for many counties, LRT station areas added proportionately more households with children. In addition, LRT station areas added proportionately more householders in all age groups than their respective counties. The evidence suggests that before the pandemic, people and households were beginning to displace jobs and this trend may accelerate in the post-pandemic era. LRT station areas also added proportionately more owner- and renter-occupied housing units than their respective counties. However, based on household incomes rising faster in LRT station areas than in their respective counties, along with other factors, gentrification is evident in at least 13 of the 17 LRT systems studied, with the rest poised for the same trend. Finally, overall, more than a quarter (28 percent) of all new workers living in LRT station areas commute to work via modes other than the automobile, compared to about a fifth (21 percent) for the rest of their respective counties. The evidence suggests that post-pandemic planning and policy must facilitate the demand for people and households to live in LRT station areas.

OVERVIEW

This report is the first comprehensive assessment of the extent to which light rail transit (LRT) station areas attract jobs, people and households, influence commuting mode choice, reduce vehicle kilometers traveled (VKT) as well as transportation costs, influence real estate value, and engender gentrification. Research is based on17 LRT systems between the Great Recession of 2007-2009 and the global COVID-19 pandemic of 2020-2023. The article begins with literature reviews, theoretical perspectives, and research questions relating to the role of LRT station proximity on various economic and demographic outcomes within 800 meters (about 0.50-mile) of transit stations, which is called the "station area." It continues with a framework for analyzing outcomes. This is followed by sections presenting research designs, hypotheses, methods, results, and interpretations relating to the association between LRT station proximity and outcomes with respect to jobs, people, households, commuting, and real estate values. Key findings include the following:

- Within 800 meters, LRT station areas added more than 990,000 jobs during the study period, accounting for about 28 percent of all new jobs in counties with LRT systems. Offices in LRT station areas accounted for 35 percent of all new jobs in their respective counties, as well as 25 percent of all new education jobs, 23 percent of all new health care jobs, 27 percent of new retail-food-lodging jobs, and 41 percent of the new arts-entertainment-recreation jobs. Yet, overall and across all economic groups, the pace of new jobs was lower in LRT station areas than in their respective counties, indicating that jobs are dispersing, albeit gradually.

- LRT station areas also added nearly 330,000 people, accounting for 15 percent growth in the LRT county, again on less than one percent of LRT counties' urbanized land area. Yet, while non-Whites accounted for about 87 percent of LRT county growth, Whites accounted for about 35 percent of the population growth in LRT station areas. In addition to population growing at a faster pace in LRT station areas than in their respective counties, the dominance of White population growth indicates gentrification is occurring.

- LRT station areas accounted for 20 percent of the change in households. Unexpectedly however, they accounted for proportionately more households with children than nearly all LRT counties. They also accounted for 32 percent of LRT county growth among single-person households and 18 percent of the growth among >1 adult households with no children.

- Although the number of householders under 25 years of age fell in LRT counties overall, they increased in LRT station areas. LRT station areas also accounted for 36 percent of LRT counties' growth among householders between 25 and 44 years of age as well as 20 percent and 11 percent of the growth among householders of 45 to 64, and 65 or more years of age, respectively. In many cases, nearly all LRT station areas gained proportionately more households in each of these age groups than their respective counties.

- Moreover, household incomes rose at a faster pace overall during the study period in LRT station areas than LRT counties. This trend was evident among most of the LRT systems. Combined with White dominance of growth near stations and other factors, this is a clear indication that gentrification is occurring among most of the systems studied and may be poised to occur in others as well.

- Moreover, LRT station areas accounted for 11 percent of the LRT county change in renters compared to 30 percent of homeowners, in both cases adding proportionately more of these households by tenure than their respective counties.

- Of the nearly 1.9 million new workers living in LRT counties (as opposed to workers with jobs in the county), nearly 35,000 or about 18 percent moved into LRT station areas. They accounted for about 28 percent of the share of change in LRT station area commuters using modes other than the auto in their journey to work. Although working from home accounted for only 12 percent of the change in how new workers living in station areas get to work, this figure predates the pandemic.

- However, the relationship between retail and multifamily rents with respect to LRT transit station proximity is disappointing. While associations are mixed with respect to office rents, results are mostly negative or statistically insignificant with respect to retail and multifamily rents. That is, where one would expect proximity to LRT stations to confer a rent premium on retail and multifamily rents, they do not. These results call into question the efficacy of LRT station planning, location, and design for most transit station areas if their intent is to achieve the desired real estate investment outcomes. There are some exemplary individual LRT systems worth emulating, nonetheless.

Using insights from research, the article offers lessons for post-pandemic LRT transit policy and planning. Notably, it concludes with a call to make LRT station areas more attractive places for people to live.

What follows is a review of LRT literature and theory along with research questions.

Light Rail Transit Station Proximity Development Literature, Theories, and Research Questions

Cities and their metropolitan areas are formed and grow in large part by creating agglomeration economies (Glaeser 2011). This occurs in part when the average cost of production falls as firms pool their resources, such as labor, to increase productivity (Anas, Arnott and Small 1998). As more related firms cluster together, average production costs fall as productivity increases. Agglomeration economies can spill over into complementary sectors, thereby creating even more jobs (Holmes 1999). Cities become ever larger when agglomeration economies are exploited (Ciccone and Hall 1996).

Highways make it possible to sustain agglomeration economies by increasing the size of market areas. But increasing demand for highways can lead to congestion which reduces worker productivity and accessibility to markets, thereby undermining agglomeration economies (Glaeser and Kohlhase 2004). Indeed, new highway investments have been shown to reduce agglomeration economies resulting in a net cost to society (Boarnet 1997; Boarnet and Haughwout 2000). A key role of transit is to facilitate agglomeration economies by mitigating the transportation congestion effects of automobile traffic induced by agglomeration. Since public transit is essentially noncongestible, it can sustain agglomeration economies in high-density nodes as well as along the corridors that connect them (Voith1998).

Research shows that public transit enhances economic development, in part because of its role in facilitating agglomeration economies (Graham 2007; Nelson et al, 2009; Litman 2023). Transit thus plays a pivotal role in the development of metropolitan areas, especially near transit stations (Belzer et al., 2011). Not only is job growth facilitated but transit stations also attract households and their workers who seek improved accessibility to jobs as well as other services (Nelson et al. 2015). This can reduce automobile dependence by expanding mobility options.[1] Moreover, transit stations confer proximity rent premiums that increase land and real estate values near them (Higgins and Kanaroglou 2016). But there is an underlying concern that this increase in rental costs near transit stations can lead to gentrification (Padeiro, Louro and da Costa 2019).

In focusing on LRT transit, this section presents literature and identifies theories with respect to the association between LRT transit station proximity and change in the share of regional jobs, population generally—as well as among Whites/non-Whites, households by type and age—along with their housing tenure and median household income, change in mode choice in the commute to work, reduction in vehicle kilometer traveled (VKT) [2] and associated reduction in transportation cost, and rents for office, retail, and multifamily rent.

[1] See https://tod.itdp.org/what-is-tod/eight-principles-of-tod.html.
[2] This metric is also known as vehicle miles traveled or VMT.

Literature, Theory, and Research Questions Relating to Light Rail Transit Station Proximity and Jobs

In theory, LRT systems should facilitate economic development near stations because they reduce transportation costs and support higher intensity land uses (Shen 2013). Unfortunately, the literature on the association between the change in jobs and jobs by economic sector and proximity to LRT stations is thin.

Nelson et al. (2009) outline a series of economic arguments supporting rail transit investments such as facilitating agglomeration economies, increasing real estate values, and enhancing connectivity between people and jobs. In one of the few studies to do so, Nelson et al. (2013) directly assessed the extent to which jobs are attracted to transit investments. For instance, their case study of the Eugene-Springfield, Oregon bus rapid transit (BRT) system found enhanced growth in jobs relative to the rest of the metropolitan area within 0.25 miles of BRT stations. Growth was not consistent across job sectors however, which is consistent with Belzer et al.'s (2011) analysis of location patterns of different employment sectors near transit. On the other hand, Kolko (2011) found among 204 rail transit stations in California that growth in employment near stations varied considerably, with more station areas losing jobs than gaining. Studies thus show transit investments do not automatically lead to economic development and outcomes vary by transit mode.

Focusing on just LRT systems, Cervero et al. (2004) reviewed development outcomes around LRT stations in several metropolitan areas. They found that in the early 2000s almost all of Portland's LRT stations had seen some new office, retail, and multifamily development. They also found that strong market demand around Dallas Area Rapid Transit LRT stations contributed to the near-term success of that system. In San Diego, Higgins, Ferguson, and Kanaroglou (2014) observe that although the southern end of the Trolley leading to the Mexican border has impressive ridership, development along the line has not occurred likely because of its alignment within an industrial corridor served by freight rail. Otherwise, their review of the academic literature revealed sparse analysis of land use changes around LRT stations and virtually none around LRT stations as of the early 2010s.

There are very few comparative studies of outcomes to LRT station proximity. Assuming LRT and streetcar systems are reasonably comparable, work by Hinners, Buchert and Nelson (2018) offers insights. They studied economic development outcomes in terms of jobs for areas within 0.25 miles (about 400 meters) of three streetcar stations along four lines in Portland, Salt Lake City, Seattle, and New Orleans. Employment three years prior to the start of streetcar construction was compared with employment within the three streetcar station areas in 2013. They also compared outcomes to 10 bus stops within each urbanized area selected as ''controls'' because they were quantitatively comparable to each streetcar station area studied. Shift-share analysis showed that Portland's system showed strong economic development consistency followed by New Orleans. The Salt Lake City and Seattle lines, however, did not perform consistently. They concluded that station location, planning and design may account for differences in outcomes.

One impediment to development in rail transit corridors including LRTs could be social stigmas. For example, Loukaitou-Sideris and Banerjee (2000) find that unattractive neighborhood characteristics such as low income, high unemployment, and crime, along with physical barriers to transit stations and deteriorating housing stock along Los Angeles' Blue Line created a "derelict and forbidding" (p. 10) climate for investors.

There is some evidence that policies incentivizing development near transit stations makes a difference. Fogarty and Austin (2011) note that new private investment around LRT stations in the central areas of Minneapolis and Charlotte is attributable to local policies facilitating development in TODs (transit-oriented developments) combined with growing regional economics, suitable land, and good transit connections at the neighborhood level. But not all TODs have seen desired levels of development. In Denver, development along the Southeast LRT Corridor transit line was hampered by its location within a highway median (Fogarty and Austin 2011).

In Phoenix, Valley Metro (2013) reported that nearly $7 billion in new development had been invested in TODs served by LRT transit stations since 2004. Nonetheless, more development may have been hindered by real estate speculation shortly after LRT station locations were announced (Kittrell 2012) combined by the Great Recession which impacted the metropolitan Phoenix area especially hard. Credit's (2018) later analysis of Phoenix used a pre-post design to measure the change in jobs around light rail stations based on 0.25-, 0.50-, and 1.00-mile (about 400-, 800, and 1,600-meter) buffers, finding increases in knowledge, retail, and service sector jobs. More recent research has shown that jobs tend to concentrate near rail transit stations in Cleveland (Pasha et al. 2020).

On the other hand, other literature shows insignificant or ambiguous associations between job change and transit station proximity. In a review of four US metropolitan areas with new transit stations between 2000 and 2015, Tyndall (2021) found that rail station proximity reduced employment density. Moreover, in their study of Atlanta's heavy rail transit system, Bollinger and Ihlanfeldt (1997) found only small increases in employment around rail stations.

Lai, Zhou, and Xu's (2024) review of literature conclude that there is limited analysis of the link between employment change and transit stations, and that more studies are needed to close this gap. One thing emerges from a review of the literature, however: there is a dearth of research into LRT employment outcomes. Indeed, there is no research into the association between job change and proximity to LRT stations, and no research assesses change comprehensively among large numbers of transit systems. This article aims to close the gap.

The overarching research questions guiding research are:

> Is there an association between LRT station proximity and an increase in jobs?
>
> If so, does this association vary by groups of jobs in economic sectors?

Literature on the influence of LRTs on the distribution of people and households, change in household income and change in housing tenure (own/rent) over time is reviewed next.

Literature, Theory, and Research Questions Relating to Light Rail Transit Station Proximity and Demographic Change and Gentrification

Chapple and Loukaitou-Sideris (2019:91) lament:

> The vast literature on neighborhood change pays little attention to the role of infrastructure, particularly transit, in reshaping areas—and who lives in them.

An early study addressed population and housing change for all transit systems in the United States during the 2000s—the Center for Transit Oriented Development (2014)—but it did not differentiate by type of system or distance from transit stations, nor did it provide details on the race/ethnicity of people, households by age and type and income, or housing based on tenure. With limited focus, Hurst and West (2014) found a significant increase in single-family and multifamily development around LRT stations in Minneapolis which increased population density in those areas. Another study of the LRT system in Dallas found similarly (Al Quhtani and Anjomani 2021).

In their work using the American Community Survey (ACS) for 2013 and 2014, Nelson and Hibberd (2023) provided a national summary of the change in such demographic features as race/ethnicity, household type and age, and tenure for transit systems but provided no data for specific systems. More detailed use of ACS data to measure demographic change over time was used by McKenzie (2015) to evaluate the demographic profiles of rail-accessible neighborhoods in the Washington, DC region. Special reverence to the age profile of people living in transit-oriented developments (TODs) is offered by Wood, Horner, Duncan, and Valdez-Torres (2016). A key finding was that people 65 years and older were a smaller share of the total population residing in TODs in both 2000 and 2010. Their conclusion was that if TODs are intended to help meet the accessibility needs of aging people, more research is needed to learn how to attract them to TODs.

No studies however evaluate detailed demographic changes with respect to LRT station proximity. The study and analytic method used by Landis (2016) helps frame the research questions addressed in this article:

> During the study period, did the concentration of population change and, if so, did the demographic composition of the population and households also change terms of household type, householder age, median household income, and housing tenure with respect to LRT station proximity?

The specific role of LRT station proximity in engendering gentrification is addressed next.

There is a large literature exploring the extent to which transit station proximity displaces existing residents and replaces them with higher income ones through a process called "gentrification".

What is "gentrification"? Marcuse (1985) characterized its features as including the arrival of younger, mostly White, highly educated professionals in highly paid jobs. These new households replace older, working-class, lower-income, and minority households in neighborhoods near downtown that are ripe for reinvestment (Bourne 1967). When near transit stations, gentrification can include changes to the socioeconomic composition of existing residents or other changes that shift the racial, ethnic socioeconomic, or housing characteristics of impacted neighborhoods (Delmelle 2017).

Delmelle (2021) presents the conundrum succinctly. An overall goal of transit is to improve mobility, especially of lower-income and minority communities. Doing so elevates the economic opportunities available to residents, such as access to higher-paying jobs (Andersson et al. 2018, Jin and Paulsen 2018). But this can increase the demand for housing near transit stations which raises housing prices. This results in higher income households displacing lower-income ones through a process called "transit-induced displacement and gentrification" (Delmelle and Nilsson 2020). The process is further stimulated when transit-oriented developments (TODs) intentionally create dense, mixed-use and walkable developments near transit stations (Calthorpe 1993). This can lead to the displacement of vulnerable residents (Rayle 2015). Rising housing prices may reduce the supply of housing that is affordable to them near transit stations, thus exacerbating social inequity (Newman and Wyly 2006) especially if transit investments are not proactive in assisting lower-income households to move toward transit opportunities.

However, empirical research is mixed when testing for the presence of gentrification near transit stations. Delmelle (2021) notes several studies found the racial and ethnic composition of neighborhoods remain unchanged after transit stations are introduced (Pollack et al. 2010; Barton and Gibbons 2017; Deka 2017; Nilsson and Delmelle 2018,)

Indeed, as Delmelle (2021) points out, many neighborhoods do not change at all after a transit station is built nearby. If they do change, it is mostly in line with existing trends. Moreover, even with an influx of new households, increasing housing supply need not lead to displacement of existing residents (Dong 2017; Baker and Lee 2019).

Delmelle (2021) concludes that "(t)he current state of the literature increasingly suggests that the impacts of transit on neighborhoods is either marginal or very difficult to quantify" (Delmelle 2021: 184). Qualitative research may be needed to uncover more subtle changes among neighborhoods near transit. Also, given that most studies have focused on system-wide outcomes, including this report, more research is needed at the micro scale of individual transit stations. More long-term research is also needed because neighborhood composition is often slow to change as households occupy their homes for decades, if not generations. Finally, because most studies in this genre did not use micro-scale control areas to measure treatment outcomes in areas near transit stations, this is an area in need of additional research.

Heeding the call in the latter two respects is Qi (2023) who used census block groups (CBG) near transit stations as the treatment regime and compared change over long periods of time with matching control CBGs based on the *MatchIt* algorithm.[3] Based on this research, Qi concludes (with emphases added):

[3] See https://gking.harvard.edu/matchit.

> "… **rail is more likely to induce gentrification than Bus Rapid Transit (BRT)** and that (gentrification) is more evident over long term than over short term for rail-served neighborhoods. These findings thus imply that the **BRT could help sustain the transit service to the most vulnerable**." (Qi 2023: 1)

Other research casts doubt on the whole notion that transit station proximity leads to gentrification per se. ACS and several other data sources were used by Baker and Lee (2019) to assess how rail transit impacts gentrification in 14 metropolitan areas, finding little association. A review of relevant studies that evaluate the association between transit station proximity and median household income is offered by Padeiro, Louro, and da Costa (2019). They conducted a review of gentrification outcomes associated with transit proximity among papers published between 2000 and 2018 concluding that gentrification is associated more with local dynamics than transit station proximity. Similarly, Dong's (2017) analysis of development near LRT stations in Portland, Oregon, found that housing supply mattered most in either effecting or ameliorating gentrification outcomes based on demographic analysis.

In sum, there is very little research into the association between LRT station proximity and gentrification does not exist. Again, using Landis' (2016) framework, the relevant research questions in this context are:

> During the study period, was there evidence of gentrification with respect to LRT station proximity?

Literature on the extent to which LRT station proximity influences changes in commuting mode over time is reviewed next.

Literature, Theory, and Research Questions Relating to Light Rail Transit Station Proximity and Change in Commuting Mode, and Household Transportation Costs

There is scant research into the association between transit station proximity generally and specifically with respect to LRT station proximity addressing the change in commuting mode over time. This avenue of inquiry assesses the association between LRT station proximity and:

- Reduced dependency on commuting to work via the automobile.

Literature, theory, and hypotheses related to each are reviewed below.

Reduced Automobile Dependency

In theory, LRT station proximity should be associated with higher levels of walking, biking, and transit in their journey to work as compared to more distant locations (Renne, 2009; Kwoka, Boschmann, and Goetz 2015; Ewing, Tian, and Lyons 2018). Indeed, households will self-select by moving toward transit stations to gain access to transit, whether they are transportation disadvantaged or prefer that option over others (Lund 2006; Guerra, Li, and Reyes 2022). However, there is no systematic research on how commuting modes vary with respect to proximity to transit stations, including transit (Litman 2023b), walking and biking, or even working at home.

Given the foregoing, this research question is posed:

> Is proximity to LRT stations associated with increasing shares of walking, biking, transit use, and working at home, and if so, is there variation by type of transit system?

As simple as this question appears, there is no literature addressing the proposition.

Reduced Transportation Costs with Social Equity Implications

Conventional theory of location and land-use holds that household demand for location is a function of income, household size, and location costs. Location costs means in part the cost of transporting occupants to work, shopping, services, recreation, and other destinations. In theory, lower transportation costs are capitalized by the market into higher home prices or rents (Alonso 1964; Mills; Muth 1969). In effect, a household would be willing to pay more for a home that has lower transportation costs than alternatives. Unfortunately, mortgage lenders do not consider transportation costs in their underwriting. Home buyers thus "drive until they qualify" for a home that meets their needs even if high transportation costs are incurred. Hence, urban sprawl occurs along with its environmental, social, and economic inefficiencies.

In recent years a growing body of literature has argued that housing and transportation costs need to be considered together when considering housing affordability.[4] Ewing and Hamidi (2015) note that HUD's definition of affordability—where no more than 30 percent of a household's income would be spent on housing—along with indexes of others are "structurally flawed in that they only consider costs directly related to housing, ignoring those related to utilities and transportation" (Ewing and Hamidi: 5). Suppose total housing plus transportation costs consume 50 percent of a household's income. If the household's transportation costs could be reduced by half, however, it would not use the savings to buy a better home because mortgage underwriting would not recognize it.

Conceptually, transportation cost savings are realized by locating in or near such places as downtowns, mixed-use developments, and transit stations. Studies only estimate these savings in two ways. First, a suite of studies based on work by the Center for Neighborhood Technology uses secondary data to estimate the share of trips by mode and household type at the block group, and then derive vehicle miles traveled through inferences based on other secondary data. The actual distance from block groups to such points as downtowns and transit is not estimated directly.[5] For several household types, CNT's studies estimate housing costs that are constant across large geographies such as counties while transportation costs vary by block group.

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[4] See HUD's Location Affordability Portal for literature and other materials on the concept of housing plus transportation ("H+T") costs (see http://www.locationaffordability.info/).
[5] CNT has produced two significant generations of these studies. The first is reported in http://htaindex.cnt.org/map/ and the second in http://www.locationaffordability.info/default.aspx.

In an automobile-dependent economy, the number of vehicle miles traveled is directly associated with transportation costs.[6] Thus, locations that reduce household VKT also reduce transportation costs. Reductions in VKT can be converted into cost savings.

Unfortunately, the literature on the association between transit station proximity and household transportation costs is also thin. Although research shows that household transportation costs vary by density and location generally (Guerra and Kirschen 2016), none measures transportation cost savings with respect to distance from specific destinations. In a recent study, Dong (2021) found that households within a sample of TODs incurred fewer transportation costs than a control group outside them. Otherwise, Dong's assessment is that literature on the association between transit stations and VKT as well as costs is small and inconclusive (Dong 2021: 1). The research reported below helps close this gap.

There is also a social equity implication that is not addressed in literature. Although one aim of transit is to broaden accessibility options to lower-income households, the implicit objective is also to reduce accessibility costs (see Sanchez and Brenman 2008, Brenman and Sanchez 2022). This could be accomplished by reducing household VKT and associated transportation costs. There is no research into this.

The research questions posed in these respects are:

> Do household transportation costs vary by proximity to LRT stations?
>
> If so, do lower-income households realize transportation cost savings with respect to proximity to LRT stations?

The next discussion reviews the theory and literature on the influence of LRT station proximity and real estate rents.

Literature, Theory, and Research Questions Relating to Transit Station Proximity and Real Estate Rents

Real estate markets send important signals about the efficacy of public policy and planning. For instance, locating landfills near residential areas depresses nearby residential property value (Nelson, J. Genereux and M. Genereux 1992). Creating open spaces beyond urban growth boundaries creates amenity value that increases urban residential property value inside the boundary but also creates externality value that depresses farmland value outside of it (Nelson 1986). In the context of transit stations, there can be both positive and negative residential price effects depending on the extent to which transit station externalities are mitigated through planning and design (Nelson and McClesky 1990, Nelson 1992).

The literature begins with J. H. von Thünen (1826) who was the first to formalize the relationship between the center of cities and land value: as distance is reduced land values rise because land capitalizes both transportation cost savings and higher densities lead to more

[6] For a review and data, see https://data.bts.gov/stories/s/Transportation-Economic-Trends-Transportation-Spen/bzt6-t8cd/.

economic exchange. More than a century later, a trio of urban economists—Alonso (1964), Mills (1967) and Muth (1969)—adapted von Thünen's model to create modern urban location theory. By assuming that all jobs are in the central business district (CBD), the "AMM theory" shows that as transportation costs increase from the CBD, land values fall at a declining rate. In the CBD, where transportation costs are the lowest, land prices are thus the highest. Only those land uses that can outbid others secure land in the center, forcing losing bidders to locate farther away in a process known as urban land use invasion and succession (Park et al. 1925).

But urban areas are not "monocentric." As one relaxes the constraints of the AMM monocentric city model, it is possible to imagine the same principles at work only at smaller scales (Hajrasouliha and Hamidi 2017; Bogart 1998). For instance, rail transit stations are often located in or sometimes create small-scale versions of CBDs. Some land uses can realize transportation cost savings if they locate near transit stations and may be willing to pay more for proximity (in the form of rent) compared to other land uses. Numerous studies show negative bid-rent gradients with respect to distance from rail transit stations, meaning that as distance from transit stations increase real estate values fall, *ceteris paribus* (Al-Mosaind et al. 1993; Cervero 1984; Cervero and Duncan 2002; Debrezion et al. 2007; Hamidi et al. 2016; Mulley et al. 2016; Nelson and McClesky 1990; Nelson 1992; Nelson et al. 2015). In effect, station areas can become small scale downtowns. At the regional scale, major centers such as "Edge Cities" may emerge (Garreau 1991).

Refining the Standard Model to Include Externality Value

Theory often becomes messy when confronted with reality. In the case of the standard model of urban land rent, it may not always be the case that the revealed bid rent curve is downward sloping from the center. Instead, it can be upward sloping if the centers or nodes are sources of negative externalities. The concept of externalities as a necessary refinement to urban rent theory was first hypothesized by Richardson (1977) and expanded by Li and Brown (1980). Ten years later, Nelson and McClesky adapted these concepts to their analysis of single-family home values near heavy rail transit stations in Atlanta, Georgia (1990). Externalities can include environmental, physical, social, or other factors that reduce the attractiveness of being at or near the center (Nelson 1992). Their insights are reviewed here.

The urban land market capitalizes both "accessibility" value of rail station proximity as well as "externality" value associated with station noise, lights and glare, vehicle congestion during peak hours, and other nuisances. So long as accessibility value exceeds externality value, the urban land rent gradient will slope downward away from rail transit stations. However, it is possible for externality value to exceed accessibility value for reasons theorized by Richardson (1977), and Li and Brown (1980). Exhibit 1 shows potential relationships between transit stations considering both accessibility and externality value:

> The line R^a shows the land rent (R) curve with accessibility ("a") value from a rail transit station, u_0, outward to a point, u_1, where the accessibility effects of rail transit proximity are negligible, beyond which the overall market rent, unaffected by the presence of the rail transit station, R^m is revealed.

Externality value of rail transit stations are shown in line R^n ("n" for negative externality). As distance from the rail station increases, the externality effects are reduced until they become zero at u^1.

Accessibility and externality effects interact in the market leading to revealed positive or negative bid rent curves with respect to distance from rail transit stations to u_1. Line $R^a + R^n_1$ is revealed where overall accessibility effects outweigh externality effects. Line $R^a + R^n_2$ is revealed where overall externality effects outweigh amenity effects. Combined effects disappear at u_1 beyond which market rent, R^m ("m" for market) in the absence of accessibility and externality effects is revealed.

The literature addressing the combined effects of accessibility and externality values is inconclusive because it lacks systematic application of theoretical nuances we pose in this article. The theoretical framework presented in Exhibit 1 can be disaggregated into at least four component parts that are revealed in the market and illustrated in Exhibit 2 including:

Downward-sloping relationship where rents fall as distance from stations increases in a liner or curvilinear form without an inflection point. This is the standard von Thünen/Alosno expectation. It reveals itself when there are no externality effects internalized in the market. This is a desirable real estate market outcome.

Upward-sloping relationship where rents rise as distance from stations increases in a linear or curvilinear form without an inflection point. This may occur when the station itself is an unattractive location in the real estate market as development wants to position itself away from stations. This is an undesirable real estate market outcome.

Concave relationship where externality value exceeds accessibility value at or near transit stations. As station distance increases, externality value dissipates as accessibility value associated with station proximity increases. At an inflection point, accessibility value exceeds externality value. This is a signal that the market reflects externality value that might be overcome through better planning, station location, and station area design.

Convex relationship where rent falls with respect to transit station distance to an inflection point after which it rises. The implication is that transit station accessibility value exceeds externality value but at a declining rate to a point beyond which accessibility value is not revealed in the market.

While these are highly generalized relationships, they help to describe transit station effects on real estate rent in the manner described in more detail later. Next is a review of research into the association between transit station proximity and real estate values, reporting mixed results.

Higgins and Kanaroglou offer the most complete review of studies into this relationship (2016 (see also Berawi et al. 2020; Zhang and Yen 2020). Nearly all studies focus on a particular metropolitan market, usually applied to a single mode, and frequently involving only a few to a few hundred cases. The vast majority of studies address associations between single-family home sales prices and proximity to transit stations even though transit stations are usually located in high intensity commercial and multifamily nodes. Thus, it is difficult to imagine credible transit station area policies and planning relying on just single-family home sales prices, yet this seems to be the case. Very few studies assess the association between transit station proximity and office, retail, or multifamily values and those that do typically use a 0.25-mile (about 400 meters) to 0.50-mile (about 800 meters) buffer around transit stations, assessing outcomes of properties within those circles compared to those outside.

The summary critique is that there is no coherent, systematic analysis of the relationship between LRT station proximity and office, retail, and multifamily values. Research reported below closes this gap by addressing the following research question:

> Is there an association between commercial real estate rent (per square meter) and proximity to LRT stations holding other factors constant?

This is followed by a nuanced question:

> If there is an association, is there evidence of negative externality or amenity effects with respect to LRT station proximity?

The analytic framework guiding this article is presented next.

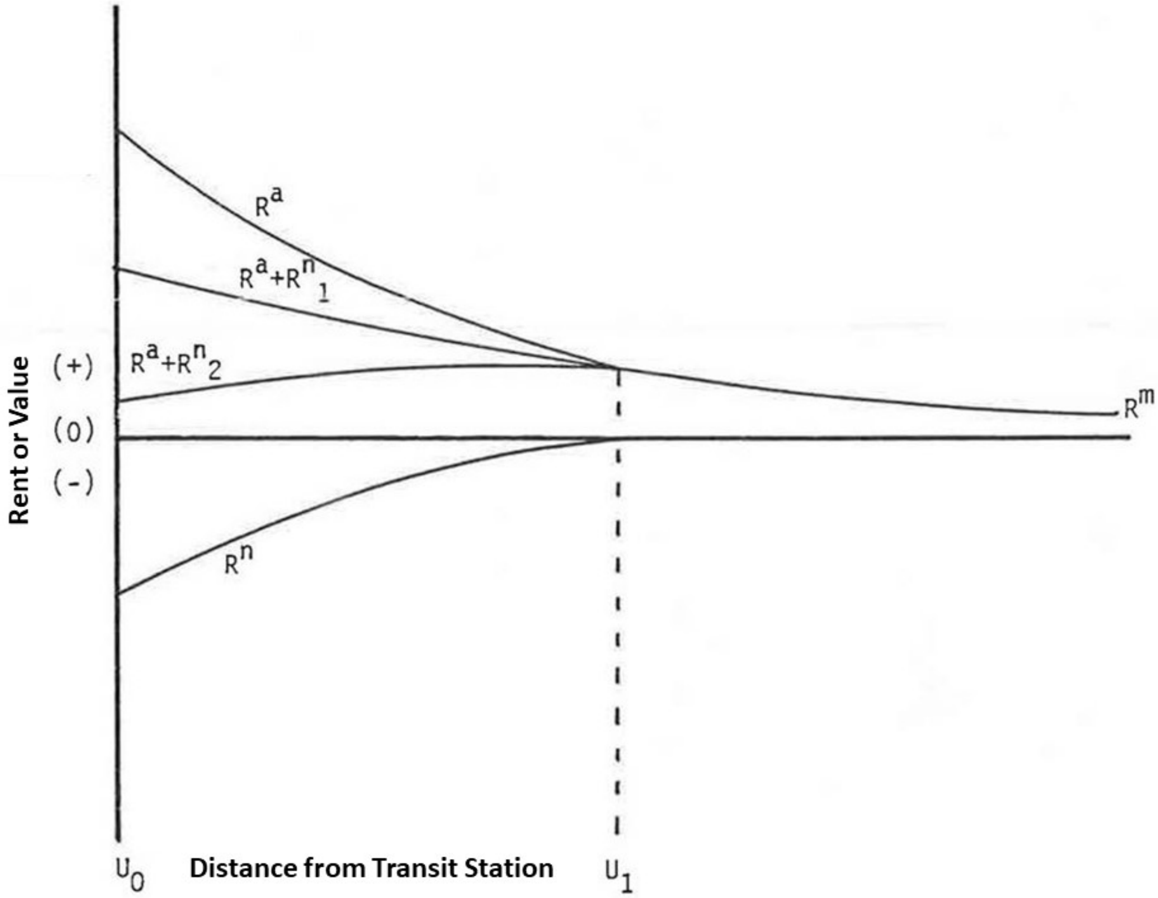

Exhibit 1
Amenity (R^a) and Externality (R^n) influences of transit stations/stops on proximate urban land rent (see text)
Source: Nelson and McClesky (1990).

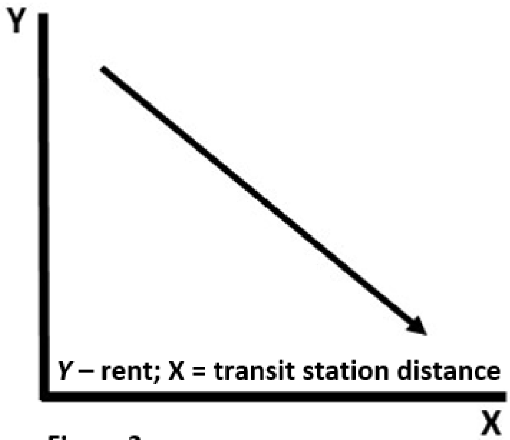

Figure 2a
Downward-sloping relationship where rents fall as distance from stations increases.

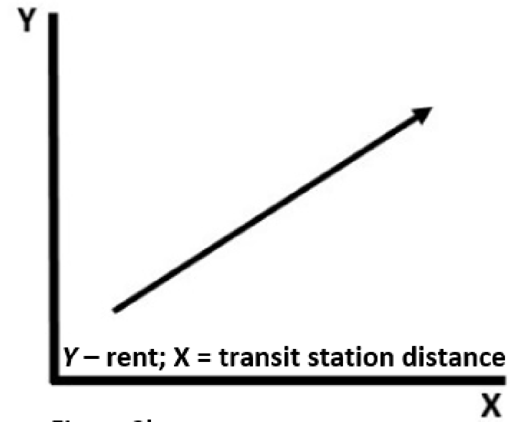

Figure 2b
Upward-sloping relationship where rents rise as distance from stations increases.

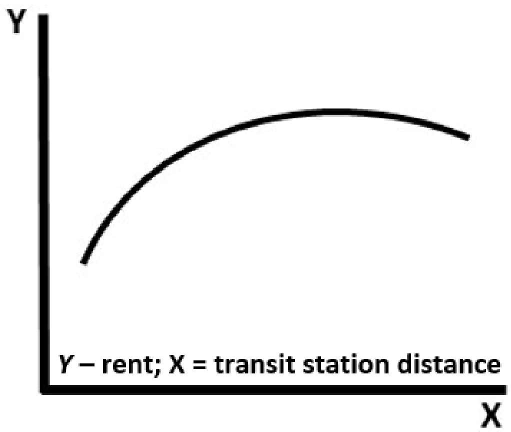

Figure 2c
Concave relationship where rents rise to an inflection point and then fall.

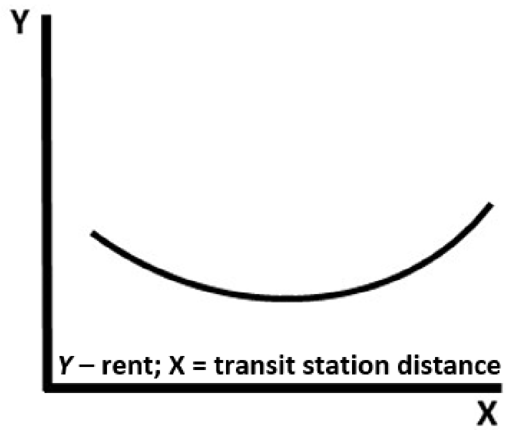

Figure 2d
Convex relationship where rents fall to an inflection point and then rise

Exhibit 2
Four alternative urban rent gradients with respect to transit station proximity
Source: Arthur C. Nelson

ANALYTIC FRAMEWORK

This article assesses how the distribution of jobs, demographic change, household income, housing tenure, and commute mode were influenced by LRT station proximity between 2010 and 2019. This study period is thus between two of the most disruptive events in recent American history. The "Great Recession," which extended from December 2007 through June 2009, was the nation's most severe economic downturn since the Great Depression.[7] This was followed by the COVID-19 global pandemic, the most severe since the "Spanish Flu" a century ago (Aassve et al. 2021). These twin economic disruptions changed financial markets on the one hand[8] and accelerated work-from-home trends on the other (Peiser and Hugel 2022). While the pandemic reduced transit ridership considerably as people worked from home to avoid crowds, ridership is now recovering with many systems at or near pre-pandemic levels.[9] Indeed, the share of those working from home is also falling[10] although it seems unlikely that it will reach pre-pandemic levels for reasons noted in Peiser and Hugel (2022). Besides, the use of transit for commuting to work has been exaggerated, as non-work ridership is leading much of the transit recovery.[11]

The article also assesses the relationship between transit station proximity and real estate values in 2019, the year before the pandemic.

In all, 17 LRT systems were studied (see Exhibits 3 and 4). All became operational before 2010, the first year of the study period. In addition, the selected systems included sufficient rent data allowing for regression analysis described later. The research includes the largest number of LRT systems operating in the largest number of metropolitan areas that have been researched to date.

Exhibit 5 highlights key LRT design and performance features.

The comparative study areas are called "LRT counties" which are all the counties in a metropolitan area served by the LRT system being studied. Also, LRT systems are labeled after the principal city of the central county in which they are located.

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[7] For a review of causes and consequences, see https://www.federalreservehistory.org/essays/great-ecession-of-200709.
[8] For discussion on the longer term effects of the Great Recession on financial markets, see https://www.federalreservehistory.org/essays/great-recession-and-its-aftermath.
[9] Several perspective on COVI-19's effects on transit and recover are offered in https://www.brookings.edu/articles/ensuring-the-intertwined-post-pandemic-recoveries-of-downtowns-and-transit-systems/.
[10] For changing office market trends since COVID-19, see https://www.forbes.com/sites/davidmorel/2023/11/06/future-of-work-is-a-return-to-the-office-inevitable/?sh=6991f7f514fb.
[11] See note 3.

Exhibit 3
LRT Transit Systems Studied with Metropolitan Abbreviations

LRT Transit System	Year
BUF Buffalo	1984
CHR Charlotte	2007
CLE Cleveland	1980
DAL Dallas	1996
DEN Denver	1994
HOU Houston	2004
MSP Minneapolis-St. Paul	2004
NOR Norfolk	2011
PHX Phoenix	2008
PIT Pittsburgh	1984
PDX Portland	1986
SAC Sacramento	1987
SLC Salt Lake City	1999
SD San Diego	1981
SJ San Jose	1987
SEA Seattle	2003
STL St. Louis	1993

Source: Authors

Exhibit 4
LRT Systems Studied

Source: Authors

Exhibit 5
Key Features of LRT Transit Systems

Light Rail Transit (LRT)	
Right-of-way	Exclusive rail
Rolling Stock	1 to 4 cars
Station Spacing	1 to 5 kilometers or more
Hourly Capacity	18,000-20,000
Typical Seats	25 per car
Typical Length	10-100 kilometers
Typical Max. Speed	90 kph

Sources: Image from https://www.oregonmetro.gov/max-tunnel-study LRT features are composites of parameters assembled by the authors.

The individual LRT station study areas are comprised of census blocks (CBs) and census block groups (CBGs), depending on the data used for analysis.

Data for jobs is provided annually by the Longitudinal Employment-Household Dynamics (LEHD) database.[12] These data are reported at the CB level. Demographic, housing, and commuting data are provided through the 5-year samples of the American Community Survey (ACS)[13] at the CBG level.[14] The 5-year samples used are for the periods of 2010-2014 and 2015-2019. Where 2014 or 2019 is just used in the ACS context, it means the respective sampling years.

Based on prior research, the LRT study area is 800 meters (about 0.50-miles) from LRT stations (Guerra, Cervero and Tischler 2012). There are three LRT station bands. Because block groups are comprised of about four to ten census blocks, their spatial extent covers up to the first two city blocks from the station. Although there is no standard size for a city block, a common width is about 300 to 360 feet[15] or roughly 100 meters. The first station band thus extends 100 meters from station centroids. The next two bands extend inclusively 400 (about 0.25-miles) and 800 meters (about 0.50-mile) from BRT stations, respectively. The total area within 800 meters of LRT stations is called the "station area." Any portion of a CB or CBG falling within the closest station band is assigned to it. LRT station area bands comprise very small shares of their LRT counties, being less than one quarter of one percent for the station band, about one percent for the 400-meter band inclusively, and less than one percent for the entire 800-meter LRT station area.

In addition, proprietary rent data provided by CoStar is used to estimate the market rent premium for LRT station proximity for office, retail, and multifamily rental property for the year 2019, the year before the COVID-19 pandemic. With few exceptions noted below, these data are continuous.

It is acknowledged that this research is not a counterfactual analysis in that one cannot know what would have happened in the absence of LRT station intervention. LRT stations are usually placed in existing, built-up urban and suburban areas. Moreover, LRT stations are not randomly selected but are instead an outcome of a decision-making process that chooses them from among many options. There is thus a selection bias. Nonetheless, the aim of this analysis is to assess whether there is an association between LRT station areas and outcomes.

As noted earlier, the analysis is based on the period after the Great Recession of 2007–09 and before the COVID-19 pandemic of 2020–23. The study thus avoids analytic complications associated with these disruptive economic and social events. As such, the work may be viewed as the benchmark period that provides context for analysis addressing pandemic and post pandemic

[12] https://lehd.ces.census.gov/. For an orientation, see https://lehd.ces.census.gov/.
[13] For a review, see https://www.census.gov/data/developers/data-sets/acs-5year.html.
[14] Census block groups are comprised roughly of four to ten census blocks with considerable variation at the lower and higher end. For a description, see https://www2.census.gov/geo/pdfs/reference/GARM/Ch11GARM.pdf.
[15] See https://www.vintageisthenewold.com/game-pedia/what-is-the-average-size-of-a-city-block.

outcomes. The nature of market responses to transit station proximity during this period can be used to frame guidance for transit station and land use planning during the post pandemic period.

Except for the regression analyses, descriptive analysis is used where changes are measured numerically and converted into percentages and ratios as the context warrants. All differences in change over the time periods are significant to at least $p < 0.10$ of the two-tailed t-test. Descriptive statistical tests and outcomes are thus not reported for brevity. Significance tests and other performance metrics are reported and interpreted for regression analyses, however.

The next section assesses LRT station area outcomes with respect to jobs.

LRT Transit Station Proximity and Change in Jobs by Economic Group

This section presents results from a national analysis of the extent to which LRT station proximity influences employment near those stations generally and for broad economic groups. It starts with the research design, data, and analytic method, and is followed by results and interpretations along with implications for post pandemic transit policy and planning. To summarize key points made earlier, there is scant research into the association between change in jobs and transit station proximity. The research questions guiding research presented here are:

> Is there an association between LRT station proximity and an increase in jobs?
>
> If so, does this association vary by economic group?

The null hypotheses relating to both questions assert no difference in the concentration of jobs with respect to LRT station proximity during the study period.

Research Design, Data, and Analytic Method

The data come from the LEHD for the years 2010 and 2019. Although data are available at the census block level, they are assembled to the block group level for comparability with ACS 5-year sample data (see above). LEHD data are assembled into economic groups comprised of economic sectors shown in Exhibit 6. These groups were selected because they align with common, large-scale land use categories for planning purposes. As such, they do not include natural resources sectors such as agriculture, forestry, fishing, and mining, or construction, because its employment is transient.

The analytic method uses the location quotient approach to measure the relative change in concentration over time between the base year, 2010, and the end year, 2019. This is called a ***station quotient*** (SQ) because the analysis focuses on change in concentrations over time with respect to LRT station band or the LRT station area. Change in concentration over time is compared to "LRT counties" which are all the counties served by the specific LRT system being studied. Of particular interest is determining whether, over time, the concentration of jobs compared to the LRT counties increase (SQ > 1.0), decrease (SQ < 1.0), or stay about the same (SQ = 1.0).

Results are reported cumulatively for each distance band, meaning the 800-meter band includes data for the station band and the 400-meter band plus the increment to 800 meters. Exhibit 7 reports results for all LRT systems as well as each LRT system for all eight employment groups noted in Exhibit 6. Although statistical tests of significance are not reported in the following exhibits, all differences are significant to at least the 0.10 level of the two-tailed t-test. One reason for this is that the data themselves are not samples, but rather actual counts based on data reported by firms.[16]

Results and interpretations are offered next.

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[16] See https://lehd.ces.census.gov/data/.

Exhibit 6
Assignment of Economic Sectors into Economic Groups for Analysis

NAICS	Economic Sector and Combination into Economic Groups
	Industrial
22	Utilities
	Manufacturing
42	Wholesale Trade
t	Transportation and Warehousing
	Retail, Food, Lodging
44-45	Retail Trade
72	Accommodation and Food Services
	Office
51	Information
52	Finance and Insurance
53	Real Estate and Rental and Leasing
54	Professional, Scientific, and Technical Services
55	Management of Companies and Enterprises
56	Administrative and Support and Waste Management and Remediation Services
81	Other Services (except Public Administration)
92	Public Administration
	Education
61	Educational Services
	Health
62	Health Care and Social Assistance
	Entertainment
71	Arts, Entertainment, and Recreation

Source: North American Industrial Classification System (NAICS).

Results and Interpretations

Exhibit 7 reports descriptive results of job change by economic groups during the study period for all LRT systems combined and individual systems. Results are reported in three ways:

- Total numerical LRT county change in jobs overall and for each economic group as well as change in jobs for each of the three station bands;

- Percent share of LRT county change occurring in each of the station bands cumulatively; and

- Station quotients (SQs) for each station band where coefficients SQ <1.0 mean the station band lost share or concentration of jobs compared to the LRT county during the study period while coefficients SQ >1.0 mean the station band gained share or concentration of jobs compared to the LRT county and where SQ = 1.00 means there was no change.

Readers are encouraged to study results for individual LRT systems of interest to them. What follows are highlights of outcomes followed by an overall assessment.

Job Highlights Overall

Overall, LRT station areas accounted for nearly one million new jobs or 28 percent of the job growth in LRT counties. This is an impressive outcome considering that LRT station areas comprise less than one percent of their transit regions. On the other hand, with SQs <1.0 are shown in 11 of 17 LRT station areas meaning they *lost share* of jobs compared to LRT counties, sometimes considerably, such as in Houston, Norfolk, and Phoenix. Indeed, only four station bands have SQs > 1.0—Buffalo, Charlotte, Minneapolis-St. Paul, and San Jose—meaning they gained share of jobs overall compared to LRT counties. As will be seen below, population and households gained share in nearly all LRT counties, suggesting that people may be pushing jobs away from LRT station areas.

Industrial Economic Group Highlights

Inasmuch as industrial activities are usually land-extensive, one would not expect LRT stations areas to attract many of those jobs, and with few exceptions, they do not. Overall, more than 66,000 industrial jobs were added to LRT station areas, accounting for about 16 percent of LRT county gains. Only two LRT systems had SQs substantially higher than 1.0—Seattle (SQ = 1.12) and St. Louis (SQ = 1.13). Otherwise station areas and most of the station bands had SQs < 1.0, often substantially so.

Office Economic Group Highlights

At nearly 460,000 new jobs during the study period, office jobs in LRT station areas accounted for more than half of all jobs gained, and 35 percent of all the office jobs added to LRT counties. Yet, the share of such jobs compared to LRT counties fell among 11 of the 17 LRT systems studied, while only Charlotte and San Jose had SQs substantially > 1.0 at 1.04 and 1.07, respectively. As these are pre-pandemic outcomes, future research will need to assess the extent to which LRT systems are resilient to economic shocks (see Nelson, Stoker and Hibberd 2017).

Education Economic Group Highlights

LRT systems are often designed to serve educational institutions, especially those of higher education. It is not surprising therefore to see that nearly 150,000 education jobs were added to LRT station areas during the study period, accounting for a quarter of all new jobs in this economic group among LRT counties. However, aside from Cleveland (SQ = 1.23), Portland (SQ = 1.05), Salt Lake City (SQ = 1.05), and San Jose (SQ = 1.12), all other systems lost or mostly maintained share.

Health Economic Group Highlights

Like educational institutions, LRT systems are often planned to serve heath care institutions. Overall, jobs increased by about 30,000 in LRT station areas which was about 23 percent of the new health care jobs in LRT counties. But there was considerable variation between systems. On the one hand, SQs for Charlotte (SQ = 1.23), Denver (SQ = 1.49), Minneapolis-St. Paul (SQ = 1.23), Portland (SQ = 1.08), and Sacramento (SQ = 1.49) were substantial. On the other hand, SQs were near or mostly below 1.00 headlined by Pittsburgh (SQ = 0.65) and Salt Lake City (SQ = 0.43), indicating deconcentration of health jobs away from LRT systems during the study period.

Retail-Food-Lodging Economic Group Highlights

Another land use LRT systems are often designed to serve are nodes of engagement such as downtowns, convention centers, lifestyle centers, and so forth. Accordingly, LRT station areas might be expected to be associated with job gains in the retail-food-lodging economic group, but this is not entirely the case. While LRT station area jobs increased by nearly 170,000 accounting for about 27 percent of LRT county growth, shares of jobs on this economic group fell in 13 of 17 LRT station areas. The two notable exceptions are Cleveland (SQ = 1.17) and Denver (SQ = 1.13). In contrast, several LRT station areas lost considerable job shares in this economic group such as Buffalo (SQ = 0.78), Charlotte (SQ = 0.80), and Pittsburgh (SQ = 0.71).

Arts-Entertainment-Leasure Economic Group Highlights

Finally, LRT systems are often designed to serve nodes of arts, entertainment and recreation. Indeed, during the study period, LRT station areas added more than 32,000 jobs in this economic group accounting for 41 percent of the change in jobs among LRT counties. This group was the only one among all eight economic groups in attracting substantially more jobs compared to LRT counties, where the SQ = 1.04. Moreover, only six of the 17 LRT systems saw station area SQs <1.0 during the study period. The most impressive shifts in share included Buffalo (SQ = 1.49), Cleveland (SQ = 1.21), Minneapolis-St. Paul (SQ = 1.14), Sacramento (SQ = 1.38), and Seattle (SQ = 1.30). The SQs of many other LRT station areas were also at or above 1.00.

Overall Assessment

With few although notable exceptions, LRT systems added jobs albeit at lower shares than regional trends. However, considering the pandemic, LRT systems may lose share of regional office jobs though this needs further analysis as more current data become available. While many LRT station areas saw gains in share of education, health, and retail-food-lodging jobs relative to their counties, most of them did not. Only the arts-entertainment-recreation economic group performed consistently above SQ > 1.0. The biggest unknown going forward is the extent to which the pandemic has affected jobs in all economic groups with respect to LRT station proximity, or whether certain groups have proven to be more resilient compared to their regions (Nelson, Stoker, Hibberd 2017).

The association between LRT station proximity and change in demographic outcomes is presented next.

Exhibit 7. LRT Transit Station Area Job Change and Station Quotients by System
[Station Quotients (SQs) > 1.0 means the station band/area gained a higher share of change than the LRT county 2010-2019.]

Measure	All	BUF	CHR	CLE	DAL	DEN	HOU	MSP	NOR	PHX	PIT	PDX	SAC	SLC	SD	SJ	SEA	STL
		1984	2007	1980	1996	1994	2004	2004	2011	2008	1984	1986	1987	1999	1981	1987	2003	1993
Total Jobs	3,545,413	19,640	238,758	48,014	588,968	312,388	379,350	159,858	(2,905)	474,066	36,474	216,405	106,211	159,898	220,424	262,870	259,223	65,771
Station Band	428,138	5,924	30,456	4,982	71,245	46,827	2,150	33,686	(8,555)	18,295	(1,164)	56,861	12,346	30,538	31,988	85,886	8,075	(1,402)
400m Band	828,668	813	59,340	8,974	132,129	119,984	9,580	53,104	(8,091)	46,521	(2,403)	110,481	24,061	48,900	52,366	110,901	51,514	10,494
800m Band	990,562	(673)	60,705	8,288	171,543	149,783	12,616	52,799	(7,509)	66,590	2,397	118,049	38,044	74,695	51,584	125,379	55,888	10,384
Station Share	12%	30%	13%	10%	12%	15%	1%	21%	294%	4%	NA	26%	12%	19%	15%	33%	3%	NA
400m Share	23%	4%	25%	19%	22%	38%	3%	33%	279%	10%	NA	51%	23%	31%	24%	42%	20%	16%
800m Share	28%	NA	25%	17%	29%	48%	3%	33%	258%	14%	NA	55%	36%	47%	23%	48%	22%	16%
Station Quotient	0.94	1.06	1.07	1.00	0.91	0.99	0.85	1.01	0.85	0.85	0.94	0.98	0.92	0.92	0.97	1.04	0.85	0.92
400m Quotient	0.98	0.97	1.08	1.01	0.92	1.03	0.87	1.03	0.88	0.90	0.93	1.02	0.93	0.94	0.99	1.03	0.97	0.98
800m Quotient	0.97	0.95	1.06	1.00	0.93	1.03	0.87	1.01	0.91	0.90	0.96	1.00	0.95	0.95	0.95	1.03	0.94	0.97
Industrial	420,363	4,000	24,660	3,211	71,565	32,322	70,019	8,434	(640)	55,701	(3,054)	31,546	8,985	23,350	32,255	14,619	34,107	9,283
Station Band	26,105	186	3,296	(2,886)	(1,532)	3,926	(4,686)	(2,314)	(1,136)	(1,055)	(465)	9,198	2,201	3,793	5,096	(1,631)	8,532	5,582
400m Band	68,913	(406)	3,416	(4,086)	9,575	8,102	(5,223)	445	(955)	3,882	(592)	19,994	(2,015)	5,334	10,200	(591)	12,857	8,976
800m Band	66,928	(584)	3,233	(4,103)	4,408	11,718	(6,400)	(3,077)	(1,560)	4,119	(1,471)	16,060	(1,655)	15,333	8,225	1,659	14,708	6,315
Station Share	6%	5%	13%	NA	NA	12%	NA	NA	178%	NA	NA	29%	24%	16%	16%	NA	25%	60%
400m Share	16%	NA	14%	NA	13%	25%	NA	5%	149%	7%	NA	63%	NA	23%	32%	NA	38%	97%
800m Share	16%	NA	13%	NA	6%	36%	NA	NA	244%	7%	NA	51%	NA	66%	25%	11%	43%	68%
Station Quotient	0.92	1.11	1.10	0.64	0.82	1.09	0.75	0.85	0.67	0.78	0.95	1.05	0.96	0.92	0.95	0.91	1.14	1.21
400m Quotient	0.96	0.83	1.06	0.70	0.89	0.99	0.76	0.97	0.77	0.89	0.97	1.10	0.80	0.92	1.01	0.93	1.14	1.27
800m Quotient	0.94	0.83	1.02	0.72	0.85	1.01	0.75	0.87	0.82	0.88	0.91	1.01	0.82	0.98	0.96	0.95	1.12	1.13
Office	1,318,989	10,869	118,621	29,251	246,873	112,658	129,263	52,579	1,491	167,277	20,728	83,911	(1,385)	59,850	41,648	129,104	87,559	28,692
Station Band	214,604	2,763	21,404	7,512	46,454	7,154	15,649	18,189	(2,446)	11,410	206	28,095	(4,120)	13,846	(296)	63,280	(11,469)	(3,027)
400m Band	407,418	2,988	44,554	9,837	66,814	54,721	19,402	20,792	(1,738)	29,729	(2,040)	48,570	(1,275)	24,394	(2,390)	73,255	14,809	4,996
800m Band	456,766	4,087	45,673	6,781	94,174	64,879	18,747	19,234	(1,642)	33,094	(776)	52,807	(2,314)	35,499	(4,685)	74,051	12,990	4,167
Station Share	16%	25%	18%	26%	19%	6%	12%	35%	NA	7%	1%	33%	297%	23%	NA	49%	NA	NA
400m Share	31%	27%	38%	34%	27%	49%	15%	40%	NA	18%	NA	58%	92%	41%	NA	57%	17%	17%
800m Share	35%	38%	39%	23%	38%	58%	15%	37%	NA	20%	NA	63%	167%	59%	NA	57%	15%	15%
Station Quotient	0.95	1.01	1.07	1.03	0.99	0.85	0.96	1.05	0.83	0.87	0.92	0.97	0.96	0.92	0.91	1.16	0.74	0.87
400m Quotient	0.98	1.00	1.05	1.03	0.93	1.00	0.97	1.01	0.88	0.96	0.90	1.02	1.00	0.98	0.89	1.11	0.92	0.96
800m Quotient	0.97	1.02	1.04	0.97	0.96	1.01	0.95	1.00	0.89	0.92	0.91	1.02	0.99	0.98	0.88	1.07	0.90	0.95

Exhibit 7. LRT Transit Station Area Job Change and Station Quotients by System—continued
[Station Quotients (SQs) > 1.0 means the station band/area gained a higher share of change than the LRT county 2010-2019.]

Measure	All	BUF	CHR	CLE	DAL	DEN	HOU	MSP	NOR	PHX	PIT	PDX	SAC	SLC	SD	SJ	SEA	STL
		1984	2007	1980	1996	1994	2004	2004	2011	2008	1984	1986	1987	1999	1981	1987	2003	1993
Education	577,224	(1,536)	36,024	7,948	99,220	57,108	76,899	7,693	84	86,092	(1,033)	35,871	25,094	23,478	49,749	30,445	45,942	(1,854)
Station Band	61,556	(757)	1,910	2,079	7,148	7,608	2,534	(3,690)	(8)	4,742	50	6,768	3,824	7,660	8,738	7,245	5,661	44
400m Band	113,828	(1,287)	5,713	2,893	11,866	12,167	2,661	(223)	(928)	9,061	2,191	13,256	5,278	9,704	15,402	12,910	12,981	183
800m Band	146,948	(1,304)	5,988	3,236	22,675	13,959	3,515	2,988	(971)	12,245	472	15,012	8,308	15,097	15,817	17,234	12,072	605
Station Share	11%	NA	5%	26%	7%	13%	3%	NA	NA	6%	NA	19%	15%	33%	18%	24%	12%	NA
400m Share	20%	NA	16%	36%	12%	21%	3%	NA	NA	11%	NA	37%	21%	41%	31%	42%	28%	NA
800m Share	25%	NA	17%	41%	23%	24%	5%	39%	NA	14%	NA	42%	33%	64%	32%	57%	26%	NA
Station Quotient	0.99	0.88	0.91	1.26	0.93	1.00	0.94	0.83	0.99	1.04	1.01	0.94	1.07	1.08	0.99	1.05	1.05	1.01
400m Quotient	1.01	0.85	1.06	1.24	0.91	0.96	0.92	0.95	0.84	1.02	1.13	0.96	0.96	1.04	1.01	1.09	1.11	1.02
800m Quotient	1.01	0.88	1.02	1.23	0.97	0.95	0.93	1.03	0.86	1.05	1.03	0.96	1.00	1.05	0.97	1.12	1.01	1.03
Health	128,409	(6,726)	18,965	(4,476)	49,252	16,374	(12,996)	14,244	(2,646)	15,081	(6,643)	4,064	2,566	20,424	482	10,799	13,473	(3,828)
Station Band	(2,865)	(587)	498	(3,996)	7,010	8,446	(14,301)	12,728	(2,188)	(1,961)	(3,112)	76	1,985	(10,574)	2,114	1,722	481	(1,206)
400m Band	22,408	(1,037)	1,329	(3,590)	25,986	9,195	(14,348)	11,774	(1,336)	(5,381)	(4,326)	4,343	4,115	(9,779)	4,947	1,293	343	(1,120)
800m Band	29,317	(1,557)	1,376	(3,569)	21,745	17,812	(8,957)	12,578	(1,343)	(5,994)	(5,921)	5,363	4,266	(9,151)	554	2,138	870	(893)
Station Share	NA	NA	3%	NA	14%	52%	NA	89%	NA	NA	NA	2%	77%	NA	439%	16%	4%	32%
400m Share	17%	NA	7%	NA	53%	56%	NA	83%	NA	NA	NA	107%	160%	NA	1026%	12%	3%	29%
800m Share	23%	NA	7%	NA	44%	109%	NA	88%	NA	NA	NA	132%	166%	NA	115%	20%	6%	23%
Station Quotient	0.91	0.97	1.21	0.61	0.88	1.38	0.69	1.35	0.90	0.84	0.38	0.96	1.37	0.27	1.13	1.37	1.36	0.92
400m Quotient	0.98	0.91	1.50	0.78	1.14	1.21	0.72	1.25	1.03	0.77	0.72	1.07	1.30	0.34	1.22	0.96	0.88	0.98
800m Quotient	0.98	0.89	1.23	0.80	1.03	1.49	0.87	1.23	1.03	0.79	0.65	1.08	1.25	0.43	1.01	0.99	0.89	1.00
RFL	626,513	7,264	21,774	2,099	66,072	40,791	59,431	50,956	(862)	84,307	6,562	30,656	50,730	15,143	64,689	53,767	39,655	33,479
Station Band	88,229	3,444	641	(638)	6,426	14,566	11,190	5,035	(2,685)	1,014	278	7,801	3,534	10,875	12,163	9,934	2,699	1,952
400m Band	129,220	(683)	701	566	5,165	20,747	16,037	12,689	(2,896)	3,101	(235)	14,997	9,226	11,382	16,120	14,743	6,602	958
800m Band	167,195	(3,517)	363	2,465	11,540	22,037	14,918	13,787	(1,743)	13,313	(3,822)	16,559	19,915	6,743	24,444	17,508	9,120	3,565
Station Share	14%	47%	3%	NA	10%	36%	19%	10%	NA	1%	4%	25%	7%	72%	19%	18%	7%	6%
400m Share	21%	NA	3%	27%	8%	51%	27%	25%	NA	4%	NA	49%	18%	75%	25%	27%	17%	3%
800m Share	27%	NA	2%	117%	17%	54%	25%	27%	NA	16%	NA	54%	39%	45%	38%	33%	23%	11%
Station Quotient	0.98	1.17	1.05	0.85	0.87	1.67	0.94	0.91	0.82	0.73	1.01	0.97	1.00	1.30	1.18	0.97	1.45	0.91
400m Quotient	0.96	0.88	0.90	1.05	0.82	1.29	0.98	0.98	0.84	0.76	0.93	0.97	0.93	1.16	1.15	1.02	1.07	0.83
800m Quotient	0.96	0.78	0.80	1.17	0.86	1.13	0.96	0.95	0.94	0.88	0.71	0.97	0.96	0.96	1.03	1.04	0.93	0.87

Exhibit 7. LRT Transit Station Area Job Change and Station Quotients by System—continued
[Station Quotients (SQs) > 1.0 means the station band/area gained a higher share of change than the LRT county 2010-2019.]

Measure	All	BUF	CHR	CLE	DAL	DEN	HOU	MSP	NOR	PHX	PIT	PDX	SAC	SLC	SD	SJ	SEA	STL
		1984	2007	1980	1996	1994	2004	2004	2011	2008	1984	1986	1987	1999	1981	1987	2003	1993
AER	79,102	3,003	4,412	5,272	8,324	8,709	6,028	8,600	(77)	11,896	3,306	3,598	1,154	3,373	947	4,290	7,037	(770)
Station Band	15,900	906	(157)	2,686	1,715	1,012	1,822	2,831	(16)	2,159	998	757	497	997	(1,386)	661	1,169	(751)
400m Band	29,266	1,144	370	2,952	2,370	2,539	1,235	4,783	(175)	2,028	1,728	1,410	1,777	1,651	519	2,146	2,860	(71)
800m Band	32,038	2,035	829	3,082	1,959	3,321	1,250	4,867	(177)	2,313	1,919	2,090	1,952	1,871	(973)	2,490	3,175	35
Station Share	20%	30%	NA	51%	21%	12%	30%	33%	NA	18%	30%	21%	43%	30%	NA	15%	17%	98%
400m Share	37%	38%	8%	56%	28%	29%	20%	56%	NA	17%	52%	39%	154%	49%	55%	50%	41%	9%
800m Share	41%	68%	19%	58%	24%	38%	21%	57%	NA	19%	58%	58%	169%	55%	NA	58%	45%	-5%
Station Quotient	0.99	1.11	0.69	1.31	0.99	0.92	1.04	1.07	1.03	1.07	1.07	0.91	1.12	0.98	0.70	0.87	1.15	0.88
400m Quotient	1.05	1.16	0.81	1.22	0.99	0.95	0.93	1.14	0.88	1.01	1.08	0.95	1.43	1.03	1.04	1.07	1.28	1.03
800m Quotient	1.04	1.49	0.88	1.21	0.91	0.99	0.93	1.14	0.88	1.01	1.10	1.00	1.38	1.00	0.90	1.11	1.30	1.04

Comments: The station band ("Station") extends from the station to 200 meters, the 400-meter band ("400m") extends from the station to 400 meters, and the 800-meter band ("800m") includes the entire station area. See Exhibit 3 for abbreviation names. See text for description of Station Quotients (SQs). For clarity of interpretation, station shares (including the 400m and 800m bands) with "NA" means the change in the LRT county and/or in the band was negative. RFL means retail-food-lodging and AER means arts-entertainment-recreation.

LRT Station Proximity and Demographic Change with Special Reference to Gentrification

This section presents the association between LRT station proximity and change in several demographic indicators overall and for each LRT system. Observations with respect to gentrification are also made. The relevant research questions in this context are:

> During the study period, did the concentration of population change and, if so, did the demographic composition of the population and households also change in terms of household type, householder age, median household income, and housing tenure with respect to LRT station proximity?
>
> In addition, during the study period, were there differences in outcomes between pre-2010 and 2010-2019 LRT systems?

The null hypotheses relating to both questions assert no difference in the concentration over time with respect to LRT station proximity and those features. The next section reviews research design, data, and analytic methods.

Research Design, Data, and Analytic Methods

The research design features noted above for the analysis of jobs apply here as well. Analyses are reported with respect to:

- Change in population in general as well as White (defined as white non-Hispanic) and Non-White persons (Exhibit 8);
- Change in households as well as change in households with children, one or more adult households without children, and single person households (Exhibit 9);
- Change in householder age based on categories of under 25 years of age, 25 to 44, 45 to 64, and 65 years of age of or older (Exhibit 10);
- Change in median household income (Exhibit 11); and
- Change in housing tenure, own or rent (Exhibit 11).

Data come from the ACS 5-year samples for 2010-2014, a period after the Great Recession of 2007-2009, and 2015-2019, the period before the COVID-19 pandemic of 2020-2022. If reference is made to 2010 in this context it means the ACS 5-year period of 2010-2014 and if reference is made to 2019 in this context it means the ACS 5-year period of 2015-2019.

Descriptive analysis is used where changes are measured numerically and change in concentration is measured by SQs (station quotients) as described above. As noted earlier, all differences in change over the time periods are significant to at least $p < 0.10$ of the two-tailed t-test.

Results and interpretations are offered next.

Results and Interpretations

Discussion is offered with respect to population overall as well as for two population groups: White non-Hispanic (referred to as “White”) and all other persons (referred to as “non-White”), as shown in Exhibit 8. This is followed by results and interpretations for households by type (Exhibit 9), householder age (Exhibit 10), and household income with tenure (Exhibit 11). Only certain trends are highlighted below. Readers are encouraged to evaluate results for individual systems of interest to them.

Overall Population

For the pool of all LRT systems, Exhibit 8 shows that LRT station areas added nearly a third of a million people or about 15 percent of the growth of LRT counties during the study period. Only three systems lost share of population compared to LRT counties: Buffalo, Houston, and Norfolk. Otherwise, LRT station areas gained share of population compared to their counties.

White and non-White Population

Exhibit 8 also shows population change for Whites and non-Whites. Overall, non-Whites accounted for nearly 90 percent of the population change in LRT counties, 1.9 million compared to 2.1 million. But Whites accounted for a disproportionate share of growth in LRT station areas at 35 percent, although non-Whites accounted for 65 percent of the change. From another perspective, although more than 40 percent of the growth in the White population occurred in station areas, only about 10 percent of non-Whites did. This can be an indicator of gentrification which will be explored in more detail below.

Notably, at least one station band added White population even as Whites lost population overall in LRT counties including Buffalo, Cleveland, Norfolk, Pittsburgh, Sacramento, and San Jose. Three of these LRT systems saw reductions in non-White population, apparently as Whites were displacing non-Whites; they were Buffalo, Cleveland, and Norfolk.

There are also extremes in outcomes. For instance, Houston saw more Whites added to station areas than the LRT county added (109 percent growth) while non-Whites had a negligible increase (0 percent). In contrast, 35 percent of Portland’s non-White population growth occurred in LRT station areas compared to 22 percent of Whites, and non-Whites accounted for 73 percent of the total population change.

Trends with respect to households by type are reviewed next.

Exhibit 8. LRT Transit Station Area Population Station Change and Station Quotients by System
[Station Quotients (SQs) > 1.0 means the station band/area gained a higher share of change than the LRT county 2010-2019.]

Measure	All	BUF	CHR	CLE	DAL	DEN	HOU	MSP	NOR	PHX	PIT	PDX	SAC	SLC	SD	SJ	SEA	STL
		1984	2007	1980	1996	1994	2004	2004	2011	2008	1984	1986	1987	1999	1981	1987	2003	1993
Total Population	2,142,930	(1,339)	106,016	(20,062)	420,150	227,108	377,022	84,923	(144)	381,428	(7,428)	115,031	75,023	69,976	132,930	85,901	186,505	(20,134)
Station Band	128,264	(374)	284	2,808	14,917	12,533	6,581	6,187	439	9,159	928	9,286	9,846	10,917	13,407	25,876	3,194	2,276
400m Band	253,063	(103)	8,435	713	34,739	27,379	16,276	11,196	1,065	17,874	(731)	26,059	19,108	22,930	21,662	36,505	15,698	839
800m Band	326,407	(1,149)	9,339	(353)	49,130	38,634	6,514	17,457	(1,550)	28,632	164	34,399	19,350	28,905	31,250	38,915	27,101	(331)
Station Share	6%	28%	0%	NA	4%	6%	2%	7%	NA	2%	NA	8%	13%	16%	10%	30%	2%	NA
400m Share	12%	8%	8%	NA	8%	12%	4%	13%	NA	5%	10%	23%	25%	33%	16%	42%	8%	NA
800m Share	15%	86%	9%	NA	12%	17%	2%	21%	NA	8%	NA	30%	26%	41%	24%	45%	15%	NA
Station Quotient	1.07	0.97	0.92	1.14	1.07	1.09	1.03	1.08	1.03	1.08	1.03	1.01	1.13	1.11	1.05	1.18	1.06	1.07
400m Quotient	1.03	1.00	1.08	1.03	1.03	1.03	0.99	1.05	1.04	1.04	1.00	1.01	1.06	1.08	1.02	1.08	1.05	1.02
800m Quotient	1.01	0.99	1.04	1.01	1.01	1.02	0.95	1.05	0.96	1.03	1.01	1.01	1.02	1.04	1.01	1.04	1.06	1.01
Total White	276,023	(14,708)	23,048	(34,649)	64,534	111,723	5,153	15,210	(1,624)	110,145	(23,703)	43,543	(4,303)	26,595	(95)	(19,443)	33,192	(32,000)
Station Band	51,176	474	1,384	622	6,887	8,957	3,955	3,313	459	4,861	69	4,147	1,537	6,214	2,330	5,161	880	(74)
400m Band	91,100	213	6,691	126	11,646	18,530	10,094	4,864	634	7,015	(1,311)	6,137	1,096	13,942	4,802	4,597	7,234	(1,255)
800m Band	115,670	(175)	6,853	(10)	18,220	24,575	5,624	8,161	(499)	9,576	(531)	9,412	(951)	17,292	4,192	4,320	11,684	(2,073)
Station Share	19%	NA	6%	NA	11%	8%	77%	22%	NA	4%	-0%	10%	NA	23%	NA	NA	3%	NA
400m Share	33%	NA	29%	NA	18%	17%	196%	32%	NA	6%	6%	14%	NA	52%	NA	NA	22%	NA
800m Share	42%	NA	30%	NA	28%	22%	109%	54%	NA	9%	2%	22%	NA	65%	NA	NA	35%	NA
Station Quotient	1.10	1.11	1.22	1.10	1.21	1.15	1.27	1.11	1.11	1.15	1.03	1.02	1.06	1.12	1.04	1.20	1.08	1.03
400m Quotient	1.06	1.03	1.31	1.05	1.11	1.06	1.19	1.07	1.09	1.07	1.01	0.99	1.02	1.09	1.03	1.09	1.14	1.01
800m Quotient	1.04	1.02	1.20	1.05	1.09	1.04	1.11	1.07	0.98	1.05	1.02	1.00	1.00	1.06	1.02	1.07	1.12	1.01

Exhibit 8. LRT Transit Station Area Population Station Change and Station Quotients by System—continued
[Station Quotients (SQs) > 1.0 means the station band/area gained a higher share of change than the LRT county 2010-2019.]

Measure	All	BUF	CHR	CLE	DAL	DEN	HOU	MSP	NOR	PHX	PIT	PDX	SAC	SLC	SD	SJ	SEA	STL
		1984	2007	1980	1996	1994	2004	2004	2011	2008	1984	1986	1987	1999	1981	1987	2003	1993
Total Non-White	1,866,907	13,369	82,968	14,587	355,616	115,385	371,869	69,713	1,480	271,283	16,275	71,488	79,326	43,381	133,025	105,344	153,313	11,866
Station Band	77,088	(848)	(1,100)	2,186	8,030	3,576	2,626	2,874	(20)	4,298	859	5,139	8,309	4,703	11,077	20,715	2,314	2,350
400m Band	161,963	(316)	1,744	587	23,093	8,849	6,182	6,332	431	10,859	580	19,922	18,012	8,988	16,860	31,908	8,464	2,094
800m Band	210,737	(974)	2,486	(343)	30,910	14,059	890	9,296	(1,051)	19,056	695	24,987	20,301	11,613	27,058	34,595	15,417	1,742
Station Share	4%	NA	NA	15%	2%	3%	1%	4%	NA	2%	5%	7%	10%	11%	8%	20%	2%	20%
400m Share	9%	NA	2%	4%	6%	8%	2%	9%	29%	4%	4%	28%	23%	21%	13%	30%	6%	18%
800m Share	11%	NA	3%	NA	9%	12%	0%	13%	NA	7%	4%	35%	26%	27%	20%	33%	10%	15%
Station Quotient	1.03	0.84	0.72	1.15	0.99	1.00	0.94	1.00	0.99	1.01	1.09	0.96	1.19	1.06	1.05	1.17	0.99	1.10
400m Quotient	1.00	0.93	0.91	0.99	0.97	0.98	0.92	0.98	1.02	1.00	0.97	1.02	1.08	1.02	1.00	1.07	0.94	1.02
800m Quotient	0.98	0.92	0.91	0.97	0.95	0.98	0.89	0.99	0.95	0.99	0.96	1.01	1.03	0.98	0.99	1.03	0.96	1.00

Comments: The station band (“Station”) extends from the station to 200 meters, the 400-meter band (“400m”) extends from the station to 400 meters, and the 800-meter band (“800m”) includes the entire station area. See Exhibit 3 for abbreviation names. See text for description of Station Quotients (SQs). For clarity of interpretation, station shares (including the 400m and 800m bands) with “NA” means the change in the LRT county and/or in the band was negative. Comments: White means non-Hispanic or Latino and Non-White means all others.

Households

Exhibit 9 shows changes in households with children, households comprised of one or more adults during the study period. Overall, LRT counties added about 805,000 households during the study period with about 163,000 or 20 percent of them moving into station areas. As seen in Exhibit 9, nearly all station bands and stations areas had SQs >1.0 with respect to household change during the study period. The exception is Buffalo, which has an SQ of nearly 1.0 overall. This is another indicator that people and households may be displacing jobs near LRT stations.

Households by Type

Contrary to popular belief, the closest LRT station band, with an SQ of 1.04, attracts households with children. Indeed, all LRT systems have at least one station band with an SQ >1.0, meaning that they attracted proportionately more households with children compared to LRT counties. Notably, SQs for several LRT systems at the closest station band are Cleveland (SQ = 1.12), Norfolk (SQ = 1.15), Sacramento (SQ = 1.14) San Jose (SQ = 1.17), Seattle (SQ = 1.10), and St. Louis (SQ = 1.13). Based on this evidence, planners should consider the demand for households with children to be attracted to LRT station areas.

Consistent with gentrification expectations, with an SQ of 1.05, single-person households were attracted to LRT station areas proportionately more than their respective counties. Indeed, SQs were at or more than 1.0 for all but two LRT systems (Buffalo and Charlotte). Moreover, the closest LRT station showed substantially higher rates of attraction than LRT counties for Cleveland (SQ = 1.23), Dallas (SQ = 1.35), Norfolk (SQ = 1.36), San Jose (SQ = 1.26) and Seattle (SQ = 1.48). However, San Jose is anomalous in that it is the only LRT system and county that lost single-person households. The reason may be the famously high housing costs plus housing shortages forces persons to share living quarters even if they do not want to.

On the other hand, households with one or more adults and no children (">1 Adult Households") dominated change in households with more than 90,000 more of those households added to LRT station areas compared to about 65,000 for single-person households and about 6,000 households with children. Moreover, they added proportionately more households in the closest LRT station band than the other two household types. Notable systems that added these households in the closest station band during the study period include Dalles (SQ = 1.31), Minneapolis-St. Paul (SQ = 1.27), Salt Lake City (SQ = 1.21), San Jose (SQ = 1.31), and Seattle (SQ = 1.31).

The change in LRT station area householders by age is considered next.

Exhibit 9. LRT Transit Station Area Household Type Change and Station Quotients by System
[Station Quotients (SQs) > 1.0 mean the station band/area gained a higher share of change than the LRT county 2010-2019.]

Measure	All	BUF	CHR	CLE	DAL	DEN	HOU	MSP	NOR	PHX	PIT	PDX	SAC	SLC	SD	SJ	SEA	STL
		1984	2007	1980	1996	1994	2004	2004	2011	2008	1984	1986	1987	1999	1981	1987	2003	1993
Households	804,558	7,802	39,145	6,244	143,666	80,662	143,366	26,049	1,956	127,852	14,096	42,458	23,573	26,710	41,475	25,501	73,299	7,414
Station Band	64,741	(146)	487	1,816	11,140	5,856	3,595	3,473	860	3,328	1,127	5,066	2,318	4,993	4,349	12,496	2,636	1,347
400m Band	128,283	248	3,913	1,246	21,350	14,611	9,815	6,193	1,002	7,968	1,352	13,298	5,062	10,435	7,758	16,230	9,809	1,588
800m Band	163,561	95	3,910	1,399	29,451	18,446	6,641	7,794	930	11,812	2,271	16,821	6,082	13,590	10,828	16,325	14,250	2,916
Station Share	8%	-2%	1%	29%	8%	7%	3%	13%	44%	3%	8%	12%	10%	19%	10%	49%	4%	18%
400m Share	16%	3%	10%	20%	15%	18%	7%	24%	51%	6%	10%	31%	21%	39%	19%	64%	13%	21%
800m Share	20%	1%	10%	22%	20%	23%	5%	30%	48%	9%	16%	40%	26%	51%	26%	64%	19%	39%
Station Quotient	1.10	0.95	0.99	1.18	1.25	1.11	1.06	1.15	1.16	1.07	1.04	1.03	1.06	1.14	1.05	1.26	1.32	1.06
400m Quotient	1.06	0.99	1.09	1.03	1.12	1.06	1.04	1.09	1.09	1.06	1.00	1.03	1.03	1.11	1.02	1.11	1.11	1.02
800m Quotient	1.03	0.98	1.03	1.02	1.07	1.03	0.99	1.07	1.04	1.04	1.01	1.02	1.01	1.06	1.02	1.06	1.08	1.03
HHs w/Children	90,597	(5,391)	2,469	(9,497)	25,926	9,599	38,311	3,194	(874)	25,577	(6,042)	2,699	1,436	2,635	(202)	(5,252)	17,174	(8,530)
Station Band	5,746	(192)	(271)	111	150	421	691	3	121	341	(71)	18	923	693	479	1,746	249	334
400m Band	7,438	(162)	183	(300)	1,953	472	1,109	147	(48)	986	(918)	224	1,401	635	824	1,632	250	(259)
800m Band	5,800	(934)	(219)	(547)	2,161	944	(136)	344	(74)	2,063	(1,327)	239	1,393	517	1,116	39	780	(559)
Station Share	6%	NA	NA	NA	1%	4%	2%	0%	NA	1%	NA	1%	64%	26%	NA	NA	1%	NA
400m Share	8%	NA	7%	3%	8%	5%	3%	5%	NA	4%	NA	8%	98%	24%	NA	NA	1%	NA
800m Share	6%	NA	NA	6%	8%	10%	-0%	11%	NA	8%	NA	9%	97%	20%	NA	NA	5%	NA
Station Quotient	1.04	0.85	0.77	1.12	0.97	1.04	1.07	0.99	1.15	1.04	1.03	0.99	1.14	1.08	1.04	1.17	1.10	1.13
400m Quotient	1.00	1.01	1.02	1.03	1.02	0.99	0.98	1.00	1.01	1.03	0.96	0.99	1.07	1.01	1.02	1.07	0.96	1.02
800m Quotient	0.99	0.93	0.95	1.02	1.00	1.00	0.93	1.01	1.02	1.04	0.96	0.99	1.04	1.00	1.02	1.02	0.99	1.02
>1Adult HHs	513,799	6,280	20,151	7,558	74,902	57,084	68,928	14,704	937	72,463	9,791	30,883	19,956	18,980	39,330	33,029	51,363	6,440
Station Band	33,098	282	288	558	5,012	3,241	1,275	1,859	(114)	1,913	610	3,013	1,156	2,748	2,320	8,064	1,096	(223)
400m Band	67,208	463	2,063	337	8,107	8,680	3,383	2,696	(79)	4,132	1,049	6,943	3,482	6,596	4,111	11,372	5,338	(190)
800m Band	92,955	542	2,444	282	12,041	11,889	2,490	3,679	(308)	6,520	1,733	9,966	3,889	8,227	7,199	13,757	8,210	395
Station Share	6%	4%	1%	7%	7%	6%	2%	13%	NA	3%	6%	10%	6%	14%	6%	24%	2%	NA
400m Share	13%	7%	10%	4%	11%	15%	5%	18%	NA	6%	11%	22%	17%	35%	10%	34%	10%	NA
800m Share	18%	9%	12%	4%	16%	21%	4%	25%	NA	9%	18%	32%	19%	43%	18%	42%	16%	6%
Station Quotient	1.13	1.16	1.00	1.14	1.31	1.14	1.02	1.27	0.91	1.13	1.04	1.05	1.04	1.21	1.03	1.31	1.31	0.94
400m Quotient	1.06	1.04	1.14	1.00	1.09	1.08	1.00	1.12	0.95	1.10	1.01	1.02	1.04	1.19	1.00	1.12	1.18	0.96
800m Quotient	1.04	1.01	1.09	0.98	1.06	1.05	0.97	1.10	0.91	1.09	1.02	1.02	1.00	1.10	1.00	1.08	1.13	0.99

Exhibit 9. LRT Transit Station Area Household Type Change and Station Quotients by System—continued
[Station Quotients (SQs) > 1.0 mean the station band/area gained a higher share of change than the LRT county 2010-2019.]

Measure	All	BUF	CHR	CLE	DAL	DEN	HOU	MSP	NOR	PHX	PIT	PDX	SAC	SLC	SD	SJ	SEA	STL
		1984	2007	1980	1996	1994	2004	2004	2011	2008	1984	1986	1987	1999	1981	1987	2003	1993
1-Person HHs	200,162	6,913	16,525	8,183	42,838	13,979	36,127	8,151	1,893	29,812	10,347	8,876	2,181	5,095	2,347	(2,276)	4,762	9,504
Station Band	25,897	(236)	470	1,147	5,978	2,194	1,629	1,611	853	1,074	588	2,035	239	1,552	1,550	2,686	1,291	1,236
400m Band	53,637	(53)	1,667	1,209	11,290	5,459	5,323	3,350	1,129	2,850	1,221	6,131	179	3,204	2,823	3,226	4,221	2,037
800m Band	64,806	487	1,685	1,664	15,249	5,613	4,287	3,771	1,312	3,229	1,865	6,616	800	4,846	2,513	2,529	5,260	3,080
Station Share	13%	NA	3%	14%	14%	16%	5%	20%	45%	4%	6%	23%	11%	30%	66%	NA	27%	13%
400m Share	27%	NA	10%	15%	26%	39%	15%	41%	60%	10%	12%	69%	8%	63%	120%	NA	89%	21%
800m Share	32%	7%	10%	20%	36%	40%	12%	46%	69%	11%	18%	75%	37%	95%	107%	NA	110%	32%
Station Quotient	1.11	0.87	1.10	1.23	1.35	1.11	1.07	1.14	1.36	1.03	1.04	1.05	1.01	1.12	1.08	1.26	1.48	1.11
400m Quotient	1.08	0.94	1.04	1.05	1.20	1.09	1.10	1.12	1.24	1.04	1.02	1.07	0.99	1.12	1.07	1.13	1.15	1.06
800m Quotient	1.05	0.98	0.99	1.05	1.13	1.04	1.05	1.08	1.18	1.01	1.02	1.05	1.01	1.11	1.03	1.08	1.11	1.05

Comments: The station band ("Station") extends from the station to 200 meters, the 400-meter band ("400m") extends from the station to 400 meters, and the 800-meter band ("800m") includes the entire station area. See Exhibit 3 for abbreviation names. See text for description of Station Quotients (SQs). For clarity of interpretation, station shares (including the 400m and 800m bands) with "NA" means the change in the LRT county and/or in the band was negative. "HHs" means households. ">1 Adult HHs" means households with more than one adult but no children.

Households by Householder Age

Exhibit 10 is especially interesting. Of the more than 163,000 new householders added to LRT station areas during the study period, nearly 80,000 or about half are attributed to householders between the ages of 35 and 44 while another third is comprised of more than 52,000 householders aged 65 years or over. Only about 400 householders under 25 years of age were added to LRT station areas while those between 45 and 64 years of age accounted for less than a fifth of the change, or about 31,000.

Put differently, among age groups, LRT station areas overall accounted mathematically for all new LRT county householders under 25 years of age, because LRT county growth overall was negative while LRT station area growth was positive. They also accounted for 36 percent of those between 25 and 44 years of age, 20 percent of those between 45 and 64 years of age, and 11 percent of those 65 years of age and older.

Several LRT station areas added more householders under 25 years of age than their respective counties, including those that lost such households overall. They are Charlotte, Dallas, Houston, Minneapolis-St. Paul, Norfolk, Phoenix, Salt Lake City, and St. Lous. Indeed, all but three LRT station areas had SQs of 1.0 or more.

To some extent, literature focusing on householders under 25 years of age predates this study. As such, many of those householders aged into the next cohort reported in this study, being 25 to 44 years of age; indeed, one could characterize them as the “new” young householders. The SQs for these householders were >1.0 for all but the Buffalo and Norfolk station areas. SQs were the highest in the statin areas for Charlotte (SQ = 1.08), Dallas (SQ = 1.15), Denver (SQ = 1.08), Minneapolis-St. Paul (SQ = 1.10), and Seattle (SQ = 1.09).

Except for the Buffalo and Cleveland LRT station areas, householders aged 45 to 64 years of age gained share compared to respective LRT counties. San Jose stands out as the leader with an SQ = 1.09. But most of the other LRT systems saw changes with SQs roughly around 1.0 or roughly proportionate to LRT county change.

Although the eldest cohort, comprised of households aged 65 years and older, includes only 7 LRT station areas with SQs of more than 1.0 (Cleveland, Minneapolis-St. Paul, Norfolk, Portland, Salt Lake City, San Diego and San Jose), it accounted for more than 50,000 or a third of the change in LRT station area householders, second only to the 25-to-44 years of age cohort. Indeed, the 65-and-over cohort added more households to LRT station areas than any other householder cohort in Buffalo, Cleveland, Norfolk, Portland, San Diego and St. Louis.

The analysis shows that, overall, householders of all age groups are attracted to LRT station areas. To some extent, this undermines a key gentrification indicator suggesting that only younger householders would be attracted to transit station areas.

More insights into gentrification are offered next with respect to household income and housing tenure.

Exhibit 10. LRT Transit Station Area Householder Age Change and Station Quotients by System
[Station Quotients (SQs) > 1.0 means the station band/area gained a higher share of change than the LRT county 2010-2019.]

Measure	All	BUF	CHR	CLE	DAL	DEN	HOU	MSP	NOR	PHX	PIT	PDX	SAC	SLC	SD	SJ	SEA	STL
		1984	2007	1980	1996	1994	2004	2004	2011	2008	1984	1986	1987	1999	1981	1987	2003	1993
HHs < 25	(34,505)	(1,426)	106	1,519	(4,231)	(4,892)	(1,409)	(4,071)	(616)	(5,070)	97	(2,531)	(4,236)	(509)	(9,236)	824	1,643	(976)
Station Band	2,707	(248)	87	362	545	453	628	245	199	861	(42)	(654)	(292)	279	(595)	410	111	358
400m Band	2,431	(136)	416	138	388	(715)	1,228	(187)	181	1,487	(228)	(672)	(253)	620	(1,420)	287	1,081	844
800m Band	403	(255)	351	34	104	(1,333)	556	262	22	1,811	(3)	(1,046)	(701)	292	(2,433)	464	1,616	662
Station Share	NA	NA	82%	24%	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	50%	7%	NA
400m Share	NA	NA	392%	9%	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	35%	66%	NA
800m Share	NA	NA	331%	2%	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	56%	98%	NA
Station Quotient	1.17	0.70	1.18	1.34	1.29	1.31	1.32	1.30	1.70	1.42	0.89	0.92	1.01	1.17	1.04	1.21	1.18	1.27
400m Quotient	1.11	1.02	1.26	0.98	1.12	1.03	1.18	1.10	1.36	1.32	0.86	1.03	1.15	1.16	1.01	1.02	1.28	1.32
800m Quotient	1.07	1.00	1.16	0.94	1.08	1.00	1.13	1.18	1.11	1.28	0.99	1.00	1.08	1.07	0.98	1.03	1.23	1.16
HHs 25-44	222,606	3,116	8,186	1,192	31,840	30,266	49,957	9,490	1,224	15,360	10,719	12,031	5,015	8,619	8,365	699	35,064	82
Station Band	34,518	7	351	1,207	5,701	3,335	1,792	2,023	350	1,206	602	2,655	810	2,731	1,777	7,779	1,392	800
400m Band	63,621	398	2,391	738	11,720	8,492	4,950	3,392	(72)	2,951	1,254	5,302	3,164	4,465	3,580	7,350	4,762	576
800m Band	79,519	262	2,107	988	15,968	11,275	3,018	4,338	159	5,031	1,603	7,159	3,386	5,556	3,914	5,203	8,181	1,371
Station Share	16%	0%	4%	101%	18%	11%	4%	21%	29%	8%	6%	22%	16%	32%	21%	1113%	4%	976%
400m Share	29%	13%	29%	62%	37%	28%	10%	36%	NA	19%	12%	44%	63%	52%	43%	1052%	14%	702%
800m Share	36%	8%	26%	83%	50%	37%	6%	46%	13%	33%	15%	60%	68%	64%	47%	744%	23%	1672%
Station Quotient	1.15	0.98	1.08	1.36	1.29	1.17	1.07	1.22	1.16	1.10	1.04	1.07	1.06	1.20	1.06	1.38	1.37	1.11
400m Quotient	1.09	1.04	1.17	1.06	1.20	1.10	1.06	1.12	0.94	1.10	1.02	1.04	1.10	1.11	1.05	1.15	1.09	1.03
800m Quotient	1.06	1.00	1.08	1.07	1.15	1.08	1.01	1.10	0.99	1.10	1.01	1.04	1.06	1.07	1.03	1.07	1.09	1.05
HHs 45-64	156,087	(4,471)	16,532	(10,396)	58,536	13,728	37,821	(4,906)	(532)	46,609	(10,137)	4,143	4,293	5,554	3,194	4,074	8,685	(11,086)
Station Band	14,236	(14)	91	(93)	3,195	1,074	906	543	47	1,019	(293)	1,140	1,391	1,026	878	2,633	659	34
400m Band	25,191	(283)	933	(760)	5,417	3,652	2,380	1,126	404	1,743	(780)	2,287	490	2,559	565	4,725	2,100	(461)
800m Band	31,449	(452)	1,248	(1,408)	7,911	3,786	1,813	540	192	2,597	(927)	2,691	1,177	3,103	2,265	5,648	2,035	(770)
Station Share	9%	NA	1%	NA	5%	8%	2%	NA	NA	2%	NA	28%	32%	18%	27%	65%	8%	NA
400m Share	16%	NA	6%	NA	9%	27%	6%	NA	NA	4%	NA	55%	11%	46%	18%	116%	24%	NA
800m Share	20%	NA	8%	NA	14%	28%	5%	NA	NA	6%	NA	65%	27%	56%	71%	139%	23%	NA
Station Quotient	1.09	1.02	0.96	1.02	1.26	1.07	1.08	1.11	1.05	1.08	1.00	1.05	1.15	1.10	1.05	1.18	1.31	1.05
400m Quotient	1.04	0.98	1.05	0.98	1.07	1.08	1.04	1.10	1.17	1.02	1.00	1.03	1.00	1.10	1.01	1.12	1.13	1.02
800m Quotient	1.02	0.99	1.04	0.95	1.04	1.04	1.01	1.04	1.06	1.01	1.01	1.02	1.01	1.06	1.02	1.09	1.06	1.02

Exhibit 10. LRT Transit Station Area Householder Age Change and Station Quotients by System—continued
[Station Quotients (SQs) > 1.0 means the station band/area gained a higher share of change than the LRT county 2010-2019.]

Measure	All	BUF	CHR	CLE	DAL	DEN	HOU	MSP	NOR	PHX	PIT	PDX	SAC	SLC	SD	SJ	SEA	STL
		1984	2007	1980	1996	1994	2004	2004	2011	2008	1984	1986	1987	1999	1981	1987	2003	1993
HHs 65 and over	460,370	10,583	14,321	13,929	57,521	41,560	56,997	25,536	1,880	70,953	13,417	28,815	18,501	13,046	39,152	19,904	27,907	19,394
Station Band	13,280	109	(42)	340	1,699	994	269	662	264	242	860	1,925	409	957	2,289	1,674	474	155
400m Band	37,040	269	173	1,130	3,825	3,182	1,257	1,862	489	1,787	1,106	6,381	1,661	2,791	5,033	3,868	1,866	629
800m Band	52,190	540	204	1,785	5,468	4,718	1,254	2,654	557	2,373	1,598	8,017	2,220	4,639	7,082	5,010	2,418	1,653
Station Share	3%	1%	NA	2%	3%	2%	0%	3%	14%	0%	6%	7%	2%	7%	6%	8%	2%	1%
400m Share	8%	3%	1%	8%	7%	8%	2%	7%	26%	3%	8%	22%	9%	21%	13%	19%	7%	3%
800m Share	11%	5%	1%	13%	10%	11%	2%	10%	30%	3%	12%	28%	12%	36%	18%	25%	9%	9%
Station Quotient	1.03	1.00	0.74	1.07	1.19	0.99	0.87	1.04	1.10	0.89	1.09	1.00	0.94	1.06	1.10	1.12	1.25	0.93
400m Quotient	1.02	0.97	0.86	1.09	1.02	0.98	0.92	1.09	1.11	1.02	1.00	1.04	0.96	1.12	1.05	1.06	1.05	0.95
800m Quotient	0.99	0.98	0.85	1.10	0.97	0.95	0.88	1.07	1.06	0.97	1.00	1.02	0.94	1.10	1.01	1.03	1.00	0.98

Comments: HHders means householders. The station band ("Station") extends from the station to 200 meters, the 400-meter band ("400m") extends from the station to 400 meters, and the 800-meter band ("800m") includes the entire station area. See Exhibit 3 for abbreviation names. See text for description of Station Quotients (SQs). For clarity of interpretation, station shares (including the 400m and 800m bands) with "NA" means the change in the LRT county and/or in the band was negative. "HHs < 25," "HHs 25-44," "HHs 45-64," and "HHs 65 and over" means householders under 25 years of age, between 25 and 44 years of age, between 45 and 64 years of age, and 65 years of age or older, respectively.

Household Income

As seen in Exhibit 11 and except for the Buffalo, Charlotte, and Cleveland LRT station areas, all station areas saw household incomes increase at a faster rate than their counties, which is a clear indication of gentrification. Overall, the income SQ was 1.05 during the study period, indicating that LRT stations areas' household incomes rose faster during the study period than their counties. Denver saw the largest change with an SQ of 1.09, followed by Portland at 1.05 and San Diego and San Jose each at 1.04. Otherwise, SQs for household income change in LRT station areas compared to counties are about the same.

However, the station band closest to LRT stations tells a somewhat different story, where, with an SQ of 1.08, incomes rose substantially compared to counties. Several LRT systems followed suit, such as Denver (1.08), Sacramento (1.12), San Diego (1.08), San Jose (1.08), and Seattle (1.07). For the most part, these shifts in income are reflected in increasing shares of homeownership, which is presented next.

Housing Tenure

Exhibit 11 also shows trends in renter and owner tenure. Of the 163,000 households added in the LRT station areas, about 47,000 or 19 percent were homeowners and the remaining 116,000 or 81 percent were renters.

With the exceptions of Buffalo (SQ = 0.97) at the low end and Cleveland (SQ = 1.04), Houston (SQ = 1.04), Salt Lake City (SQ = 1.04), and Seattle (SQ = 1.05), homeownership change in LRT station areas was reasonably comparable to their respective counties. However, SQs closest to LRT stations showed remarkable increases in homeownership proportions compared to LRT counties overall (SQ = 1.06) and for Cleveland (SQ = 1.06), Dallas (SQ = 1.14), Houston (SQ = 1.06), Pittsburgh (SQ = 1.09), Sacramento (SQ = 1.12), Salt Lake City (SQ = 1.09), San Jose (SQ = 1.11), Seattle (SQ = 1.08), and St. Louis (SQ = 1.11). Consistent with gentrification concerns, rising shares of homeownership close to LRT stations may signal that renters are being displaced.

But the homeownership trend should not be overstated because renters accounted for 81 percent of the tenure choice of households added to LRT station areas. Indeed, while renters added to LRT station areas accounting for 30 percent of all the change in households during the study period, homeowners accounted for only 8 percent. In addition, the LRT station area SQ for renters was higher than for homeowners at 1.04 compared to 1.01, respectively. Moreover, except for Buffalo, Cleveland, and Houston, SQs were at or more than 1.0 for all other LRT station areas. Many of the closest LRT station bands had remarkable SQs including Cleveland (SQ = 1.22), Dallas (SQ = 1.26), Denver (SQ = 1.17), Minneapolis-St. Paul (SQ = 1.20), Norfolk (SQ = 1.35), Salt Lake City (SQ = 1.18), San Jose (SQ = 1.36), and Seattle (SQ = 1.46).

Implications for Gentrification

In terms of LRT station areas compared to their respective counties during the study period, indicators of gentrification include increased share of: Whites; people under 25 years of age as well as the next older age cohort of 25 to 44 years of age; single-person households; 1+ adult households without children; and homeownership. A related indicator is household income increasing at a higher pace compared to LRT counties.

Overall, most LRT station areas underwent various levels of gentrification during the study period and those that did not may face rising gentrification pressures in the future. Coincidentally, homeowner SQs of 1.0 or greater in all station bands were also seen in those LRT systems. Station bands among these LRT systems also saw White population change that dominated trends of their respective counties.

Exhibit 12 categorizes all LRT systems in terms of whether gentrification trends during the study period appear strong, moderate, or weak. Strong trends are evident if (a) all SQs are equal to or great than 1.0 or (b) if household income for an individual system had an SQ of more than 1.01. Trends are “moderate” if at least one SQ is <1.0 but the household income SQ for an individual system was more than 1.01. Trends are “weak” if the household income SQ is <1.0. Using this scheme, 11 of the 17 LRT systems are facing strong gentrification pressures and another two face moderate pressures. But all systems may face gentrification pressures over time.

Policy responses to gentrification are outlined at the end.

The change in the mode of journey to work, with implications, is presented next.

Exhibit 11. LRT Transit Station Area Median Household Income and Tenure Change and Station Quotients by System
[Station Quotients (SQs) > 1.0 means the station band/area gained a higher share of change than the LRT county 2010-2019.]

Measure	All	BUF	CHR	CLE	DAL	DEN	HOU	MSP	NOR	PHX	PIT	PDX	SAC	SLC	SD	SJ	SEA	STL
		1984	2007	1980	1996	1994	2004	2004	2011	2008	1984	1986	1987	1999	1981	1987	2003	1993
Income Change	$7,179	$359	$3,462	$2,093	$1,557	$17,652	$313	$129	($62)	$12,357	$230	$131	$12,345	$346	$16,931	$33,725	($415)	$1,584
Station Band	$11,243	$1,612	($2,385)	($7,904)	$2,026	$17,239	$2,709	$4,644	$352	$8,792	$1,324	$498	$18,077	$1,525	$17,900	$38,731	$4,673	$2,300
400m Band	$9,737	$1,071	$1,273	($1,261)	$591	$20,894	$573	$2,666	$458	$9,551	$58	$1,078	$14,480	$1,142	$17,286	$33,888	$2,968	$2,770
800m Band	$8,928	$504	$2,131	($55)	($57)	$19,965	$962	$1,144	$974	$9,525	$386	$615	$12,637	$1,114	$15,808	$33,227	$2,318	$2,346
Station Quotient	1.08	1.04	0.93	0.87	1.01	1.08	1.04	1.08	1.01	1.04	1.02	1.01	1.12	1.02	1.08	1.08	1.07	1.02
400m Quotient	1.06	1.02	0.98	0.92	0.99	1.10	0.99	1.04	1.00	1.07	1.00	1.02	1.09	1.01	1.07	1.04	1.04	1.02
800m Quotient	1.05	1.01	0.98	0.96	0.98	1.09	1.01	1.02	1.02	1.05	1.00	1.01	1.03	1.01	1.04	1.04	1.03	1.02
Owners	412,239	2,859	13,565	(6,726)	61,504	55,632	62,817	12,557	608	91,693	3,552	34,331	16,077	19,800	21,692	11,002	37,668	(6,592)
Station Band	15,999	(76)	66	134	1,865	1,066	1,022	344	(53)	718	1,018	1,786	1,776	1,667	1,199	2,427	381	659
400m Band	33,995	28	1,189	30	2,180	4,708	3,084	1,224	175	1,424	691	4,655	2,322	4,772	3,244	3,482	2,009	(200)
800m Band	47,097	(269)	934	283	3,327	6,967	3,014	1,241	127	2,324	881	7,025	2,991	6,272	4,882	3,676	3,355	67
Station Share	4%	NA	0%	NA	3%	2%	2%	3%	NA	1%	29%	5%	11%	8%	6%	22%	1%	NA
400m Share	8%	1%	9%	NA	4%	8%	5%	10%	29%	2%	19%	14%	14%	24%	15%	32%	5%	NA
800m Share	11%	NA	7%	NA	5%	13%	5%	10%	21%	3%	25%	20%	19%	32%	23%	33%	9%	NA
Station Quotient	1.06	0.92	0.97	1.06	1.14	1.01	1.06	1.02	0.96	1.04	1.09	1.01	1.12	1.09	1.03	1.11	1.08	1.11
400m Quotient	1.02	0.99	1.11	1.02	0.99	1.02	1.05	1.04	1.03	1.00	1.01	1.00	1.02	1.09	1.03	1.04	1.06	1.01
800m Quotient	1.01	0.97	1.03	1.04	0.98	1.01	1.04	1.02	1.00	0.99	1.01	1.00	1.01	1.04	1.02	1.02	1.05	1.02
Renters	392,319	4,943	25,580	12,970	82,162	25,030	80,549	13,492	1,348	36,159	10,544	8,127	7,496	6,910	19,783	14,499	35,631	14,006
Station Band	48,742	(70)	421	1,682	9,275	4,790	2,573	3,129	913	2,610	109	3,280	542	3,326	3,150	10,069	2,255	688
400m Band	94,288	220	2,724	1,216	19,170	9,903	6,731	4,969	827	6,544	661	8,643	2,740	5,663	4,514	12,748	7,800	1,788
800m Band	116,464	364	2,976	1,116	26,124	11,479	3,627	6,553	803	9,488	1,390	9,796	3,091	7,318	5,946	12,649	10,895	2,849
Station Share	12%	NA	2%	13%	11%	19%	3%	23%	68%	7%	1%	40%	7%	48%	16%	69%	6%	5%
400m Share	24%	4%	11%	9%	23%	40%	8%	37%	61%	18%	6%	106%	37%	82%	23%	88%	22%	13%
800m Share	30%	7%	12%	9%	32%	46%	5%	49%	60%	26%	13%	121%	41%	106%	30%	87%	31%	20%
Station Quotient	1.12	0.95	0.98	1.22	1.26	1.17	1.04	1.20	1.35	1.10	0.96	1.07	1.01	1.18	1.06	1.36	1.46	1.00
400m Quotient	1.07	0.98	1.04	1.00	1.17	1.10	1.01	1.11	1.13	1.10	0.98	1.08	1.04	1.14	1.02	1.17	1.12	1.01
800m Quotient	1.04	0.98	1.00	0.99	1.11	1.06	0.96	1.09	1.07	1.09	1.00	1.06	1.02	1.09	1.01	1.10	1.09	1.01

Comments: The station band ("Station") extends from the station to 200 meters, the 400-meter band ("400m") extends from the station to 400 meters, and the 800-meter band ("800m") includes the entire station area. See Exhibit 3 for abbreviation names. See text for description of Station Quotients (SQs). For clarity of interpretation, station shares (including the 400m and 800m bands) with "NA" means the change in the LRT county and/or in the band was negative.

Exhibit 12.
Gentrification Classification for LRT Station Areas by System

Station Area	**All**	**BUF**	**CHR**	**CLE**	**DAL**	**DEN**	**HOU**	**MSP**	**NOR**	**PHX**	**PIT**	**PDX**	**SAC**	**SLC**	**SD**	**SJ**	**SEA**	**STL**
Indicator, SQ>1.0; Year		**1984**	**2007**	**1980**	**1996**	**1994**	**2004**	**2004**	**2011**	**2008**	**1984**	**1986**	**1987**	**1999**	**1981**	**1987**	**2003**	**1993**
White population	0.99	0.93	0.95	1.02	1.00	1.00	0.93	1.01	1.02	1.04	0.96	0.99	1.04	1.00	1.02	1.02	0.99	1.02
Persons Under 25	1.07	1.00	1.16	0.94	1.08	1.00	1.13	1.18	1.11	1.28	0.99	1.00	1.08	1.07	0.98	1.03	1.23	1.16
Single-Person HHs	1.05	0.98	0.99	1.05	1.13	1.04	1.05	1.08	1.18	1.01	1.02	1.05	1.01	1.11	1.03	1.08	1.11	1.05
1+Adult HHs	1.04	1.01	1.09	0.98	1.06	1.05	0.97	1.10	0.91	1.09	1.02	1.02	1.00	1.10	1.00	1.08	1.13	0.99
Homeownership	1.01	0.97	1.03	1.04	0.98	1.01	1.04	1.02	1.00	0.99	1.01	1.00	1.01	1.04	1.02	1.02	1.05	1.02
Household Income	1.05	1.01	0.98	0.96	0.98	1.09	1.01	1.02	1.02	1.05	1.00	1.01	1.03	1.01	1.04	1.04	1.03	1.02
Gentrification		Weak	Weak	Weak	Weak	Strong	Moderate	Strong	Strong	Strong	Moderate	Strong	Strong	Strong	Strong	Strong	Strong	Strong

Note: During the study period 2010-14 to 2015-19, LRT transit areas show "strong" gentrification trends if (a) all SQs are equal to or great than 1.0 or (b) if household income SQ for an individual system was more than 1.01. Trends are "moderate" if at least one SQ is <1.0 but the household income SQ for an individual system was more than 1.01. Trends are "weak" if the household income SQ is <1.0.

LIGHT RAIL TRANSIT STATION PROXIMITY AND COMMUTING MODE CHOICE

Theory posits that LRT station proximity is associated with increasing shares of commuting via transit, walking, biking, and working from home. Using ACS data, this section outlines the research design, choice of data, and analytic method. After presenting results, it concludes with implications for post-pandemic transit and land use planning.

Given the literature and theory presented earlier, the research question is:

> Is proximity to LRT stations associated with increasing shares of walking, biking, transit use, and working at home?

The null hypothesis asserts there is no change in the non-auto commute by mode to work with respect to LRT station proximity.

Research Design, Data, and Analytic Method

The same research design features noted earlier apply to the analyses presented here as well. The analyses include the following, all reported in Exhibit 13:

- Change in "resident workers" living in LRT station areas as opposed to those working in them (as reported in Exhibit 7)
- Change in resident workers commuting via automobile;
- Change in resident workers commuting via transit;
- Change in resident workers walking or biking to work; and
- Change in resident workers working from home.

The treatment group is the LRT station areas with respect to LRT counties which is the control. ACS data are used for descriptive analysis. In all cases, differences are significant to at least the 0.10 level of the two-tailed t-test.

Results and Interpretations

Exhibit 13 reports outcomes for change in workers living in LRT counties and LRT station areas as well as the mode journey to work or working from home.

Resident Workers Living in LRT Station Areas

Overall, the LRT station areas added nearly 350,000 workers accounting for 18 percent of the change in workers living in LRT counties, on less than one percent of the urbanized land area. Indeed, the concentration of workers living in LRT station areas compared to LRT counties increased during the study period among all LRT systems except Buffalo and Norfolk. Excluding those systems, the range for individual LRT systems is 3 percent for Houston to 41 percent for Salt Lake City. followed by 37 percent for San Jose, 33 percent for Portland, 25 percent for St. Louis, 24 percent for Sacramento, and 20 percent for Denver.

Resident Workers Living in LRT Station Areas who Commute via the Automobile

At first glance, it appears that workers living in LRT transit areas increased their propensity to commute to work via the automobile overall and compared to respective counties, apart from Houston and Norfolk. However, closer inspection shows that other modes to work gained larger shares as will be seen below.

Resident Workers Living in LRT Station Areas who Commute via Transit

Residents living in areas served by LRT are expected to increase their transit use for commuting, and the data shows this to be generally true although there is some variation across systems. Exhibit 13 shows that, overall, commuting to work via transit increased by 36 percent. The largest gains were seen in Phoenix (87 percent), Salt Lake City (82 percent), Denver (70 percent), Dallas (56 percent), Sacramento (56 percent), San Diego (56 percent), and Portland (52 percent). In contrast, transit use fell in LRT station areas in Buffalo, Cleveland, Norfolk, and Pittsburgh.

Resident Workers Living in LRT Station Areas who Commute via Walking or Biking

A pleasant surprise is that 57 percent of the new workers living in LRT station areas walked or biked to work during the study period. Indeed, there were very large increases among several systems such as Houston at 132 percent, Charlotte at 118 percent, Portland at 87 percent, and Salt Lake City at 80 percent. Moreover, aside from Norfolk, all LRT station areas gained in share of commuting via walking or biking compared to their respective counties. Why this is the case is not known. Perhaps LRT routes became friendlier to those who walk or bike to work during the study period. Or perhaps new workers choosing to live in LRT corridors were already predisposed to walking or biking to work. This is an area in need of future research.

Resident Workers Living in LRT Station Areas who Work from Home

The role of working from home notes special discussion. For people working from home, access to transit may be attractive if it connects them to shopping, services, and leisure as well as access to airports and long-distance trains. This is one reason why demand for LRT station accessibility may increase in the future even if new residents do not use transit in their commute to work. Indeed, in the post-pandemic world, working from home has become much more prevalent than before, although perhaps not to the degree it was during the pandemic (Peiser and Hugel 2022). Accordingly, the SQs for working from home are likely smaller before the pandemic than going forward afterward. This is clearly an area in need of research in the post-pandemic era. Nonetheless, working from home increased by 12 percent overall. The largest increase was in San Jose with a 37 percent change followed by 25 percent in Salt Lake City and 19 percent in Portland.

An Interesting Finding

The bottom of Exhibit 13 reveals an interesting finding. Recall that in LRT station areas, jobs *lost* share compared to respective counties among nearly all LRT systems. In contrast, LRT station areas *gained* share of workers living in them compared to their respective counties. Moreover, of the nearly 350,000 new workers who live in station areas, 28 percent use modes other than the auto in their commute to work. Leaders include Seattle at 75 percent, Houston at 40 percent, Minneapolis-St. Paul at 39 percent, and Portland at 37 percent, and Denver at 35 percent. In contrast, only 21 percent of new workers who live in the balance of LRT counties use modes other than the auto in their commute tom work.

Why would LRT station areas gain more workers proportionately than their respective counties, while jobs in station areas fell proportionately more than those counties? One reason could be that station areas attract more households than their respective counties because of the increased mobility options. Consider that only 15 percent of transportation trips are work related.[17] Households living near LRTs may use them for non-work trips. But these types of trips are not reported in the ACS data.

Another reason is that LRTs typically connect downtowns with major activity nodes where mobility options are the highest in the region. That advantage is implied in Exhibit 13, showing that in LRT station areas, most of the non-auto commutes to work are by walking or biking.

The association between LRT station proximity and vehicle kilometers traveled (VKT) and transportation costs by household type is presented next.

[17] See https://www.bts.gov/statistical-products/surveys/national-household-travel-survey-daily-travel-quick-facts#:~:text=WHY%20WE%20TRAVEL%20*%2045%20percent%20of,of%20daily%20trips%20are%20taken%20for%20commuting..

Exhibit 13. LRT Transit Commute to Work Mode Change and Station Quotients by System
[Station Quotients (SQs) > 1.0 means the station band/area gained a higher share of change than the LRT county 2010-2019.]

Measure	All	BUF	CHR	CLE	DAL	DEN	HOU	MSP	NOR	PHX	PIT	PDX	SAC	SLC	SD	SJ	SEA	STL
		1984	2007	1980	1996	1994	2004	2004	2011	2008	1984	1986	1987	1999	1981	1987	2003	1993
Resident Workers	1,913,783	14,147	84,461	17,832	300,092	207,496	221,167	82,360	7,405	303,276	24,925	120,274	88,180	69,478	163,709	99,641	152,161	26,657
Station Area	111,749	(8)	1,161	1,810	14,703	11,375	5,390	5,904	868	7,223	1,118	10,804	7,203	8,698	10,277	19,781	3,030	2,412
To 400m	239,957	27	7,885	2,150	27,226	27,467	13,454	9,053	1,642	15,655	2,366	27,905	16,482	20,557	24,382	29,472	15,867	3,757
To 800m	348,945	(12)	9,726	2,962	43,642	41,149	7,253	15,099	212	27,230	4,590	40,097	21,546	28,197	38,222	37,242	24,916	6,874
Station Share	6%	NA	1%	10%	5%	5%	2%	7%	12%	2%	4%	9%	8%	13%	6%	20%	2%	9%
To 400m Share	13%	NA	9%	12%	9%	13%	6%	11%	22%	5%	9%	23%	19%	30%	15%	30%	10%	14%
To 800m Share	18%	NA	12%	17%	15%	20%	3%	18%	3%	9%	18%	33%	24%	41%	23%	37%	16%	26%
Station Quotient	1.11	0.97	0.99	1.15	1.19	1.15	1.08	1.17	1.10	1.12	1.02	1.04	1.13	1.15	1.03	1.22	1.17	1.08
To 400m Quotient	1.06	0.97	1.12	1.04	1.06	1.06	1.03	1.06	1.09	1.08	1.00	1.03	1.08	1.12	1.03	1.08	1.14	1.04
To 800m Quotient	1.05	0.97	1.08	1.05	1.05	1.06	0.97	1.08	0.95	1.09	1.02	1.03	1.04	1.07	1.03	1.05	1.11	1.05
Auto Commute	1,456,416	12,363	65,144	12,833	252,450	150,262	194,515	56,946	6,485	250,982	9,530	82,276	75,057	51,957	124,948	72,035	71,337	19,253
Station Area	76,744	(209)	728	1,142	11,218	6,750	3,849	3,382	531	4,846	1,230	6,326	5,975	5,371	8,578	14,140	446	2,441
To 400m	160,511	235	4,739	902	22,426	15,415	8,930	5,159	1,116	11,203	1,386	16,572	14,508	14,310	20,185	20,454	4,033	2,787
To 800m	239,401	667	6,226	2,028	35,828	25,673	4,505	8,316	539	21,490	3,181	24,153	19,711	20,363	30,656	24,988	5,659	5,418
Station Share	5%	NA	1%	9%	4%	4%	2%	6%	8%	2%	13%	8%	8%	10%	7%	20%	1%	13%
To 400m Share	11%	2%	7%	7%	9%	10%	5%	9%	17%	4%	15%	20%	19%	28%	16%	28%	6%	14%
To 800m Share	16%	5%	10%	16%	14%	17%	2%	15%	8%	9%	33%	29%	26%	39%	25%	35%	8%	28%
Station Quotient	1.10	0.91	0.98	1.13	1.16	1.12	1.06	1.17	1.05	1.10	1.07	1.03	1.15	1.10	1.06	1.19	1.00	1.13
To 400m Quotient	1.05	0.99	1.07	1.02	1.06	1.03	1.00	1.07	1.07	1.08	1.02	1.02	1.10	1.10	1.04	1.06	1.07	1.04
To 800m Quotient	1.04	1.00	1.06	1.05	1.05	1.04	0.96	1.07	0.98	1.10	1.04	1.03	1.06	1.06	1.03	1.03	1.03	1.05
Transit	81,132	588	49	(1,471)	2,496	5,794	(3,360)	5,055	(187)	275	4,563	13,635	(947)	3,218	4,463	11,466	41,012	(2,299)
Station Area	12,645	(47)	129	373	729	1,554	(193)	1,760	67	388	(551)	2,008	224	1,583	1,103	2,634	1,177	(293)
To 400m	22,799	(291)	543	354	570	3,363	439	1,665	(141)	430	(400)	5,941	(196)	2,106	1,585	3,369	3,652	(383)
To 800m	29,448	(811)	573	240	1,408	4,035	(248)	2,417	2	240	(174)	7,075	(529)	2,654	2,477	4,384	6,376	(671)
Station Share	16%	NA	263%	NA	29%	27%	NA	35%	NA	141%	NA	15%	NA	49%	25%	23%	3%	NA
To 400m Share	28%	NA	1108%	NA	23%	58%	NA	33%	NA	156%	NA	44%	NA	65%	36%	29%	9%	NA
To 800m Share	36%	NA	1169%	NA	56%	70%	NA	48%	NA	87%	NA	52%	NA	82%	56%	38%	16%	NA
Station Quotient	1.18	0.88	1.37	1.52	1.30	1.40	0.96	1.41	1.33	1.20	0.77	1.01	1.23	1.67	1.18	1.33	1.25	0.89
To 400m Quotient	1.08	0.84	1.33	1.19	1.03	1.26	1.22	1.11	0.84	1.08	0.87	1.07	1.00	1.25	1.08	1.07	0.96	0.97
To 800m Quotient	1.06	0.78	1.25	1.13	1.09	1.19	1.02	1.11	1.04	1.02	0.91	1.04	0.96	1.16	1.08	1.04	0.98	0.96

Exhibit 13. LRT Transit Commute to Work Mode Change and Station Quotients by System—continued

[Station Quotients (SQs) > 1.0 means the station band/area gained a higher share of change than the LRT county 2010-2019.]

Measure	All	BUF	CHR	CLE	DAL	DEN	HOU	MSP	NOR	PHX	PIT	PDX	SAC	SLC	SD	SJ	SEA	STL
		1984	2007	1980	1996	1994	2004	2004	2011	2008	1984	1986	1987	1999	1981	1987	2003	1993
Walk-Bike	64,393	(1,212.0)	1,039	1,030	5,544	5,887	909	4,035	5,057	6,407	1,150	5,532	(1,350)	2,414	6,068	5,526	19,048	(277)
Station Area	11,479	245.0	212	233	1,588	792	1,204	141	26	733	506	836	(3)	663	1,330	1,686	1,161	126
To 400m	26,174	(56.0)	1,141	497	1,908	1,976	2,616	1,515	385	1,459	799	2,129	101	1,671	1,765	2,409	6,853	210
To 800m	36,480	(63.0)	1,230	378	2,980	2,722	1,201	2,798	(8)	1,641	668	4,789	(172)	1,928	2,108	3,280	10,429	571
Station Share	18%	NA	20%	23%	29%	13%	132%	3%	1%	11%	44%	15%	NA	27%	22%	31%	6%	NA
To 400m Share	41%	NA	110%	48%	34%	34%	288%	38%	8%	23%	69%	38%	NA	69%	29%	44%	36%	NA
To 800m Share	57%	NA	118%	37%	54%	46%	132%	69%	NA	26%	58%	87%	NA	80%	35%	59%	55%	NA
Station Quotient	1.15	1.50	1.42	1.12	1.61	1.06	1.66	0.94	0.67	1.10	1.78	1.02	1.07	1.15	1.10	1.61	1.39	1.08
To 400m Quotient	1.12	1.06	1.54	1.15	1.20	1.06	1.30	1.06	0.93	1.08	1.19	1.02	1.09	1.19	1.05	1.30	1.24	1.06
To 800m Quotient	1.11	1.07	1.27	1.08	1.22	1.05	1.18	1.10	0.63	1.03	1.09	1.10	1.05	1.11	1.03	1.22	1.19	1.10
Work Home	281,152	3,163	16,720	5,364	41,245	43,463	27,244	13,262	(4,638)	41,164	10,532	16,691	13,098	12,418	18,201	8,423	18,036	9,184
Station Area	8,298	(33)	168	15	1,046	1,978	802	453	131	1,047	(130)	1,383	607	1,064	(1,108)	634	231	10
To 400m	23,463	(1)	1,440	219	2,415	5,738	1,848	263	179	1,850	608	2,531	1,359	2,369	(348)	2,184	736	875
To 800m	32,799	207	1,495	73	3,346	7,549	1,953	722	(393)	2,700	938	3,164	1,311	3,106	482	3,105	1,758	1,283
Station Share	3%	NA	1%	0%	3%	5%	3%	3%	NA	3%	NA	8%	5%	9%	NA	8%	1%	0%
To 400m Share	8%	NA	9%	4%	6%	13%	7%	2%	NA	4%	6%	15%	10%	19%	NA	26%	4%	10%
To 800m Share	12%	7%	9%	1%	8%	17%	7%	5%	NA	7%	9%	19%	10%	25%	3%	37%	10%	14%
Station Quotient	0.99	0.66	0.87	0.81	1.11	1.46	1.22	1.09	3.50	1.43	0.61	1.12	1.10	1.36	0.71	1.07	1.09	0.77
To 400m Quotient	1.00	0.77	1.42	0.90	1.05	1.17	1.03	0.84	3.17	1.24	0.87	0.97	1.00	1.16	0.82	1.16	0.96	1.13
To 800m Quotient	0.98	0.92	1.19	0.82	0.97	1.09	1.16	0.89	1.48	1.20	0.87	0.94	0.86	1.04	0.86	1.15	1.05	1.07
Workers to 800m	348,945	(12)	9,726	2,962	43,642	41,149	7,253	15,099	212	27,230	4,590	40,097	21,546	28,197	38,222	37,242	24,916	6,874
Non-Auto Change	98,727	(667)	3,298	691	7,734	14,306	2,906	5,937	(399)	4,581	1,432	15,028	610	7,688	5,067	10,769	18,563	1,183
Non-Auto Share	28%	5558%	34%	23%	18%	35%	40%	39%	-188%	17%	31%	37%	3%	27%	13%	29%	75%	17%
Balance Workers	1,564,838	14,159	74,735	14,870	256,450	166,347	213,914	67,261	7,193	276,046	20,335	80,177	66,634	41,281	125,487	62,399	127,245	19,783
Non-Auto Change	327,950	3,206	14,510	4,232	41,551	40,838	21,887	16,415	631	43,265	14,813	20,830	10,191	10,362	23,665	14,646	59,533	5,425
Non-Auto Share	21%	23%	19%	28%	16%	25%	10%	24%	9%	16%	73%	26%	15%	25%	19%	23%	47%	27%

Comments: The station band ("Station") extends from the station to 200 meters, the 400-meter band ("400m") extends from the station to 400 meters, and the 800-meter band ("800m") includes the entire station area. See Exhibit 3 for abbreviation names. See text for description of Station Quotients (SQs). For clarity of interpretation, station shares (including the 400m and 800m bands) with "NA" means the change in the LRT county and/or in the band was negative.

TRANSIT STATION PROXIMITY AND REDUCED VEHICLE KILOMETERS TRAVELED WITH ASSOCIATED REDUCTION IN TRANSPORTATION COSTS

It seems an article of faith that travel demand measured in terms of distance traveled falls with respect to distance away from downtowns, activity centers, and transit stations. There is no research testing this in the context of transit stations, however. The research reported below is the first to do so in the context of distance to LRT stations. Future research can be expanded to include other transit modes.

The research question is:

> Do household vehicle kilometers traveled (VKT) vary by proximity to transit stations?

If so, then using parameters of such a finding can lead to estimates of transportation cost savings with respect to transit station proximity. This question leads logically to two more research questions posed earlier:

> Do household transportation costs vary by proximity to transit stations?
>
> If so, do lower-income households realize transportation cost savings with respect to proximity to transit stations?

The null hypotheses assert there is no statistically significant relationship between transit station proximity and VKT, and savings in transportation costs. What follows is the research design, data, and analytic method followed by results and interpretations.

Research Design, Data, and Analytic Method

The research question lends itself to quasi-experimental, cross-section analysis. Spatially related, cross-section data for household transportation cost is provided by the Department of Housing and Urban Development's Location Affordability Index (LAI). HUD has three LAI versions with the most recent, Version 3 based on census tracts (CTs) applied to the 2016 5-year ACS.[18] Because it covers much of the study period, those data are used for this analysis.

The LAI estimates household housing and transportation costs at the census tract level based for the following six household prototypes used in this analysis:

> Median-Income Family comprised of four persons with two commuters where the household earning the median household income (MHHI);
>
> Working individual being a single person earning 50 percent of the MHHI;
>
> Single Professional being also a single person though earning 135 percent of the MHHI;

[18] HUD has not updated its LAI database. The version used in this study, Version 3, is available at https://www.huduser.gov/portal/elist/2019-may_23.html.

Single-Parent Family being one adult with two dependents earning 50 percent of MHHI;

Moderate-Income Family being comprised of a family of three with one worker earning 80 percent of the MHHI; and

Dual-Professional Family comprised of four persons with two who together earn 150 percent of the MHHI.

Exhibit 14 reports the number of people and commuters for each household type.

The analysis applies HUD's LAI database to 17 LRT systems extending 3,200 meters (about two miles) from the closest LRT stations. Standard-form ordinary least squares regression model is adapted for analysis. The general model is:

Household VKT = ***f****(Households, Location, Metropolitan Area, Place Typology, LRT Station proximity)*

Where:

Household VKT is the dependent variable. This variable is logged with allows for interpretations of place typology and distance variables to ne percent change with respect to a unit change in VKT.

Households is the number of households in the CT, logged, to control for the variability of households occupying census geographic units. There is no *a priori* expectation for association between households in a CT and VKT.

Location means distance to the nearest freeway ramp (*freeway distance*). Other location controls are embedded in the Place Typology construct described below. Because freeways enable longer commutes (see Angle and Blei 2015), a positive association between freeway distance and VKT is hypothesized.

Metropolitan controls are simply the location of the CT in a given metropolitan area where an LRT system operates. (Norfolk is the referent as it is the smallest in terms of stations and track distance.) This variable is effectively a composite index of attributes unique to each metropolitan area and as such there are no *a priori* directions of association.

The spatial unit of analysis are census tracts, which are large spatial units with many containing one or more transit stations. Because of this, measuring distances from non-station CTs to those with CTs is problematic. The solution is to create a typology called "***Place Typology***" which is assigned to CTs. The typology is derived from cluster analysis that creates an index variable comprised of:

Jobs per acre;
Proportion of jobs that are retail and arts;
Total population per acre;

Total households per acre;
Percent of households with no children;
Percent of owner-occupied housing;
Intersections per square mile; and
Proportion of intersections with 3 to 4 vertices.

The method uses LEHD and census data to produce four statistically unique place types which also conform to *a priori* expectations. (For details about how this construct is specified, tested, and applied, see Nelson, Hibberd, Currans, and Iroz-Elardo 2021). They are:

High Mixed-Use/Accessibility (***High-MA***) Centers such as downtowns, suburban nodes, and other areas with high concentrations of jobs and people, high land use, and high levels of accessibility;

Moderate Mixed-Use/Accessibility (***Moderate-MA***) areas such as large combinations of CTs with modest mixes of jobs and people and lower connectivity between land uses, and often surrounding High-MA centers;

Low Mixed-Use/Accessibility (***Low-MA***) areas which are usually low density, residential areas that some might characterize as urban sprawl, and which are usually found between Moderate-MA and Poor-MA areas; and

Poor Mixed-Use/Accessibility (***Poor-MA***) areas which are dominated by very low-density residential development with no employment centers and the lowest levels of accessibility between land uses. *Poor-MA* will be used as the referent in analysis meaning that the variation in rents attributable to Place Typology will be estimated with respect to this variable, all other factors considered.

Theoretically, controlling for all factors, VKT will be lowest in the *High-MA* places and highest in the *Poor-MA* places, which are the referent.

LRT Station Proximity is the distance of the CT centroid to the nearest transit station in 200-meter increments to 3,200 meters (about two miles). It is hypothesized that the closer a CT is to a transit station the lower the VKT per household,

Related to this, if VKT is reduced, so are transportation costs as a share of household income, which is also reported.

Results are presented next along with interpretations.

Exhibit 14
HUD LAI Household Types

Household Type	Income	Persons in Household	Number of Commuters
Median-Income Family	100% of MHHI	4	2
Working Individual	50% of MHHI	1	1
Single Professional	135% of MHHI	1	1
Single-Parent Family	50% of MHHI	3	1
Moderate-Income Family	80% of MHHI	3	1
Dual-Professional Family	150% of MHHI	4	2

Note: MHHI means median household income for the metropolitan areas of the subject census tract.
Source: HUD (2019).

Results and Interpretations

Exhibit 15 reports regression results as well as change in household transportation costs. A total of 8,557 CTs are included in the analysis. The coefficients of determination show that 40 percent to 60 percent of the variation in mean household VKT is explained by the equations. The collinearity matrix (not reported for brevity) does not reveal problematic collinearities. Interpretations of regression results are followed by implications for transportation costs.

Results for Place Typologies show that, compared to the Poor-Mixed Use/Accessibility referent, households incurred progressively less VKT the closer CTs were to transit stations. Second, compared to households in CTs that are more than 3,200 meters from the nearest LRT station, VKT declines progressively with respect to station distance. While these results may be expected *a priori* they are nonetheless the first time these expectations have been confirmed. In other words, popular perceptions are supported by the evidence. These outcomes are consistent with hypotheses. But there are subtleties that need exploration.

The variation between household types is instructive. Four of the six household types have reasonably similar outcomes with respect to LRT station proximity: Median Household, Single-Parent, Moderate-Income, and Dual-Professional. Generally, VKT declines by about 12 to 15 percent across the study area.

In contrast, Working Individual Households at 50 percent of MHHI enjoyed the largest reduction in VKT at nearly 42 percent, followed by the Single-Professional Households at 135 percent of MHHI at nearly 23 percent. These relationships are illustrated in exhibit 19. Why are these household types so much more sensitive to transit station location than the others? Perhaps as single-person households they have more flexibility to locate near transit stations than other household types because they can afford to live near them. In particular, single-person households can afford higher rent per square meter if their total space needs are modest, allowing them to live in smaller units. Also recall from above that single-person households are attracted to transit stations more than other household types. Given their single status, if transit station proximity improves their access to jobs or other destinations, single-person households should be expected to locate near them more than other households, which they do.

Exhibit 15 also shows cost savings attributable to transit station proximity. Transportation costs as a share of income fall for all household types with respect to transit station proximity. There is an anomaly, however. Single-parent households have the lowest income but also the highest transportation costs relative to income at 31.2 percent. Yet, proximity to LRT stations does not reduce their transportation costs much, at less than 14 percent in the closest distance band. Perhaps for these households, transit accessibility does not substitute for child-related trips transit does not serve. However, Exhibit 16 goes on to simulate transportation cost savings that combine Place Typology with selected LRT station distances. When this is done, the single-parent household costs near LRT stations in High MA and Moderate MA Place Typologies fall substantially, more so than other household types that benefit as well, nonetheless.

The last analytic section evaluates the transit station proximity rent premiums for office, retail, and multifamily real estate. This is followed by implications for post-pandemic transit policy and planning.

Exhibit 15
Association between Vehicle Kilometers Traveled (VKT) and Light Rail Transit Station Proximity with to Household Type

Variable	Median-Income HH	Working Individual HH	Single Professional HH	Single-Parent HH	Moderate-Income HH	Dual-Professional HH
Constant	10.29	9.73	9.85	9.93	9.97	10.30
Household Control						
CT Households (log)	0.9%	1.7%	0.7%	0.6%	0.6%	1.0%
Location Control						
Freeway Distance (km)	**2.7%**	**4.2%**	**3.4%**	**2.7%**	**2.5%**	**2.6%**
Metropolitan Control						
Buffalo	-3.0%	-4.9%	-5.0%	-3.7%	-3.5%	-2.9%
Charlotte	-3.5%	-1.6%	-1.0%	-0.2%	-0.1%	-3.4%
Cleveland	-5.8%	-5.7%	-5.9%	-4.9%	-4.6%	-5.7%
Dallas	-1.1%	2.0%	1.7%	2.0%	1.9%	-1.1%
Denver	0.4%	-1.3%	0.1%	0.9%	0.9%	0.4%
Houston	-7.1%	-7.2%	-6.2%	-3.7%	-3.4%	-6.9%
Minneapolis-St. Paul	-5.0%	-6.2%	-6.5%	-3.6%	-3.3%	-4.8%
Phoenix	-5.9%	-5.3%	-4.6%	-2.8%	-2.5%	-5.8%
Pittsburgh	-9.7%	-19.2%	-13.5%	-10.0%	-9.4%	-9.5%
Portland	-2.0%	0.5%	-1.9%	-0.4%	-0.3%	-2.0%
Sacramento	1.3%	8.5%	5.5%	5.6%	5.2%	1.3%
Salt Lake City	1.9%	3.0%	0.2%	1.3%	1.3%	1.9%
San Diego	2.8%	11.0%	6.8%	5.4%	5.0%	2.8%
San Jose	3.6%	10.4%	5.7%	5.6%	5.4%	3.6%
Seattle	-2.7%	-16.4%	-3.8%	-0.3%	-0.1%	-2.6%
St. Louis	-1.2%	0.9%	-0.6%	0.3%	0.3%	-1.2%

Exhibit 15
Association between Vehicle Kilometers Traveled (VKT) and Light Rail Transit Station Proximity with to Household Type—continued

Variable	Median-Income HH	Working Individual HH	Single Professional HH	Single-Parent HH	Moderate-Income HH	Dual-Professional HH
Place Typology Control						
Low MA	-9.6%	-12.9%	-11.8%	-10.4%	-9.8%	-9.5%
Moderate MA	-19.7%	-26.4%	-23.7%	-20.6%	-19.4%	-19.4%
High MA	-30.7%	-54.4%	-38.1%	-31.4%	-29.4%	-30.1%
LRT Distance Band						
<200 meters	-14.5%	-41.8%	-22.8%	-13.7%	-12.3%	-13.9%
200-<400 meters	-14.1%	-32.0%	-17.8%	-12.9%	-11.9%	-13.7%
400-<600 meters	-14.7%	-21.2%	-18.0%	-13.6%	-12.5%	-14.3%
600-<800 meters	-14.7%	-20.9%	-17.7%	-13.1%	-12.1%	-14.3%
800-<1,000 meters	-12.6%	-15.9%	-14.4%	-12.0%	-11.2%	-12.3%
1,000-<1,200 meters	-11.4%	-15.8%	-13.5%	-10.9%	-10.2%	-11.2%
1,200-<1,400 meters	-12.2%	-14.8%	-13.0%	-11.3%	-10.5%	-12.0%
1,400-<1,600 meters	-9.9%	-15.2%	-12.3%	-8.8%	-8.2%	-9.6%
1,600-<1,800 meters	-9.5%	-11.5%	-10.4%	-8.3%	-7.8%	-9.3%
1,800-<2,000 meters	-10.8%	-12.4%	-11.4%	-10.0%	-9.5%	-10.7%
2,000-<2,200 meters	-9.0%	-12.5%	-10.3%	-8.4%	-8.0%	-8.9%
2,200-<2,400 meters	-7.0%	-8.3%	-7.4%	-6.5%	-6.1%	-6.9%
2,400-<2,600 meters	-8.0%	-9.5%	-8.7%	-7.3%	-7.0%	-7.9%
2,600-<2,800 meters	-7.2%	-23.8%	-8.8%	-6.8%	-6.4%	-7.1%
2,800-<3,000 meters	-7.1%	-10.8%	-9.7%	-7.4%	-7.0%	-6.9%
3,000-<3,200 meters	-7.0%	-9.4%	-7.7%	-6.6%	-6.3%	-6.9%

Exhibit 15
Association between Vehicle Kilometers Traveled (VKT) and Light Rail Transit Station Proximity with to Household Type—continued

Variable	Median-Income HH	Working Individual HH	Single Professional HH	Single-Parent HH	Moderate-Income HH	Dual-Professional HH
Performance Metrics						
Mean Annual VKT	42,262	24,095	26,115	29,409	30,898	42,710
Cases	8,557	8,557	8,557	8,557	8,557	8,557
R^2 adjusted	0.514	0.633	0.425	0.468	0.468	0.515
Standard Error of Estimate	0.122	0.394	0.186	0.132	0.123	0.119
F-ratio	245.959	379.498	172.074	204.543	204.493	246.256
Household Metrics						
Mean Household Income	$68,658	$31,829	$85,939	$31,829	$50,927	$95,488
Mean Annual Trans. Percent	23.0%	27.2%	12.1%	31.2%	21.4%	16.1%
Transportation Cost Simulation with Place Typology and Selected LRT Station Distances						
<200 meters @ High MA	-34.2%	-96.2%	-60.9%	-45.1%	-41.7%	-44.0%
600-<800 mewers @ Mod. MA	-29.2%	-47.3%	-41.4%	-33.7%	-31.5%	-33.7%
1,400-<1,600 meters @ Low MA	-19.5%	-28.1%	-24.1%	-19.2%	-18.0%	-19.1%

Note: All coefficients are significant at $p < 0.10$.
Comments: HH means household; CT means census tracts; km means kilometer; LRT means light rail transit; MA means mixed land use and accessibility; and coefficients in bold are significant at p < 0.10 of the one-tailed since the direction of association is predicted. Significance is not reported for household and metropolitan variables because they are controls.

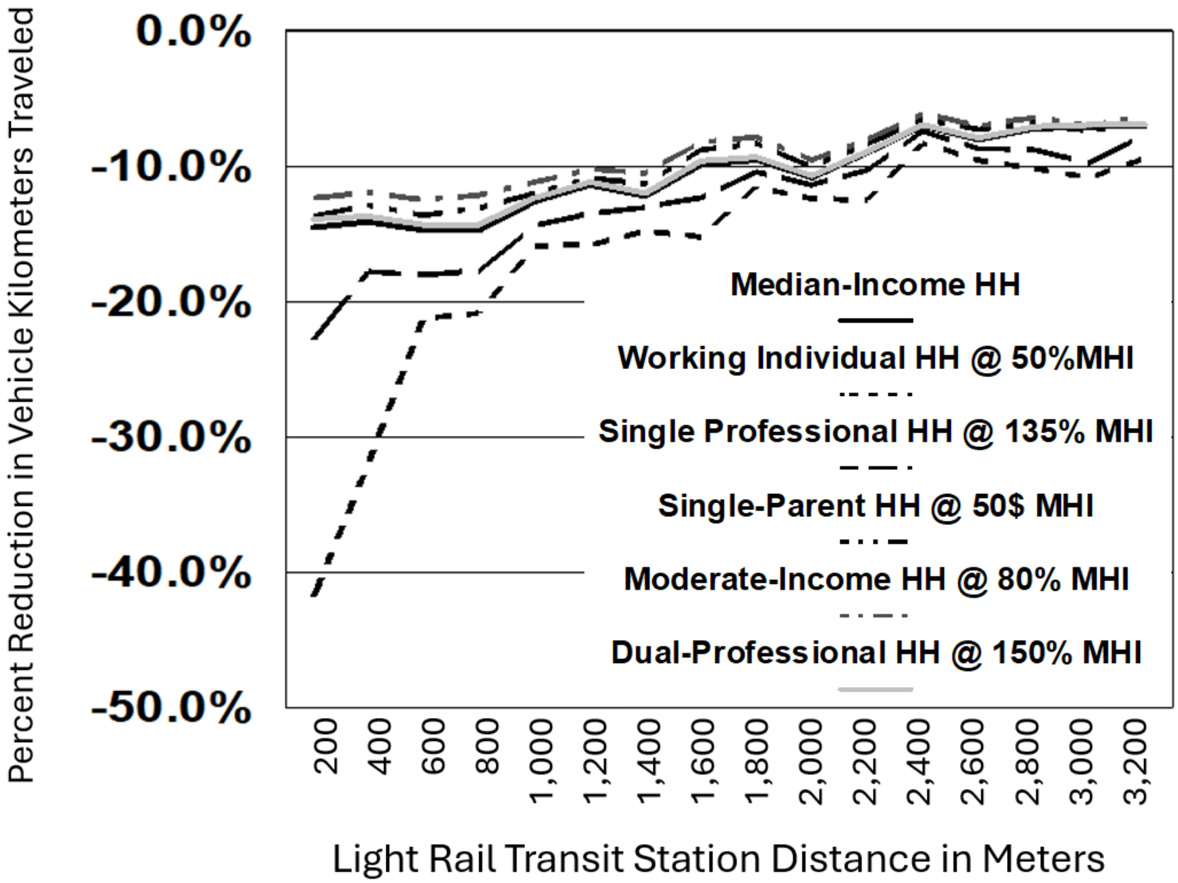

Exhibit 16
Variation in VKT Reduction by Household Type with Respect to LRT Station Distance

LIGHT RAIL TRANSIT STATION PROXIMITY AND OFFICE, RETAIL, AND MULTIFAMILY RENTS

The last analytical section addresses the extent to which the real estate market values proximity to LRT stations. CoStar commercial rent data are used for analysis. As will be shown, there is considerable variation in the influence of LRT station proximity for each real estate type evaluated. An overall picture emerges to help guide post-pandemic transit and land use planning.

In review, the principal research question is:

> Is there an association between commercial real estate rent (per square meter) and proximity to LRT stations holding other factors constant?

But this question is nuanced as follows:

> If there is an association, is there evidence of negative externality or amenity effects with respect to LRT station proximity?

The research design, hypothesis, data, and analytic method is presented next. This is followed by results and interpretations, and then implications form post-pandemic transit and land use planning.

Research Design, Hypothesis, Data, and Analytic Method

The research questions lend themselves to cross-section analysis that compare changes in real estate rent with respect to LRT station proximity overall and by individual systems. The null hypothesis posits no relationship. However, two outcomes can be revealed, both of which are consistent with theory. The accessibility theory noted earlier would result in a downward sloping rent gradient away from LRT stations because as distance increases, accessibility is reduced. On the other hand, if LRT stations themselves are sources of externalities such as noise, congestion, unattractive urban design and so forth, there would be an upward sloping rent gradient away from stations thereby offsetting the accessibility rent premium. At some point away from LRT stations, the accessibility premium is expected to overcome externality effects (Nelson and McClesky 1990, Nelson 1992). Before that inflection point, however, both outcomes would be consistent with accessibility and externality theories.

The analysis requires data about real estate value. Many studies reviewed earlier used local property tax assessor data mostly for sales or assessed value of single-family residential property. This land use is popular because the number of cases is usually large. However, when evaluating LRT systems in several states where the efficacy of assessor data varies because of state and local regulations as well as data quality, other data are needed. For instance, to get around this limitation in their cross-section analysis of the association between BRT station proximity and single-family home values, Acton, Le and Miller (2022) used CoreLogic home sales data before and after the inauguration of the 15 BRT systems. Their study was limited to sales of single-family homes within or beyond 800 meters (about 0.50-mile) of BRT stations, however.

Like all transit stations, LRT station areas are often comprised of multiple land uses such as offices, retail operations, and multifamily projects. Unfortunately, there are no large-scale cross-section analyses of the relationship between different types of real estate and LRT station proximity.

This study overcomes limitations of prior work through a national-scale, cross-section analysis of the association between real estate rents for three common types of real estate—office, retail, and residential—and LRT station proximity using fine-grained buffers of 100 meters to 800 meters from stations. The 100-meter buffer is roughly comparable to standard city block widths. It overcomes limitations of continuous functional form approaches such as linear, log, inverse, quadratic models because they mask important interactions between proximity and value close to transit stations. The 100-meter band approach can reveal associations in roughly the first city block around LRT stations and every successive city block outward.

The analysis reported in this article uses CoStar commercial rent data. CoStar is the nation's largest centralized source of commercial real estate data.[19] CoStar rent data are used for office, retail, and multifamily residential rent for 2019, which was the year before the COVID-19 pandemic. CoStar's rent data are converted into dollars per square meter per year.

Rent data are preferred over sales data for two reasons. First, there are many more rent cases than sale cases thus increasing sample size. For instance, whereas there are 109,688 LRT rent cases in this study, analysis using just CoStar sales would include fewer than 2,000 cases. The large number of rent cases thus increases confidence in outcomes and allows for more fine-grained analysis of each system. Second, rent is a better indicator of current market conditions than sales because rent data reflect local economic conditions at the time, not conditions years or decades earlier when properties were sold.

The result is that this study is the nation's largest, most complete assessment of the relationship between LRT station proximity and office, retail, and multifamily residential property values in terms of rent.

Multivariate ordinary least squares analysis is used to tease out the influence of LRT station proximity on office, retail, and multifamily rent per square meter from among various features of properties. Using theoretical and research design foundations reviewed earlier as a guide, the following general model is developed for empirical application (adapted from Nelson 2017).

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[19] See https://www.costargroup.com/.

$$\mathbf{R}_{\boldsymbol{i}} = \boldsymbol{f}\,(\mathbf{S}_{\boldsymbol{i}}, \mathbf{SES}_{\boldsymbol{i}}, \mathbf{LU}_{\boldsymbol{i}}, \mathbf{C}_{\boldsymbol{i}}, \mathbf{M}_{\boldsymbol{i}}, \mathbf{DB}_{\boldsymbol{i}}) \tag{1}$$

Where:

R is the asking rent per square meter for property *i*;

S is the set of structural attributes of property *i*;

SES is the set of socioeconomic characteristics of the vicinity of property *i*;

LU is the land use mix of the block group within which property *I* is located;

C is a set of centrality attributes of property *i* in this case being distance to the central business district (CBD) and nearest freeway/expressway ramps;

M is the metropolitan area within which property *i* is located—as metropolitan area conditions and markets vary between them, identifying the location of property *i* within its respective market helps control for metropolitan-specific influences; and

DB is the distance band in units of 100 meters of property *i* to a transit station.

Dependent Variable

R is the ***Asking Rent per Square Meter***. The study includes the universe of all office, retail, and multifamily properties from which all data are available as reported by CoStar. As CoStar data come from real estate brokerages participating in its network, its data exclude non-participating brokerages or entities that own properties not for rent such as owner-occupied properties. By logging the dependent variable, the semi-log model allows for coefficients to be interpreted as the percent change in rent attributable to a one-unit change in an independent variable such as an individual 100-meter distance band (Statistical Data Services 2018).

Control Variables

S is the bundle of structure and lease restriction attributes for property *i* reported by CoStar including:

Gross Leasable Area in square meters with the expectation that there will be a positive association between office and multifamily building area and rent because larger buildings presumably include more amenities than smaller ones.

Effective Year Built which is the latter year of construction or year of renovation as reported by CoStar with the expectation that newer buildings will command higher rent than older ones.

Vacancy Rate as reported by CoStar with the expectation that the higher the vacancy rates the lower the rent. However, this may not always be the case as high demand markets could result in high vacancy rates as owners wait for higher paying tenants. Accordingly, signs may not be predictable, especially considering that the study area is comprised of stable to rapidly growing central counties.

The number of ***Stories*** includes with the expectation that the taller the building the higher the mean rent.

For office real estate, this includes ***Class A*** and ***Class B*** office space which are considered the highest and next highest quality in the office market, commanding rents accordingly. ***Class C*** office space is the referent.

For retail real estate, this includes ***Regional/Community Mall***, ***Power Center***, ***Lifestyle Center***, ***Strip Retail***, and ***General Retail*** as defined by CoStar with the referent being all other retail property.

For multifamily real estate, this includes ***Subsidized*** units such as Section 8 rental vouchers and Low-Income Housing Tax Credit units among others, and ***Restricted*** units such as those for students or persons 55 years of age and older, among others. While one may assume *a priori* that subsidized and restricted units rent for less than market rate units, because the unit of measure is rent per square meter it is conceivable that these units rent for more per square meter than market rate units even if the units themselves rent for less. Accordingly, signs of association cannot be predicted.

The **SES** dimension is comprised of ***Median Household Income*** from the five-year sample of the 2019 American Community Survey (ACS) for the block group within which a CoStar property is located. A positive association is expected with respect to rent (Xiao 2016).

LU is an index of the land-use mix in the block group within which property *i* is located such as the nature of surrounding land uses, street characteristics, and related. This variable is based on work by Ewing and Hamidi (2018) who devised an index comprised of land use and transportation features. The higher the index score, the greater the mix. Higher rents should result because of efficiencies gained in the interaction between land uses. However, if LU mix is associated with congestion, poor urban design and other externalities, a negative association will be revealed. Both directions of association are thus possible (see also Nelson and Hibberd 2021).

Two variables comprise the **C** dimension: distance from the 100 percent corner[20] of the central business district (***CBD***) in meters and distance from the nearest ***Freeway*** ramp also in meters. Both are computed from geographic information systems. Negative associations between rent and CBD and Freeway proximity are expected.

The **M** dimension is comprised of the individual metropolitan areas within which the LRT stations are located. As these are controls which account for idiosyncrasies of metropolitan markets, no direction of associations is predicted.

[20] For a review of this concept, see https://en.wikipedia.org/wiki/100_percent_corner.

DB is a proxy measure for functional form based on 100-meter distance bands from LRT stations. It is preferred over other functional forms because it gives planners direct information on the extent to which the real estate market responds to transit station proximity in relatively fine-grained distance units. As noted earlier, the alternative linear, semi-log, doble-log, quadratic and other functional forms do not generate the kind of insights planners need to choreograph land uses and infrastructure investment proximate to transit stations. While some studies use distance bands as well, they are usually limited to 0.25- or 0.50-mile distance (400 or 800-meter) bands or occasionally both. But that assumes all relevant interactions which are useful for planners occur only within those large distance bands (Higgins and Kanaroglou 2016; Nelson 2017). The 100-meter distance band approach also allows for fine-grained tests of statistical significance for each distance band separately. Building from prior work by Nelson and Hibberd (2019) and Nelson et al. (2021), the 100-meter distance band approach extends to 800 meters or equivalent to the half-mile circle (Guerra, Cervero, and Tischler 2012). As a reminder, the 100-meter band is equivalent roughly to a typical city block width, although there are variations.

Exhibit 17 summarizes the control and treatment variables, sources of data, measures, and predicted signs.

The database used in this analysis is comprised of more than 48,000 cases, making it the largest cross-section analysis of the association between real estate value and LRT station proximity reported in the literature.

Results and interpretations come next.

Results and Interpretations

Overall results based on the total samples are reported in Exhibit 18 for office real estate, Exhibit 20 for retail real estate, and Exhibit 22 for multifamily real estate. Results focusing only on LRT station distance and performance outcomes for specific systems are reported in Exhibits 19, 21, and 23 for those real estate types, respectively.

Although there are no *a priori* expectations of goodness of fit outcomes, literature suggests that ordinary least squares regression analysis usually explains about one fifth to two-thirds of the dependent variable variation with respect to the control and treatment variables. Note that while some analysts are preoccupied with achieving high level regression model coefficients of determination (R^2), too many variables can lead to over-specification. It is best to emphasize that the variables most relevant to the question, along with relevant controls, are sufficient to avoid serious omitted variable bias (a form of endogeneity) in the model.

Because the direction of association with respect to metropolitan controls is not predicted, significance-test outcomes are not reported for them. For other variables where significance is $p < 0.10$ of the one-tailed t-test (because directions of association are predicted), coefficients are highlighted in bold. The bottom of the exhibits reports metrics for mean rent per square meter ("m^2"), the number of cases for each regression, the adjusted coefficient of determination ("R^2"), the standard error of estimate, the F-Ratio, and the mean rent per square meter for the study area.

Exhibit 17
Variables, Data Sources, Measurement Type, and Predicted Associations with Respect to Rent per Square Meter

Variable	Data Source	Measure	Predicted Sign
	DEPENDENT VARIABLE		
Rent			
Rent per Square Meter (logged)	CoStar	Continuous	NA
	CONTROL VARIABLES		
Structure Controls			
Gross Leasable Area (100m^2)	CoStar	Continuous	+
Mean Unit Size (100m^2), Multifamily	CoStar	Continuous	-
Stories	CoStar	Continuous	+
Effective Year Built	CoStar	Continuous	+
Vacancy Rate	CoStar	Continuous	+/- *See text*
Structure Controls—Office			
Class A Office	CoStar	Binary	+
Class B Office	CoStar	Binary	+
Class C Office	CoStar	Binary	Referent
Structure Controls—Retail			
Regional/Community Mall	CoStar	Binary	NA
Power Center	CoStar	Binary	NA
Lifestyle Center	CoStar	Binary	NA
Strip Retail	CoStar	Binary	NA
Retail General	CoStar	Binary	NA
All Other Retail	CoStar	Binary	Referent
Structure Controls—Multifamily			
Subsidized	CoStar	Binary	NA
Restricted	CoStar	Binary	NA
All Other Multifamily	CoStar	Binary	Referent
Socioeconomic Control			
Median Household (HH) Income	Census ACS	Continuous	+
Land Use Control			
Land-Use Mix Index	Computed	Continuous	+/- *See text*
Centrality Control			
Distance from CBD	Computed	Continuous	-
Distance from Freeway Ramp	Computed	Continuous	-

Exhibit 17
Variables, Data Sources, Measurement Type, and Predicted Associations with Respect to Rent per Square Meter—continued

Variable	Data Source	Measure	Predicted Sign
Metropolitan Control			
Metropolitan Area Location	Census	Binary	NA
Tacoma excluded from SCT*	Census	Binary	Referent
TREATMENT VARIABLES			
Station Distance Band Treatment			
0-100m	Computed	Binary	+/- *See text*
>100m-200m	Computed	Binary	+/- *See text*
>200m-300m	Computed	Binary	+/- *See text*
>300m-400m	Computed	Binary	+/- *See text*
>400m-500m	Computed	Binary	+/- *See text*
>500m-600m	Computed	Binary	+/- *See text*
>600m-700m	Computed	Binary	+/- *See text*
>700m-800m	Computed	Binary	+/- *See text*
Beyond 800 meters	Computed	Binary	Referent

*These systems were selected as referents because they are the smallest of their modes in terms of passenger miles.
Comment: NA means no direction of association is predicted—see text for discussion; “m” means meters and m^2 means square meters; HH means households.

The bottom of the following exhibits labels two revealed directions of association of rents with respect to LRT station distance bands. The first reports whether there is a significant coefficient for the first 100-meter station band, and if so, where it is "positive" or "negative."

The second reports the functional form revealed across the first four 100-meter distance bands. The rules for this determination are: (1) there are at least two significant coefficients and (2) at least one of them is for the first or second distance bands. Consistent with theoretical outcomes described earlier and where coefficients meet the rules noted above, there are four functional form choices:

- "Downward" with respect to distance from transit stations thus revealing that accessibility value dominates because value falls as LRT distance increases.

- "Upward" with respect to distance from transit stations thus revealing that externality value dominates because value rises as LRT distance increases.

- "Concave" where the slope starts downward from the station then goes upward after an inflection point revealing accessibility value prevails over externality value beyond the inflection point.

- "Convex" where the slope starts upward from the station and then goes downward after an inflection point revealing externality value prevails over accessibility value beyond the inflection point.

Results and interpretations for office, retail, and multifamily rents with respect to LRT station proximity are presented next.

Results and Interpretations for Office Rents

Exhibit 18 shows overall results for office rents with respect to LRT station proximity, which reveal impressive associations. Controlling for all other influences, rent *fell* by 0.7 percent compared to the mean within the first 100 meters of an LRT station. Rent then rises by 1.4 percent in the second 100-meter band and then by 3.9 percent in the third 100-meter band. The fourth band has an ambiguous coefficient while the remaining bands show smaller, positive associations than reported in the third band. Results near LRT stations show classical externality value that offset accessibility value, meaning that the office market discounts rent with respect to LRT station proximity. Transit station area planning and urban design is needed to overcome negative rent associations near LRT stations.

Exhibit 19 reports results for each of the LRT systems. There are three broad categories: those without significant coefficients at the station band, and those with positive and negative coefficients at the LRT station band.

Minneapolis-St. Paul, Norfolk, Phoenix, and Portland do not have significant coefficients at the station band, implying that the office rental market does not value LRT station proximity. The Portland regression question shows a positive coefficient in the second 100-meter distance band but there are no other significant coefficients to the 400-meter band and others beyond. The Phoenix regression equation, however, shows a negative coefficient in the second distance band followed by a positive coefficient in the third and then a negative coefficient in the fourth. The overall interpretation for Phoenix is that its office market does not value LRT station proximity. To the extent that LRT station proximity should confer positive rent premiums based on transit accessibility, these outcomes are not encouraging among these LRT systems.

Also discouraging are results for Dallas, Pittsburgh, San Diego, San Jose, Seattle, and St. Louis where there are negative coefficients at the LRT station band. Only St. Louis shows positive coefficients beyond the station band, but the fourth distance band turns negative. As noted by the systems above, these are not encouraging outcomes from the perspective that LRT station proximity should confer accessibility value.

Only seven of the 17 LRT systems have positive rent coefficients at the station band: Buffalo, Charlotte, Cleveland, Denver, Houston, Sacramento, and Salt Lake City. However, significant rent coefficients for the next one or more distance bands are higher than those of the station band for all but Sacramento. The implication is that externalities at the station push rents down compared to station bands father away. Only Sacramento has the classic downward sloping rent gradient from the station band, but it extends only to the second 100-meter band, after which the third band has an ambiguous coefficient while the fourth is negative.

On balance, regression results show that office rents do not respond favorably to LRT station proximity. To say this is surprising may be an understatement. With very few exceptions, station area planning and urban design has failed to make LRT stations attractive to the rental office market.

There is another consideration: How will the post-pandemic office market respond to LRT station proximity when the pre-pandemic market did not value it much?

Results from the retail rent are reported next.

Results and Interpretations for Retail Rents

Exhibit 20 reports results for retail rents with respect to LRT station proximity overall. Retail rents start at 10.4 percent above the mean at the station band and fall to 8.5 percent above the mean in the third distance band after which there are no significant rent coefficients. Results indicate a strong market response to locating retail opportunities close to LRT stations.

Exhibit 21 reports results for the individual systems. Using the framework for reporting noted above, only coefficients for Charlotte, Sacramento, Salty Lake City, and San Jose are significant at the station band and have at least two significant coefficients to the 400-meter band. And they all have different functional forms. Charlotte's and Sacramento's rent coefficients fall downward from the station and fall to the third or second station band, respectively, with no further significant coefficients. (Note is made of Denver with a similar downward form to the third distance band although its station band coefficient is insignificant/) The rent coefficients rise from the Salt Lake City station band to the second but then fall to the third suggesting externality effects at the station that dissipate a short distance away. San Jose also has a rent coefficient that is higher in the third station than the station band also indicating the presence of externalities at the station.

The association between LRT station proximity and multifamily rents completes this analysis of market outcomes.

Results and Interpretations for Multifamily Rents

Aside from the station band itself, Exhibit 22 shows that rent coefficients for multifamily real estate are significant through the entire 800-meter study area. The pattern is for rents to rise with respect to distance from LRT stations to a peak of 5.5 percent above the mean in the third distance band, and then fall to 4.9 percent above the mean in the 400-meter distance band and then mostly continue to fall thereafter. As one might expect, residential land would be influenced negatively by LRT transit station proximity, this is confirmed.

Exhibit 23 reports results for all systems individually. Charlotte, Houston, and Salt Lake City show rent coefficients fall away from LRT stations suggesting that in these cases, the multifamily real estate market values LRT station proximity. This is the case for Pittsburgh as well but only because the negative externality value increases with respect to distance away from LRT stations. Otherwise, LRT station proximity is associated with negative rent coefficients at the station only (such as for Dallas and Portland), or coefficients are ambiguous.

Overall insights are discussed next.

Insights From Rent Analyses

Regression results are disappointing. In theory, LRT stations must influence real estate markets by increasing the value of real estate nearby. However, LRT stations do not appear to have positive influences on rent for office, retail, and multifamily real estate. Negative or ambiguous results suggest the market is responding in undesirable ways that need to be overcome by mitigating externalities (see Nelson and McClesky 1990). In particular, since post-pandemic office demand is unlikely to return to pre-pandemic levels over the next several years (Peiser and Hugel 2022), planners and policymakers may no longer be able to depend on meeting the demand for offices as a reason for making new LRT investments. Something else is needed.

Results for multifamily rent are especially disappointing. This seems incongruous with results reported earlier showing substantial population and household growth near LRT stations, because growth near them should affect rent premiums. Perhaps multifamily development is attracted to LRT stations despite problematic location and urban design.

The final section summarizes key findings and offers insights into LRT station area planning in the post-pandemic era.

Exhibit 18
Variation in Office Rents Total Sample with Respect to LRT Station Proximity

LRT Variables	LRT Beta
Constant	**2.286**
Structure Controls	
GLA (1000 m2)	-1.183E-004
Class A	**0.313**
Class B	**0.098**
Stories	**0.003**
Effective Year Built	**0.001**
Vacancy	**-0.001**
Socioeconomic Control	
Med. HH Inc ($1000)	**1.497E-003**
Land-Use Control	
Land Use Mix	**-0.009**
Centrality Controls	
CBD (m)	**-1.581E-006**
Freeway (m)	**-4.206E-006**
Metropolitan Controls (Norfolk Referrent)	
Buffalo	-0.205
Charlotte	0.158
Cleveland	-0.182
Dallas	0.137
Denver	0.136
Houston	0.155
Minneapolis-St. Paul	0.096
Phoenix	0.090
Pittsburgh	-0.112
Portland	0.207
Sacramento	0.133
Salt Lake City	-0.054
San Diego	0.339
San Jose	0.790
Seattle	0.407
St. Louis	-0.069

Exhibit 18
Variation in Office Rents Total Sample with Respect to LRT Station Proximity—continued

LRT Variables	LRT Beta
Station Distance Band Treatment	
0-100m	**-0.007**
>100m-200m	**0.014**
>200m-300m	**0.039**
>300m-400m	-0.001
>400m-500m	**0.022**
>500m-600m	**0.030**
>600m-700m	**0.011**
>700m-800m	**0.019**
Performance Metrics	
R^2	0.570
Standard error	0.232
F-ratio	2478.789
Cases	63,664
Mean Rent/ m^2/year	$253.68
Station Sign	***Negative***
Functional Form	***Upward***

Comments: "GLA" means gross leasable area; "Med. HH Inc." means median household income; "m" means meter while "m^2" means square meter; bold coefficients mean $p < 0.10$ for relevant variables (see text).

Exhibit 19
Office Rent with Respect to LRT Transit Station Proximity

Variable	ALL	BUF	CHR	CLE	DAL	DEN	HOU	MSP	NOR	PHX	PIT	PDX	SAC	SLC	SD	SJ	SEA	STL
Station Distance																		
0-100m	**-0.007**	**0.146**	**0.095**	**0.107**	**-0.030**	**0.019**	**0.115**	-0.006	0.016	0.001	**-0.041**	0.007	**0.042**	**0.029**	**-0.086**	**-0.152**	**-0.042**	**-0.053**
>100m-200m	**0.014**	0.004	**0.144**	**0.169**	**-0.074**	**0.033**	-0.011	-0.013	na	**-0.089**	0.041	**0.054**	**0.005**	**0.061**	**-0.036**	**-0.107**	**-0.012**	**0.064**
>200m-300m	**0.039**	**0.266**	**0.095**	**0.108**	0.011	**0.083**	**0.117**	**0.052**	na	**0.115**	**0.111**	0.004	0.079	**0.114**	**-0.129**	**-0.057**	**0.095**	**0.065**
>300m-400m	-0.001	**0.209**	0.054	**0.054**	-0.061	**0.162**	0.039	-0.032	-0.005	**-0.052**	0.048	-0.029	**-0.124**	**0.119**	**-0.114**	**-0.113**	**0.124**	**-0.066**
>400m-500m	**0.022**	0.005	0.049	0.048	**-0.086**	**0.064**	0.053	-0.020	-0.041	**-0.109**	-0.025	0.014	**0.050**	**0.117**	**-0.126**	**-0.054**	**-0.069**	-0.033
>500m-600m	**0.030**	0.018	0.053	0.178	**0.151**	-0.017	**0.116**	0.036	0.075	**-0.107**	**0.059**	0.018	**0.087**	0.011	**-0.064**	**-0.061**	0.021	0.034
>600m-700m	**0.011**	-0.023	0.130	0.104	**-0.121**	-0.014	-0.066	-0.029	-0.075	-0.022	0.096	**0.048**	**0.114**	-0.029	**-0.060**	0.005	0.002	-0.015
>700m-800m	**0.019**	**0.165**	0.058	0.114	**0.265**	-0.091	0.163	0.023	0.032	-0.027	0.013	**0.064**	-0.015	**0.098**	-0.012	**-0.102**	0.061	0.047
Performance																		
R2	0.570	0.247	0.419	0.313	0.236	0.197	0.182	0.085	0.201	0.304	0.457	0.293	0.359	0.277	0.358	0.319	0.450	0.313
Error	0.232	0.168	0.171	0.181	0.226	0.225	0.234	0.255	0.156	0.188	0.187	0.173	0.182	0.210	0.252	0.319	0.197	0.199
F-ratio	2478.79	33.63	123.63	61.95	118.12	68.89	75.51	21.08	2.55	124.54	56.78	51.23	50.27	38.53	145.08	200.64	140.36	57.72
Cases	63,664	1,791	3,058	2,404	6,840	4,994	6,126	3,291	360	8,070	1,915	4,108	2,692	2,232	4,060	4,179	4,395	3,149
Rent/m2/year	$253.68	$162.20	$243.29	$165.34	$238.47	$242.32	$239.45	$227.26	$297.48	$222.02	$185.63	$244.94	$228.91	$197.10	$295.73	$517.66	$321.98	$192.44
Station Sign	Negative	Positive	Positive	Positive	Negative	Positive	Positive				Negative		Positive	Positive	Negative	Negative	Negative	Negative
Functional Form	Upward	Upward	Convex	Convex	Down	Upward	Upward			Upward	Upward		Down	Upward	Convex	Upward	Convex	Upward

Comments: See Exhibit 3 for abbreviation names. Bold coefficients are $p < 0.10$ (see text). Empty cells mean insufficient observations. By multiplying by 100, significant coefficients can be interpreted as higher or lower rents per square meter as a percentage of the mean. “Station Sign” refers only to significant coefficients that are either ***Positive***, meaning that rents are higher than the mean at the station, or ***Negativ***e, meaning rents are lower than the mean at the stations. “Functional Form” is the shape of association based on at least two significant coefficients among the closest four to the transit station where at least one is first or second closets distance bands. ***Upward*** means upward sloping significant coefficients revealing externality value exceeds accessibility value close to transit stations. ***Down*** means downward sloping significant coefficients from the first distance band revealing accessibility value exceeds externality value close to transit stations. ***Convex*** means upward sloping significant coefficients from the first station band to an inflection point after which significant coefficients are downward sloping revealing accessibility value exceeds externality value beyond the inflection point. ***Concave*** means downward sloping significant coefficients from the first station band to an inflection point after which significant coefficients are upward sloping revealing accessibility value exceeds externality values to the inflection point after which externality value exceeds accessibility value. Blank entries in station distance cells means there were insufficient cases. No functional form noted means there is an ambiguous, non-significant association between rent and transit station proximity revealed within the distance bands used for this determination as noted above.

Exhibit 20
Variation in Retail Rents Total Sample with Respect to LRT Station Proximity

LRT Variables	LRT Beta
Constant	**-1.212**
Structure Controls	
GLA (1000 m2)	**-0.000E+000**
Reg/Com Mall	**0.116**
Power Center	**0.202**
Lifestyle Center	**0.281**
Strip Retail	**-0.037**
Retail General	**0.053**
Effective Year Built	**0.002**
Vacancy Rate	**0.000**
Socioeconomic Control	
Med. HH Inc ($1000)	**2.862E-003**
Land-Use Control	
Land Use Mix	0.014
Centrality Controls	
CBD (m)	**-0.000E+000**
Freeway (m)	**-0.000E+000**
Metropolitan Controls	
Buffalo	-0.184
Charlotte	0.249
Cleveland	-0.156
Dallas	0.124
Denver	0.318
Houston	0.161
Minneapolis-St. Paul	0.056
Phoenix	0.070
Pittsburgh	-0.063
Portland	0.259
Sacramento	0.102
Salt Lake City	0.086
San Diego	0.539
San Jose	0.651
Seattle	0.432
St. Louis	-0.033

Exhibit 20
Variation in Retail Rents Total Sample with Respect to LRT Station Proximity—continued

LRT Variables	LRT Beta
Station Distance Band Treatment	
0-100m	**0.104**
>100m-200m	0.029
>200m-300m	**0.085**
>300m-400m	0.028
>400m-500m	0.010
>500m-600m	0.011
>600m-700m	0.021
>700m-800m	-0.007
Performance Metrics	
R^2	0.281
Standard Error	0.339
F-ratio	192.968
Cases	17,644
Mean Rent/m2/year	$226.72
Station Sign	*Positive*
Functional Form	*Downward*

Comments: "GLA" means gross leasable area; "Med. HH Inc." means median household income; "m" means meter while "m^2" means square meter; bold coefficients mean $p < 0.10$ for relevant variables (see text).

Exhibit 21
Retail Rent with Respect to LRT Transit Station Proximity

Variable	ALL	BUF	CHR	CLE	DAL	DEN	HOU	MSP	NOR	PHX	PIT	PDX	SAC	SLC	SD	SJ	SEA	STL
Station Distance																		
0-100m	**0.104**	-0.184	**0.325**	-0.118	0.315	0.137	**-0.374**	-0.092	0.235	-0.048		0.104	**0.484**	**0.310**	-0.126	**0.282**	0.343	
>100m-200m	0.029	-0.069	-0.037	0.154	0.159	**0.099**	-0.019	-0.067	0.410	0.089		0.084	**-0.170**	**0.542**	-0.151	0.193	-0.163	0.154
>200m-300m	**0.085**	**0.458**	**0.271**	-0.474	0.072	**0.057**	-0.222	-0.119	**-0.027**	-0.020	**2.021**	**0.266**	-0.156	**0.194**	**-0.258**	**0.512**	**0.259**	**0.490**
>300m-400m	0.028	**0.415**		-0.110	**0.245**	0.014	0.000	**0.374**	-0.237	0.105	**-0.445**	0.043	0.176	0.119	0.113	0.197	**-0.454**	0.004
>400m-500m	0.010		0.003	**-0.547**	**0.333**	0.022	-0.223	-0.170	**-0.034**	**-0.253**	-0.018	-0.049	-0.106	0.066	**-0.232**	0.153	0.161	**0.565**
>500m-600m	0.011		-0.077		0.109	-0.009	0.105	0.036		0.003		0.078	-0.017	**-0.231**	0.128	0.038	0.139	0.131
>600m-700m	0.021	0.597	-0.436	**0.673**	**-0.204**	0.013	-0.237		**0.058**	0.106		-0.108	0.033	-0.091	0.072	-0.254	0.205	0.104
>700m-800m	-0.007				**-0.419**	-0.004	-0.005	-0.185	-0.146	0.132	0.051	-0.010	0.248	-0.109	-0.109	-0.080	-0.107	0.301
Performance																		
R2	0.281	0.074	0.250	0.112	0.240	0.102	0.230	0.049	0.018	0.251	0.269	0.154	0.176	0.169	0.130	0.094	0.206	0.187
Error	0.339	0.382	0.372	0.363	0.379	0.266	0.457	0.503	0.316	0.369	0.388	0.386	0.311	0.388	0.429	0.468	0.404	0.397
F-ratio	192.968	1.656	5.975	3.068	20.628	59.813	16.443	1.817	1.045	21.916	6.952	3.083	4.322	4.360	4.423	2.477	6.550	6.141
Cases	17,644	140	269	295	1242	10347	1035	288	46	1249	260	230	312	331	459	285	430	426
Rent/m2/year	$224.65	$141.79	$234.31	$140.51	$187.20	$237.70	$205.62	$192.85	$169.48	$180.52	$167.29	$229.27	$182.45	$193.04	$292.73	$376.47	$270.53	$166.00
Station Sign	**Positive**		**Positive**				**Negative**						**Positive**			**Positive**		
Functional Form	**Down**		**Down**			**Down**							**Down**	**Convex**		**Upward**		

Comments: See Exhibit 3 for abbreviation names. Bold coefficients are $p < 0.10$ (see text). Empty cells mean insufficient observations By multiplying by 100, significant coefficients can be interpreted as higher or lower rents per square meter as a percentage of the mean. “Station Sign” refers only to significant coefficients that are either ***Positive***, meaning that rents are higher than the mean at the station, or ***Negativ***e, meaning rents are lower than the mean at the stations. “Functional Form” is the shape of association based on at least two significant coefficients among the closest four to the transit station where at least one is first or second closets distance bands. ***Upward*** means upward sloping significant coefficients revealing externality value exceeds accessibility value close to transit stations. ***Down*** means downward sloping significant coefficients from the first distance band revealing accessibility value exceeds externality value close to transit stations. ***Convex*** means upward sloping significant coefficients from the first station band to an inflection point after which significant coefficients are downward sloping revealing accessibility value exceeds externality value beyond the inflection point. ***Concave*** means downward sloping significant coefficients from the first station band to an inflection point after which significant coefficients are upward sloping revealing accessibility value exceeds externality values to the inflection point after which externality value exceeds accessibility value. Blank entries in station distance cells means there were insufficient cases. No functional form noted means there is an ambiguous, non-significant association between rent and transit station proximity revealed within the distance bands used for this determination as noted above.

Exhibit 22
Variation in Multifamily Rents Total Sample with Respect to LRT Station Proximity

LRT Variables	LRT Beta
Constant	**-3.850**
Structure Controls	
GLA (1000 m2)	**0.000E+000**
Stories	**0.026**
Average Unit Size	**-0.001**
Subsidized	**-0.101**
Restricted	**-0.223**
Effective Year Built	**2.000E-003**
Vacancy Rate	**0.004**
Socioeconomic Control	
Med. HH Inc ($1000)	**3.104E-003**
Land-Use Control	
Land Use Mix	**0.083**
Centrality Controls	
CBD (m)	**-0.000E+000**
Freeway (m)	**-0.000E+000**
Metropolitan Controls	
Buffalo	0.032
Charlotte	-0.094
Cleveland	-0.134
Dallas	0.059
Denver	0.256
Houston	-0.048
Minneapolis-St. Paul	0.111
Phoenix	-0.077
Pittsburgh	-0.006
Portland	0.170
Sacramento	0.119
Salt Lake City	-0.016
San Diego	0.444
San Jose	0.628
Seattle	0.378
St. Louis	-0.136

Exhibit 22
Variation in Multifamily Rents Total Sample with Respect to LRT Station Proximity—continued

LRT Variables	LRT Beta
Station Distance Band Treatment	
0-100m	0.025
>100m-200m	**0.043**
>200m-300m	**0.055**
>300m-400m	**0.049**
>400m-500m	**0.021**
>500m-600m	**0.026**
>600m-700m	**0.056**
>700m-800m	**0.026**
Performance Metrics	
R^2	0.593
Standard Error	0.252
F-ratio	1178.518
Cases	28,380
Mean Rent m2/year	$186.44
Station Sign	*Ambiguous*
Functional Form	*Convex*

Comments: "GLA" means gross leasable area; "Med. HH Inc." means median household income; "m" means meter while "m^2" means square meter; bold coefficients mean $p < 0.10$ for relevant variables (see text).

Exhibit 23
Multifamily Rent with Respect to LRT Transit Station Proximity

Variable	ALL	BUF	CHR	CLE	DAL	DEN	HOU	MSP	NOR	PHX	PIT	PDX	SAC	SLC	SD	SJ	SEA	STL
Station Distance																		
0-100m	0.025	0.094	**0.302**	0.044	**-0.038**	-0.021	**0.123**	0.005	-0.061	0.035	**-0.241**	**-0.030**	-0.112	**0.121**	0.104	-0.056	0.056	-0.107
>100m-200m	**0.043**	-0.070	**0.229**	**0.129**	0.004	0.069	**-0.039**	0.071	**0.172**	-0.018	**-0.311**	-0.019	**0.184**	0.095	**0.133**	0.022	0.030	-0.010
>200m-300m	**0.055**	**0.284**	**0.220**	**0.092**	-0.029	-0.035	0.200	**-0.023**	**0.274**	**0.113**	**-0.156**	-0.013	**0.072**	**0.114**	**0.114**	0.036	0.104	-0.013
>300m-400m	**0.049**	**0.173**	**0.165**	**0.150**	-0.013	0.039	**0.124**	-0.065	**0.295**	**0.049**	**-0.262**	0.031	0.003	**0.054**	**0.056**	0.009	**0.060**	**0.098**
>400m-500m	**0.021**	**0.142**	0.096	0.029	**-0.058**	-0.004	**0.174**	0.022		**0.111**	**-0.216**	0.025	0.005	-0.033	0.018	-0.022	0.025	**-0.102**
>500m-600m	**0.026**	**0.220**	0.074	0.060	0.010	**-0.069**	**0.081**	**-0.052**	0.174	**0.088**	-0.065	**0.067**	0.021	**0.075**	-0.007	**-0.131**	**0.075**	0.045
>600m-700m	**0.056**	0.078	0.081	0.072	0.001	-0.022	**0.175**	0.033	**0.373**	0.033	0.074	**0.049**	**0.067**	0.054	-0.001	0.002	**0.153**	0.021
>700m-800m	**0.026**	0.130	0.019	**0.112**	0.027	0.015	0.060	0.009	0.105	0.025	-0.078	0.008	0.019	0.059	0.021	-0.135	0.038	0.064
Performance																		
R2	0.593	0.330	0.552	0.300	0.427	0.392	0.512	0.346	0.495	0.402	0.357	0.529	0.351	0.396	0.350	0.319	0.507	0.337
Error	0.252	0.257	0.212	0.252	0.202	0.241	0.194	0.213	0.201	0.203	0.278	0.246	0.220	0.209	0.259	0.311	0.267	0.259
F-ratio	1178.518	9.138	40.632	21.274	132.586	81.152	128.868	62.138	13.066	87.807	24.489	119.052	36.130	16.902	100.761	44.911	161.003	23.007
Cases	28,380	315	613	900	3368	2359	2321	2200	223	2453	806	1995	1237	461	3515	1778	2955	824
Rent/m2/year	$186.44	$153.38	$139.66	$130.10	$154.33	$203.47	$144.69	$167.14	$147.37	$133.91	$160.38	$184.26	$162.01	$146.37	$228.16	$313.79	$247.99	$131.02
Station Sign			**Positive**		**Negative**		**Positive**				**Negative**	**Negative**		**Positive**				
Functional Form	**Convex**		**Down**	**Concave**			**Down**		**Upward**		**Convex**		**Down**	**Down**	**Down**			

Comments: See Exhibit 3 for abbreviation names. Bold coefficients are $p < 0.10$ (see text). Empty cells mean insufficient observations. By multiplying by 100, significant coefficients can be interpreted as higher or lower rents per square meter as a percentage of the mean. "Station Sign" refers only to significant coefficients that are either ***Positive***, meaning that rents are higher than the mean at the station, or ***Negativ***e, meaning rents are lower than the mean at the stations. "Functional Form" is the shape of association based on at least two significant coefficients among the closest four to the transit station where at least one is first or second closets distance bands. ***Upward*** means upward sloping significant coefficients revealing externality value exceeds accessibility value close to transit stations. ***Down*** means downward sloping significant coefficients from the first distance band revealing accessibility value exceeds externality value close to transit stations. ***Convex*** means upward sloping significant coefficients from the first station band to an inflection point after which significant coefficients are downward sloping revealing accessibility value exceeds externality value beyond the inflection point. ***Concave*** means downward sloping significant coefficients from the first station band to an inflection point after which significant coefficients are upward sloping revealing accessibility value exceeds externality values to the inflection point after which externality value exceeds accessibility value. Blank entries in station distance cells means there were insufficient cases. No functional form noted means there is an ambiguous, non-significant association between rent and transit station proximity revealed within the distance bands used for this determination as noted above. "NA" means there are no cases in the distance band.

Summary of Findings with Implications for Post-Pandemic LRT Planning and Development

This concluding section summarizes key findings and offers approaches to meeting the market demand for living near transit stations while also addressing potential gentrification concerns. Concluding observations for post-pandemic LRT planning and development are also offered.

Key Findings

Overarching findings of this research are provided with respect to LRT station proximity and jobs, people and households, commuting mode, and real estate rental premiums.

Jobs

The change in jobs during the study period (2010 and 2019) was measured with respect to cumulative distance bands from LRT stations to 200 meters—called the "station band", then to 400 meters cumulatively, and finally to 800 meters cumulatively. All bands comprise the "station area." Despite the 800-meter transit station areas occupying less than one percent of their LRT counties' urbanized land area, these LRT station areas added 990,000 jobs and accounted for 17 percent of the job growth in their respective counties.

Nearly all station bands added jobs in all economic groups. The strongest group gaining the most jobs was the office economic group, but this was before the pandemic. Future research should address the extent to which offices were more, or less, resilient during and after the pandemic as compared to other economic groups. Surprising strength was seen in the industrial economic group. The weakest was the health economic group perhaps because it is more dependent on large areas of land that would seem to be expensive near transit stations. As the only economic group with SQs >1.0 overall and for most of the individual LRT systems, arts-entertainment-recreation was the strongest in terms of attracting more than its proportionate share of LRT county jobs but the overall job gains are small, second only to health.

However, despite the impressive outcomes noted above, most distance bands for most economic groups lost share of jobs relative to their transit regions. One reason may be that people and households are pushing jobs outward.

People and Households

This article explored the change in demographic composition with respect to LRT station bands and station areas in terms of population generally as well as among Whites and non-Whites, households by type and age, household income, and housing tenure (own or rent).

Overall and for most LRT systems, station area SQs were >1.0 for population and households, meaning that they attracted proportionately more than their respective counties. In contrast. SQs for jobs in most and sometimes all economic groups were <1.0, implying that people and households are displacing jobs though at a small rate.

During the study period, non-Whites dominated the change in population and many lost White residents. However, LRT station areas gained the largest share of the population among Whites and non-Whites overall. Despite accounting for 87 percent of LRT county growth, non-Whites accounted for 65 percent of the growth in station areas. Indeed, in many individual systems, Whites added to LRT station areas accounted for all LRT county growth, mathematically, while non-Whites lost population in several LRT station areas. This White/non-White disparity is an indicator of gentrification for several LRT systems,

Consistent with population change, households overall as well as by type grew at a faster pace within the LRT station areas as compared to their counties. Notably, LRT station areas attracted proportionately more households with children in closer-in station bands for all systems overall and with respect to many individual counties. They also gained proportionately more single-person households and >1 adult households without children overall and with respect to all LRT counties. This is a further indicator that households may be displacing jobs in LRT station areas. Or perhaps the jobs-worker balance is improving, although more research is needed to establish this.

A key indicator of gentrification is the extent to which the change in households is dominated by younger householders. The study period, however, saw declining numbers of households under 25 years of age among LRT counties overall and for many of them individually. This is a function of changing demographics. Nonetheless, all but three LRT station areas gained share of such householders relative to their counties. Indeed, in some cases, LRT station areas accounted for all the change in these householders countywide. Moreover, LRT station areas overall added higher shares of growth among householders between 25 and 44, 45 and 64, and 65 and over years of age, which was also the case for nearly all individual LRT systems.

Importantly, household incomes rose faster overall in LRT station areas than in their counties. Analysis also shows that with few exceptions, LRT station area household income increased compared to their counties. This gentrification indicator is consistent with Qi (2023) for light rail systems.

Change in housing tenure is another gentrification indicator. Overall, rental housing tenure accounted for 30 percent of the share of the change in rental homes during the study period, compared to 11 percent among owner-occupied homes. Both forms of tenure, however, had SQs >1.0 for nearly all LRT systems, meaning that LRT stations areas gained proportionately more owners and renters than their respective counties during the study period.

The evidence reveals that gentrification affects 11 of the 17 systems strongly with another two systems experiencing moderate levels of gentrification. Approaches to managing gentrification are offered later.

Commuting Mode Choice and Transportation Costs

Analysis shows that commuting via transit and walking or biking with respect to LRT station areas increased at a faster pace than for LRT counties as a whole as well as for nearly all individual systems. However, between the Great Recession and the pandemic, the share of workers working from home increased more rapidly in LRT counties (14 percent) than in LRT station areas. Updated research is needed to determine whether this trend continued after the pandemic. On the other hand, commuting via modes other than the automobile increased at far faster rates within LRT station areas than their respective counties.

Analysis also showed that household vehicle kilometers traveled and transportation costs increased as distance from LRT stations increased, across all household types.

Real Estate Markets

The final analysis presented evaluates the association between office, retail, and multifamily rents with respect to LRT station proximity. This is the largest and most comprehensive analysis reported in the literature.

The association between commercial rents and proximity to LRT stations is mixed and mostly negative or ambiguous where there is no statistically significant outcome. Office rents reveal more robust associations with respect to LRT station proximity than retail or multifamily rents. However, analysis of most individual systems also revealed downward sloping rent gradients at and near LRT stations, indicating the presence of externality value that offsets accessibility value. Post-pandemic analysis is needed to test whether and the extent to which office real estate continues to value proximity to LRT stations.

The outcomes with respect to multifamily real estate proximity to LRT stations are very disappointing. Disappointment also extends to retail real estate, though less so. Overall, these results call into question the efficacy of LRT station planning, location, and design to achieve desired results in the multifamily and retail real estate markets. Nonetheless, there are several exemplars among individual systems to warrant their use as models for other systems to emulate. Moreover, given the shift in office workplace dynamics after the pandemic, policymakers and planners may need to shift priorities to make transit more attractive to retail and multifamily real estate investment. This is discussed in more detail next.

The article concludes with observations moving forward in a post-pandemic world.

Concluding Observations for Post-Pandemic Transit Policy and Planning

The COVID-19 pandemic changed everything, or so it seems, especially the role of LRT systems. For the most part, LRT systems are primarily designed to facilitate downtown mobility, as opposed to connecting residents and visitors between downtown and outlying areas. LRTs are thus more dependent on the vitality of downtowns than other transit systems that serve other nodes. Future research is needed to determine the extent to which downtowns recover after the pandemic, and how variations in recovery affect LRT use.

In terms of downtown recovery after the pandemic, Forouhar et al. (2024) offer the following insights based on analysis of 66 US downtowns:

- Between 2019, before the pandemic, into 2023, after the pandemic, downtown recovery rates varied from an average of about 76 percent to a low of 53 percent (St. Louis) and a high of 95 percent (San Jose).

- Southern and medium-sized city downtowns experienced the strongest recoveries, while northern and larger city downtowns were challenged in regaining visitors.

- Downtowns dominated by sectors conducive to remote work had slower recovery rates while downtowns dominated by sectors that require physical presence experienced greater resilience and faster recovery rates.

- Higher population density, crime rates, and education levels were also associated with slower recovery, as were harsh weather conditions and longer commute times. On the other hand, lower-density and auto-oriented downtowns usually surpassed pre-pandemic downtown activity levels.

This does not mean to imply that all downtown transit systems suffered equally as shown in Exhibit it 24. (Buffalo and Norfolk were not included in the Forouhar et al. study.) In this exhibit, about 40 percent (6 of 15) of all LRT downtowns did as well or better than the overall average recovery percent (including Charlotte at 75 percent compared to the overall average of 76 percent).

The research reported in this article suggests that in a post-pandemic world, reliance on offices served by such transit systems as LRT needs to be rethought. Consider findings by Nelson and Hibberd (2024) in *Cityscape* showing that more than half of American households want to live in walkable communities that include mobility options. Yet, only about 13 percent live in such communities (Koschinsky and Talen 2015). By one reckoning, if all new homes built were in walkable communities it would take 35 years just to meet current demand, let alone future demand. Perhaps the time has come to recast LRT systems to serve people primarily. But how? After all, analysis shows no or even negative associations between LRT station proximity and multifamily rents. A call is made to planners and urban designers to find ways to make LRT proximity valuable in the market.

Exhibit 24
Rank-Ordered Pandemic Recovery Rates of LRT Downtowns, 2019-2023
Downtowns with Minimum 75% Recover in Italics

LRT System	Recovery
San Jose	*95%*
Phoenix	*89%*
Salt Lake City	*82%*
San Diego	*80%*
Cleveland	*78%*
Charlotte	*75%*
Dallas	70%
Denver	67%
Pittsburgh	66%
Sacramento	66%
Houston	64%
Portland	61%
Seattle	57%
Minneapolis-St. Paul	56%
St. Louis	53%

Note: Buffalo and Norfolk not included in the analysis.
Source: Adapted from Forouhar et al. (2024).

A Note on Gentrification

As gentrification is prevalent in nearly all LRT station areas, the following outlines strategies to ameliorate adverse outcomes.

First, consider that existing residents and new, lower-income ones benefit from the cost-of-living advantages of living along LRT corridors.[21] These advantages include transportation cost savings and lower housing costs, at least until market demand exceeds supply and pushes housing costs up. The principal danger of gentrification is that existing lower-income households would be pushed out of their homes and replaced by higher-income households. This circumstance can occur if existing housing stock is bought by investors and repurposed for higher-income households or demolished altogether and replaced with more expensive housing.

Second, lower-income residents provide much of the ridership that transit needs to be financially feasible. Typically, as household income increases, the use of public transit falls. Research is needed to determine the extent to which new residents in LRT station areas use transit compared with existing residents with respect to income.

LRTs raise housing supply concerns among lower- and moderate-income households. Expanding housing supply for these market segments may be challenging, but it is important to consider options such as:

- Instituting inclusionary zoning policies such that new residential development would be required to add housing that is dedicated to lower-income households.[22]

- Encouraging housing agencies to give additional weight to applications for Low-Income Housing Tax Credits (LIHTC) [23] that are located along LRT routes and in LRT station areas.[24] Locating near LRT stations would increase the odds of gaining approval.

- Expanding local public, private, nonprofit, and philanthropic lower-income housing efforts near LRT stations.

- Leveraging Community Reinvestment Act (CRA) resources to expand housing supply near LRT stations. The CRA requires federally chartered financial institutions to use a portion of their revenue to improve local communities.[25] These institutions could be made

[21] Several perspectives of Boarnet et al. (2017) are applied here.
[22] For a review if inclusionary housing generally and a suite of effective examples, see https://www.lincolninst.edu/sites/default/files/pubfiles/inclusionary-housing-full_0.pdf.
[23] This approval would be done through a rule-making process linking what would be considered a qualifying Complete Street for HUD purposes with the LIHTC program, which is managed by the U.S. Department of the Treasury.
[24] For details about how LIHTCs work, see https://www.huduser.gov/portal/datasets/lihtc.html. Generally, each state receives an annual tax credit allotment. These allotments are used to leverage other private and nonprofit funds to build affordable housing. Because tax credits are in demand, many housing agencies cannot fund all proposals. Indeed, some states give additional or preferential points to projects located near transit stations. The same concept can be adapted to Complete Streets.
[25] See https://www.federalreserve.gov/consumerscommunities/cra_about.htm.

aware of LRT benefits to target populations, allowing them to leverage other funds to expand the housing supply.

- Adjusting local fee structures to reflect cost savings associated with LRT development. For instance, transportation impact fees[26] are among the highest of all impact fees where they are assessed. They are often based on regional highway needs serving distant suburban communities. However, closer-in areas already have the transportation capacity needed to serve new development, or new development's impact on transportation facilities is reduced because of such multimodal facilities as LRT station areas. Impact fees should be adjusted accordingly. Likewise, more compact developments, such as those found along LRT routes, do not have the same water and wastewater impact as lower-density development, meaning that those impact fees can be reduced.

Demand-side approaches are also an option, principally increasing the income of target households living near LRT stations, thereby enabling them to afford to live there. These approaches include but are not limited to the following:

- Creating rental housing subsidies in which participating landlords receive supplemental income from the local community for renting to qualifying households near LRT stations.

- Exempting qualifying housing from property taxes. Under certain conditions, nonprofit housing providers in some states are exempt from local property taxes. Inasmuch as property taxes are often the single largest budget item for rental housing, exemptions enable local housing agencies to serve more households. The reduced rent effectively increases tenant income.

- Considering applications of the basic income concept.[27] Conceptually, qualifying households receive a supplement to their incomes, without strings attached, to be used as they wish. The concept is not broadly used but is gaining support among local governments and, in one case, the state of California.[28] For instance, Cambridge, Massachusetts, pays qualifying households $500 per month.[29] Its program is applied citywide. A version of this concept could be applied to targeted LRT station areas, perhaps financed in part from new taxes generated by LRT routes.

No one approach will be appropriate for all situations, and some situations will likely require new approaches. Where gentrification may be a concern, perhaps programs can be created in advance so that potential adverse outcomes can be addressed before they become a crisis.

[26] For a review of impact fee theory, practice, law, and applications, see Nelson et al., 2023.
[27] See https://basicincome.stanford.edu/about/what-is-ubi/.
[28] See https://www.cdss.ca.gov/inforesources/guaranteed-basic-income-projects.
[29] See https://www.cambridgema.gov/riseup.

People and Households are Poised to Dominate the Future of LRT Station Areas

In review, accounting for less than one percent of the urbanized land area of counties in which LRTs are located, LRTs accounted for nearly one million new jobs among the 17 LRT systems studied, between the Great Recession of 2007-2009 and 2019, but before the COVID-19 pandemic. Yet, LRT station areas lost share of total job growth compared to their counties. On the other hand, LRT station areas added proportionately more people and households than their respective counites. Indeed, overall and for many counties, LRT station areas added proportionately more households with children. In addition, LRT station areas added proportionately more householders in all age groups than their respective counties. The evidence suggests that before the pandemic, people and households were beginning to displace jobs and this trend may accelerate in the post-pandemic era. LRT station areas also added proportionately more owner- and renter-occupied housing units than their respective counties. However, based on household incomes rising faster in LRT station areas than in their respective counties, along with other factors, gentrification is evident in up to 13 of the 17 LRT systems studied, with the rest poised for the same trend. Finally, overall, more than a quarter (28 percent) of all new workers living in LRT station areas commute to work via modes other than the automobile, compared to about a fifth (21 percent) for the rest of their respective counties. The evidence suggests that post-pandemic planning and policy must facilitate the demand for people and households to live in LRT station areas.

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