Transit Accessibility and Residential Segregation

by

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Submitted to the Graduate Faculty of

the Dietrich School of Arts and Sciences in partial fulfillment

of the requirements for the degree of

Doctor of Philosophy

University of Pittsburgh

2021

UNIVERSITY OF PITTSBURGH

DIETRICH SCHOOL OF ARTS AND SCIENCES

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University of Pittsburgh, 2021

Residential segregation by income and race is a salient feature of most US cities. An important determinant of residential location choice is access to desirable urban amenities via affordable travel modes. The first chapter of the dissertation studies residential and travel mode choices of commuters in US cities to estimate the heteregenous demand for access to neighborhoods offering faster commutes and to characterize what that means for how the gains from mass transit improvements are distributed among rich and poor commuters. I show that cities where transit improvements would be most effective at generating new transit ridership and overall welfare gains are ones where the gains accrue more to higher income commuters.

Within cities, who gentrify transit-accessible neighborhoods and ride mass transit depends on the type (e.g. bus versus rail) and location of the transit improvements. The second chapter of this dissertation models household choices of where to live and how to travel in a stylized city with a competitive housing market. I characterize when and where marginal improvements in transit access reduce residential segregation by income instead of exacerbating it, and I show that an urban planners trying to maximize transit ridership is often incentivized to expand the transit network where it increases income segregation.

Residential segregation has important implications for inequality. The third chapter of the dissertation studies how racially segregated housing markets have historically exacerbated racial inequality in US cities. The Great Migration of black families from the rural South to northern cities in the 1930s saw a growing number of segregated city blocks transition racially. Over a single decade, while rental prices soared on city blocks that transitioned from all white to majority black and pioneering black families paid large premiums to buy homes on majority white blocks, such homes quickly lost value on blocks that transitioned from majority white to majority black. These findings suggest that segregated housing markets eroded much of the gains for black families moving out of ghettos.

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Preface

The most important ingredient was not my own faith in my ability to pull off this dissertation, but the unshakeable faith of my advisors. I spent years testing it, and here is something to show for it.

1.0 Introduction

Residential segregation by income and race is a salient feature of most US cities. An important determinant of residential location choice is access to desirable urban amenities via affordable travel modes. And access to such desirable residential neighborhoods are dictated by competitive housing markets. This dissertation explores the relationships between public transit accessibility, housing markets, and residential segregation in US cities over three chapters.

The first chapter studies residential sorting by income among commuters in US cities to learn about the heterogeneous gains from access to faster public transit commutes. Lower income commuters are more likely to ride and reside near public transit within cities, but do they also benefit more from faster transit travel? Combining survey data on travel behavior with web-scraped data on counterfactual travel times for millions of trips across 49 large US cities, I estimate a structural model of travel mode and residential location choice. I characterize the heterogeneity across income and groups and cities in commuters' willingness to pay for access to faster transit and the expected increase in transit ridership in response to marginal transit improvements. I find that richer transit riders sort more aggressively into the fastest transit routes and are, on average, willing to pay more for faster commutes. Improvements in transit speed are most effective at generating transit ridership and welfare gains where transit is already fast (relative to driving), in cities with a greater share of rail-based transit and where the gains are larger for high-income commuters. Transit improvements benefit low-income commuters more where transit is relatively slow, in cities with more bus transit, and where the overall marginal gains are small. So, the most effective transit improvements are unlikely to be equitable.

While the first chapter of the dissertation looks at segregation to learn about preferences for access to faster transit, the second chapter turns the question around: what are the implications of mass transit improvements for residential income segregation within cities? I model a stylized city where heterogeneous households choose where to live and how to travel given a spatial distribution of travel times and a competitive housing market. I characterize when and where marginal improvements in transit access reduce income segregation isntead of exacerbating it. I show that a planner trying to maximize the city's transit ridership is incentivized to improve low-speed transit (e.g. buses on shared lanes) where it reduces income segregation but improve high-speed transit (e.g. subways) where it increases income segregation. These results are consistent with recent changes in transit ridership and neighborhood incomes in US cities.

Residential segregation has important implications for inequality. The third chapter of the dissertation is a joint work that studies how racially segregated housing markets have historically exacerbated racial inequality in US cities. Housing is the most important asset for the vast majority of American households and a key driver of racial disparities in wealth. This chapter studies how residential segregation by race eroded black wealth in prewar urban areas. Using a novel sample of temporally matched addresses from prewar American cities, we find that over a single decade rental prices soared by roughly 50 percent on city blocks that transitioned from all white to majority black. Meanwhile, pioneering black families paid a 28 percent premium to buy a home on a majority white block. Yet, such homes sold at a -10 percent discount on blocks that had transitioned from majority white to majority black. These findings strongly suggest that segregated housing markets cost black families much of the gains associated with migrating to the North.

2.0 Who Benefits from Faster Public Transit?

2.1 Introduction

In a rapidly urbanizing world, governments and financial institutions are investing large sums on high-speed inner-city mass transit infrastructure in order to tackle growing road congestion and to reduce carbon emissions.[1] Faster public transit networks are expected to increase transit ridership and reduce the number of vehicles on the road. They are also widely believed to reduce inequality by disproportionately improving mobility and labor market access for the urban poor (Kalachek, 1968). How effective are improvements in travel speed at increasing transit ridership? How are the ridership and welfare gains from faster transit travel distributed across rich and poor commuters? And are the more effective transit improvements also more equitable?

To answer these questions, I develop a discrete choice model of residential location and travel mode choices within cities that reflect heterogenous preferences over travel times by high and low income commuters. To estimate the model, I combine census data on commuting flows and mode choices within US cities with rich web-scraped travel time and route data for millions of counterfactual commuting choices in order to derive the demand for access to faster transit and driving commutes. To the best of my knowledge, this paper is the first to investigate how the demand for faster travel by transit (relative to driving) varies across cities, across commuting routes within cities, and by commuter income. In doing so, I show that improvements in transit speed are most effective at generating overall welfare and transit ridership gains where they benefit higher income commuters relatively more. So, the most effective transit improvements (and the ones likely to be realized) are unlikely to be equitable!

[1]For instance, China spent USD 100 billion on rail transit infrastructure in 2017 (OECD, 2019) and opened over 45 subway lines across 25 cities just between August 2016 and December 2017. Hannon et al. [2020] estimates cities and transit providers to undertake at least USD 1.4 trillion in new mass transit infrastructure investments by 2025. Over USD 100 billion of it will be committed to mass transit in North America.

My main findings are as follows. First, I find large differences across cities in commuters' demand for faster public transit commutes. In particular, the marginal willingness to pay (MWTP) for faster transit is significantly higher in cities where transit is already fast (relative to driving) or where a large share of transit usage is via rail transit. For example, the mean MWTP for a one percent increase in commuting speeds among transit riders ranges from \$374 per year in San Francisco CA (and a value of travel time saving of around \$19 per hour) to just \$9 per year in Las Vegas NV.[2] These differences have important implications for the effectiveness of transit improvements at attracting new transit riders. For instance, a one percent increase in transit speeds throughout San Francisco increases transit ridership by roughly 3.5 percentage points (over 20 percent of baseline transit ridership). In contrast, a one percent increase in transit speeds in Las Vegas increases transit ridership by only 0.2 percentage points (or 6 percent). These city-level patterns mask even larger variation by the location of transit improvements *within* cities. Most notably, the demand for faster transit is significantly higher along commuting routes where transit is already fast relative to driving (such as along rail routes or congested driving routes).

Second, I find that higher income commuters tend to have a higher willingness to pay for faster travel conditional on travel mode choice. Transit improvements attract and benefit lower income commuters more where transit is already slow (relative to driving), as it typically is in most US cities. But transit improvements attract and benefit higher income commuters more where transit is relatively fast. For instance, in New York (the city with the fastest transit speeds in my sample), commuters with annual incomes greater than \$75,000 are 67% more likely to switch to riding transit than commuters with incomes less than \$35,000. In contrast, in Los Angeles (where the transit network is relatively sparse and primarily bus-based), commuters with incomes greater than \$75,000 are only half as likely to switch to transit than commuters with incomes less than \$35,000. Within cities, the income elasticity of demand for faster transit is positive and higher along commuting routes where transit is relatively fast. Together with my first set of results, they imply that the transit improvements most effective at increasing overall welfare and transit ridership are those that

[2]Differences across cities in incomes and housing costs play an important role. However, for comparison, the MWTP for a one percent increase in commuting speeds for drivers is \$302 in San Francisco CA (lower than the MWTP of transit riders) and \$17 in Las Vegas NV (much higher than the MWTP of transit riders).

benefit and attract higher income commuters relatively more (such as in cities and along popular commuting routes where transit is already fast and driving is slow). This result calls into question the extent to which public transit improvements can be both efficient and equitable.

Additionally, this paper makes two distinct methodological innovations. The first is a data innovation. While we know anecdotally that travel on public transit is typically slower than on privately-owned vehicles, we have limited understanding of how much faster public transit trips would be on private vehicles (and vice versa) and how they compare across cities and across different parts of the same city. Much of our formal knowledge of travel times to date originates from household travel surveys. But surveys only impart partial information on selected trips which are not directly comparable across mode choices.[3] This paper innovates by leveraging a newly emerging source of big data, Google Maps, to predict travel times on both observed and counterfactual trips by each travel mode between the same sets of origin-destination pairs at the same time of day.[4] The rich variation in travel times across millions of simulated trips allows me to systematically compare transit and driving travel speeds both across and within US cities (and across high- and low-income commutes within cities).

The paper's second methodological innovation is developing an empirical framework to evaluate the demand for counterfactual transit improvements based off of aggregate cross-sectional data on commuting behavior. To do so, I build on the discrete choice framework developed by McFadden [1978] and extended by Bayer et al. [2004] and Bayer et al. [2007] to recover household preferences for location attributes in the presence of sorting on unobservables. Income sorting into travel modes and neighborhoods necessarily induces correlations between location attributes endogenous to incomes and other unobservable (and observable) location attributes.[5] My empirical framework gets around such endogeneity concerns by allowing choices to condition on unobservable attributes of travel modes and

[3]Self-reported travel times are also subject to recall bias, anchoring and related measurement concerns.

[4]Google Maps exploits historical and real-time data from tracking the movement of smartphones combined with information on transit schedules to predict travel times that have been shown to credibly capture variation in travel times from real driving trips (Akbar et al., 2018).

[5]For instance, higher-income neighborhoods may be higher-quality or have higher travel speeds because of better-funded local amenities and infrastructure.

residential neighborhoods. In addition, my paper extends on this class of residential sorting models by conditioning out mean preferences across income groups over the unobservable attributes of travel modes (thus essentially controlling for the income sorting). Then, preferences over commuting speeds are identified from the residual variation in individual workers' commutes to their given work locations within the city.

Identifying preferences off of net variation in commuting speeds instead of proximity to transit (as is common among studies of inner-city transit) makes a big difference to the estimated distributional gains from faster transit: because while poorer commuters tend to reside closer to transit stops in typically high-density neighborhoods, I show that richer commuters are the ones who enjoy the fastest transit commutes within cities. Who benefits more from improvements in transit speed (and how much) depends on how fast transit is (already) relative to driving.

My investigation has important implications for three broad groups of literature. First, the paper's findings help us better understand public transit's role in neighborhood gentrification and inequality. Because poorer commuters have been shown to be more likely to ride transit and reside near new transit stops (Baum-Snow and Kahn, 2000, 2005, Pathak et al., 2017), public transportation in the US is frequently portrayed as an inferior good and a poverty magnet (Glaeser et al., 2008). This paper shows that transit is indeed more likely to attract poorer commuters where it is slow relative to driving (as it is on most commutes). But as we make transit faster, it becomes relatively more attractive to the rich (and a normal good). This result is consistent with recent individual case studies of high-speed transit expansions, which often find incomes to have gone up in newly transit accessible neighborhoods (Heilmann, 2018) and richer commuters to have benefited just as much or more (Tsivanidis, 2019). It may be that realized high-speed transit expansions often attract the rich more because planners are focusing on efficiency rather than equity (as suggested by my results), and transit expansions that are more attractive to the poor would also be less effective overall (as in Gaduh et al., 2020).

Second, this paper informs us of the value of travel time savings on public transit. Papers comparing the effect of different public transit expansions have overwhelmingly focused on proximity to transit stations or distance along transit routes assuming anecdotal or constant speeds (Kahn, 2007, Glaeser et al., 2008, Gu et al., 2019, Pathak et al., 2017 to name a few). In contrast, my data allows me to directly estimate preferences for faster transit commute (instead of proximity to transit). There is a large literature on measuring people's opportunity cost of time spent traveling and using it to inform transportation policies at the intensive margin, such as for congestion pricing (Small, 2012, Bucholz et al., 2020, Goldszmidt et al., 2020). While the value of travel time savings (VTTS) has been extensively studied based on driving trips, this paper tells us about the VTTS on public transit and how it compares to driving across income brackets and across cities with different transit networks. The distinction proves important because I estimate VTTS among mass transit riders that are, on average, half the VTTS among drivers.[6]

Third, this paper contributes to the literature quantifying the gains from investing in inner-city mass transit infrastructure. A growing number of case studies of individual mass transit expansions investigate transit's general equilibrium effects on the spatial distribution of economic activity within cities (Heblich et al., 2018, Severen, 2019, Tsivanidis, 2019, Warnes, 2020). In order to precisely estimate the heterogeneity in preferences for faster transit commutes, I deviate from these quantitative spatial models by foregoing much of the restrictions on preferences imposed by their model structure. Instead, I use a more flexible utility specification that allows me to more precisely identify the heterogeneity in preferences across income groups and across space.[7] Understanding this heterogeneity is key to be able to generalize case studies to inform policy making. For instance, how informative are model predictions for one city about potential transit improvements in another? I show that the demand for faster commutes varies widely but systematically across cities and across locations within cities.

This paper focuses only on the direct travel time gains from mass transit improvements, which Tsivanidis [2019] found to have accounted for 60-80% of the total welfare gains in general equilibrium from expanding Bus Rapid Transit in Bogotá. There are also studies that explore mass transit's implications for population decentralization (Gonzalez-Navarro

[6]Craig [2019] also uses residential location and travel mode choices to estimate the value of commuting time in Vancouver, but their model does not distinguish the value of time by each mode of travel. Also, their variation in travel time is based on reported transit schedules and survey-reported driving times.

[7]In doing so, I also forego the ability (of these models) to simulate mass transit's longer term implications for urban residents beyond the immediate gains from faster travel.

and Turner, 2018, Lin, 2017), income segregation (Akbar, 2020), congestion (Anderson, 2014, Gu et al., 2019), car ownership (Mulalic et al., 2020), air pollution (Gendron-Carrier et al., 2020), property values (Bowes and Ihlanfeldt, 2001, Cervero and Kang, 2011, Gupta et al., 2020), labor market informality (Zárate, 2020), gender inequality (Kwon, 2020, Kondylis et al., 2020) and long-term growth of cities (Heblich et al., 2018) among other things.

The rest of this paper is organized as follows. Section 2.2 describes the available data on observed commutes and the data estimation process for counterfactual commutes. Section 2.3 documents differences in transit ridership and transit travel times relative to driving both across cities and within cities. It also documents differences across income groups in their access to high-speed transit and driving commuting routes. Section 2.4 presents a model of travel mode and residential location choices within cities and an estimation strategy to identify the demand for faster transit commutes. Section 2.5 presents the estimated preferences in terms of commuters' willingness to pay for faster travel and characterizes the heterogeneous gains in transit ridership and welfare from marginal improvements in transit speeds across cities. Section 2.6 concludes.

2.2 Data

This paper studies the residential neighborhood and travel mode choices of commuters in the 2006-10 American Community Survey (ACS). A 'city' in this paper is a metropolitan area (CBSA) and I focus on the 49 metropolitan areas with population over 300,000 where at least 2% of the commutes are by public transportation.

2.2.1 Commuting Flows

Data on the flow of commuters between each pair of residence and work census tracts comes from the 2006-10 Census Transportation Planning Package (CTPP), which are aggregations of the ACS microdata for the corresponding years. I use the breakdown of the population of commuters by their household income bracket and their means of transportation to work.[8] Household income brackets are fixed for all metropolitan areas at (1) under $35,000, (2) $35,000-50,000, (3) $50,000-75,000 and (4) over $75,000. I restrict my analysis to workers over 16 years old who commute to work within the extent of my CBSAs and who either drive, ride public transportation or walk to work.[9] For the rest of the paper, I use the term 'transit' to refer exclusively to public transportation.

Across all cities, my sample covers roughly 61 million commutes across 2 million observed residence-work tract pairs. The vast majority of commuters in each city choose to drive. The fraction of commutes by transit is 4% in the median CBSA in my sample and is as high as 31% (in New York, NY). The fraction of commutes by 'walking' is around 3% in the median CBSA and as high as 11% (in Boulder, CO).

In addition to the aggregate counts of commuting flows, my analysis relies on housing expenditure data on individual workers from the 5% sample of microdata from IPUMS (Ruggles et al., 2019) and aggregate demographic data on residential census tracts and block groups (with more detailed breakdown on household incomes and choices than the CTPP data) from the National Historic Geographic Information System (NHGIS). I use population-weighted centroids and crosswalks between geographies from the Missouri Census Data Center. To measure housing prices, I use standardized property prices on single-family parcels at the census tract level from Davis et al. [2020].

2.2.2 Travel Times

The analysis in this paper relies on knowing the travel times faced by each worker from their observed residential locations and travel modes as well as from (the unchosen) alternative locations and modes. To construct these counterfactual travel times, I simulate a series of trips on Google Maps by driving, transit, and walking. These include trips from every block group in the CBSA to nearby popular shopping malls, restaurants, schools, pharmacies and 15 other destination types from Google's directory of "place types". The

[8] CTPP data for more recent years do not include these tabulations for the interaction of household income and means of transportation. Thus, my analysis is limited to ACS years 2006-10.

[9] Driving pools together both those who ride their own vehicle and those who carpool with others on privately owned vehicles. Unfortunately, walking includes bicycling as the ACS lumped together counts of commuters who walk to work with those who bike.

exact trip destinations depend both on the destination's popularity as a Google search result as well as on its proximity to the trip origin. In addition, I define trips from every block group to the 5 most popular work destinations in the corresponding county as well as trips to the 5 most popular work destinations of commuters residing in the corresponding census tract (based on commuting flows observed in the CTPP data).

Google's travel time predictions on trips by driving or walking are based on their historical data on smartphone movements.[10] In contrast, travel time predictions on trips by transit are based on schedules shared by local transit authorities (sometimes in real-time) and the open-source General Transit Feed Specification (GTFS). These transit travel times include waits between transfers as well as time spent walking to transit stops. For trips with no viable transit routes nearby, Google returns the predicted walking times. Since transit travel times are sensitive to the timing of the Google Maps query and the departure time (which are not planned relative to the transit schedules unlike most real transit trips), I search each trip at five different times of the day and consider a weighted average of the travel times in subsequent analyses.[11] I only do so for transit trips as the driving and walking travel times returned by Google are already historical weighted averages across time of day and days. Appendix Section A.1 includes additional details on identifying trip destinations and querying trips on Google Maps.

Importantly, I also predict the counterfactual commuting times faced by individual workers from their observed work tracts to each residential tract within the CBSA by each travel mode. There are 38 million residence-work location combinations faced by commuters across my 49 cities. Since the full matrix of possible trips between these location pairs by each travel mode is too large (and expensive) to query individually on Google Maps, I rely on an alternative approach that proceeds in three steps. First, I identify the shortest routes between all trip origin-destination pairs (including for the non-commuting trips queried on Google Maps) along major road networks downloaded from OpenStreetMap (OSM) and compute the overlap between these routes and the city's tract boundaries. Second, using the trips for which I have travel times from Google Maps, I estimate the average speed of

[10] Google also makes real-time travel time predictions but they are more susceptible to idiosyncratic shocks and the timing of the data collection.

[11] The weights are proportional to the hourly frequency of trips (by trip purpose) in the 2017 NHTS.

travel through each tract.[12] Third, I use the estimated tract speeds and the overlaps between tracts and routes to predict travel times on the remaining (commuting) trips. I repeat the second and third steps of the process separately for each of the three modes of travel and for each CBSA.

Let τ_{cqm} denote the travel time on trip q in CBSA c using travel mode m. I can decompose it into a sum of travel times through each overlapping tract on its route:

$$\tau_{cqm} = \sum_{k \in K_c} l_{ckq}/s_{ckm} \tag{2.2.1}$$

where l_{ckq} is the trip length overlapping tract k, s_{ckm} is the mode-specific travel speed through tract k, and K_c is the set of census tracts within a convex hull of the CBSA's geographic extent. To determine the overlap l_{ckq} between trips and tracts, I compute each trip's shortest route along the network of non-residential streets and intersect it with all tract boundaries. Then, using the set of trips for which I also have total trip travel times τ_{cqm} from Google Maps, I estimate travel speeds s_{ckm} from (2.2.1) using an OLS regression of the trip travel times on the trip lengths overlapping each tract (with coefficients $1/s_{ckm}$). I run these regressions separately for each CBSA and travel mode. Then I plug the estimated speeds into (2.2.1) to predict travel times on the commuting trips that did not get queried on Google Maps. See Appendix Section A.2 for further details on estimating tract speeds and commuting times.

Note that the trip lengths l_{ckq} are not necessarily the traveled road distances and do not vary with travel modes. Accordingly, the estimated speeds s_{ckm} measure both the speed of travel on the road as well as the directness of the travel route (relative to the shortest street route). For example, higher transit speeds on a trip may correspond to either a more direct transit connection (such as one with fewer detours or less time spent walking and waiting along the way) or a faster transit route (such as one with fewer stops in between or

[12] In this version of the paper, the Google Maps travel times to non-residential amenities (such as restaurants, shopping malls and parks) only serve to help me predict travel times on commutes since this study focuses only on commuting trips. An extension (in progress) investigates worker preferences on both commuting trips and trips to amenities.

by subway instead of bus).[13] Similarly, driving speeds reflect both the directness of chosen driving routes (relative to the shortest route along major arteries) and how fast traffic flows along these routes.

An advantage of the commuting travel times predicted from these tract-level speeds (as opposed to travel times directly from a Google Maps trip between the centroids of tracts) is that they are less sensitive to the precise locations of the trip origins and destinations within tracts. It pertains even more to transit travel times because transit routes can be sparse and walking times to and from transit stops can vary significantly depending on where the trip starts and ends. The tract level speeds smooth out this variation within tracts. So, while the predicted commuting times may not be the best predictor of actual travel times between the tract centroids, they may be more representative of average travel times between the tracts.

As a quality check, I use the estimated speeds to also predict travel times for a randomly selected test sample of trips for which I already have Google travel times but which I do not use in the speed estimation. The predicted travel times are strongly correlated with the Google travel times: for the median city, the correlation for driving and walking travel times are 95% and 97% respectively. The median correlation between transit travel times is slightly lower (but still reasonably high) at 84%.

2.3 Travel Speeds, Mode Choices and Incomes

Henceforth in the paper, trip ‘distance’ refers to the length of the shortest OSM route and the (average) trip ‘speed’ is this shortest route distance divided by the predicted travel time. Table 1 shows mean travel times, distances and speeds across all commuting trips in my sample conditional on each commuter choosing their observed residence, work location and travel mode. On average, driving commutes are longer than transit commutes (both in

[13]The transit speeds do not include scheduling costs related to when to start the trip. For instance, Google Maps may ask the traveler to start their trip at a particular departure time to have them coincide with the arrival of a bus or train at the designated stop. The difference between the scheduled departure time and the time the trip is queried is not included in the travel times. In subsequent analyses in Section 2.4 onwards, this schedule cost is covered by travel mode-origin fixed effects. Note, however, that wait times between transit transfers are included in the travel times.

Table 1: Mean distances, times and speeds on observed commutes

	Travel Mode	All commuters	<$35k	$35k-$50k	$50k-$75k	>$75k
Distance (in km)	driving	23.2	20.2	21.4	22.6	24.3
	transit	22.6	15.2	17.2	19.4	27.2
	walking	8.2	7.7	7.9	8.0	8.7
Travel time (in min)	driving	22.7	20.3	21.2	22.1	23.5
	transit	74.5	58.0	62.6	67.4	84.8
	walking	87.6	81.4	84.6	85.0	93.8
Speed (in km/h)	driving	55.2	52.6	53.8	54.9	55.9
	transit	17.1	14.8	15.6	16.4	18.5
	walking	4.9	4.8	4.9	4.9	4.9

Note: Means are over all observed one-way commutes, i.e. conditional on each commuter choosing their observed residence, work location and travel mode. Table pools together all cities in my sample.

distance and time), which are longer than walking commutes. Driving commutes are also faster than transit commutes, which are faster than walking commutes. And across all modes of travel, higher income commuters tend to commute longer and faster than lower income commuters.

Travel speeds also vary greatly across cities. Table 2 shows a partial ranking of cities by their mean transit speeds across all observed residence-work location pairs *unconditional on travel mode choice*.[14] The table also reports the means of transit speeds as a function of driving speeds on corresponding trips. On average, transit is slower than driving everywhere. In the fastest transit cities, driving is roughly three times faster than riding transit. In the slowest transit cities, driving is roughly five times faster. Cities with relatively faster transit have a higher share of commuters who ride transit. These cities are also likely to have a higher share of their transit commutes using rail-based transit as opposed to road-based transit (such as buses). But there are exceptions, consistent with the speeds reflecting both how fast commuters move along their transit routes as well as how well-connected transit routes are. Most notably, Seattle WA has the third highest average transit speed but 95% of its transit commutes are by bus, whereas Vallejo-Fairfield CA has the lowest average transit

[14] A complete ranking of cities is available in the appendix.

Table 2: Ranking of cities by mean commuting speeds on transit

Rank	City	Transit speed (in km/h)	Ratio of transit to driving speed	% commuters riding transit	Rail share of transit riders
1	New York, NY	20.2	0.35	30.7%	86.7%
2	San Francisco, CA	18.9	0.31	15.5%	51.6%
3	Seattle, WA	17.8	0.30	8.6%	5.2%
4	Chicago, IL	17.7	0.28	11.9%	69.8%
5	Philadelphia, PA	17.1	0.30	9.7%	46.0%
	-				
10	Atlanta, GA	15.7	0.21	3.5%	30.8%
	-				
15	Minneapolis, MN	15.1	0.20	4.8%	5.8%
	-				
26	San Diego, CA	13.9	0.24	3.5%	11.0%
	-				
37	Austin, TX	12.8	0.21	2.8%	1.1%
	-				
49	Vallejo-Fairfield, CA	8.8	0.18	2.7%	33.3%

Note: Speeds are relative to shortest road distance (not necessarily the travel distance). Speeds and ratios of travel times are means across all trips between observed work-residence location pairs (unconditional on travel mode choice) ignoring the top and bottom 5% of outliers. Rail share is the fraction of transit commutes via rail transit in the city.

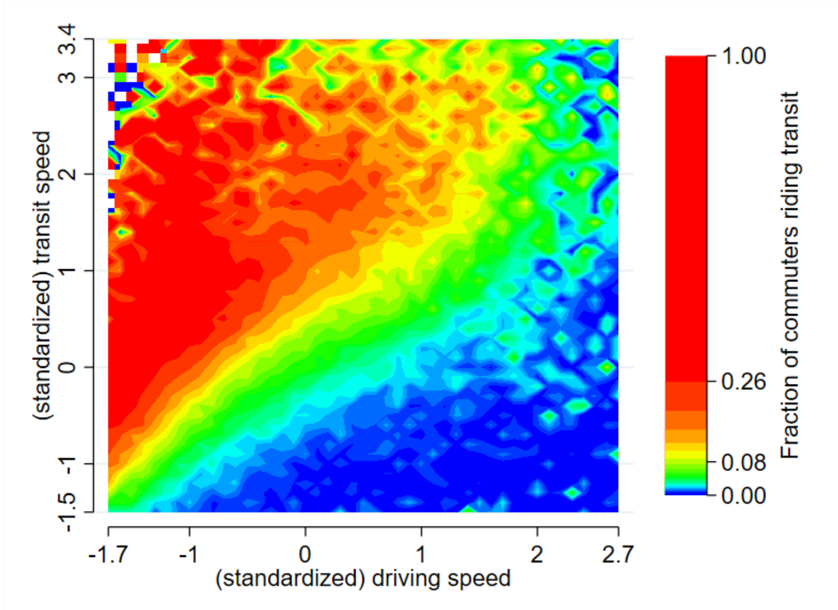


Figure 1: Share of commuters riding transit as a function of travel speeds

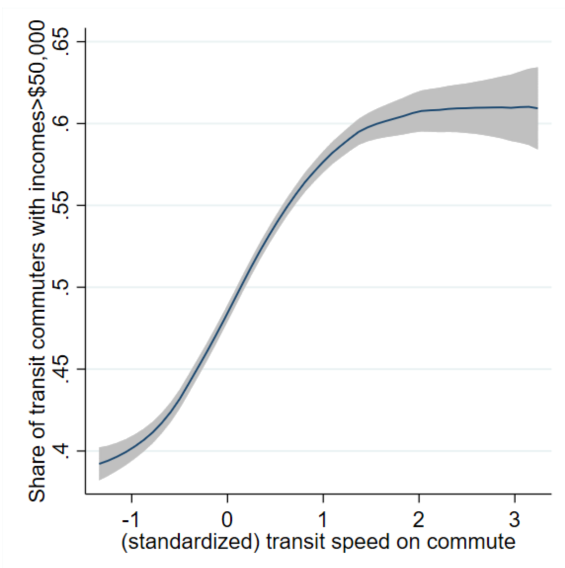
Note: Figure pools together commutes across all cities. Speeds are standardized (to mean 0 and std. dev. 1) across trips between observed work-residence pairs within each CBSA. Trips at the top and bottom percentiles of speeds are ignored. White spaces in the graph correspond to 0.1-by-0.1 cells with fewer than 20 commutes.

speed but a third of its fewer transit riders are more likely to use commuter rail.

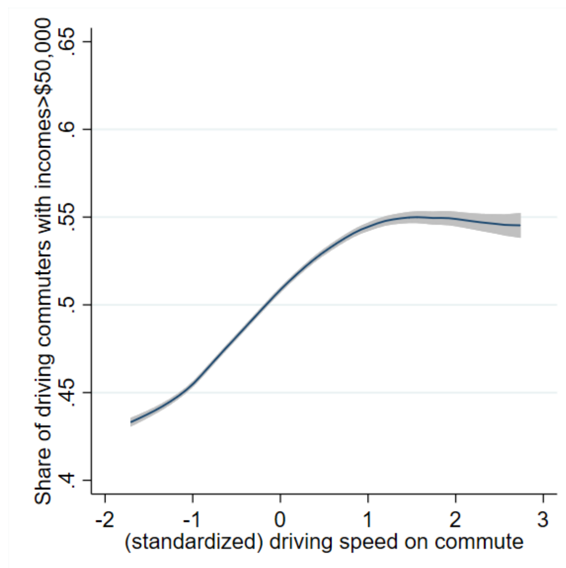
Within cities, the likelihood of riding transit depends on the speed of transit relative to driving. Figure 1 plots the probability of riding transit across commuters within cities with standardized commuting speeds by driving and transit on the x- and y-axes (on trips between observed residence-work location pairs). Conditional on driving speed, transit ridership is higher on trips where transit is fast. Also, conditional on transit speed, transit ridership is higher on trips where driving is slow. As such, transit and driving are substitutable alternatives: commuters choose more of one when the price of travel (in terms of inverse travel speeds) on the other is higher.

The income composition of transit riders also varies systematically over travel speeds. As shown in Panel A of Figure 2, higher income transit riders are more likely to enjoy faster transit commutes.[15] A similar pattern can be observed for drivers too. Panel B of Figure 2 shows that higher income drivers are more likely to enjoy the fastest driving commutes (but

[15]The observed relationship is robust to alternative high income cutoffs too besides $50,000.



(A) High-income share of **transit riders**



(B) High-income share of **drivers**

Figure 2: Share of commuters who are high-income by (standardized) speed of travel

Note: The figures pool together commutes across all CBSAs. Horizontal axis depicts travel speeds on chosen mode standardized (to mean 0 and std. dev. 1) across all observed commutes on the same made within each CBSA. Trips at the top and bottom percentiles of speeds are ignored. Speed, in this context, is the shortest road distance divided by travel time. Confidence intervals are in grey.

the mean differences are smaller than among transit riders). These patterns could be due to an income-elastic preference for faster commutes that is missed if we focus only on travel times instead of speeds. As explored further in Apprendix Section A.5.1, when commuters travel faster, they also commute longer. And, as seen in Table 1, higher income commuters have higher average travel times (and distances) on their chosen travel mode despite higher travel speeds.

Having said that, unconditional on mode choice, higher income commuters are more likely to sort into commutes where driving is fast. Figure 3 shows average commuter incomes by driving and transit speeds between their work and residence. Given both driving and transit commutes appear to be normal goods and driving is typically faster (cheaper in time) than transit, it is unsurprising that average commuter incomes are higher where driving is faster. In a few cases, incomes are also high where transit is fast and driving is not. The model developed in the following section formalizes the intuitions presented so far. More importantly, it allows me to isolate the extent to which the observed income sorting into work-residence location pairs and travel modes informs us about heterogenous preferences for faster travel as opposed to other spatially correlated features.

2.4 A Model of Travel Mode and Residential Location Choice

Suppose each city is composed of a fixed population of heterogeneous workers, a set of residential neighborhoods n and work locations j, and three modes of travel $m \in M = \{\text{driving}, \text{transit}, \text{walking}\}$. Workers classify under one of four income groups y, each with a fixed population in the city and a different distribution of jobs across work locations. Each worker i is exogenously assigned a work location and an income w_i, and choose their residential neighborhood and mode of travel to maximize their gains from shorter commutes given heterogenous preferences over mode and neighborhood characteristics. The rest of this section characterizes (and parameterizes) the worker's decision problem and outlines a strategy to estimate the preference parameters from available data.

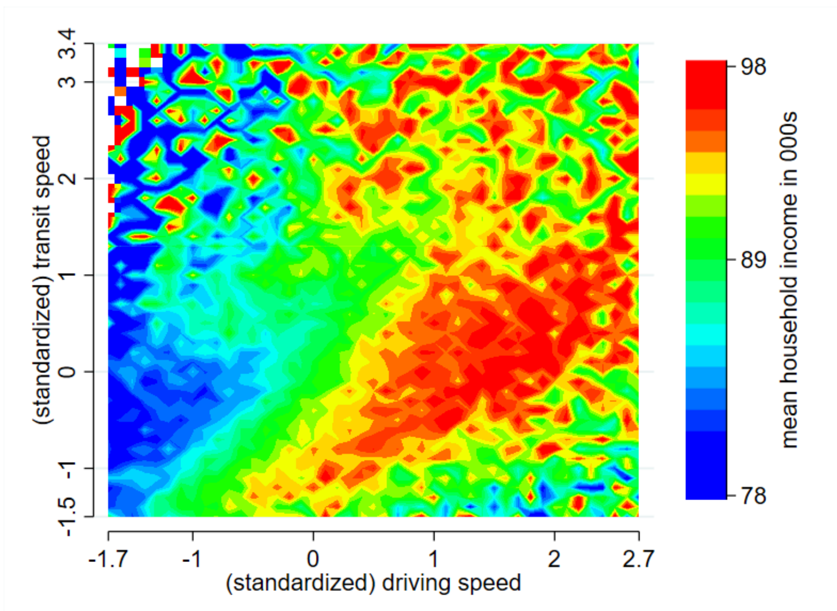


Figure 3: Mean incomes of commuters as a function of driving and transit speeds

Note: Figure pools together commutes across all cities. Household incomes are means across commutes of medians of income brackets (based on micro-data). Speeds are standardized (to mean 0 and std. dev. 1) across trips between observed work-residence pairs within each CBSA. Trips at the top and bottom percentiles of speeds are ignored. White spaces in the graph correspond to 0.1-by-0.1 cells with fewer than 20 commutes.

2.4.1 Specification

Work locations determine the set of commuting times workers face to each residential neighborhood by each travel mode, and workers from different income groups may have different preferences over these commuting times. For instance, if higher income commuters have a higher opportunity cost of time, they are likely to have a stronger prefernce for shorter commutes. Commuting times (in log) can be decomposed into the (log) distance D_{jn} from work to residential neighborhoods minus the (log) average speed S_{jmn} along the route on the chosen travel mode. The utility gain from commuting distance D_{jn} at speed S_{jmn} is denoted:

$$\alpha_{my}^{S} S_{jmn} - \alpha_{y}^{D} D_{jn}$$

where parameters α_{my}^{S} and α_{y}^{D} dictate the income group-specific preferences over speeds and distances (respectively). Note that when $\alpha_{my}^{C} = \alpha_{y}^{D}$, they are just the coefficient on (log) commuting time. But I allow preferences over speed α_{my}^{S} to also vary with the choice of travel mode m. The value of travel time spent riding the transit may differ from the time spent driving (or walking), and consequently, so may preferences for travel times savings on each travel mode (and differentially across income groups).

On the other hand, parameters α_{y}^{D} reflect the net gains from shorter commutes unconditional on mode choice. Since workers have different work locations within the city, they differ in their distances to high quality residential neighborhoods and, consequently, in their accessibility gains from a longer commuting distance. So, α_{y}^{D} also encapsulate differences in the geography of high- and low-income jobs within the city. Workers from an income group with more jobs farther away from desirable neighborhoods are likely to be more willing to commute longer and have a smaller α_{y}^{D}.[16]

Neighborhoods differ in their supply of developable land and a competitive housing market determines the equilibrium housing prices p_n (per unit of space) faced by the neighborhood's residents. While prices depend on the aggregate demand for housing space in each neighborhood, each worker takes these prices as given when making housing

[16] Alternatively, if jobs are more substitutable across space (e.g. in terms of wages) for one income group, they may have a stronger preference for more centrally located jobs and a higher α_{y}^{D}. Modeling the geography of jobs (and work location choices) explicitly is beyond the scope of this paper.

consumption and location choices. Housing is a normal good and individual demand for housing space is increasing with income and decreasing with the price of housing. More specifically, conditional on residing in neighborhood n, the housing consumption of worker i is:

$$h(p_n, w_i) = (p_n)^{\alpha_h} (w_i)^{\alpha_w} \tag{2.4.1}$$

where $\alpha_h < 0$ is the price elasticity and $\alpha_w > 0$ is the income elasticity of housing demand.

Net of preferences over housing costs and commuting times, each worker's preferences over neighborhoods and travel modes can be decomposed into two components: a common preference across all workers in an income group and an idiosyncratic preference. Let δ_{mny} denote the income group-specific utility from choosing neighborhood n and travel mode m. This utility shifter captures differences across modes in the monetary cost of travel (such as of vehicle ownership or transit fare) that affects each income group differently. They also capture differences in the quality of residential amenities (such as schooling and crime) as well as in location-specific attributes of travel (such as convenience of parking or waiting at the nearest transit stop). The latter may include differences in how well (on average) the commuting mode connects the residential neighborhood to non-commuting destinations and non-residential amenities such as restaurants and shopping malls. While the (unobserved) mode choices on non-commuting trips may be different from the observed mode choice on commutes, the gains from owning a vehicle or a bus pass are greater when they improve access to more than just the immediate work location.

Workers also have idiosyncratic preferences over neighborhood-mode alternatives and I let ϵ_{imny} denote their idiosyncratic utility gains from choosing neighborhood n and mode m. Assume ϵ_{imny} are random draws from a type 1 extreme value (T1EV or Gumbel) distribution that is identical across workers and independent of their commuting and housing preferences. Together with the aforementioned deterministic components of utility, workers' choices in equilibrium maximize the following (indirect) utility function:

$$U_{mn|ijy} \equiv \alpha_{my}^{S} S_{jmn} - \alpha_{y}^{D} D_{jn} + \frac{(w_i)^{1-\alpha_w}}{1-\alpha_w} - \frac{(p_n)^{1+\alpha_h}}{1+\alpha_h} + \delta_{mny} + \epsilon_{imny} \tag{2.4.2}$$

The parameters α_w and α_h determine the diminishing marginal utility from higher incomes and the marginal disutility from higher prices (respectively). The housing demand function in (2.4.1) follows from Roy's Identity.[17]

Preference parameters α^S_{my}, α^D_y, α_w and α_h may vary across cities, but I drop the city subscripts to simplify notation. That means preferences over commuting and housing depend on city-level attributes such as (but not limited to) the spatial distribution of high- and low-income jobs with respect to the travel network and city-level housing constraints. These city-level attributes are exogenous with respect to each worker's decision problem.

Finally, given the distribution of the logit error term ϵ_{imny}, the probability of a worker from income group y and work location j choosing mode m and neighborhood n is

$$\pi_{mn|jy} = \frac{\exp\left(V_{mn|jy}\right)}{\sum_{m' \in M} \sum_{n'} \exp\left(V_{m'n'|jy}\right)} \tag{2.4.3}$$

$$\text{where } V_{mn|jy} \equiv \alpha^S_{my} S_{jmn} - \alpha^D_{my} D_{jn} + \delta_{mny} - \frac{(p_n)^{1+\alpha_h}}{1+\alpha_h}$$

2.4.2 Identification

In applying this utility specification to data, I address three important empirical challenges to identifying preferences for faster commutes. First, travel times on commutes depend on both the spatial distribution of transportation infrastructure (such as transit routes and highways) and the spatial distribution of jobs relative to residential neighborhoods. If work locations for higher income groups are farther away from desirable residential neighborhoods, they may appear to have a smaller disutility from longer commutes despite having a higher opportunity cost of travel time. Decomposing commuting times into shortest-route road distances D_{jn} and mode-specific speeds S_{jmn} allows me to isolate the two effects and identify preferences over access to faster commutes conditional on proximity to jobs. Furthermore, conditional on the income group-specific fixed effects, I am identifying the coefficient on speed using variation across individuals in the same income group.

[17] By Roy's Identity:

$$h(p,w) = -\frac{dU/dp}{dU/dw}$$

Second, commuting speeds may be correlated with other (unobservable) attributes of residential neighborhoods and travel modes. For example, if transit planners are more likely to expand high-speed transit routes into neighborhoods with attributes more desirable to the rich, then unless I control for these correlated neighborhood attributes in my regression, higher income commuters would appear to have a higher coefficient on transit speed than they actually do. My inclusion of alternative-specific constants for each income group δ_{mny} (fixed effects) essentially controls for preferences over unobservable neighborhood-mode attributes.

Third, commuting speeds may be systematically correlated with the locations of high- and low-income jobs. For example, if work locations of some income groups are better connected by high-speed transit than driving relative to the work locations of others, then these income groups would appear to have a higher coefficient on transit speed than they actually do. To address this concern, I standardize the commuting speeds and distances faced by each worker to mean 0 (and standard deviation 1) conditional on travel mode. In doing so, any mean preference for one travel mode over another within an income group y is absorbed by the group's corresponding alternative-specific constant δ_{mny}. So, conditional on commuting distance and income group-alternative-specific constants, the coefficients on speed α^S_{my} are the gains from shorter commuting time identified off of mode-specific variation in speeds to different work locations in the city.[18]

In addition to the coefficients on commuting speed, I need to estimate housing demand parameters α_w and α_h to be able to compare preferences for access to faster commutes in terms of workers' willingness to pay for housing. This exercise poses two additional econometric challenges. First, the price elasticity of housing demand α_h is not identifiable from the utility specification because housing prices p_n are necessarily correlated with neighborhood characteristics captured by the fixed effects δ_{mny}. Second, the choice probabilities in (2.4.3) do not inform us at all about the income elasticity of housing demand α_w. So, I need to identify these parameters separately. To do so, I exploit the housing expenditure patterns of a representative micro-sample of each city's working population. Consider the log of the housing demand function in (2.4.1), which I can rewrite as a linear

[18]Later on, I transform the speeds and distances back to their unstandardized levels for evaluating willingness to pay and transit ridership responses to a percent change in travel speeds.

relationship between the log of total housing expenditure as a share of income (on the left) and the logs of housing prices and incomes (on the right):

$$\ln\left(\frac{h_{in}p_n}{w_i}\right) = (1+\alpha_h)\ln(p_n) + (\alpha_w - 1)\ln(w_i) \tag{2.4.4}$$

Then the price and income elasticities of housing demand follow directly from the coefficients of (log) price and (log) income above.

2.4.3 Estimation

Estimation of the model parameters proceeds separately for each city and in two stages. The first stage estimates the housing demand parameters α_w and α_h using micro-data on individual housing expenditures in an OLS estimation based on (2.4.4). For each worker in the census micro-sample, I observe both precise household incomes and the share of that income spent on housing expenditures. I can combine them with tract-level standardized housing prices from Davis et al. [2020].[19] Then I regress the log of housing expenditure share on log housing price and log household income as below.

$$\ln\Big(\text{HousingExpShare}\Big) = \bar{\alpha}_h \ln\Big(\text{Price}\Big) + \bar{\alpha}_w \ln\Big(\text{Income}\Big) \tag{2.4.5}$$

where the coefficients are $\bar{\alpha}_h = 1 + \alpha_h$ and $\bar{\alpha}_w = \alpha_w - 1$. See Appendix Section A.3 for estimation details and results. Having estimated α_h, the housing price component of each worker's choice probabilities $-(p_n^{1+\alpha_h})/(1+\alpha_h)$ is just a neighborhood-specific constant from here on.

The second stage estimates parameters α^S_{my} and α^D_y together with fixed effects δ_{mny} using the data on observed commuting flows and counterfactual travel times in a maximum likelihood estimation based on (2.4.2). The estimation maximizes the probability that the model correctly matches each worker in the city to their observed nieghborhood and mode

[19] I do not observe the workers' tracts of residence in the microdata. The smallest known geography of residence is the PUMA, which are slightly larger. So, instead, I assign each worker the expected housing price experienced by workers in the same income bin and PUMA. See Appendix Section A.3 for details.

in the CTPP data. In particular, estimated parameters maximize the following sum across all workers of the log-likelihood of their observed choices:

$$L = \sum_{y} \sum_{j} \sum_{n} \sum_{m \in M} P_{jmny} \ln \left(\pi_{mn|jy} \right) \tag{2.4.6}$$

where P_{jmny} is the observed population of commuters in income group y and work location j who choose mode m and residence n. The estimation procedure then consists of numerically searching over the twelve α^S_{my} parameters and the four α^D_y parameters as well as the full matrix of fixed effects δ_{mny} in order to maximize L.

The set of work locations are the census tracts in the city that receive non-zero commutes. The choice set of residential neighborhoods in each city is the set of census tracts with non-zero observed population of workers.[20] The number of residential tracts ranges from 58 in my smallest city (Trenton, NJ) to 3050 in my largest (New York, NY). So, given the large number of fixed effects to be estimated for every mode, neighborhood and income group combination, I exploit a contraction mapping approach popularized by Berry et al. [1995] to speed up convergence to the optimal parameter estimates. See Appendix Section A.4 for details.

Across all cities, income groups and travel modes, I estimate 588 different coefficients on commuting speed. To make them comparable across cities and income groups, I combine the estimated coefficients with my parameter estimates from the first stage to characterize preferences in terms of the implied marginal willingness to pay (MWTP) in annual housing costs for faster commutes.[21] Appendix Table 20 reports the distribution of the (raw) estimated coefficients on commuting distance and speed (α^D_y and α^S_{my}) across the 49 cities. The following section explores how the implied MWTP varies across cities and income groups.

[20] Commuters with either residence or work location outside of the extent of the city are dropped from the sample.

[21] The marginal willingness to pay (MWTP) for higher commuting speed is $-\frac{dU/dS_{jmn}}{dU/dp_n}$.

2.5 Estimated Preferences for Faster Transit

This section presents the estimated preferences for faster transit commutes in three stages. First, I characterize the value of travel time conditional on travel mode choice. In other words, how much are transit riders willing to pay for faster commutes (compared to drivers)? Second, I characterize the marginal propensity of consumers to ride transit in response to shorter transit travel times. In other words, how do increases in transit speed affect transit ridership? Third, I combine the two results to characterize the overall expected welfare gains from increases in transit speed (unconditional on mode choices) and how these gains compare for rich and poor commuters.

2.5.1 Willingness to Pay for Faster Commutes

Conditional on travel mode choices, the mean estimated MWTP (per year) for a one percent increase in travel speed on commutes (across all cities) is $98 among transit riders and $142 among drivers. Assuming workers commute 5 days a week and commutes make up 35% of their total time spent traveling (based on reported travel times in the 2017 NHTS)[22], the mean MWTP estimates for speed imply a mean value of travel time savings (VTTS) among transit riders of $7.4 per hour (and roughly 40% of the median transit rider's wage). In comparison, the mean VTTS among drivers is $15.5 per hour (which is 86% of the median driver's wage).[23] My mean driving estimates are similar to contemporary value-of-time estimates from other papers using alternative methodologies (Small, 2012), such as means of $13-$14 per hour in Prague (Bucholz et al., 2020) and Vancouver (Craig, 2019). There are no comparable estimates in the literature of the value of travel time on transit.

As shown in Table 3, the mean estimates mask large variation across cities. The table reports the mean MWTP for faster travel by mode choice and city ranked by the MWTP

[22] The share of total travel time spent on commutes to work is calculated from the share of reported travel times spent on trips to work in the 2017 US National Household Travel Survey (NHTS). I assume increases in travel speed on commutes also increases travel speeds on all other trips at the same rate.

[23] One reason for the VTTS among transit riders being a smaller share of wages than the VTTS among drivers is that transit riders are primarily concentrated in higher-income cities. So, across all cities, the average transit rider has a higher income than the average driver.

among transit riders.[24] Because of the large number of commutes informing these preference estimations, asymptotic standard errors are tiny (typically around one cent or less in MWTP) and omitted from the tables.[25] Focusing first on transit users, in San Francisco (the top ranked city on the list), the MWTP for faster transit is $374 per year, almost four times the average across all commuters. To benchmark these magnitudes, consider MWTP estimates for other locational attributes. For example, Bayer and McMillan [2012] estimate MWTP (per year) in the San Francisco Bay area of: $236 for access to schools with (1 standard deviation) higher average test scores, $126 for 10% more college-educated neighborhoods and $436 for neighborhoods with $10,000 higher average incomes.

While city-level MWTP for faster commutes for drivers are similar in magnitude to those for transit riders, the rank ordering is different. When interpreting these preference estimates, bear in mind that they reflect how aggressively transit riders and drivers bid for access to (and sort into) locations with faster commutes. So, some of these cross-city differences in mean MWTP also stem from differences in housing market constraints and urban amenities that make housing in some cities more expensive than in others.

Incomes are another important determinant of a commuter's MWTP estimate. Table 4 decomposes the mean MWTP by commuter's income bracket and reports it for the two largest cities in my sample. Unsurprisingly, richer transit riders have higher MWTP for faster transit commutes than poorer transit riders. Also, richer drivers have higher MWTP for faster driving commutes than poorer drivers. The estimates are consistent with the rich having a higher overall value of travel time savings than do lower income commuters. When I aggregate my estimates across all commuters, the magnitude of the income differences are comparable to extant reduced form estimates in the literature.[26] Some of the income elasticity of MWTP are undoubtedly due to differences in the mean *ability* to pay (and richer commuters generally spending more on housing). More notably, based on the differences across income brackets, the income elasticity of the demand for faster travel appears to be higher among transit riders than drivers. Table 5 pools together commuters across all 49

[24] A table of results for the full list of cities is in the Appendix.

[25] In work in progress, I bootstrap the standard errors with Monte Carlo simulations to derive more credible estimates.

[26] Small [2012] reviews contemporary empirical estimates of value of time savings (VTTS) on commutes and cites income elasticities of VTTS typically between 0.5 and 0.7.

Table 3: Cities ranked by mean MWTP for faster transit commutes

Rank	City	MWTP for faster transit	MWTP for faster driving
1	San Francisco, CA	$ 374	$ 302
2	Seattle, WA	$ 188	$ 179
3	New York, NY	$ 178	$ 345
4	San Jose, CA	$ 169	$ 139
5	Boston, MA	$ 148	$ 189
6	Washington, DC	$ 129	$ 156
7	Vallejo-Fairfield, CA	$ 119	$ 69
8	Chicago, IL	$ 116	$ 179
9	Los Angeles, CA	$ 114	$ 102
	-		
20	Miami, FL	$ 64	$ 75
	-		
29	Phoenix, AZ	$ 44	$ 47
	-		
36	Urban Honolulu, HI	$ 32	$ 19
	-		
49	Las Vegas, NV	$ 9	$ 17

Note: Cities are ranked by the mean MWTP for faster transit. MWTP values are means across all commuters for 1% change in travel speed on their observed commutes (i.e. conditional on commuters choosing their observed modes and neighborhoods). See mean MWTP estimates for full list of cities in the Appendix.

Table 4: Mean MWTP for 1% increase in commuting speed

City	**Mode**	< **$35k**	**$35k-$50k**	**$50k-$75k**	>**$75k**
New York	transit	$43	$69	$125	$219
	driving	$134	$211	$273	$401
Los Angeles	transit	$42	$62	$80	$146
	driving	$51	$81	$81	$123

Note: MWTP values are means across all commuters for 1% increase in travel speed on their observed commutes (i.e. conditional on commuters choosing their observed modes and neighborhoods). Asymptotic standard errors are less than a cent.

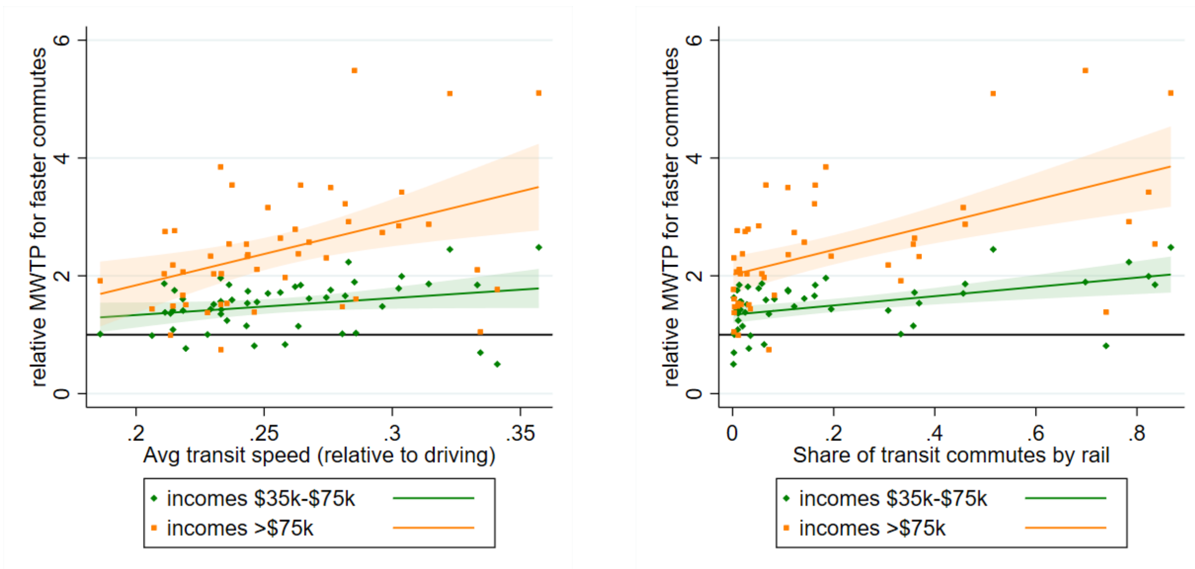
Table 5: Mean relative MWTP across all cities

Mode	**< $35k**	**$35k-$50k**	**$50k-$75k**	**>$75k**
transit	1.00	1.40	2.00	3.24
driving	1.00	1.47	1.86	2.57

Note: Reported values are the MWTP estimates for 1% increase in commuting speed divided by the lowest income group's MWTP and averaged over commutes across all cities.

cities and, for comparability across cities, presents the MWTP estimates as multiples of the lowest income group's MWTP. The average transit commuter with income over $75,000 is willing to pay over three times more for a one percent increase in commuting speed than the average transit commuter with income below $35,000. This is not just driven by differences in the ability to pay. The table also shows the relative MWTP across income groups among drivers, and the income elasticity of the willingness to pay for faster commutes is much smaller among drivers than among transit riders (like in New York and Los Angeles).

Panel A of Figure 4 plots these relative MWTP estimates by city against mean transit speeds relative to driving (from column 4 of Table 2). The rich have higher MWTP for increase in transit speed relative to the poor in cities with faster transit. This figure highlights a key finding of my work: transit improvements are relatively more attractive to the rich when transit is fast. Another dimension of transit which is often associated with use by the wealthy is rail transit versus bus transit. Rail transit typically has higher velocity than buses, so the rail composition of a city's transit network can proxy for average travel velocity on transit (and an alternative to my measure of travel speeds). Panel B of Figure 4 plots the relative MWTP estimates against each city's rail share of transit usage (from column 6 of Table 2). Unsurprisingly, transit improvements are relatively more attractive to the rich when transit is more rail-based.



(A) by mean (relative) transit speeds

(B) by rail share of transit commutes

Figure 4: Mean MWTP for 1% increase in transit speed (relative to lowest income group)

Note: Each observation corresponds to a city. Vertical axis depicts the MWTP for faster transit as a fraction of the MWTP of commuters with incomes less than $35,000 (indicated by solid black line at 1). Horizontal axis depicts either (a) the ratio of driving to transit travel times (across all observed commutes) in the city or (b) the share of transit riders in the city who commute by rail transit. Confidence intervals for each linear fit are shaded in corresponding color. For commuters with incomes $35k-$75k, figures plot population-weighted means of the MWTP estimates for the two middle-income groups in my data.

2.5.2 Willingness to Ride Transit

So far, I have focused on heterogeneity in MWTP for transit speed (or, if you will, the demand for faster travel) among commuters who ride transit. MWTP is central to evaluating welfare from the perspective of transit users, but transit policy is often predicated on a broader set of concerns including reducing congestion and climate change concerns. Evaluating policy along these dimensions requires assessing how policies impact the decision to use transit instead of driving. To this end, I use my model to estimate the probability of non-transit commuters switching to riding transit if transit is made faster. Let R_{jny} denote the transit ridership among income group y on commutes between neighborhood n and work location j. I can solve for a commuter's marginal willingness to ride transit (or, in aggregate terms, the marginal change in transit ridership), denoted MWTT, in response to a percent increase in transit speed on their commuting route.[27] The MWTT measures the predicted change in the probability of transit use along a given work-residence commuting route in response to a percent increase in speed along the route.

Table 6 reports the mean MWTT across all commuters in a city conditional on observed residential location choices. The cities at the top of the list, where marginal improvements in transit speed would be most effective at generating new transit ridership, are likely to be cities with high pre-existing transit ridership (but not always). The top of the list includes both cities with high rail transit usage among transit riders (such as Chicago, Washington and Boston) and ones with very low rail transit usage (such as Seattle, Portland and Pittsburgh).

These cities also attract transit riders at different rates across income groups. Table 7 compares the MWTT across income groups for New York and for Los Angeles. In New York, a one percent increase in transit speeds everywhere increases transit ridership more among higher income commuters than lower income commuters. However, the opposite is true in Los Angeles, where lower income commuters are twice as likely to increase transit ridership. The case of Los Angeles is more common among other cities, but there is also a

[27] Formally, the marginal willingness to ride transit (MWTT) is defined:

$$MWTT_{jny} = \frac{dR_{jny}}{dS_{j\text{transit}n}} \equiv \frac{d}{dS_{j\text{transit}n}} \left(\frac{\pi_{\text{transit}n|jy}}{\sum_{m \in M} \pi_{mn|jy}} \right) = \alpha^{S}_{\text{transit}y} R_{jny}(1 - R_{jny})$$

Table 6: Cities ranked by MWTT from 1% increase in transit speeds

Rank	City	%age pt change in transit ridership	Baseline transit ridership (in %)
1	San Francisco, CA	3.52	15.5
2	Chicago, IL	2.97	11.9
3	Washington, DC	2.97	14.5
4	Seattle, WA	2.88	8.6
5	Boston, MA	2.76	12.4
6	Portland, OR	2.22	6.6
7	New York, NY	2.22	30.7
8	Philadelphia, PA	1.81	9.7
9	Pittsburgh, PA	1.77	6.0
	-		
18	Miami, FL	0.80	3.8
	-		
25	Urban Honolulu, HI	0.71	8.2
	-		
34	Phoenix, AZ	0.55	2.3
	-		
49	Rochester, NY	0.13	2.1

Note: Cities are ranked by the MWTT in response to a 1% increase in transit speed along all observed commutes (i.e. conditional on commuters choosing their observed neighborhoods). See mean MWTT for full list of cities in the Appendix.

generalizable pattern here. Cities with high (baseline) transit ridership among commuters are more likely to have high MWTT among richer commuters (relative to the MWTT among poorer commuters). Table 8 groups together cities by each city's (baseline) transit ridership. For comparability across cities, I present the MWTT estimates as fractions of the lowest income group's MWTT. In most cities, baseline transit ridership is low and poorer commuters have much larger MWTT. However, in the five cities where more than 10% of the commutes are by transit, the MWTT is similar if not larger for richer commuters.

These five cities (New York, San Francisco, Chicago, Boston and Washington DC) also happen to be (among the seven) cities with more rail transit riders than road transit riders. Since higher income transit riders benefit more from improvements in rail-heavy transit networks (as I showed in Section 2.5.1), it is unsurprising that these improvements also increase transit usage relatively more among higher income commuters.

Table 7: Mean MWTT from 1% increase in commuting speed

City	< **$35k**	**$35k-$50k**	**$50k-$75k**	>**$75k**
New York	1.5%	1.3%	1.9%	2.5%
Los Angeles	1.8%	1.4%	1.2%	0.9%

Note: Table reports percentage point change in total transit ridership across all commuters in response to 1% increase in transit speeds.

Table 8: Mean relative MWTT across cities

Cities with . . .	< **$35k**	**$35k-$50k**	**$50k-$75k**	>**$75k**
less than 10% commuters riding transit	1.00	0.61	0.52	0.40
more than 10% commuters riding transit	1.00	0.86	1.15	1.53

Note: Reported values are means across all commuters of their MWTT estimate divided by the lowest income group's MWTT over the same commuting route.

More generally, cities with higher overall (baseline) transit ridership and higher overall marginal transit ridership (namely higher overall MWTT) have larger relative MWTT among higher income commuters. Figure 5 illustrates this point by plotting the relative MWTT across income groups as a function of both the city's overall baseline transit ridership and overall MWTT.[28] In cities with higher baseline transit ridership and where transit improvements are most effective at generating new ridership, transit improvements also increase ridership relatively more among higher income commuters.

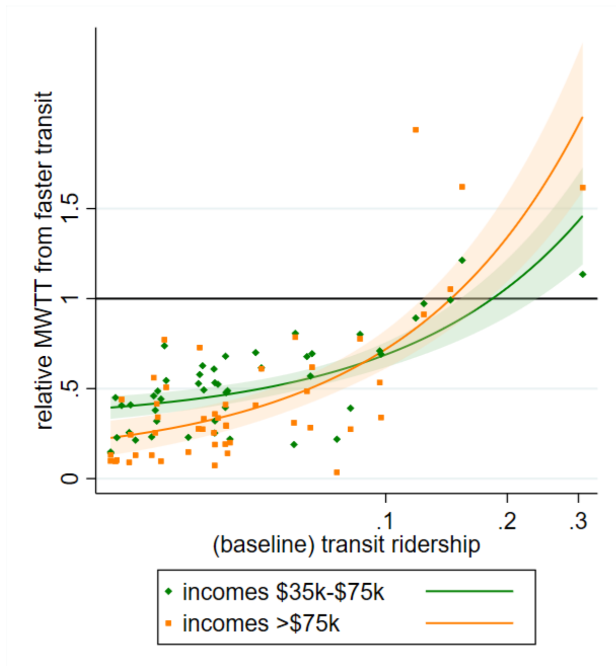
2.5.2.1 Within Cities

The data show similar patterns in marginal transit ridership across locations *within* cities. So far, the analysis has focused on city-wide improvements in transit speeds. For evaluating MWTT within cities, I now consider increasing speeds only along particular commuting routes. To illustrate general patterns, I plot means for the route-specific results aggregated along two dimensions: (standardized) driving speed and (standardized) transit speed.[29] I plot these results for commuters in each of three income brackets. Figure 6 shows contour plots for New York and Los Angeles of the MWTT from an increase in transit speed at different points along the city's observed commuting network.[30] The x- and y-axes depict existing driving and transit speeds on the route. The axes scales are fixed so that the colors representing the MWTT are comparable across income groups and cities.

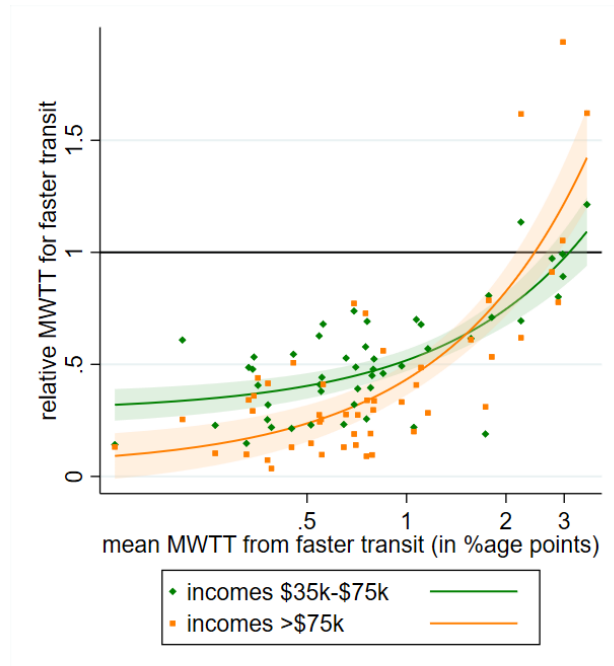
[28]Income differences in mean MWTT across cities are also correlated with mean transit speeds relative to driving and the city's rail share of transit usage. Appendix Figures 24 plot the relative MWTT across income groups as a function of both the city's rail share of transit commutes and its mean transit speed relative to driving.

[29]As before, for comparability across cities, speeds are normalized across all commutes within each city.

[30]Note that the MWTT does not capture commuters moving across residential neighborhoods, and hence the graphs depict the change in transit ridership among commuters given their (observed) work and residence. Section 2.5.3 relaxes this assumption.



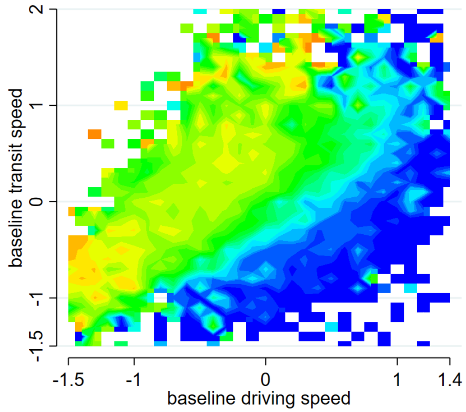
by (baseline) share of commuters riding transit



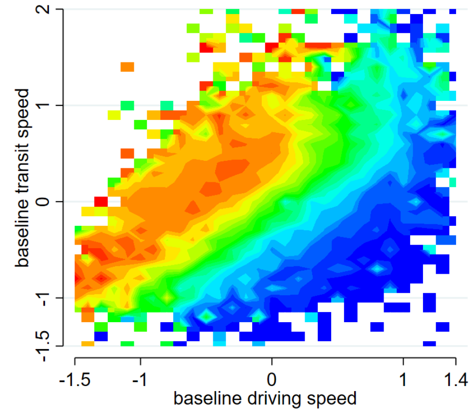
by overall MWTT (across all commuters)

Figure 5: Mean MWTT from 1% increase in transit speed (relative to lowest income group)

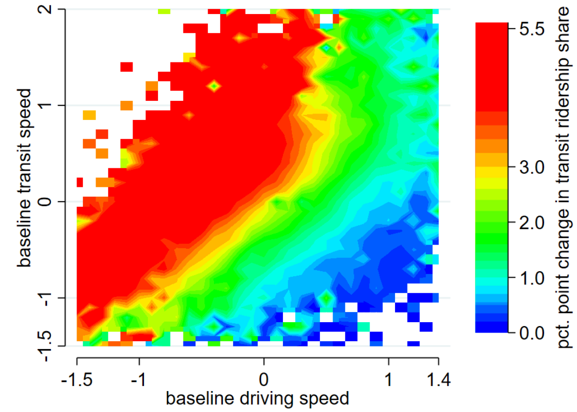
Note: Each observation corresponds to a city. Vertical axis depicts the MWTT for faster transit as a fraction of the MWTT of commuters with incomes less than $35,000 (indicated by solid black line at 1). Horizontal axis depicts in log scale either (a) the baseline transit ridership (across all observed commutes) in the city or (b) the mean MWTT across all commuters. Confidence intervals for each linear fit are shaded in corresponding color. For commuters with incomes $35k-$75k, figures plot population-weighted means of the MWTT estimates for the two middle-income groups in my data.



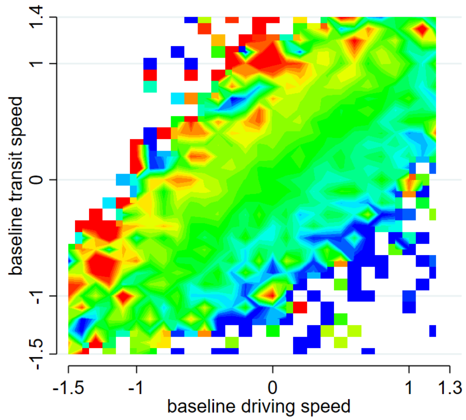
New York, Incomes<$35k



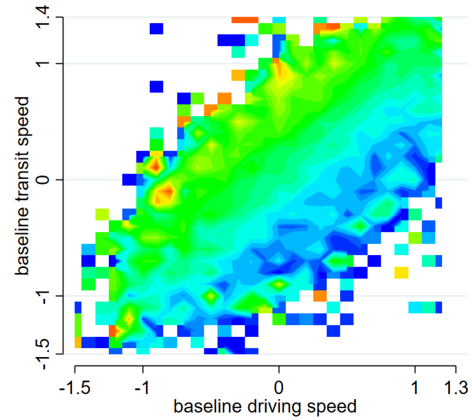
New York, Incomes $35k-$75k



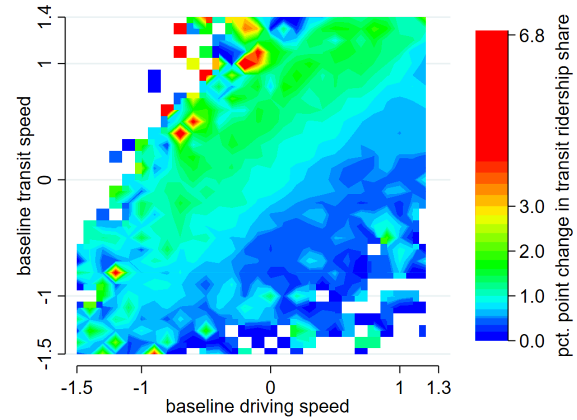
New York, Incomes>$75k



Los Angeles, Incomes<$35k



Los Angeles, Incomes $35k-$75k



Los Angeles, Incomes>$75k

Figure 6: Mean MWTT by location of transit improvement

Note: The x- and y-axes depict standardized driving and transit speeds (resp.) on the commuting route. The z-axis depicts the percantage point change in transit ridership in response to a 1% increase in transit speed along the commuting route. The z-axis colours are fixed across all graphs. Speeds are standardized (to mean 0 and std. dev. 1) across trips between observed work-residence pairs within each CBSA.. Trips at the top and bottom percentiles of speeds are ignored. White spaces in the graphs correspond to 0.1-by-0.1 cells with fewer than 20 commutes.

I highlight two regularities that are clear from these graphs. First, as seen from the increasingly reddish shades at the top-left of each graph, the maginal gains in transit ridership are higher along routes where transit is already relatively fast (or driving is relatively slow). The figures suggest that the relationship between transit ridership and transit speed is convex. Marginal transit improvements may seem ineffective at the beginning when transit is slow, but would yield increasingly larger ridership returns.

Second, in New York, the ridership gains among higher income commuters are much larger (compared to lower income commuters) where driving is relatively slow. Whereas in Los Angeles, it is the opposite: lower income commuters are the ones more likely to increase transit ridership along the (relatively) slow driving routes. The graphs for other rail-transit cities like Chicago, Washington DC and San Francisco with high overall transit ridership resemble that of New York in that high-income commuters have a larger MWTT where driving is relatively slow. Whereas, graphs for most other cities look like those of Los Angeles where low-income commuters have a larger MWTT when driving is relatively slow.[31] There are, however, exceptions like Seattle (where transit is fast and only 5% of transit commutes are by rail transit) where the distribution of the ridership gains for high and low income commuters look similar (see Appendix Figure 25).

More generally, the routes where marginal transit improvements are most effective at generating new transit ridership across all income groups (such as where driving is relatively slow to begin with) are ones: (a) where the ridership gains are larger among the rich in high-speed rail-transit cities like New York or (b) where the gains are larger among the poor in low-speed road-transit cities like Los Angeles.

2.5.3 Distribution of Welfare Gains

Finally, what are the welfare gains across income groups from faster transit commutes? In Section 2.5.1, I presented the gains from faster travel for transit riders and drivers conditional on their observed mode and location choices. Now, having characterized how higher transit

[31] While the increase in transit ridership (in terms of percentage point change) is larger among lower-income commuters, the percentage change from baseline transit ridership is larger among higher income commuters, who have very low transit usage in cities like Los Angeles.

speeds affect the probability of riding transit (conditional on neighborhood choices), this section quantifies the average commuter's expected marginal gains (in terms of their marginal willingness to pay) from increase in travel speeds *unconditional* on their mode and location choice, denoted unconditional MWTP or 'uMWTP' for short. In other words, I compute the marginal gains from increases in transit speed for all commuters (not just transit riders) accounting for re-sorting across both travel modes and residential locations.[32]

Table 9 compares estimates of uMWTP for a one percent increase in travel speeds by driving and transit in New York and Los Angeles. The uMWTP for an increase in transit speeds are an order (or two) of magnitude smaller than the uMWTP for an increase in driving speeds, which is unsurprising given generally low baseline transit ridership. Higher income commuters have a higher willingness to pay than lower income commuters for faster driving commutes, but the income elasticity of the gains from faster transit commutes varies by city. In New York, the uMWTP for faster transit is higher among richer commuters. Whereas in Los Angeles, the uMWTP for faster transit is higher among poorer commuters. Table 10 generalizes this result across all cities and presents the uMWTP estimates relative to that of the lowest income group's. As in Los Angeles and New York, higher income commuters consistently benefit more from increases in driving speeds. However, the lowest income commuters benefit most on average from increases in transit speeds. And as with transit ridership in the previous section, the gains from increases in transit speeds are (over four times) larger for poorer commuters in cities with low baseline transit ridership but (over two times) larger for richer commuters in cities with high baseline transit ridership.

[32]Note that welfare gains in this context only refer to the direct utility gains from shorter commuting times as formalized in Section 2.4. They do not account for general equilibrium effects, such as through changes in congestion or the locations of jobs and residential amenities.

Table 9: Mean u(nconditional)MWTP for 1% increase in travel speeds

City	Mode	< $35k	$35k-$50k	$50k-$75k	>$75k
New York	transit	$18	$24	$33	$44
	driving	$131	$231	$316	$478
Los Angeles	transit	$2.9	$2.9	$2.2	$0.9
	driving	$62	$101	$101	$154

Note: uMWTP values are means across all commuters in the income group for 1% change in travel speeds everywhere. Asymptotic standard errors are less than a cent.

Table 10: Mean relative uMWTP across all cities

	Mode	< $35k	$35k-$50k	$50k-$75k	>$75k
All cities	driving	1.00	1.56	2.00	2.83
	transit	1.00	0.84	0.83	0.92
with less than 10% transit ridership	transit	1.00	0.70	0.48	0.24
with more than 10% transit ridership	transit	1.00	1.13	1.54	2.33

Note: uMWTP estimates are divided by the lowest income group's and averaged over commutes across all cities.

How do these distributional effects compare to the overall welfare gains from faster transit? Table 11 ranks cities by their overall mean uMWTP for faster transit (across all income groups).[33] Cities with higher overall uMWTP (across all commuters) for faster transit are ones where both overall (baseline) transit ridership and the rail share of transit ridership are high. Most remarkably, the five cities with the highest uMWTP are also the only cities in my sample where commuters with incomes above $75,000 have a larger uMWTP for faster transit than commuters with incomes below $35,000. These cities are able to attract disproportionately more high income transit riders (as seen in Section 2.5.2), and higher income transit riders have a higher willingness to pay for faster commutes especially when

[33]While some of the cross-city differences in the magnitudes of uMWTP may be attributable to city-specific housing markets, cities with higher uMWTP for faster transit also have higher uMWTP for transit relative to driving. Column 6 of the table presents the ratio of the uMWTP for faster transit to the uMWTP for faster driving, and a ranking of cities based on this ratio is strongly correlated to the ranking presented. See Appendix for a complete ranking of cities by uMWTP for faster transit.

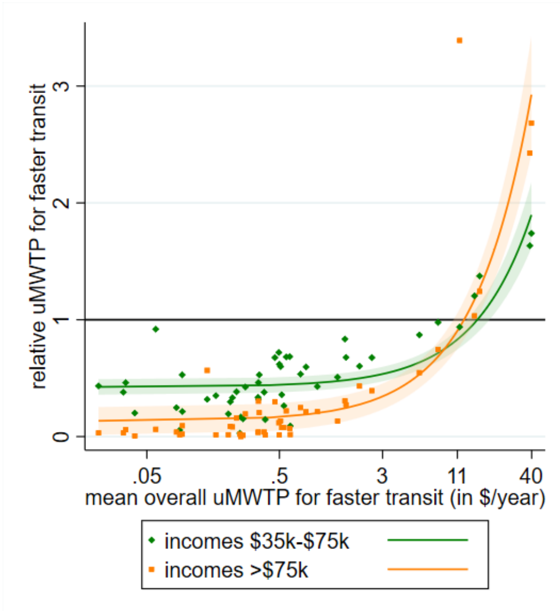
transit is already relatively fast and rail transit is more prevalent (as seen earlier in Section 2.5.1).

More generally, this result reflects the fact that as I move up the ranking of cities, richer commuters stand to benefit increasingly more (relative to poorer commuters) from marginal improvements in transit speed. Panel A of Figure 7 illustrates this point by plotting each city's mean uMWTP for faster transit of higher income commuters relative to commuters with incomes below $35,000. The horizonal axis depicts the mean uMWTP across all commuters (in log scale). Cities with the highest per capita gains from marginal transit improvements are also ones where the welfare gains are more likely to accrue to the rich. And these are also the cities where transit improvements are most effective at generating new transit ridership, as shown in Panel B of Figure 7. After all, overall gains in transit ridership are higher when, as shown earlier in Section 2.5.2, the gains are also disproportionately higher for the rich than the poor.

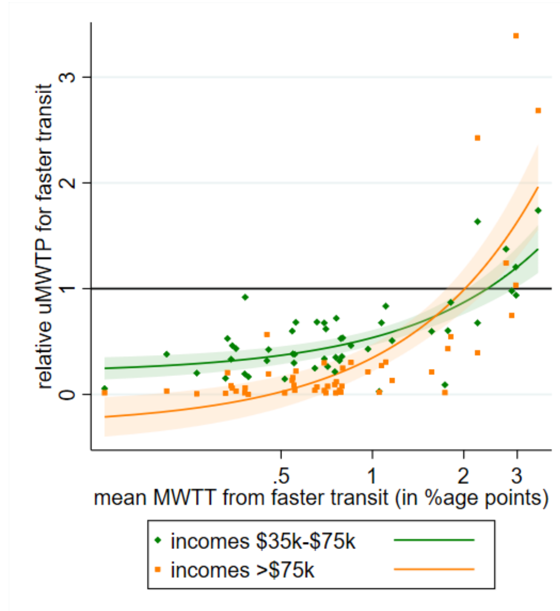
Table 11: Cities ranked by uMWTP for faster transit

		uMWTP for faster transit			**Relative to driving**
Rank	**City**	**all commuters**	**incomes <$35k**	**incomes >$75k**	**all commuters**
1	San Francisco, CA	$ 39.82	$ 17.24	$ 46.26	0.118
2	New York, NY	$ 38.75	$ 18.22	$ 44.21	0.095
3	Boston, MA	$ 16.19	$ 12.90	$ 16.04	0.075
4	Washington, DC	$ 14.81	$ 13.86	$ 14.31	0.087
5	Chicago, IL	$ 11.44	$ 4.81	$ 16.29	0.053
6	Seattle, WA	$ 7.87	$ 9.33	$ 6.96	0.038
7	Philadelphia, PA	$ 5.69	$ 8.20	$ 4.49	0.038
8	Portland, OR	$ 2.49	$ 4.26	$ 1.67	0.023
9	Pittsburgh, PA	$ 2.01	$ 3.51	$ 1.52	0.018
	-				
21	San Diego, CA	$ 0.51	$ 1.37	$ 0.18	0.005
	-				
35	Phoenix, AZ	$ 0.24	$ 0.65	$ 0.10	0.004
	-				
49	Provo-Orem, UT	$ 0.02	$ 0.06	$ 0.00	0.001

Note: Cities are ranked by their mean uMWTP (across all commuters) for 1% increase in transit speeds. Reported uMWTP values are estimates of mean MWTP across all commuters unconditional on their choices of mode and neighborhood. Ratio in column 6 divides uMWTP estimates in column 3 by estimates of the city's mean uMWTP for 1% increase in driving speeds. See rankings for full list of cities in the Appendix.



(A) by mean uMWTP across all commuters



(B) by mean MWTT across all commuters

Figure 7: Mean unconditional MWTP for a 1% increase in transit speed

Note: Vertical axis depicts the income group's mean (relative to commuters with income below $35,000) and horizontal axis depicts (in log scale) the mean across all commuters of either (a) uMWTP or (b) MWTT. Each observation corresponds to a city. Confidence intervals for each linear fit are shaded in corresponding color. For incomes $35k-$75k, I plot population-weighted averages of the uMWTP of the two middle-income groups in my data.

2.6 Conclusion

In this paper, I introduce a methodology for evaluating the demand for faster commutes by public transit and driving based on observed residential location and travel mode choices within cities. In doing so, I address two important empirical challenges that has limited past work on this topic. The first one is a (sparse) data challenge: I need to compare chosen (and observed) commutes to unchosen (and unobserved) ones. To measure the latter, I combine millions of scraped trip queries on Google Maps with data on street networks to predict travel times on all possible alternative commutes between census tracts in US cities. The second challenge is to disentangle the extent to which observed choices and the gains from them (as reflected in housing prices) are due to differences in commuting speeds as opposed to other spatially correlated features of travel modes and neighborhoods. To that end, I propose a discrete choice model that complements my rich data environment with detailed fixed effects in order to identify heterogeneous preferences over commuting speeds. Applying this model to 49 US cities with different transit networks reveals many new insights on the expected ridership and welfare gains from transit improvements across income groups and cities.

Among other things, I show that the demand for faster transit commutes is small relative to the demand for faster driving commutes and depends importantly on the speed of transit relative to driving along commutes as well as on the prevalence of rail transit in the city. Ridership and welfare gains from transit improvements are larger for high income commuters in cities with already high transit ridership, relatively fast transit and high rail transit usage. The opposite is true (that is, larger gains for lower income commuters) in cities with low baseline transit ridership, relatively slow transit and low rail transit usage. And because higher income transit riders have a higher willingness to pay for faster transit commutes, cities where transit improvements are more attractive to the rich are also the ones where they generate more overall transit ridership and welfare. While transit improvements are often believed to reduce inequality in cities, this result suggests that transit improvements most in demand (and, consequently, more likely to be cost-effective and to be realized) are likely to trade off equity for efficiency.

While the paper's findings shed light on several important policy questions, it also opens up new ones that the paper leaves unanswered. For instance, why are transit improvements in rail-transit-heavy cities more likely to benefit the rich? One hypothesis is that because rail transit expansions can be much costlier than road transit expansions, transit planners may be under greater pressure to target efficiency (and high income commuters) over equity (and low income commuters) when choosing where to improve rail transit. Whereas, with buses, planners may focus more on equity. They may also be wary of transit-induced neighborhood gentrification and income segregation in the city. In ongoing work in progress, I am simulating the effect of counterfactual transit improvements in my 49 US cities on residential location choices in order to study who are likely to gentrify newly transit-accessible neighborhoods. In a companion theoretical paper (Akbar, 2020), I explore the decision problem of a transit planner trying to generate new transit ridership or reduce income segregation given heterogeneous preferences over commuting speed. Akbar [2020] shows that urban planners trying to maximize transit ridership have an incentive to target high-speed (such as rail) transit improvements where they are also likely to exacerbate income segregation but low-speed transit (such as shared-lane bus) improvements where they are likely to reduce segregation.

3.0 Public Transit Access and Income Segregation

3.1 Introduction

Public transportation is typically considered a means of more targeted welfare improvements for the urban poor, but is also often held responsible for concentrating poverty in cities (Kalachek, 1968, Glaeser et al., 2008). Public transit is typically cheaper and slower than private vehicles and can, thus, disproportionately benefit relatively low-income households. However, transit networks tend to also be sparsely connected relative to the urban road network. Residential neighborhoods that are close to desirable destinations by driving may be relatively poorly connected by transit (and vice versa). So when high and low income households differ in their travel mode choices, they may also differ in preferences over transit- and driving-accessible neighborhoods. Carefully planned transit expansions can improve low-income households' access to otherwise high-income residential neighborhoods. But transit expansions also have the potential to segregate the poor further in low-income (and potentially low-quality) neighborhoods.

A burgeoning literature shows that socio-economic mobility varies substantially based on where children grow up (Chetty and Hendren, 2018), and low-income families in U.S. cities tend to be segregated in lower-opportunity neighborhoods (Bergman et al., 2019). So the spatial concentration of the urban poor can contribute to the persistence of income inequality (Fogli and Guerrieri, 2019) and intergenerational poverty (Chetty et al., 2014). As a result, it can also lead to inefficient labor market equilibria (Benabou, 1993), segregation along other dimensions like race (Sethi and Somanathan, 2004), and disproportionately worse access to good schools and desirable urban amenities for the urban poor (Couture et al., 2020, Fernandez and Rogerson, 1996).

To relieve increasing levels of urban congestion and environmental pollution, local governments and international financial institutions are slated to spend large sums on mass transit systems.[1] Given the persistence of such travel infrastructure and their role in shaping

[1] For instance, China spent over USD 100 billion on rail transit infrastructure in 2017 alone (OECD, 2019)

the long-run structure of cities (Heblich et al., 2018), it is important to understand how the type and distribution of new mass transit infrastructure within cities affect residential segregation and how the accessibility gains are distributed between the rich and the poor. In particular, when might new mass transit infrastructure exacerbate residential segregation by income? As cities rush to switch more commuters to riding mass transit, how would transit improvements need to be distributed across space to minimize income segregation? And to what extent would such a transit network be consistent with policies that focus on increasing mass transit ridership and battling negative externalities of driving?

To tackle these questions, this paper models the relationship between transit expansions and residential income segregation in a stylized city. Given a network of travel times from each residential neighborhood and by each mode of travel in the city, heterogenous households in the model choose where to live and how to travel. Differences in the willingness to pay for faster travel lead high income households to ride the faster travel mode more often and low income households to ride the cheaper mode more often. As a result, conditional on other neighborhood differences, high-income households are willing to pay more to reside in the neighborhood that is more accessible by the faster mode of travel, while low-income households are willing to pay more to reside in the neighborhood that is more accessible by the cheaper mode of travel. Housing prices capitalize the demand for each neighborhood through a competitive housing market and dictate the subsequent sorting by income. I show that the effect of new transit improvements on residential income segregation is minimized either when high and low income households use both modes of travel equally often or when both neighborhoods are equally accessible by transit relative to driving. When public transit is slow relative to driving (such as buses on shared lanes) and attracts more low-income riders, income segregation is minimized by improving transit access from the richer neighborhood. Whereas, when public transit is relatively fast (such as subways) and attracts more high-income riders, income segregation is minimized by improving transit access from the poorer neighborhood.

I then endogenize the location of public transit improvements as the choice of a planner trying to maximize new transit ridership. I show that this planner's optimal policy is to

and opened over 45 subway lines across 25 cities just between Aug 2016 and Dec 2017.

improve transit access from the neighborhood with higher aggregate incomes, where there are more drivers likely to benefit from switching to riding transit. These transit improvements inadvertently exacerbate income segregation when transit has more high-income ridership (and is relatively fast) but reduce income segregation when transit has more low-income ridership (and is relatively slow). My results serve to highlight the tension between efficient and equitable policy outcomes. As fast growing cities implement new high-speed transit infrastructure to efficiently move drivers off the streets, there is an incentive to focus on areas with a high density of high-income commuters and risk further income segregation. I show that changes in public transit ridership in US cities over the last 3 decades are consistent with my model's predictions given these policy incentives. I also document a shift in recent years towards transit developments that minimize income segregation.

3.1.1 Related Literature

The literature has long recognized that the availability, speed, and price of public transportation facilities may disproportionately affect employment opportunities for black and low-income households (Kalachek, 1968). More recently, Glaeser et al. [2008] compares metropolitan areas in the U.S. and finds that the urbanization of poverty comes mainly from better access to public transportation in central cities. The intuition behind this claim is that the opportunity for poor and rich households to sort into different travel mode choices allows them to avoid competing for the same housing stock and instead segregate across more and less transit accessible neighborhoods. As such, urban public transportation acts as a poverty magnet. In constrast, I show that access to public transportation need not lead to greater income segregation for a host of possible travel configurations. In fact, the income sorting on public transit access can reduce income segregation arising from other spatial features of the city such as the distribution of amenities and driving times, making urban public transportation a potential tool for income desegregation. However, I also show that transit authorities trying to increase the city's overall transit ridership are incentivized to expand the transit network in ways that further segregate the rich and poor, consistent with the empirical observations of Glaeser et al. [2008]. To my knowledge, my paper is the first systematic attempt to generalize how the distribution of the city's public transit network translates into differential access to opportunities for low and high income households.

This paper also helps reconcile a growing body of empirical evidence from evaluations of new urban transportation infrastructure. The vast majority of these studies focus on high-speed mass transit expansions and often find evidence of more income segregation (Heilmann, 2018, Glaeser et al., 2008), but not always (Kahn, 2007, Craig, 2019, Pathak et al., 2017).[2] And even when not explicitly studying segregation, researchers have found large disparities in welfare implications for the rich and the poor that are correlated with gains in overall transit ridership in ways consistent with this paper's findings. For instance, bus rapid transit (BRT) expansions in Bogotá (Tsivanidis, 2019), led to large accessibility gains for the high-skilled and the rich as well as large gains in overall ridership. Whereas with a similarly large-scale BRT expansion in Jakarta (Gaduh et al., 2020), the gains in ridership were modest and mostly concentrated among middle and low income households, and did little to reduce road congestion. Contemporary studies of mass transit expansions also study effects on population growth and decentralization (Gonzalez-Navarro and Turner, 2018), road congestion (Gu et al., 2019) and gender inequality (Kondylis et al., 2020) among other things that are beyond the scope of this paper but also relevant to the discussion on optimal transit policy reform.

Methodologically, this paper contributes to the literature modeling and documenting the distribution of transportation infrastructure and populations within cities. A large class of spatial equilibrium models study income sorting within cities (Wheaton, 1977 and variants) and its interaction with travel mode choice (LeRoy and Sonstelie, 1983 and variants). These models tend to offer households a continuum of residential location choices over a very specific cityscape that mechanically causes a discrete number of household types (such as rich and poor) to segregate perfectly across space. Empirical studies have traditionally built on this framework to document changes in population and property prices primarily as a function of proximity to the city center (Gonzalez-Navarro and Turner, 2018, Baum-Snow, 2007). Instead, I let the cityscape be defined flexibly using only a set of travel times

[2]There are also cross-sectional studies that have linked transit availability to greater income mixing (Blumenberg and Ong, 2001, Sanchez, 2002).

with no underlying topographic constraints. Among other things, doing so allows me to consider scenarios where mass transit networks are sparse and travel times by transit are uncorrelated (or even negatiively correlated) with driving times. I also deviate from these spatial equilibrium models by having a continuum of household types sorting into a discrete number of choices, similar to Epple and Platt [1998], Sethi and Somanathan [2004] and related equilibrium sorting models where segregation can be an outcome of interest at the intensive margin. In doing so, this work connects to a number of theoretical and empirical papers outside of the transportation literature that have modeled residential location choices similarly over a discrete set of neighborhoods to study, for instance, the effect of residential segregation on labor market efficiency (Benabou, 1993) and inequality (Fogli and Guerrieri, 2019) or the effect on segregation of local amenities such as public school financing (Fernandez and Rogerson, 1996) and air pollution (Banzhaf and Walsh, 2013). Finally, while I focus on the impact of public transit on income segregation, the framework developed in this paper could be adapted to model transit-induced segregation along other demographic dimensions of interest. For instance, Baum-Snow and Kahn [2000] document disproportionately higher mass transit usage among black, female, college-educated and unmarried urban residents.

The rest of this paper is organized as follows. Section 3.2 documents income differences in urban mass transit ridership and residential location choices in data from U.S. cities. Section 3.3 introduces a model of travel mode and residential location choices by heterogenous households in a stylized city. Section 3.4 studies the effect of improving transit access on household choices in equilibrium and income segregation, and characterizes how the effect varies with the location of transit on the existing travel network. Section 3.5 characterizes optimal transit improvements from the perspective of a planner trying to maximize overall transit ridership, documents changes in observed transit ridership in US cities, and discusses their implications for income segregation. Section 3.6 shows the results' robustness to several generalizations of the baseline model. Section 3.7 concludes.

3.2 Empirical Observations

Poorer households tend to reside closer to public transportation in cities. Panel A of Figure 8 shows that median household incomes in New York city (NYC) census tracts are significantly lower closer to transit stops.[3] Housing prices near transit stops are also higher, suggesting a higher willingness to pay for better transit access (and correlated urban amenities) among poorer households. Panel B of Figure 8 plots average housing price indices from the US Federal Housing Finance Agency for each of our NYC tracts against their distance to mass transit *conditional on median household incomes*.[4] Census tracts within half a kilometer of mass transit are likely to have higher housing prices (by roughly half a standard deviation) than tracts beyond with the same median incomes. Similar patterns have been observed for other large US cities, leading Glaeser et al. [2008] to deem public transportation a poverty magnet. Figure 9 plots the inequality in median incomes across neighborhoods in US metropolitan areas as a function of the share of total commuters who ride mass public transportation. Cities that have high transit ridership also tend to have more income segregation. However, this observed relationship between transit and income segregation masks important heterogeneity in preferences for transit access.

3.2.1 Transit Ridership by Household Income

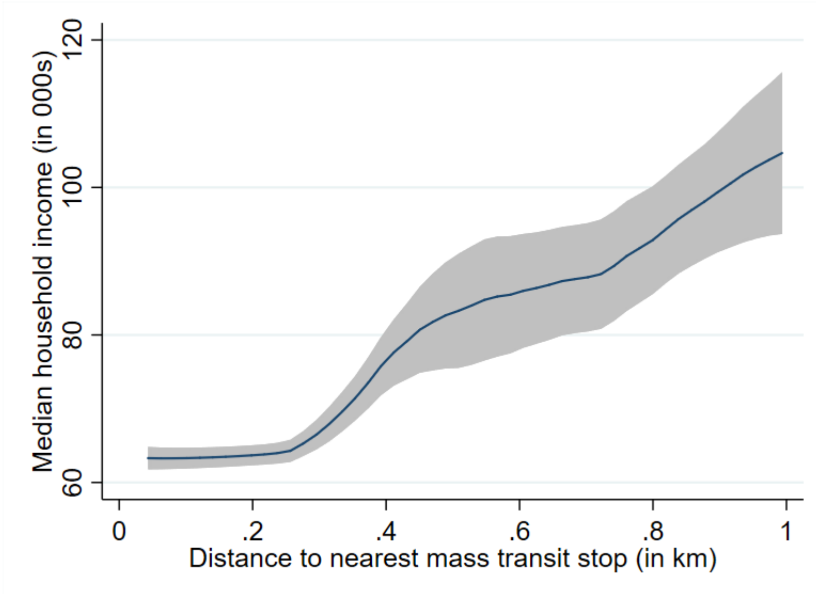
Panel A of Figure 10 plots as a function of annual household income the fraction of workers in U.S. cities for whom the primary means of commute is public transportation.[5]

[3] To make sure we are not just comparing downtowns to suburbs, I restrict the graph to only tracts within 1 km (on average) of transit stops. But even beyond 1 km, median household income continues to be higher than \$100,000.

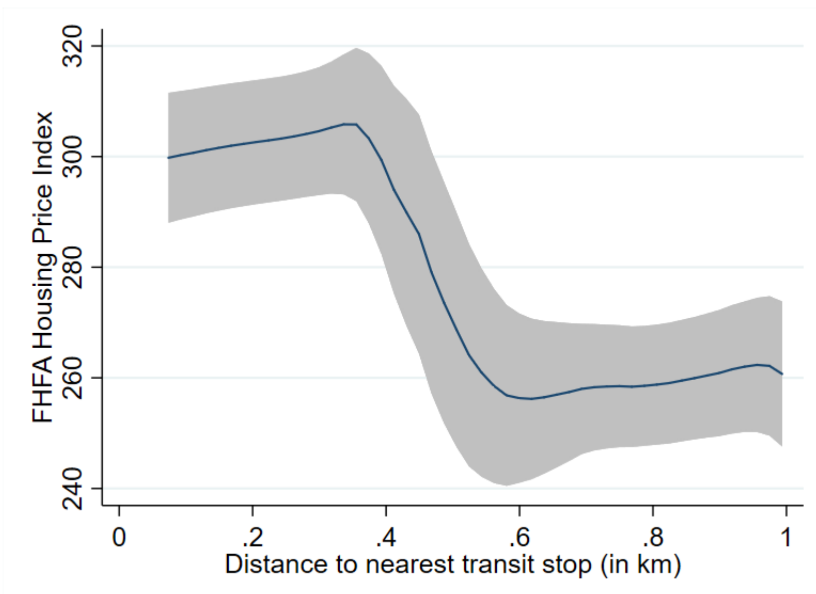
[4] The US Federal Housing Finance Agency (FHFA) publishes monthly census tract-level housing price indices based on repeat mortgage transactions on single-family properties. I use their 2017 price indices to estimate the following semi-parametric regression:

$$HousingPriceIndex = f\big(DistanceToTransit\big) + MedianHouseholdIncome$$

[5] Data is based on the American Community Survey 2013-17. The ACS surveys 5% of US households over a 5-year period. My sample (courtesy of Ruggles et al., 2019) includes all survey respondents who lived in a Census-designated city, was above 16 years of age and was working at the time of the survey. I discretize household income into 10 bins, starting at \$1, \$15,000, \$25,000, \$35,000, \$50,000, \$75,000, \$100,000, \$125,000, \$150,000, and \$200,000.



(A) Median household income in NYC census tracts from ACS 2013-17



(B) FHFA housing price index (2017) conditional on median houshold income

Figure 8: Incomes and housing prices by distance to mass transit stops in NYC

Note: Values on vertical axes are kernel-smoothed functions of distance to nearest bus, rail or subway stop for the average household in the census tract. Gray area depicts 95% confidence interval.

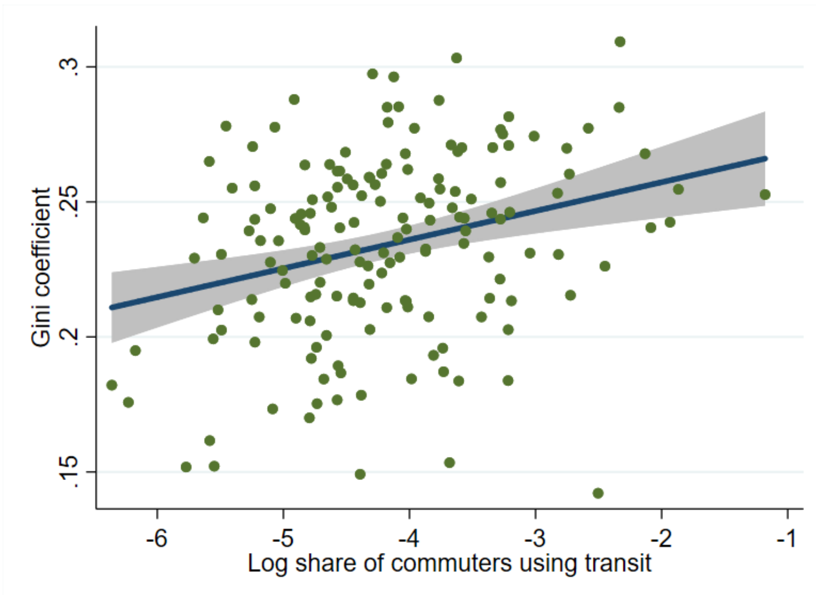


Figure 9: Residential segregation by income against share of commuters who ride mass public transit

Note: Figure covers U.S. metropolitan areas with population over 300,000. Vertical axis depicts the Gini coefficient of median household incomes across Census block groups, based on data from the 2006-10 American Community Survey.

Ridership on public transportation that share the road with car traffic, as in buses (and streetcars and trolley cars), is decreasing with household income. In contrast, ridership on subway, elevated and rail transit is increasing with income. Panel B restricts the sample to only cities with both high road and rail transit ridership to show that this income difference in transit ridership is not just due to higher incomes in cities with more rail transit. Richer households happen to have better access to rail transit within cities (despite transit-accessible neighborhoods being relative poorer). Panel C plots transit ridership across different neighborhoods of NYC.[6] Conditional on residing in a census tract that is well connected by both subway/railway and bus, the rich and poor are equally likely to ride public transit. When we look at tracts close to bus stops but far from subway/railway stops, transit ridership starts to decrease with income. The relationship slopes down even further when we look at tracts that are sparsely connected by either type of transit. So, cities with denser transit networks and more rail transit tend to have higher overall transit ridership as well as a larger share of transit riders who are high-income.[7]

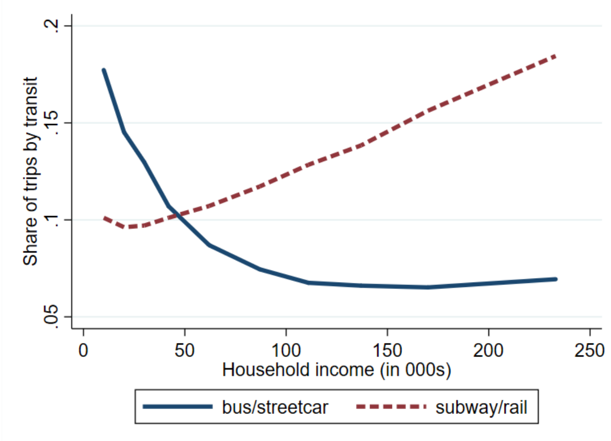
3.2.2 Changes in Public Transit and Neighborhood Incomes

Finally, I document how changes in transit correlate with income sorting across transit neighborhoods between the 2000 and 2010 censuses. Given higher public transit ridership also reflects better transit access, Figure 11 plots the relationship between changes in a neighborhood's transit ridership (as a proxy for transit access) and changes in the neighborhood's median income (conditional on city fixed effects). I restrict my sample to the 54 metropolitan areas (CBSAs) where at least 2% of the commutes use public transit and to neighborhoods within these CBSAs where at least 5% of the commutes used public transit in 2000.[8] The graph distinguishes cities where a larger share of transit commutes are rail-based (such as New York and Chicago) from cities where a larger share of transit commutes are

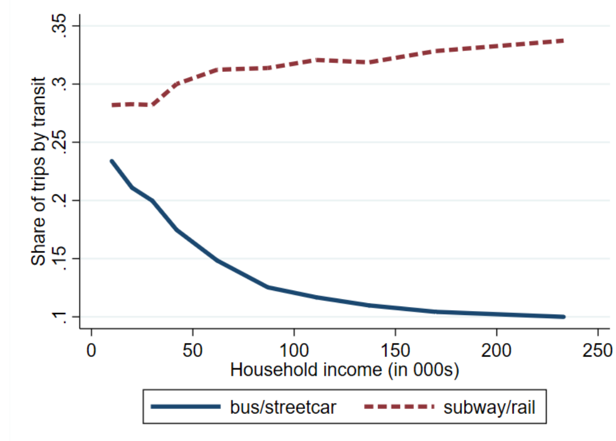
[6] To compare mass transit across neighborhoods within a city, I use the following crude measure of transit access at the level of census tracts. From each residential block in New York city, I compute the straight-line distance to the nearest mass transit stop, and take its mean within each census tract weighted by block population. This is the proximity to mass transit for the average household living in the tract.

[7] See Appendix B.1.1 for a cross-city comparison of transit ridership.

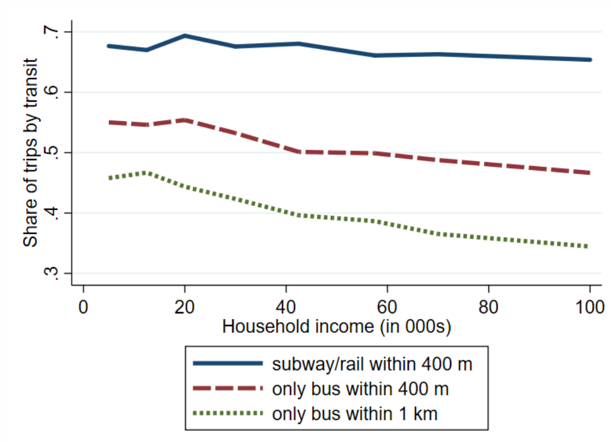
[8] I also exclude neighborhoods with over 95% public transit ridership in 2000 (to avoid mechanical boundary effects) and the top and bottom 1% of transit ridership changes.



(A) All U.S. cities



(B) Cities with both high (>5%) bus and rail transit ridership



(C) Census tracts in New York

Figure 10: Share of commuters using mass transit by household income

Note: Data is from the 2013-17 American Community Survey. Household income is censored at $300,000 per year and discretized into 10 bins. Lines connect points at the median of each bin. Panel C shows transit ridership in tracts where the average household lives within 400 meters of a subway/railway stop (solid line), has a bus stop but no subway/railway stop within 400 meters (dashed line), or has a bus stop but no subway/railway stop within 1 km (dotted line).

by bus (such as Los Angeles and Philadelphia). In cities with more bus ridership, changes in public transit ridership are negatively correlated with changes in neighborhood income, potentially due to poorer households relocating to more transit-accessible neighborhoods. However, in cities with more rail transit ridership, the relationship is U-shaped: large decreases in transit ridership coincide with larger increases in neighborhood incomes, but so do increases in transit ridership. The latter is consistent with recent empirical case studies of rail transit expansions finding higher income households gentrifying new rail transit neighborhoods (Heilmann, 2018, Kahn, 2007).

The following section presents a model of travel mode and residential location choices that formalizes the relationships observed in this section. Later on in the paper, I document strong correlations between transit ridership changes and initial neighborhood incomes across bus and rail transit-heavy US cities. I use the model's predictions to interpret these correlations as the choices of urban planners trying to maximize transit ridership or minimize income segregation.

3.3 Model

Consider a city with two generic residential neighborhoods, $n \in \{1, 2\}$. The neighborhoods may be East and West, downtown and suburb, or some other spatially separated areas of the city. The city has a continuum of measure 1 of heterogeneous households. All households are exogenously assigned to one of two income groups $g \in \{L, H\}$. There are Λ households with low income w_L and $1-\Lambda$ households with high income w_H. Each household experiences an idiosyncratic benefit ξ from choosing to living in neighborhood 1 over neighborhood 2, where ξ is independent of income and distributed uniformly between $-\Xi$ and Ξ. Households in the city are characterized completely by their income w_g and preference ξ for neighborhood 1. The city is 'closed' in that there is no possibility of migration in or out of the city and the distribution of household characteristics (w_g, ξ) are fixed. But households may relocate costlessly across residential neighborhoods within the city.

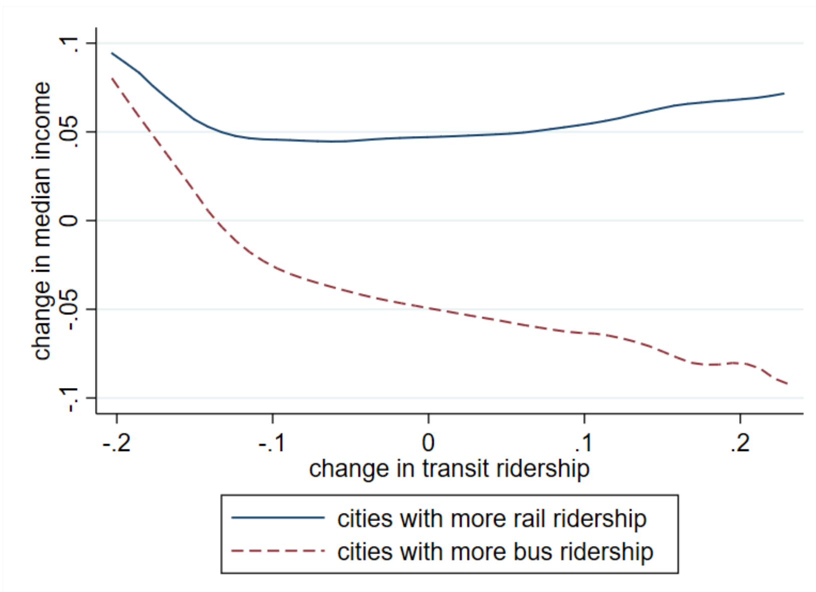


Figure 11: Change in neighborhood incomes and transit ridership between 2000 and 2010

Note: Figures covers all U.S. metropolitan areas (CBSAs) where at least 2% of commuters ride transit. Neighborhoods correspond to census tracts within 30 km of the primary city center. Vertical axis depicts the percentage change in median household incomes net of average change in the CBSA. Horizontal axis depicts percentage point change in the share of commutes by public transit.

3.3.1 Living in the City

Conditional on residing in neighborhood n, households consume a single unit of identical housing space at (endogenously determined) market price p_n. Each neighborhood n has the same fixed supply of housing and accommodates exactly half of the city's households.[9] So, the housing prices ensure that aggregate demand for housing in each neighborhood matches the fixed supply of $\frac{1}{2}$. Since all housing within a neighborhood are identical and the housing stock is fixed, the difference in housing prices $\Delta p \equiv p_1 - p_2$ captures the attractiveness of residential neighborhood 1 relative to 2.[10]

Each residential neighborhood also offers local amenities A_n for household consumption. The provision of this good is exogenously fixed and independent of other characteristics of the neighborhood (such as housing prices or average incomes of residents) and its location within the city's travel network.

3.3.2 Travel in the City

All households in the city are faced with a continuum of measure 1 trips of different types (such as to work, to grocery stores, to school, etc) indexed by q. These trip destinations need not coincide with the city's residential neighborhoods and could be located anywhere in the continuous space surrounding the neighborhoods. For each trip, a household may use one of two modes of travel $m \in \{\boldsymbol{t}ransit, \mathbf{c}ar\}$. Think of $\boldsymbol{t}ransit$ as a generic label for a publicly provided mass transit, such as a subway or a city bus, that runs on a fixed network of routes. Similarly, $\mathbf{c}ar$ could be any alternative mode of travel with a wider network of routes such as a taxi or a private vehicle. The trip travel time τ_n^m depends only on the household's neighborhood (trip origin) n and mode of travel m.[11] The residential neighborhoods are equally accessible by car so that $\tau_1^c = \tau_2^c$, but may vary in access along

[9] In section 3.6, I generalize the model to allow housing consumption and neighborhood populations to vary by letting housing demand be price elastic (instead of fixed). Doing so does not change the paper's main results.

[10] Prices p_n could be interpreted as housing rent to absentee landlords or recurring costs of home ownership (e.g. mortgage payments, maintenance, etc). But, more importantly, p_n is the price of residing in neighborhood n.

[11] Section 3.6.3 extends the model to let travel destinations (and travel times) vary with household income.

the *transit* network.[12] Households also incur a monetary cost of κ^m on each trip that is larger by **c**ar than by ***t**ransit* ($\kappa^c > \kappa^t$). The total travel cost of a trip is the sum of this monetary cost and the household's opportunity cost of the time spent traveling:

$$\tilde{C}^m_{gn} = \beta \cdot w_g \cdot \tau^m_n + \kappa^m \tag{3.3.1}$$

where $\beta > 0$ is the value of a unit of time on the road as a fraction of income.[13] There are also trip-specific benefits/costs γ_q to using ***c**ar* over ***t**ransit* (such as from having a car to carry back large groceries, or from taking the transit where parking spots are scarce) that are drawn from independent and identical uniform distributions over a broad support $[-\Gamma, \Gamma]$.[14] Let Ψ and ψ denote the c.d.f. and p.d.f. of the distribution. So, for each trip q from neighborhood n, a household from income group g chooses travel mode $m^\star_{gn}(\gamma_q)$ to minimize $\tilde{C}^m_{gn} - \gamma_q \cdot \mathbf{I}_{m=c}$. The household chooses to ride ***t**ransit* on trips where it is cheaper to do so:

$$\tilde{C}^t_{gn} < \tilde{C}^c_{gn} - \gamma_q$$

$$\Leftrightarrow \gamma_q < \tilde{C}^c_{gn} - \tilde{C}^t_{gn} \equiv \tilde{\gamma}(w_g; \Delta\tau_n, \kappa) \equiv \tilde{\gamma}_{gn} \tag{3.3.2}$$

where, henceforth, $\Delta\tau_n \equiv \tau^t_n - \tau^c_n$ denotes travel time by ***t**ransit* relative to ***c**ar*, $\kappa \equiv \kappa^c - \kappa^t$ denotes the difference in monetary cost of travel and $\tilde{\gamma}(w_g; \tau^t_n - \tau^c_n)$, or $\tilde{\gamma}_{gn}$ for short, is the γ needed to make households indifferent between choosing ***c**ar* or ***t**ransit*. The fraction of trips that is taken by ***t**ransit* from neighborhood n is $\Psi\big(\tilde{\gamma}_{gn}\big)$.[15] Note from (3.3.2) that ***t**ransit* ridership is decreasing with income w_g when ***t**ransit* is slower than **c**ar ($\Delta\tau_n > 0$), and vice versa. And the slower *transit* is, the faster *transit* ridership declines with income. This is consistent with our observations from U.S. cities in Section 3.2.

[12] Section 3.6.1 extends the model to allow travel times by *car* to vary across neighborhoods.

[13] The analysis is robust to alternative functional forms of this travel cost as long as the opportunity cost and the monetary cost are additively separable. For instance, we can include a monetary cost that varies with travel time (e.g. for gas). Doing so might make the function more realistic but would not change the model's qualitative predictions in any meaningful way.

[14] Note that γ_q may be negative e.g. when ***t**ransit* is more suitable than **c**ar for trip q.

[15] We can interpret $\tilde{\gamma}_{gn}$ as the trip-specific benefits from riding **c**ar that would make a group g resident of neighborhood n indifferent between the two travel modes.

3.3.3 Household Preferences

Besides travel and housing costs, households spend the rest of their incomes on consuming x of some composite good at a normalized price of 1. Conditional on living in neighborhood n, each household chooses their consumption x and distribution of travel modes $m^\star$ to maximize the following linear utility function:

$$U_{gn}(x, m^\star; \xi) \equiv x + A_n + \xi \cdot \mathbf{I}_{n=1} + \int_{\gamma : m^\star_{gn}(\gamma) = c} \gamma \cdot d\Psi(\gamma) \tag{3.3.3}$$

subject to budget constraint

$$x = w_g - p_n - \int_\gamma \tilde{C}_{gn}^{m^\star_{gn}(\gamma)} \cdot d\Psi(\gamma) \tag{3.3.4}$$

In words, households derive utility from consumption x, idiosyncratic taste ξ for neighborhood 1, and net benefits from choosing to ride the **c**ar (aggregated across all their trips). The household's consumption is constrained by their income w net of expenditure on housing and travel (resulting from optimal choices of travel mode across trips).

Given optimal consumption x and mode choices $m^\star$, households can compare their utilities from each neighborhood choice. For ease of notation from here on, let us subtract the utility benefits γ of riding the **c**ar from the travel costs (in 3.3.4) and aggregate across trips to define C_{gn} as the net (monetary and psychological) travel cost from neighborhood n:

$$C_{gn} \equiv \int_\gamma \tilde{C}_{gn}^{m^\star_{gn}(\gamma)} \cdot \partial\Psi(\gamma) - \int_{\gamma : m^\star_{gn}(\gamma) = c} \gamma \cdot d\Psi(\gamma)$$

$$= \left[1 - \Psi\left(\tilde{\gamma}_{gn}\right)\right] \cdot \tilde{C}^c_{gn} + \Psi\left(\tilde{\gamma}_{gn}\right) \cdot \tilde{C}^t_{gn} - \int_{\tilde{\gamma}_{gn}}^{+\infty} \gamma \cdot d\Psi(\gamma) \tag{3.3.5}$$

Note that C_{gn} is the minimized total travel cost resulting from optimal travel mode choices. Substituting the budget constraint (3.3.4) into the utility function (3.3.3) and plugging in the newly defined C_{gn} yields the following indirect utility from choosing to live in neighborhood n:

$$V_{gn} \equiv w_g - p_n - C_{gn} + A_n + \xi \mathbf{I}_{n=1} \tag{3.3.6}$$

Households that reside in neighborhood 1 in equilibrium have (w_g, ξ) such that $V_{g1} \geq V_{g2}$ at equilibrium prices p_1 and p_2. So, a household lives in neighborhood 1 if

$$\xi > C_{g1} - C_{g2} - A_1 + A_2 + p_1 - p_2 \equiv \bar{\xi}(w_g; \Delta p) \equiv \bar{\xi}_g \tag{3.3.7}$$

that is, if the household has a high enough relative taste for living in neighborhood 1 given its travel and housing costs and gains from local amenities. $\bar{\xi}(w_g; \Delta p)$, or $\bar{\xi}_g$ for short, denotes the taste difference ξ needed to make a household with income w_g indifferent between the two neighborhoods. $\bar{\xi}_g$ also characterizes the mapping of household characteristics to their choice of residential neighborhood for any given pair of housing prices. Let F denote the c.d.f. of the uniformly distributed ξ. Then the measure (and fraction) of households with income w_g living in neighborhoods 1 and 2 are $1 - F(\bar{\xi}_g)$ and $F(\bar{\xi}_g)$ respectively.

Finally, the housing price difference Δp across neighborhoods must be such that the aggregate demand for housing in each neighborhood equals the fixed housing supply:

$$\Lambda \cdot F(\bar{\xi}_L) + (1 - \Lambda) \cdot F(\bar{\xi}_H) = \frac{1}{2} \tag{3.3.8}$$

Intuitively, we are looking at a competitive equilibrium where each household best responds to the housing prices taking everyone else's best response as given. Having defined the household's decision problem, I now characterize the optimal choices of travel mode m and neighborhood n.

3.3.4 Travel Mode and Residential Location Choices

We know from (3.3.2) that $\tilde{\gamma}_{gn}$ and, hence, the fraction $\Psi(\tilde{\gamma}_{gn})$ of a household's trips by ***t**ransit* is decreasing in income when ***t**ransit* is slower than **c***ar* ($\Delta\tau_n > 0$) and increasing in income when ***t**ransit* is faster ($\Delta\tau_n < 0$). So, from either neighborhood, the higher the household's income the more they ride the faster mode of travel (as illustrated in Figure 12). As we decrease travel times by ***t**ransit*, all households increase their ***t**ransit* ridership. But because higher-income households have a higher opportunity cost of time, $\tilde{\gamma}_{Hn}$ increases more than $\tilde{\gamma}_{Ln}$ and high-income households switch to riding ***t**ransit* more than low-income households. Note the resemblance in transit ridership from Figure 12 to that within U.S.

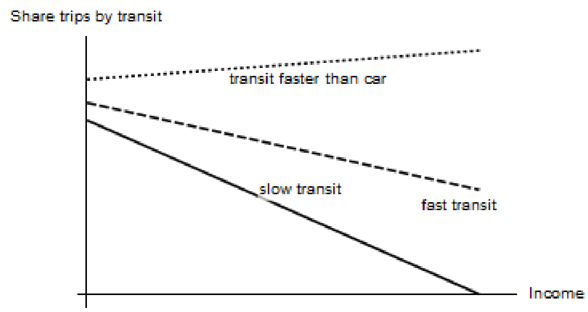


Figure 12: Fraction of trips taken by $\boldsymbol{transit}$ as a function of income

Note: Separate lines for when *transit* is: slow ($\Delta\tau_n \gg 0$), fast ($\Delta\tau_n > 0$) and faster than $\boldsymbol{car}$ ($\Delta\tau_n < 0$).

cities in Panel C of Figure 10 (and, in the case of $\boldsymbol{transit}$ faster than $\boldsymbol{car}$, to rail transit ridership in Panel A of Figure 10).

As for residential neighborhood choice, recall that at any given income w_g, households with high $\xi > \bar{\xi}_g$ live in neighborhood 1, while those with low $\xi < \bar{\xi}_g$ live in neighborhood 2. First, consider the more straightforward case where $\boldsymbol{car}$ is infinitely slow and everyone always rides $\boldsymbol{transit}$. Then $\bar{\xi}_g = \beta \cdot w_g \cdot (\tau_1^t - \tau_2^t) + A_2 - A_1 + \Delta p$ is linear in income and the difference in travel times (see Figure 13). Suppose neighborhood 1 offers shorter travel times: $\tau_1^t < \tau_2^t$. Because higher-income households have a higher opportunity cost of travel time, they require a smaller ξ to make them choose the closer neighborhood 1 over the distant one 2. Thus, $\bar{\xi}(w)$ is decreasing in income, and the closer neighborhood 1 has more high-income households, while the distant neighborhood 2 has more low-income households.[16] The larger the difference in travel times between the two neighborhoods, the steeper is the slope of $\bar{\xi}(w)$, and the worse is the sorting by income (with a constant $\bar{\xi}$ indicating perfect income mixing).

Note that the differences in housing prices Δp and neighborhood amenities $A_2 - A_1$ do not affect the degree of income sorting. They determine the intercept of $\bar{\xi}(w; \Delta p)$, but not its gradient. The intercept is such that the number of households above and below the line equal exactly half (the housing stock in each neighborhood). With two modes of travel, $\bar{\xi}$ is not

[16]If neighborhood 2 were more accessible ($\tau_1^t > \tau_2^t$), the reverse would be true (and the graph would be upward sloping).

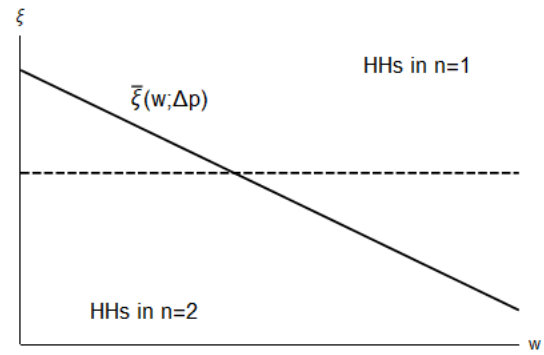


Figure 13: Income sorting under one mode of travel

Note: Graph depicts $\bar{\xi}(w;\Delta p)$ when $\tau_n^c \ggg \tau_n^t$ in both n, $\tau_1^t < \tau_2^t$ and $A_1 - p_1 < A_2 - p_2$. Households with $\xi > \bar{\xi}(w)$ live in neighborhood 1, while those with $\xi < \bar{\xi}(w)$ live in neighborhood 2. Dashed line depicts zero income segregation.

a linear function of income but its gradient is still proportional to the difference in *average* travel times (weighted by travel mode share) between the neighborhoods and independent of equilibrium housing prices.

Having characterized the city in equilibrium, the following section explores how changes in *transit* access shift household choices and income segregation. Recall that *car* travel times are fixed, so a level change in relative *transit* times $\Delta\tau_n$ is equivalent to a level change in *transit* times τ_n^t. From here on, changes in *transit* access or transit improvements are presented in terms of a change in $\Delta\tau_n$.

3.4 Income Segregation

As a formal measure of income segregation, I rely on the commonly used dissimilarity index, which is the minimum fraction of the city's population that needs to relocate to achieve perfect income mixing (i.e., the same distribution of incomes in each neighborhood). In the context of my city, income dissimilarity, denoted $DISS$ henceforth, is computed as follows:

$$DISS \equiv \Lambda \cdot \left| F\big(\bar{\xi}_L\big) - \frac{1}{2} \right| + (1 - \Lambda) \cdot \left| F\big(\bar{\xi}_H\big) - \frac{1}{2} \right| \tag{3.4.1}$$

When we substitute into it the housing market clearing constraint (3.3.8), the dissimilarity measure boils down to:

$$DISS = 2\Lambda \cdot (1 - \Lambda) \cdot \big| F\big(\bar{\xi}_L\big) - F\big(\bar{\xi}_H\big) \big| \tag{3.4.2}$$

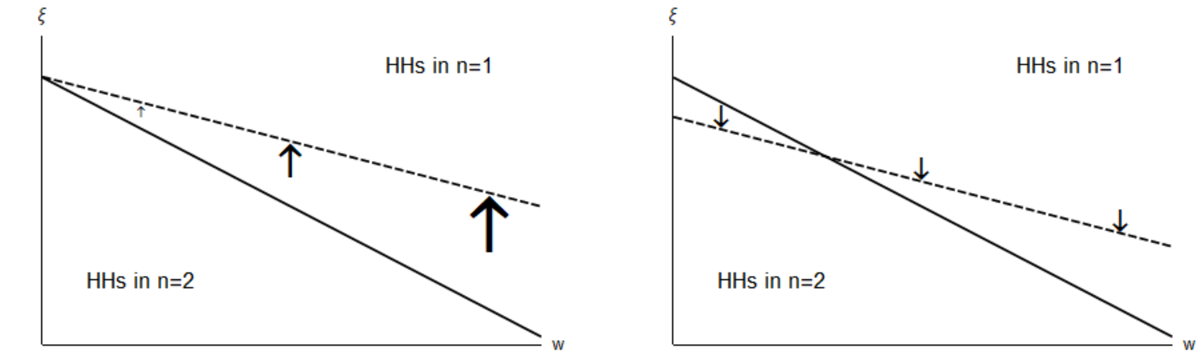
$DISS$imilarity is minimized when $\bar{\xi}_L = \bar{\xi}_H$, which is when low and high income households face similar differences in travel costs and amenity benefits across neighborhoods.

Assume from now on that tastes ξ have broad enough distributional support so that $F\big(\bar{\xi}_g\big) \in (0, 1)$ for both g and neither income group is perfectly segregated in one of the residential neighborhoods.[17] Given constant probability density $f = \frac{1}{2\Xi} > 0$ over tastes, the dissimilarity index simplifies to

$$DISS = 2\Lambda \cdot (1 - \Lambda) \cdot f \cdot \big| \bar{\xi}_L - \bar{\xi}_H \big| \tag{3.4.3}$$

For narrative convenience, a neighborhood n is deemed 'richer' or 'high-income' if the share of the city's high-income households residing in n is larger than the share of low-income households in n. Conversely, the 'poorer' or 'low-income' neighborhood's share of low-income households is larger than its share of high-income households. For example, $\bar{\xi}_L > \bar{\xi}_H$ is equivalent to a richer neighborhood 1 and a poorer neighborhood 2, and vice versa. Given the population in each neighborhood is exactly half, the richer neighborhood also has higher aggregate residential income than the poorer household.

[17] This assumption is simply for narrative convenience. As I shown in Appendix B.2.5, when either $\bar{\xi}_L$ or $\bar{\xi}_H$ is outside the distribution's support $[-\Xi, \Xi]$, travel time changes have no effect on income segregation ($\frac{dDISS}{d\Delta\tau_n} = 0 \; \forall n$). Intuitively, when $\bar{\xi}_g$ is outside of the support, all households of income w_g choose to reside in the same neighborhood ($F\big(\bar{\xi}_g\big)$ is either 0 or 1) and marginal changes in neighborhood characteristics (and $\bar{\xi}_g$) do not alter their choice.



Travel cost effect: lower C_{g2} increases demand for neighborhood 2

Housing price effect: Lower Δp reduces demand for neighborhood 2

Figure 14: $\bar{\xi}(w; \Delta p)$ when we reduce travel times τ_2^t from the poorer neighborhood 2

3.4.1 Transit Improvements and Income Segregation

How do changes in travel times by *transit* affect income sorting? First, suppose we lower (relative) *transit* travel times $\Delta\tau_2$ from neighborhood 2. Lower travel costs C_{g2} shifts $\bar{\xi}_g$ up for all households with positive *transit* ridership. The magnitude of the shift will differ by income. For example, higher income households gain more from shorter travel times on each trip (as they have a larger opportunity cost), but lower income households may make more trips by *transit*.[18] Then, as long there is non-zero *transit* ridership from neighborhood 2, aggregate housing demand goes up, forcing housing prices to also go up (and prices to go down in neighborhood 1). Higher housing prices in neighborhood 2 forces some marginal households across all income groups to move out to neighborhood 1, shifting $\bar{\xi}_g$ down by the same amount for all households. Figure 14 demonstrates this graphically for a reduction in *transit* travel times when it benefits the rich more.

In general, the income group with the larger reduction in travel costs sees a net increase in neighborhood population whereas the income group with the smaller reduction in travel costs sees a net decline in neighborhood population. This sorting dynamics leads us to the

[18]For $m = car$, the shift in $\bar{\xi}$ is always greater for higher income households.

following result on *transit*.

Lemma 3.1. *Suppose there is non-zero transit ridership in neighborhood n so that* $\Psi\big(\tilde{\gamma}_{gn}\big) > 0$ *for some g.*

- *When n is the* ***richer*** *neighborhood, a marginal reduction in transit travel times* $\Delta\tau_n$
  - ***increases*** *income segregation* ($\frac{dDISS}{d\Delta\tau_n} < 0$) *if there is large enough* ***high-income*** *transit* ***ridership*** ($w_H \cdot \Psi\big(\tilde{\gamma}_{Hn}\big) > w_L \cdot \Psi\big(\tilde{\gamma}_{Ln}\big)$), *and*
  - ***decreases*** *income segregation* ($\frac{dDISS}{d\Delta\tau_n} > 0$) *if there is large enough* ***low-income*** *transit* ***ridership*** ($w_H \cdot \Psi\big(\tilde{\gamma}_{Hn}\big) < w_L \cdot \Psi\big(\tilde{\gamma}_{Ln}\big)$)
- *When n is the* ***poorer*** *neighborhood, a marginal reduction in transit travel times* $\Delta\tau_n$
  - ***increases*** *income segregation* ($\frac{dDISS}{d\Delta\tau_n} < 0$) *if there is large enough* ***low-income*** *transit* ***ridership*** ($w_H \cdot \Psi\big(\tilde{\gamma}_{Hn}\big) < w_L \cdot \Psi\big(\tilde{\gamma}_{Ln}\big)$), *and*
  - ***decreases*** *income segregation* ($\frac{dDISS}{d\Delta\tau_n} > 0$) *if there is large enough* ***high-income*** *transit* ***ridership*** ($w_H \cdot \Psi\big(\tilde{\gamma}_{Hn}\big) > w_L \cdot \Psi\big(\tilde{\gamma}_{Ln}\big)$).

The formal proof is in the Appendix (as with all formal results from here on) but the intuition behind the result is straightforward. When we reduce *transit* travel times from some neighborhood n (keeping *car* travel times the same), we make n more attractive to potential *transit* riders. Greater demand for residing in n (along with fixed housing supply) would drive up housing prices and drive out the households with relatively low *transit* usage (and, hence, low marginal willingness to pay for faster *transit* travel). A marginal reduction in *transit* travel times benefits more the income group that spends more on *transit* travel. So, improving *transit* travel times from a neighborhood where *transit* ridership is sufficiently high-income would attract disproportionately more high-income households to the neighborhood. There is increased income segregation if the neighborhood is already the richer of the two neighborhoods but reduced income segregation if the neighborhood is the poorer one to begin with. Similarly, improving *transit* travel times from a neighborhood where *transit* ridership is sufficiently low-income would attract disproporionately more low-income households, increasing income segregation if the neighborhood was relatively poor to begin with but reducing income segregation if the neighborhood was relatively rich to begin with.

Since *transit* ridership itself is a function of travel time differences across modes and neighborhoods, we can polish the result even further. We know that *transit* riders are more likely to be high-income the faster *transit* is (as in Figure 12). Then, as long as there is non-zero *transit* ridership in the neighborhood, small improvements in *transit* travel times from a neighborhood with fast (slow) *transit* must attract disproportionately more high (low) income households to the neighborhood. This means, improving fast (slow) *transit* in the richer neighborhood or slow (fast) *transit* in the poorer neighborhood would increase (decrease) income segregation. Proposition 3.1 defines "fast" and "slow" transit in this context and rephrases the intuition above more formally. Recall that γ is uniformly distributed. To simplify the narrative, assume henceforth that the support of the distribution $[-\Gamma, \Gamma]$ is broad enough to include $\tilde{\gamma}_{gn}$ for all g and n. In other words, there is positive *car* and *transit* ridership among both income groups from both neighborhoods.

Proposition 3.1. *There exists a constant $\bar{\tau}$ such that:*

- *when n is the **richer** neighborhood, a marginal reduction in transit travel times $\Delta\tau_n$*
  - ***increases** income segregation ($\frac{dDISS}{d\Delta\tau_n} < 0$) if transit is sufficiently **fast** ($\Delta\tau_n < \bar{\tau}$), and*
  - ***decreases** income segregation ($\frac{dDISS}{d\Delta\tau_n} > 0$) if transit is sufficiently **slow** ($\Delta\tau_n > \bar{\tau}$).*
- *when n is the **poorer** neighborhood, a marginal reduction in transit travel times τ_n^t*
  - ***decreases** income segregation ($\frac{dDISS}{d\Delta\tau_n} > 0$) if transit is sufficiently **fast** ($\Delta\tau_n < \bar{\tau}$), and*
  - ***increases** income segregation ($\frac{dDISS}{d\Delta\tau_n} < 0$) if transit is sufficiently **slow** ($\Delta\tau_n > \bar{\tau}$).*

Extending Lemma 3.1 to Proposition 3.1 is straightforward. Whenever *transit* is fast enough relative to *car*, it attracts more high-income riders to the neighborhood. Whenever *transit* is relatively slow (but not slow enough to have no riders), it attracts more low-income riders.

The results so far imply that to minimize any resulting income segregation, a transit planner may want to improve high-speed public transit (like subways) in the poorer neighborhood and improve low-speed transit (like buses on shared lanes) in the richer neighborhood. Note that such a policy does not necessarily reduce overall income segregation because it may be that *transit* is already sufficiently fast in the richer neighborhood and slow in the poorer neighborhood, in which cases any marginal improvement in *transit* times will only induce more income segregation. Of course, the transit planner typically cares not only about income segregation but may want to improve *transit* times in the city anyways. They minimize income segregation more by improving *transit* times (at the margin) in the richer neighborhood when *transit* is slow and in the poorer neighborhood when *transit* is fast. Corollary 3.1 states this more formally.

Corollary 3.1. *A marginal reduction in transit travel time from neighborhood* 2 *minimizes* $DISS$*imilarity more than a marginal reduction in transit travel time from neighborhood* 1 ($\frac{dDISS}{d\Delta\tau_1} > \frac{dDISS}{d\Delta\tau_2}$) *if and only if:*

- *neighborhood* 2 *is poorer* ($\bar{\xi}_L > \bar{\xi}_H$) *and transit is fast enough to attract more high income ridership* ($\Delta\tau_1 + \Delta\tau_2 < 2\bar{\tau}$)*, OR*
- *neighborhood* 2 *is richer* ($\bar{\xi}_L < \bar{\xi}_H$) *and transit is slow enough to attract more low income ridership* ($\Delta\tau_1 + \Delta\tau_2 > 2\bar{\tau}$)*.*

3.4.2 Visualizing Income Segregation

Note that Corollary 3.1 focuses only on *marginal* changes in travel times and, in real cities, may apply more to changes at the intensive margin such as adding extra vehicles to reduce wait times between buses or adding more stops to reduce walking times. A large enough reduction in travel times (such as the opening of the city's first subway line) might turn a slow *transit* ($\Delta\tau_n > \bar{\tau}$) into a fast *transit* ($\Delta\tau_n < \bar{\tau}$) or tip the composition of *transit* riders from predominantly poor to rich. A large enough change could also flip a neighborhood from being the richer (poorer) one to the poorer (richer) one. Arguably, such events are rare and most transit development happens incrementally. In Appendix B.1.2, I solve more generally for a closed-form relationship between $DISS$imilarity and travel times.

To illustrate this relationship, Panel A of Figure 15 shows a contour plot of $DISS$ as a function of $\Delta\tau_1$ and $\Delta\tau_2$ with darker shades indicating greater income segregation. Panel B of Figure 15 graphs the travel times that minimize income segregation ($\bar{\xi}_L = \bar{\xi}_H$), depicted by two straight lines. As we move further away from these lines, income segregation increases.

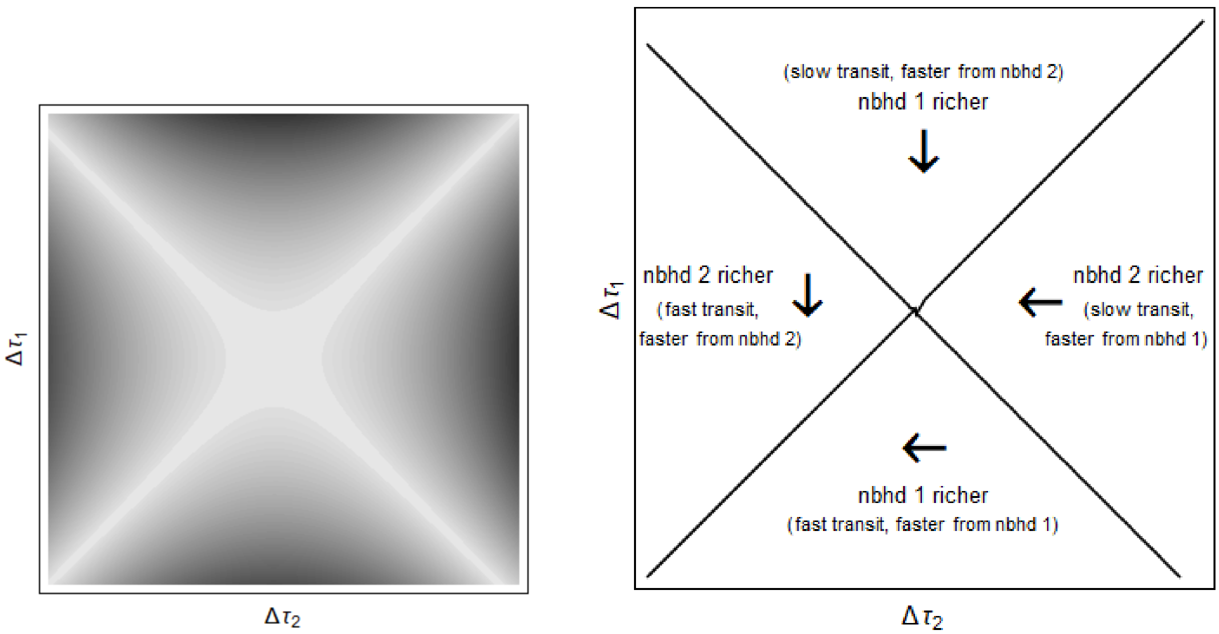
The upward sloping line is $\Delta\tau_1 = \Delta\tau_2$, when *transit* is equally fast/slow (relative to *car*) in both residential neighborhoods. There is perfect income mixing along this line. The downward sloping line is $\Delta\tau_1 + \Delta\tau_2 = 2\bar{\tau}$. Recall that $\bar{\tau}$ is the cutoff for whether *transit* is fast enough (relative to *car*) to attract more high-income than low-income ridership. When $\Delta\tau_1 + \Delta\tau_2 = 2\bar{\tau}$, the marginal benefit from shorter *transit* times (as well as *transit* ridership in the city) is the same for high and low income households in the city.[19] More generally, along $\Delta\tau_1 + \Delta\tau_2 = 2\bar{\tau}$, high- and low-income households experience the same difference in travel costs between the two neighborhoods so that differences between *transit* and *car* travel times do not induce any income sorting. Consequently, income segregation is minimized either by equalizing travel times by *transit* (relative to *car*) between the residential neighborhoods, or by equalizing the difference in the relative travel costs across rich and poor households.

When *transit* is generally slow ($\Delta\tau_1 + \Delta\tau_2 > 2\bar{\tau}$, as in the top or right quadrants of Figure 15 Panel B) but relatively faster from neighborhood n ($\Delta\tau_n < \Delta\tau_j$ for $j \neq n$), low-income households are willing to pay more for the faster *transit* access from neighborhood n. As a result, n is the poorer neighborhood. Similarly, when *transit* is generally fast ($\Delta\tau_1 + \Delta\tau_2 < 2\bar{\tau}$, as in the bottom or left quadrants) and relatively faster from neighborhood n ($\Delta\tau_n < \Delta\tau_j$ for $j \neq n$), high-income households are willing to pay more for the faster *transit* access from neighborhood n, making n the richer neighborhood. Given this income sorting on *transit* access, an immediate implication of Corollary 3.1 is as follows.

Remark. Segregation is minimized more by improving *transit* access from the neighborhood with relatively slower *transit*.

As depicted by the arrows in Panel B of Figure 15, the planner will improve *transit* access from neighborhood 1 when $\Delta\tau_1 > \Delta\tau_2$ and improve *transit* access from 2 when $\Delta\tau_1 < \Delta\tau_2$. Thus, they will move the city's network of travel times towards $\Delta\tau_2 = \Delta\tau_1$, where *transit* is equally fast across residential neighborhoods.

[19] Along this line, it may be that *transit* is much faster in 1 than in 2 so that high-income households choose to ride *transit* more (than the low-income households) from neighborhood 1 and ride the *car* more from 2, whereas low-income households ride the *car* more (than high-income households) from 1 and the *transit* more from 2. But the travel cost savings to the high-income households from riding the *transit* from 1 (as opposed to riding the *car* from 2) are the same as the savings to the low-income households from riding the *car* from 1 (as opposed to the *transit* from 2).



(A) Contour plot of $DISS$ (B) How to minimize $DISS$?

Figure 15: Income dissimilarity as a function of travel times

Note: Darker shades in Panel A correspond to larger $DISS$imilarity. Panel B shows travel time combinations with zero dissimilarity (where $\bar{\xi}_L = \bar{\xi}_H$), which corresponds to either $\Delta\tau_1 = \Delta\tau_2$ or $\Delta\tau_1 + \Delta\tau_2 = 2\bar{\tau}$. Arrows indicate where to reduce transit travel times to minimize $DISS$.

3.5 Transit Ridership

While the transit location policies we have considered so far have only focused on mass transit's effect on income segregation, public transit planners usually also have to account for transit's effect on outcomes like road congestion and air pollution that depend on transit's ability to get drivers to switch. The motives of transit planners are usually closely aligned with those of local governments.[20] So they may also be politically inclined to favor policies that lead to immediate gains in transit ridership and appear more effective in the short run. In this section, I endogenize the location of transit improvements as the choice of a transit planner trying to maximize transit ridership in the city, and analyze its implications for income segregation. I consider both policies that maximize 'short-term' *transit* ridership at households' initial residential location choices as well as policies that maximize 'long-term' *transit* ridership at the updated equilibrium housing prices and residential location choices. Then I analyze how the optimal choices for maximizing *transit* ridership compare to the optimal choices for minimizing income segregation. Finally, I document changes in transit ridership across US cities between 1990 and 2010 and discuss what that implies about the goals of transit planners and transit's role in income segregation in the future.

To constrain the set of changeable parameters, assume (i) the transit planner is restricted to only improving travel times by *transit*, and (ii) the marginal cost of improving travel times is constant.[21] Let R denote the fraction of trips by *transit* in the city across all households and neighborhoods:

$$R \equiv \Lambda \cdot r_L + (1 - \Lambda) \cdot r_H \tag{3.5.1}$$

$$\text{where } r_g \equiv \Psi\big(\tilde{\gamma}_{g2}\big) \cdot F\big(\bar{\xi}_g\big) + \Psi\big(\tilde{\gamma}_{g1}\big) \cdot \big[1 - F\big(\bar{\xi}_g\big)\big] \tag{3.5.2}$$

[20]The US Federal Transit Administration (FTA) in 2017 reported that 54% of the transit authorties in its database are departments of local (city or county) governments. Another 28% are independent public agencies and 2% are operated by state departments of transportation.

[21]In reality, marginal costs vary a lot across travel times and space. For instance, extending a subway line may be a lot more expensive than extending a bus route. This paper abstracts away from these context-specific marginal cost differences.

3.5.1 Maximizing Short-Term Transit Ridership

First, consider a "short-term" transit planner who only cares about immediate gains in transit ridership, and optimizes ridership taking the income distribution in each residential neighborhood as fixed (and exogenous to travel time changes).[22] Formally, the short-term planner assumes

$$\frac{dF\left(\bar{\xi}_g\right)}{d\Delta\tau_n} = 0 \;\forall g \in \{L, H\} \text{ and } n \in \{1, 2\}$$

and chooses to improve *transit* travel times from the neighborhood n where the marginal effect (of *transit* time) on R is larger.

Proposition 3.2. *The short-term transit planner trying to maximize transit ridership R will choose to reduce transit travel times from the residential neighborhood with* ***higher*** *aggregate income.*

The intuition behind this result is straightforward. Households with higher opportunity cost of travel time benefit more from shorter travel times. Given constant marginal *transit* ridership (due to uniformly distributed γ), the households who switch more from *car* to *transit* are the high-income households. In contrast, low-income households generally have large *transit* ridership and are less responsive to changes in *transit* travel times. We saw this in Figure 12 (right). So it is optimal for the transit planner to target ridership gains among high-income households. Since the planner ignores the fact that these households might instead relocate to a different neighborhood in response, they would reduce *transit* times from the neighborhood that already has higher residential incomes.

Recall from Proposition 3.1 that when *transit* is relatively slow ($\Delta\tau_n > \bar{\tau}$) from the high-income neighborhood, such a policy will attract more low-income riders to the richer neighborhood and reduce income segregation. Whereas when *transit* is relatively fast ($\Delta\tau_n < \bar{\tau}$) from the high-income neighborhood, the policy will exacerbate income segregation. Continued *transit* improvements (or a large enough improvement) in the richer neighborhood can make a slow *transit* fast enough to attract more high-income riders to the

[22] Alternatively, we may assume the transit planner is myopic or believes household relocation across neighborhoods to be a much slower process (e.g. due to moving costs, lease contracts, etc.) relative to households switching modes of travel across trips. In the latter case, when convergence to the new residential sorting equilibrium is slow, transit planners may be able to maximize ridership better even in the very long run by implementing the "short-term" policy.

already rich neighborhood. Once *transit* is fast enough everywhere, income segregation will only continue to increase with subsequent travel time reductions.[23]

There is one important caveat to this policy implication for income segregation. Because the two residential neighborhoods equally split the population of the city in the baseline model, the neighborhood with the higher share of high income households is also the one with higher aggregate incomes and higher marginal *transit* ridership. In reality, a neighborhood with a significantly larger share of the city's overall population (and trips) could be relatively poor (with a lower mean income) and yet have higher aggregate residential income (and marginal *transit* ridership), so that the short-term planner would choose to improve high-speed *transit* from this neighborhood and do so without increasing income segregation.[24] In real cities, neighborhoods that have seen more *transit* development (such as downtowns) do tend to be more densely populated, consistent with Proposition 3.2. My results on income segregation suggests that when these neighborhoods are relatively poor, improving low-speed transit would exacerbate income segregation while improving high-speed transit would reduce income segregation.

3.5.2 Maximizing Long-Term Transit Ridership

Where do *transit* travel time improvements maximize long-term *transit* ridership? It is still optimal for the planner to target ridership gains among high-income households. But since households relocate costlessly and compete for fixed housing stock in each neighborhood, the planner would have to improve *transit* in the neighborhood where the households that would switch more to *transit* (the high-income group) would have higher willingness to pay for housing and the reduction in transit ridership among households that get priced out would be low. There are two possible scenarios:

[23]This result holds only as long as $\tilde{\gamma}_{gn}$ are in the support of γ, as we assumed earlier in the paper. For short enough travel times by *transit*, the high-income households in the richer neighborhood n may already be riding *transit* on every trip (since $\tilde{\gamma}_{Hn} > \Gamma$) and there would be no more new ridership to attract in n ($\Psi(\tilde{\gamma}_{Hn}) = 1$). At this point. the short-term planner switches to improving *transit* in the poorer neighborhood. This boundary case is not yet relevant for most real cities where *transit* is far from the strictly dominant mode of choice for high income households.

[24]The assumption of equally-sized neighborhoods serves purely to simplify exposition. All of the paper's results continue to hold for, say, arbitrary housing supplies H_n such that $H_1 + H_2 = 1$.

(a) *transit* is faster from the richer neighborhood and more attractive to high-income households. In this case, the transit planner maximizes ridership by improving *transit* access from the richer neighborhood as it attracts more high-income *transit* ridership to the neighborhood and prices out (primarily) low income households who would retain high *transit* ridership even in the poorer neighborhood.

(b) *transit* is faster from the poorer neighborhood and more attractive to low-income households. The transit planner still maximizes ridership by improving *transit* access from the richer neighborhood as both the (primarily) high-income households that move out in response as well as the households that stay would increase their *transit* ridership.

Given the income sorting across neighborhoods is determined by differences in *transit* access, these are the only two possible scenarios.[25] So, long-term *transit* ridership is also maximized by targeting neighborhoods with higher residential incomes. Appendix B.1.3 characterizes the planner's long-term ridership-maximizing policy more formally. Like the short-term planner, the long-term planner is incentivized to improve fast transit where it would exacerbate income segregation and improve slow transit where it would reduce segregation. In reality, planners who are also trying to minimize their footprint on income segregation (if not income segregation itself), most likely implement policies that trade off some high-income transit ridership to make transit more accessible also to low-income commuters.

3.5.3 Transit Ridership vs. Income Segregation

For different combinations of $\Delta\tau_1$ and $\Delta\tau_2$, Figure 16 shows the choice of a transit planner if they had to choose one neighborhood to marginally improve *transit* times in while minimizing $DISS$ as in Corollary 3.1 (solid black arrows) or while maximizing *transit* ridership R as in Proposition 3.2 (dashed red arrows).

Suppose *transit* is fast enough to attract more high-income riders ($\Delta\tau_1 + \Delta\tau_2 < 2\bar{\tau}$).

[25]When *transit* is more attractive to the poor, the neighborhood with faster *transit* must be poorer. Whreas, when *transit* is more attractive to the rich, the neighborhood with faster *transit* must be richer. This need not hold if income sorting across neighborhoods were to also depend on factors other than *transit* access (as I explore in Section 3.6). Appendix B.1.3 characterizes the planner's long-term ridership-maximizing policy more exhaustively.

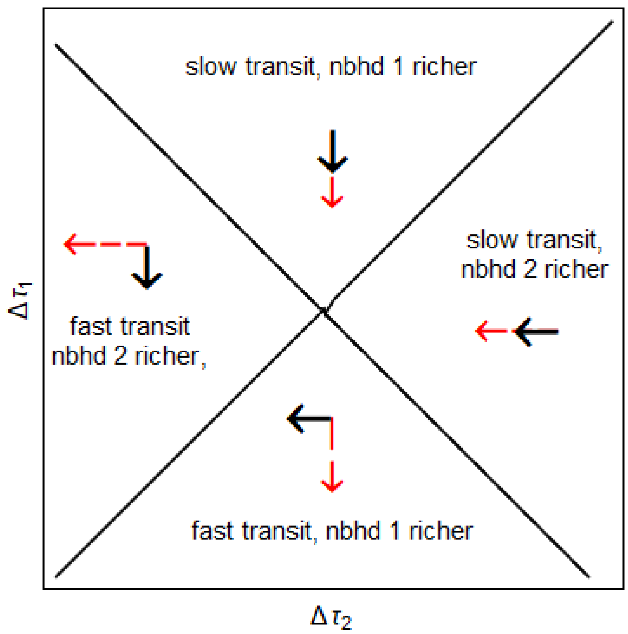


Figure 16: Optimal directions of marginal *transit* improvements to minimize $DISS$ (solid, black arrows) or to maximize Ridership (red, dashed arrows)

Note: Arrows depict where to reduce *transit* travel times based on Corollary 3.1 and Proposition 3.2. Solid lines correspond to $DISS = 0$ and $\bar{\xi}_L = \bar{\xi}_H$.

Then the $DISS$-minimizer would improve *transit* access from neighborhood 1 (move down) when 2 is the richer neighborhood (far left of graph) and improve *transit* access from 2 (move left) when 1 is the richer neighborhood (bottom of graph). In other words, the $DISS$-minimizer would improve (fast) *transit* from the poorer neighborhood. In contrast, a planner trying to maximize *transit* ridership R would do the opposite and improve (fast) *transit* from the neighborhood with higher aggregate incomes. This is true for non-marginal/large reductions in travel times too. Now, suppose *transit* is slow and attracts primarily low-income riders ($\Delta\tau_1 + \Delta\tau_2 > 2\bar{\tau}$). It is optimal for the planner to improve *transit* from the richer neighborhood at the margin, regardless of whether the planner is minimizing $DISS$ or maximizing R. However, a large enough improvement in even the poorer neighborhood might make *transit* fast and attractive enough for high-income households to gentrify the neighboorhood (that is, flip the income sorting across neighborhoods) and achieve the intended effect. Once *transit* is fast relative to *car* everywhere and attractive to both high and low income households ($\Delta\tau_1 + \Delta\tau_2 < 2\bar{\tau}$), maximizing *transit* ridership will inevitably induce more income segregation.

3.5.4 Targeting Existing Transit Ridership

In the U.S., there is a long history of routine opposition to new transit infrastructure (both 'slow' and 'fast') by local residents who fear increased traffic, crime and/or changes in the demographic composition of their neighbors (Altshuler and Luberoff, 2003). On the other hand, the most ardent proponents of new transit infrastructure tend to be communities that already rely heavily on public transit access. Understandably, transit planners might have an incentive to expand transit in neighborhoods with already high transit ridership instead of trying to maximize new ridership. In the context of my baseline model, it corresponds to developing 'slow' transit from the low-income neighborhood and 'fast' transit from the high-income neighborhood. The latter is consistent with maximizing transit ridership while the former is not. Accordingly, Turner [2019] documents that rail transit ridership in US cities has almost doubled between 1992 and 2017 while bus ridership has remained about the same (despite similar growth in the size of the bus and rail fleet in operation by public transit authorities).

More importantly, a transit location policy that prioritizes existing ridership always exacerbates segregation when the income sorting is driven primarily by differences in transit access (as in the baseline model). Improving 'slow' transit from the low-income neighborhood attracts more low-income households to the neighborhood and improving 'fast' transit from the high-income neighborhood attracts more high-income households.

3.5.5 Empirical Evidence from US Cities

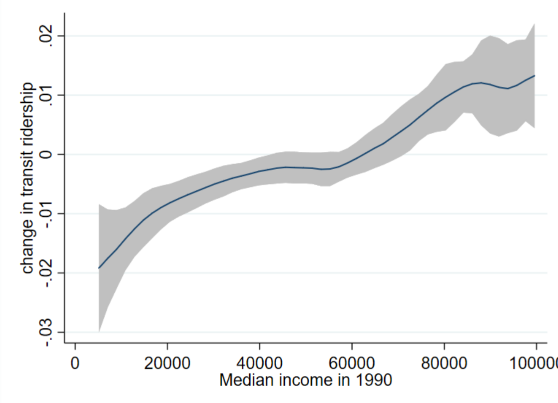
To confirm the different policy incentives and implications for 'fast' versus 'slow' transit, I compare the locations of public transit development over 3 decades across US cities with and without a large rail transit presence. As in Section 3.2 before, I restrict my sample to CBSAs with large enough transit ridership (at least 2%) and neighborhoods with some existing transit ridership (at least 5%).[26] Lacking sufficient information on transit travel times, I proxy for transit access with transit ridership. Figure 17 plots changes in a neighborhood's share of transit commuters between 1990, 2000 and 2010 against the neighborhood's median residential income.[27] [28] Consistent with transit policies trying to maximize ridership, between 1990 and 2000, cities with more rail transit riders experienced larger net increases in ridership among higher income neighborhoods. In contrast, cities with more bus transit riders experienced relatively modest differences in ridership change between high and low income neighborhoods.

Between 2000 and 2010, however, cities with more rail transit riders saw larger net ridership gains in low income neighborhoods whereas cities with more bus riders saw larger net ridership gains in high income neighborhoods. These changes are consistent with transit improvements that minimize income segregation. Indeed, as shown earlier in Figure 11, neighborhoods with higher ridership gains experienced higher incomes in rail transit cities and lower incomes in bus transit cities. Note that if the changes in transit ridership between

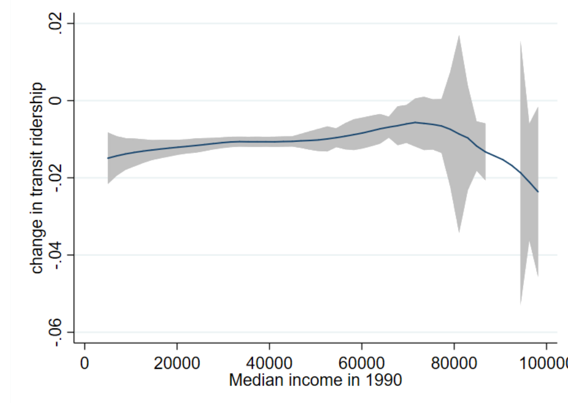
[26] As such, I am focusing primarily on transit improvements at the intensive margin (as in most of the theoretical results).

[27] Census tracts with median incomes less than \$5,000 or greater than \$100,000 are ignored. So are tracts where transit ridership is less than 5% or greater than 95% in the base year (to avoid boundary effects).

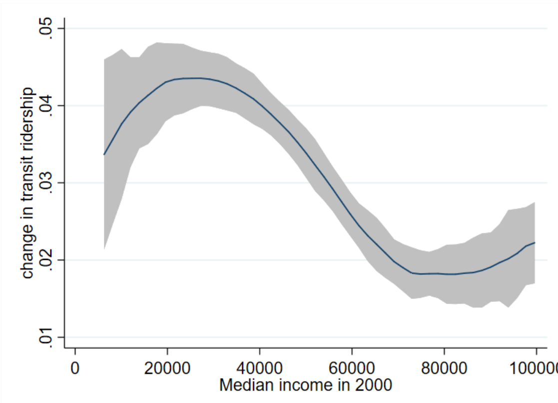
[28] I pool together cities with different levels of transit ridership, but the figures are robust to conditioning out the city fixed effects on the change in transit ridership.



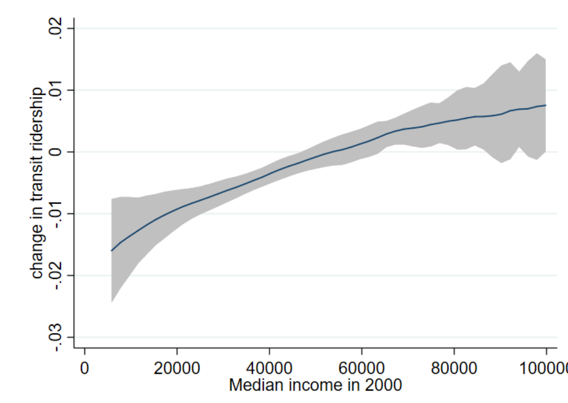
1990-2000: cities with higher **rail** transit ridership



1990-2000: cities with higher **bus** transit ridership



2000-2010: cities with higher **rail** transit ridership



2000-2010: cities with higher **bus** transit ridership

Figure 17: Change in transit ridership by median neighborhood income

Note: Data points are census tracts within 30 km of primary city centers within each CBSA. Vertical axis shows percentage points change in the share of commutes by public transit. Horizontal axis shows median dollar incomes in the census tract. Grey areas depict 95% confidence intervals.

1990-2000 and 2000-2010 were driven by increased demand for buses among high-income households or for rail transit among low-income households, the corresponding changes in neighborhood incomes would be in the opposite direction. So, the differences between 1990-2000 and 2000-2010, especially for cities with higher rail transit ridership, suggest transit planners may be starting to prioritize lower income segregation (over higher ridership), even if historically transit development may have left cities more income segregated.

It is important to note that this average trend conceals significant heterogeneity across cities. For instance, some cities like Trenton (NJ) with more rail commuters have seen even more transit ridership growth in high income neighborhoods between 2000 and 2010. At the same time, some cities like Baltimore (MD) with more bus commuters have seen more ridership growth in low income neighborhoods.

3.6 Model Generalizations

This section extends the baseline model to show that my paper's results are robust to incorporating additional features of real cities that dictate public transit's role in income segregation.

3.6.1 Travel Times by *car* and Preferences over Amenities

So far, I have modeled two equidistant neighborhoods with different *transit* access. Suppose (without loss of generality) that neighborhood 1 is closer so that it is more accessible by *car*: $\tau_1^c < \tau_2^c$ (and *car* travel times are small enough that there is non-zero *car* ridership). Now the income sorting is assymetric around *transit* access. In particular, when *transit* travel times are the same across neighborhoods, higher income households are more likely to reside in neighborhood 1 to capitalize on faster travel (see Appendix Figure 27). We can also incorporate income sorting on local amenities. Suppose the utility gains from amenities, denoted A_{gn}, varied across income groups even within the same neighborhood. For example, higher income households may have a higher willingness to pay for better quality local schools. So, all else equal, they may be more likely to reside in the neighborhood with better schools.[29] There is now an additional dimension of income sorting where (all else equal) the rich are more likely to reside in the neighborhood n that offers them higher additional utility gains from amenities (relative to the poor): $A_{Hn} - A_{Ln} > A_{Hj} - A_{Lj}$for $j \neq n$.[30]

Suppose the amenities and *car* access in neighborhood 1 are more attractive to the rich than those in neighborhood 2. Then for the rich and the poor to sort evenly across the two neighborhoods (zero income $DISS$imilarity), *transit* needs to be more attractive to the rich from neighborhood 2 or more attractive to the poor from neighborhood 1. So, unlike in the baseline model where income segregation is at its lowest when *transit* access is identical across neighborhoods, some spatial disparities in *transit* access is now desirable for a transit planner trying to minimize income segregation. However, even though the levels of income segregation are different than in the baseline model, the results so far on the marginal effect of *transit* (stated in terms of relative travel times $\Delta\tau_n \equiv \tau_n^t - \tau_n^c$ and the high- versus low-income status of neighborhoods) remain completely unchanged. Appendix B.1.2 characterizes $DISS$imilarity as a function of *transit* travel times accounting for both heterogenous preferences over amenities and different travel times by *car*.[31]

3.6.2 Housing Demand

I assumed housing consumption per household and neighborhood populations are fixed. But, in reality, households may choose smaller apartments/dwellings to continue to reside in more easily accessible neighborhoods. City centers and more transit-accessible neighborhoods do indeed tend to be more densely populated. So, when travel times by

[29]Households with higher incomes have also been observed to spend more on housing and have different preferences over neighborhood housing prices than households with lower incomes. A large urban literature tries to understand its implications for income sorting across residential locations. While the amount of housing space being consumed is fixed in my model, A_{gn} can incorporate heterogeneous preferences for housing type or other residential amenity that could induce income sorting independent of the city's travel network.

[30]Neighborhood 1 is richer when

$$\bar{\xi}_L > \bar{\xi}_H \Leftrightarrow C_{L1} - C_{L2} - A_{L1} + A_{L2} > C_{H1} - C_{H2} - A_{H1} + A_{H2}$$

[31]All proofs of formal results so far also already account for these additional dimensions of income sorting.

transit are reduced and capitalized into higher housing prices, we may wonder whether the opportunity to trade off housing space (instead of moving out of the neighborhood) dampens the effect on income segregation. Appendix B.1.4.1 presents a generalization of the model where a price-elastic housing demand implies population (and density) varies across neighborhoods. Changes in housing prices do lead to smaller population shifts (crowded out by changes in housing consumption) but continue to have no effect on income segregation, as in the baseline model. This is because the marginal utility gain from additional housing space is still the same for both low- and high-income households. So price changes shift $\bar{\xi}_g$ (where household type g is indifferent between neighborhoods) by the same amount for all households and does not affect its gradient, which determines income segregation.[32]

3.6.3 Travel Destinations

The baseline model simplfied the city's geography by assuming all households in a neighborhood have the same travel destinations, allowing me to characterize each mode's travel network with a pair of travel times. In reality, rich and poor households may commute to very different work or consumption locations as parts of a city specialize in different economic sectors. As a result, mass transit services may differ significantly in how well they connect a residence to high- versus low-income destinations.[33]

Suppose high- and low-income households in my model city have different trip destinations, and let τ^m_{ng} denote the travel time to destinations of type g (corresponding to income group g) from neighborhood n using mode m. Planners can improve travel times to particular destination types, but with some positive spillovers for everyone else

[32] Traditional urban spatial equilibrium models often suppose the demand for residential land is income elastic so that the rich have a relatively lower willingness to trade off housing space than the poor. However, empirical estimates of the income elasticity of housing demand are typically too low to explain the observed sorting of rich and poor households within cities (see Glaeser et al., 2008). Regardless, an income-elastic housing demand would change the cutoffs for when improvements in high-speed transit access minimizes income segregation more than improvements in low-speed transit access. But, qualitatively, the relationship between *transit* changes and income segregation would remain the same.

[33] For instance, Tsivanidis [2019] finds that Bogotá's new bus rapid transit service, the Transmilenio, manages to better connect residences to high-skilled job sectors as opposed to low-skilled job sectors, which are more dispersed throughout the city. Because low-skilled commuters could access low-skilled jobs relatively easily from neighborhoods further away from the Transmilenio, higher income commuters benefited more from the transit expansion and gentrified neighborhoods closer to Transmilenio stops.

in the neighborhood. Appendix B.1.4.2- B.1.4.3 presents such a model generalization where households benefit differently from travel time improvements depending on their destination. The baseline model from Section 3.3 is an extreme case of perfect network spillover where all travel destinations benefit equally from improved *transit* access to a residential neighborhood. More generally, whether the rich or the poor benefit more from *transit* improvements depends both on the income composition of *transit* ridership (and, hence, on *transit* travel times relative to driving) as in the baseline model as well as on the destinations being connected. All else equal, better access to low-income destinations attracts more low-income households to the neighborhoods, whereas better access to high-income destinations attracts more high-income households. I show that, qualitatively, the effect of lower *transit* travel times on income segregation is the same as for the baseline model and as depicted in Section 3.4. Quantitatively, the conditions for when *transit* improvements increase or decrease segregation additionally depend on the magnitude of the network spillover effects.

3.7 Conclusion

In this paper, I document income differences in urban households' willingness to pay for 'fast' and 'slow' transit and, subsequently, for residential neighborhoods with varying access to public transit. Consistent with these observations, I propose a novel theoretical framework for characterizing travel mode choices and income segregation within cities. My model predicts that, while transit is slower than driving (e.g. buses on shared lanes), improving transit access to a residential neighborhood attracts more low-income residents to the neighborhood. Whereas, improving high-speed transit access attracts more high-income residents. Consequently, from any static equilibrium of the model, improving access by either high-speed transit to the high-income neighborhood or low-speed transit to the low-income neighborhood ends up exacerbating income segregation in the city. Whereas, improving access by either low-speed transit to the high-income neighborhood or high-speed transit to the low-income neighborhood reduces income segregation.

An important implication of this relationship between transit access and income segregation is that policies that minimize income segregation are often, but not always, at odds with policies that maximize new transit ridership. In particular, improving high speed transit in low-income neighborhoods would displace low-income transit riders with high-income transit riders (thereby reducing segregation), but fail to generate as much new transit ridership as if high-speed transit was improved in high-income neighborhoods, which has more drivers who would switch to high-speed transit. On the other hand, improving low-speed transit in high-income neighborhoods is likely to increase overall transit ridership (as well as reduce segregation) more than improving low-speed transit in low-income neighborhoods, where low-speed transit ridership is already high. So, while both high- and low-speed transit access can be improved in a way that minimizes income segregation in the city, high-speed transit planners have an incentive to trade off lower income segregation for higher ridership. Such behavior is consistent with observed changes in public transit ridership in US cities between 1990 and 2000. But more recent trends in transit ridership suggest planners, on average, may be starting to recognize transit development as a tool for desegregating cities. What these shifting priorities ultimately mean for social welfare is a multi-dimensional question beyond the scope of this paper. However, they tell us that transit's role in income segregation relies importantly on the past and ongoing choices of transit planners (and not just on incomes differences in demand for transit).

The distinction between fast and slow transit developed in this paper is particularly relevant given powerful political incentives to overspend on salient mass transportation infrastructure such as rail or bus rapid transit when the negative externalities for voters are less salient (Glaeser and Ponzetto, 2018), such as the long term costs of income segregation. There are similarly strong incentives for these politicized investments to appear efficient at generating new transit ridership, and not just equitable. Consequently, faster travel by mass transit could leave poorer households with worse access to endogenously arising local amenities (often funded through taxation on local income) and greater income inequality. Unless urban planners and transit authorities already internalize these externalities in their policymaking, they may need to more actively address income segregation as a concern while expanding public transportation services in a rapidly urbanizing world.

4.0 Racial Segregation in Housing Markets and the Erosion of Black Wealth

(Joint work with Sijie Li, Allison Shertzer, and Randall P. Walsh)

"Daisy and Bill Myers, the first black family to move into Levittown, Pennsylvania, were greeted with protests and a burning cross. A neighbor who opposed the family said that Bill Myers was 'probably a nice guy, but every time I look at him I see $2,000 drop off the value of my house.'"

- Ta-Nehisi Coates, *We Were Eight Years in Power: An American Tragedy (2017)*

"During the early nineteen twenties it is estimated that more than 200,000 Negroes migrated to Harlem... It was a typical slum and tenement area little different from many others in New York except for the fact that in Harlem rents were higher... Before Negroes inhabited them, they could be let for virtually a song. Afterwards, however, they brought handsome incomes."

- Frank Boyd, *American Life Histories Manuscripts (WPA Federal Writers' Project, 1938)*

4.1 Introduction

The Great Migration – which saw millions of African Americans depart the Jim Crow South for northern cities – is a key channel through which black families sought to improve their economic standing in the middle decades of the twentieth century. Moving to the North was associated with increased wages and improved occupational status (Myrdal, 1944, Collins and Wanamaker, 2014, Boustan, 2016). Yet these earnings gains failed to close the racial wealth gap, which persisted and, in some cases, worsened over the ensuing decades (Blau and Graham, 1990, Bound and Freeman, 1992). To explain the persistence of these disparities, economists have long highlighted the role of pervasive discrimination in the labor market and in the educational system in preventing black families from accumulating wealth at the same rate as whites (Smith and Welch, 1989, Collins and Wanamaker, 2017, Bayer and Charles, 2018).

Recent scholarship has also highlighted the role of discriminatory government policies in supporting residential segregation by race and disadvantaging black wealth accumulation through reduced home ownership rates (Rothstein, 2017). Residential segregation by income has been shown to exacerbate inequality in contemporary US cities (Fogli and Guerrieri, 2019), yet we know surprisingly little about the channels through which racially segregated housing markets served to perpetuate racial inequality. Closing this gap is particularly relevant to our understanding of how residential segregation worsened and solidified the racial wealth disparities in American cities during the Great Migration.

The extant lack of empirical work stems largely from the fact that urban segregation during this time period was a city-block-level phenomenon and researchers have historically lacked data linking housing prices and demographic characteristics at the fine level of spatial detail needed to explore these dynamics. In this paper we introduce two major data innovations to overcome these limitations. First, using the full-count censuses of 1930 and 1940, we create detailed demographic data, including housing values and rents, at the city-block level for ten major northern cities. These two censuses were the first to ask about home values and rents, and they are also free of confidentiality restrictions, enabling us to observe the address for the universe of individual census records in each of our ten cities.[1] As a result, we can geocode the vast majority of these blocks. Our second data innovation is to match addresses across these two censuses. This matching allows us to track the 10-year change in an individual home's price and its exposure to city-block-level transition in racial composition during the Great Depression, a decade when black neighborhoods saw major expansions.

Our analysis begins by providing the first description of residential segregation by race at the city-block level in prewar American cities. We find high degrees of concentration, with the percent of black families living on blocks that were virtually all black ($>$ 90 percent) increasing from 52 percent in 1930 to 63 percent at the end of the decade. Racial transition was also central to the black experience in this decade. While only 4 percent of black families lived on blocks that were predominantly white ($>$ 75 percent) in 1930, fully 13 percent lived on blocks that had been predominantly white in 1930. The price dynamics on these transitioning blocks represent an essential component of black housing during the

[1]There is no systematic, address-level housing price data available for 1920 or earlier years. The 1950 census is not yet digitized and publicly available.

decade. Importantly, these blocks can be used in conjunction with our new linked sample to recover estimates of the causal impact of racial segregation and white flight on the housing prices and rents faced by black households more broadly.

Using repeated observations of addresses that were occupied by white homeowners at the start of the decade, we show that black families that were renters paid a premium of roughly 50 percent relative to white families renting equivalent housing on blocks that did not transition. Occupancy soared on these blocks as well, increasing by roughly 47 percent. While price impacts differed, home ownership provided black families no escape. To this point, we find that the first black arrivals on a majority white block were much more likely to buy their home than to rent. To induce incumbent white owners to sell to a black family, these pioneers paid a premium of roughly 28 percent relative to the prices that white homeowners were paying on the same block. The situation was much different for black homeowners on transitioned blocks which experienced a roughly 10 percent discount on their value relative to un-transitioned blocks.

Moreover, once these early pioneers had locked in their ownership at an inflated price, we find that home values declined significantly throughout the transition process. By the time a block had transitioned to majority black, homes had on average lost nearly 10 percent of their original (no premium) value.

To better understand the divergence between prices and rents, we propose a simple no-arbitrage condition to fix the relationship between rents and home prices (Kearl, 1979, Poterba, 1992). Through this lens, investors demanded higher rents to compensate for declines over time in the price of their rental properties that were anticipated as a result of racial transition. While one potential driver of the observed rent increases is the increase in occupancy rates that occurred during the racial transition process, we demonstrate that crowding cannot explain most of the key price changes. We also find that landlords provided steep discounts to white renters who stayed on blocks during the process of transition. We argue that the presence of these rental discounts for remaining white families is direct evidence of landlord discrimination. These rental markets are particularly important given that 86 percent of blacks on fully transitioned blocks were renters in our sample.

While ours is the first work of which we are aware to document that segregated housing markets led to both elevated rents and declining home values for black households, these findings are consistent with the historical record of the period.[2] Real estate historians have argued that the urban color line moved because black families who demanded better quality housing outbid whites for the purchase of homes in neighborhoods just outside of the established ghetto (Mehlhorn, 1998, Troesken and Walsh, 2019). In response to these new black arrivals, and at least in part compelled by concerns about falling home values and the quality of public services, white households subsequently fled these transitioning areas (Boustan, 2010, Derenoncourt, 2018, Shertzer and Walsh, 2019). These transitions were then associated with an increase in absentee landlords, as many former residents either rented out their home or sold it to a (white) investor.[3]

In total, our investigation documents that segregation and the process of black neighborhood expansion left African Americans both living in declining neighborhoods and doubly poorer. Applying our estimates to the modal black renter in our sample of northern cities, we find that the price shifts associated with racial transition erased roughly forty percent of the annual income gain associated with moving from the South to the North. This calculation suggests that a significant share of cumulative gains in occupational standing and earnings achieved by black families who migrated to the North were canceled out by the market dynamics associated with segregated housing markets. Segregation thus limited the degree to which black Americans could move to opportunity over the course of the Great Migration.

[2]The consensus in the literature is that segregation that arises from constraints on black housing supply will result in black families paying higher prices for similar housing relative to whites. Indeed, most papers that examine racial housing price disparities between 1940 and 1970 have argued that blacks paid such a premium (King and Mieszkowski, 1973, Yinger, 1978, Schafer, 1979). The passage of the Fair Housing Act in 1968 reduced the tools available to white families to maintain the color line, and most papers working with data from after 1970 argue that segregation was maintained by whites paying a premium to avoid black neighbors (Follain-Jr. and Malpezzi, 1981, Chambers, 1992). Using the interaction between black household and measured racial segregation in a particular city, Cutler et al. [1999] conclude that blacks paid a premium in the 1940s and whites a premium by the 1990s.

[3]See for instance United States Congress House Committee on the District of Columbia, 1935, Rent Commission: Hearings before the subcommittee on Fiscal Affairs on H.R. 3809, p. 7. The investors are described as follows: "It is a certain class of individuals in a great many cases that buys up these properties and gets as much out of them as they possibly can until the properties are condemned or fall down or are converted to some other use... In a great many other cases [the houses] have been in the family for years, and the family does not know how to get rid of it, so they just keep renting the house."

4.2 Historical Background

The Great Migration saw millions of African Americans leave the poverty and oppression of the Jim Crow South for better lives in northern cities. However, they soon discovered that the North maintained its own system of racial segregation, particularly in housing markets. Black families found themselves largely restricted to homes in existing black neighborhoods through a mixture of threats, actual violence, and discriminatory real estate practices. The narrative history emphasizes collective action taken by whites to maintain the color line, which shifted over time from angry mobs in the early days of the Great Migration to the later establishment of genteel neighborhood "improvement" associations (Massey and Denton, 1993). Such associations were created in part to lower the costs of adopting restrictive covenants, which were deed provisions prohibiting the sale of a house to a black family. Such covenants had effect until 1948 when the Supreme Court struck down their enforcement in Shelley v. Kraemer.

Still, the color line was not inviolate. The 1920s and 1930s saw significant expansions of existing black neighborhoods in most northern cities. Urban historians underscore the desperation of black families for better housing and their tendency to outbid whites for homes near the ghetto. At the same time, real estate professionals and academics were united in their belief that black entry would harm home values.[4] Such expectations made banks reluctant to underwrite a mortgage for a "pioneer" black family entering a white neighborhood where the lending institution already held loans. One urban historian summarized the dichotomy thusly: *"One of the most interesting points made in the [real estate] broker comments is the recurring theme that while sellers may not get their price from whites (who are reluctant to consider an area undergoing racial transition), they probably can from nonwhites. This is quite different from the unqualified prediction that all prices in an 'invaded' area fall"* (Laurenti, 1960).

The fact that black neighborhoods expanded even though black families on average had fewer assets to use for a down payment suggests that some banks did in fact underwrite

[4]Some social scientists had a more nuanced view of the process. For instance, Gunnar Myrdal argued in An American Dilemma that white racism was the primary cause of drops in home values as a block began transitioning and that prices should recover once the neighborhood was majority black (p. 623).

mortgages for them. While banks were typically reluctant to initiate racial transition on a block, they appear willing to have made loans in neighborhoods likely to transition. Surveys of real estate brokers from the period suggest that the first family to enter a white neighborhood often sought a mortgage from a distant bank that did not have exposure to the area in question (Schietinger, 1953, p. 172). The narrative history on the issue of mortgage terms is mixed, with some surveys finding blacks and whites received similar terms (Rapkin and Grigsby, 1960, p. 77) and other scholars arguing that African American borrowers were steered towards installment contracts where they could lose possession of their home if they were late on a single payment (Satter, 2009, p. 4).

Government policies also influenced black families' ability to finance home purchases. Beginning in 1934, at the height of the Depression, the Federal Housing Authority initiated underwriting mortgages and imposed policies that would disadvantage the low income and transitioning central-city neighborhoods where black families were likely to buy. However, FHA underwriting was still a nascent process during our sample period, particularly so in the neighborhoods that we study. As of the end of 1940, the FHA had underwritten only 60,339 mortgages on existing homes across the entire metropolitan areas of the cities we study in this paper (our analysis is limited to existing homes).[5] Further, federal urban renewal policies did not begin until the 1949 Housing Act (Collins and Shester, 2013, LaVoice, 2019). It is thus unlikely that federal housing or lending policies can explain our findings.

Of course, not all black families bought their home; in fact, the majority were renters. As we discuss below, we find that the proportion of renters increased throughout the transition process. The question of who owned properties rented to black families is thus important for interpreting our results. The census does not allow us to observe the identity of property owners in the case where the occupants are renters. We thus turn to the narrative history, which suggests white investors purchased properties in the black ghetto with the perhaps self-fulfilling expectation that their investment would sharply depreciate over time. Real

[5]This figure comes from the FHA's Annual report for 1940 (FHA, 1941). We have been unable to identify exactly how large the metropolitan areas were for this reported data. However, as an example, the FHA reported more homes insured in the New York City Metropolitan area than it reported for the entire state of New York, suggesting that they used broad metropolitan area definitions. Thus, this number should likely be viewed as a very conservative upper bound and FHA penetration into our city neighborhoods would still have been quite limited as of 1940 (likely representing well fewer than 2 percent of the homes in our sample).

estate brokers believed that houses that were converted to multi-family rentals would lose value over time and were generally unwilling to make loans for the purchase of such properties (McEntire, 1960, ch. xiii). It would thus be necessary to buy these properties with cash. It is also likely the case that some landlords were former homeowners who decided to convert the house into a rental property instead of selling. Both considerations underscore the fact that in our setting the owners of rental properties were most likely white.

4.3 Data

It is clear from the 1930 and 1940 census that black families lived in homes that, on average, both sold and rented at prices below those occupied by white families. For example, in 1930 (1940) our sample average black rent was only 77 percent (83 percent) of the average white rent and for home values the figure was 68 percent (79 percent). It is difficult to ascertain the role of quantity and quality in determining these cross-sectional differences. Specifically, we cannot directly measure the relative prices paid by black and white households when they consumed the same quantity and quality of housing.

Our data work and analytical framework are tailored to addressing this empirical challenge. In terms of the former, we construct a novel dataset composed of the universe of addresses in ten major cities matched across the 1930 and 1940 censuses. The sample cities are Baltimore, Boston, the Brooklyn and Manhattan boroughs of New York, Chicago, Cincinnati, Cleveland, Detroit, Philadelphia, Pittsburgh, and St. Louis. To create the set of addresses matched over time, we developed an algorithm designed to ensure that only true address matches are included in our sample and to prevent the inclusion of buildings for which we can't be certain about their occupants. Our basic approach is as follows:

(a) We first assign every individual living in one of our sample cities in either 1930 or 1940 to an address that is consistent across all household members. If an address is missing, we impute it using another member of the household (households with inconsistent addresses are dropped).

(b) We standardize street names to deal with variations of directional prefixes and typical suffixes ("First" vs. "1st", "st" vs. "Street"). We cross-reference street names using a digitized street file for each city: if there is no corresponding street name in the neighborhood in the digitized data, we drop everyone with an address on that street from the census data.

(c) We conduct a series of consistency checks to identify the types of errors and omissions that are common in the address field, including making sure neighbors on the same street have street numbers that change monotonically as we move down a manuscript page.

(d) We retain only observations on streets that pass our quality checks and have no address inconsistencies.

(e) We merge across the 1930 and 1940 census using standardized street names and house numbers, yielding a sample of both single-family homes and apartment buildings.

Our algorithm is conservative in that we discard everyone associated with a particular address and everyone associated with an adjacent address on the manuscript when there is a potential problem with the census data, minimizing the risk of missing true occupants of a particular address in our final dataset. Because we wish to examine both occupancy rates and prices in our matched sample, developing an accurate count of household members is essential. Further details of the address data construction can be found in the Appendices C.1 and C.2. Our final sample contains 591,780 unique addresses that could be located in both 1930 and 1940 from about 100,000 city-blocks across the sample cities (see Appendix Tables I and II).[6] We have on average 10 to 15 addresses per city-block in the unmatched data, depending on the city. We compare addresses that could be cleaned and matched to the universe of addresses in Appendix Table III. There is some evidence that addresses with fewer occupants were more likely to be matched although the differences are economically small.[7]

We aggregate households in addresses with multiple units to obtain aggregate rents and

[6]To obtain the final address-level dataset, we trim outliers that are likely transcription errors or records associated with institutionalized individuals. In particular, we drop any households with more than 10 members, any household with more than three heads, any addresses with monthly rent greater than $100, and any addresses with a value greater than $20,000.

[7]For instance, there were 7.51 individuals per address in the universe of addresses compared with 6.81 individuals on average in our matched addresses. Because of the large sample size, nearly every difference in Appendix Table III is statistically significant.

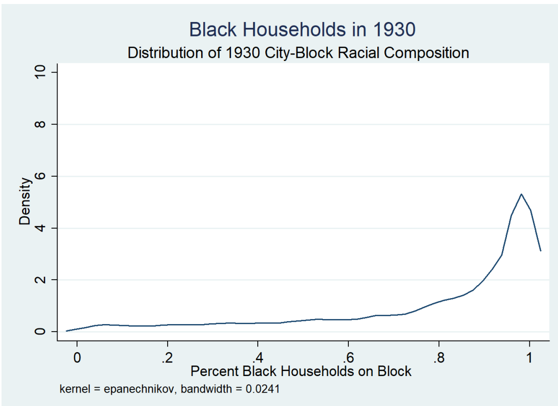
occupancy. Addresses that report both an owner and a renter are dropped from the sample. One potential concern with using self-reported valuations as a measure of home prices is accuracy. To verify the accuracy of our price data, for a sample of homes in Pittsburgh that sold in 1930 or 1940, we identified the corresponding address in the county Recorder of Deeds office and obtained the actual sales price. We plot the differential between the census valuation and the actual sales price in Appendix Figure 29. The figure suggests that there is no systematic bias.

In previous work, we constructed fine-grained, spatially-identified demographic data for neighborhoods in ten of the largest northern cities for 1900, 1910, 1920, and 1930 (Shertzer et al., 2016). We are thus able to measure a relatively broad set of baseline neighborhood characteristics at a small unit of geography, specifically at the level of the 1930 census enumeration district (typically around four city blocks in urban areas). Using our address data, we are further able to measure racial composition and other key variables at the city-block level. Blocks are delineated using postal service convention with street number intervals in the hundreds.

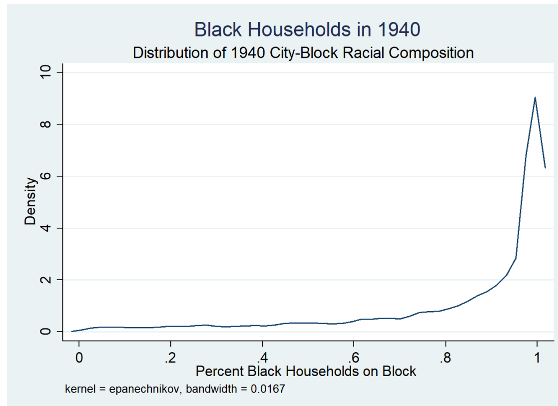
Figure 18 summarizes the block-level racial patterns in this newly constructed data. Panel A illustrates the distribution of percent black on the blocks where black families lived in 1930. Panel B presents the same data for 1940. These distributions document extremely high, and increasing, levels of segregation at the city-block level.[8] By 1940, 63 percent of all black families lived on a block that was more than 90 percent black and more than four out of every five black families lived on a block that was at least 75 percent black. Conversely, only 4 percent of black families lived on blocks that were greater than 75 percent white. Concurrent with the increase in segregation, the number of black households in our sample increased by 16 percent. Much of this growth in households was facilitated by the racial transition of previously all white blocks. As is illustrated in Panel C, nearly 8 percent of black households in 1940 lived on a city block that was less than 10 percent white in 1930.

These newly transitioned blocks are at the core of our broader identification strategy which focuses on a sample of single-family owner-occupied homes located on blocks that were

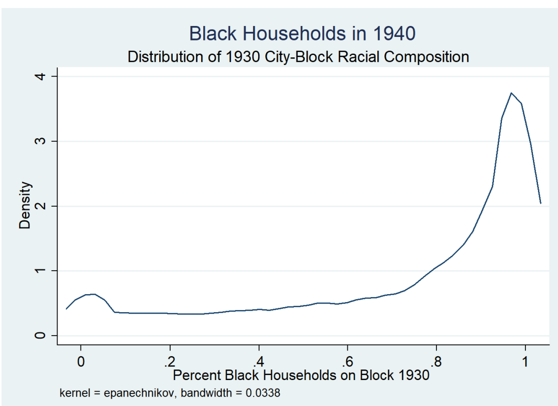
[8]Between 1930 and 1940 city-block level isolation (dissimilarity) indices increased from 80% (95%) to 85% (96%), calculated at the household level based on the matched address data set.



(A) 1930



(B) 1940



(C) 1940 (level in 1930)

Figure 18: Average city-block-level percent black exprienced by black families

Note: These figures show the distribution of percent black experienced by black households in our matched sample. Panels A and B report contemporaneous distributions (i.e. 1930 percent black on blocks where black families live in 1930). Panel C reports the distribution of percent black in 1930 for the blocks were black families were living in 1940. The basic unit of observation underlying these distributions is a black household head as identified in the 1930 or 1940 census. Note the change in scale between Panel C and Panels A and B.

all white in 1930. We present summary statistics for this sample in Table 12, subdividing the sample by whether the block had begun undergoing racial transition or not in 1940 (defined as having any black population in 1940). We first note the enormous drop in nominal home prices that accompanied the Great Depression, with homes on all blocks losing about 40 percent of their value between 1930 and 1940. Blocks that transitioned were located in neighborhoods closer to existing black neighborhoods in 1930, but other differences in neighborhood characteristics are relatively small.

Homes on blocks that transitioned were actually slightly more expensive on average in 1930, a finding we explore in more detail below. Average rents on these blocks for homes that switched to rentals in 1940 were higher relative to homes on blocks that remained white ($39.30 versus $35.10, respectively). Finally, homes on blocks that transitioned gained more occupants relative to homes on blocks that remained white (1.18 versus 1.06, respectively).

4.4 Semi-Parametric Analysis

We begin with a discussion of the overall patterns in our data, Figures 19 and 20 present the semiparametric relationship between racial transition and rents and home prices estimated using the Robinson's double residual method (Robinson, 1988). The figures are based on our baseline matched sample of homes that were single family, owner occupied and located on a block that was all white in 1930. They visualize the non-parametric relationship between the level of racial transition as of 1940 (horizontal axis) and rent or price in 1940 (vertical axis), controlling parametrically for a full set of controls including the home's value in 1930. We begin in Panel A by showing the relationship between 1940 black share and the log rent for all houses that had switched to being rentals by 1940.[9]

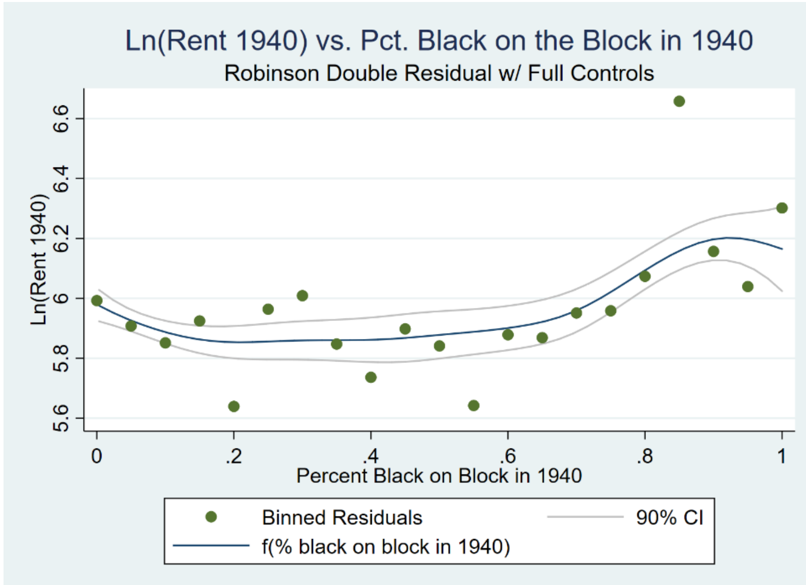
Rental prices are relatively flat at low levels of racial transition process. However, prices increase rapidly after a block attains majority black status. In total, Figure 19 suggests that

[9] That is, we estimate $\ln Price_{i40} = X_i'\beta + f\big(Blackshare_{i40}\big) + \epsilon_i$ where X_i includes controls for the log of 1930 price, occupancy at the address level, share renters and total number of addresses at the block level, and share black, share immigrant, share laborer, mean age, median home value, median rent, and median occupational score at the neighborhood level.

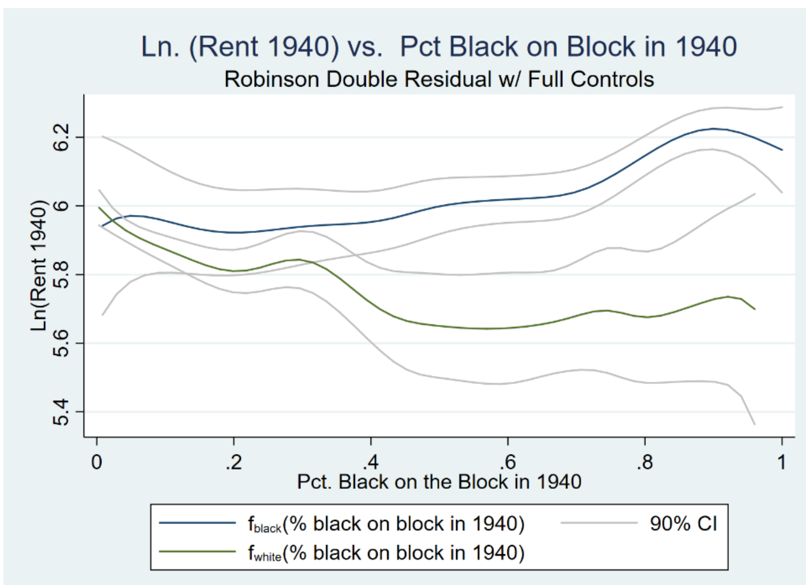
Table 12: Summary statistics for single-family home addresses

	Blocks stayed white in 1940		Blocks > 0% black in 1940	
	1930	1940	1930	1940
Address Level:				
Nominal home value	6280.37	3897.07	6654.52	4095.07
	(3466.17)	(2322.96)	(4312.74)	(2739.39)
Aggregate monthly rent	-	35.10	-	39.30
	-	(23.64)	-	(29.02)
Aggregate occupancy	4.31	4.15	4.59	4.72
	(1.84)	(2.01)	(2.03)	(2.62)
Aggregate households	1.00	1.06	1.00	1.18
	(0.05)	(0.36)	(0.07)	(0.70)
Block Level:				
Black Share	-	-	-	0.17
	-	-	-	(0.24)
Enumeration District Level:				
Laborer Share	0.03	0.03	0.04	0.05
	(0.03)	(0.03)	(0.04)	(0.04)
Foreign-Born Share	0.18	0.15	0.21	0.16
	(0.10)	(0.08)	(0.12)	(0.10)
Mean Age of Head	29.45	32.80	30.11	32.64
	(3.22)	(2.60)	(3.51)	2.91
Share of Homes Owned	1	0.76	1	0.66
	-	(0.43)	-	(0.47)
Miles to nearest black ED in 1930	1.29	-	0.64	-
	(1.46)	-	(1.11)	-
Number of owner-occupied houses	247191	187962	5590	3687
Number of rented houses	-	59229	-	1903

Note: This table reports statistics on our baseline sample of homes that were single family, owner occupied, located on a block with no black residents in 1930, and could be matched across the 1930 and 1940 censuses.



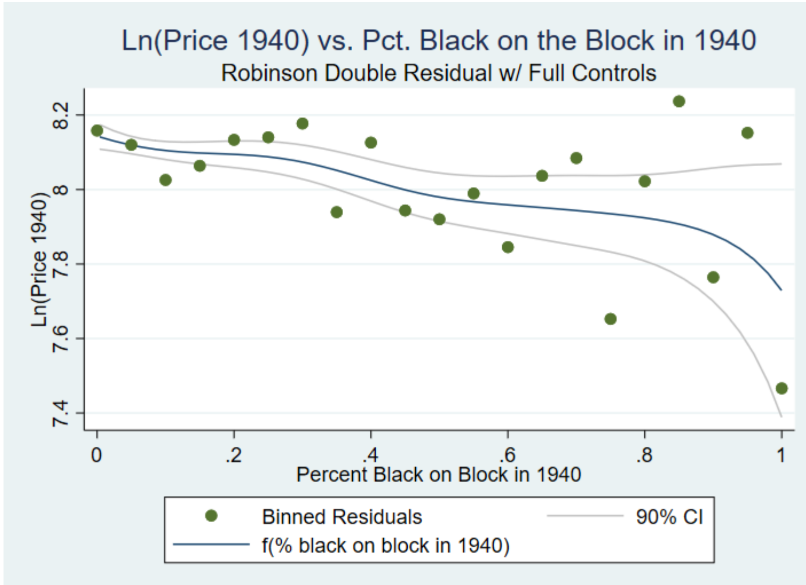
(A) Baseline sample



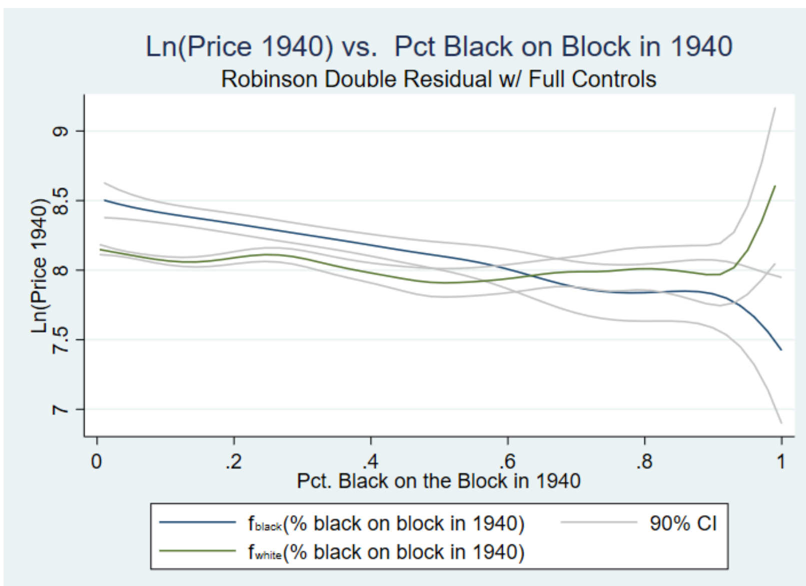
(B) Black and white households separately

Figure 19: Semiparametric relationship between percent black and rents

Note: These figures show the semiparametric relationship between percent black on the block in 1940 (independent variable) and log rent in 1940 (dependent variable) on our baseline sample of homes that were single family, owner occupied, and located on a block that had no blacks in 1930. Controls are included for 1930 price and occupancy at the address level, share renters and total number of addresses at the block level, and share black, share immigrant, share laborer, mean age, median home value, median rent, and median occupational score at the neighborhood level. The estimation method is Robinson's double residual method (1988). We also include binned residuals from the regression on each chart.



(A) Baseline sample



(B) Black and white households separately

Figure 20: Semiparametric relationship between percent black and home values

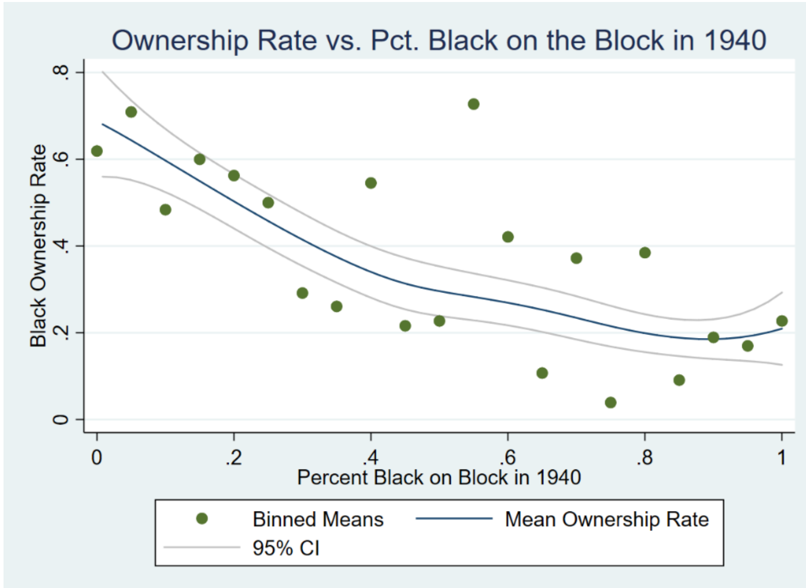
Note: These figures show the semiparametric relationship between percent black on the block in 1940 (independent variable) and log home price in 1940 (dependent variable) on our baseline sample of homes that were single family, owner occupied, and located on a block that had no blacks in 1930. Controls are included for 1930 price and occupancy at the address level, share renters and total number of addresses at the block level, and share black, share immigrant, share laborer, mean age, median home value, median rent, and median occupational score at the neighborhood level. The estimation method is Robinson's double residual method (1988). We also include binned residuals from the regression on each chart.

rents increased by 25 percent over the course of racial transition. In Panel B, we decompose rents based on the race of the occupant. The figure shows that while blacks in general always paid a premium relative to whites to rent on the same block, this premium grew significantly along with the level of transition, accelerating its growth rate at approximately 40 percent black. Thus, above this point white renters demanded, and landlords were willing to provide, a significant discount to remain on transitioned blocks. The most direct explanation for these differentials is racial discrimination.

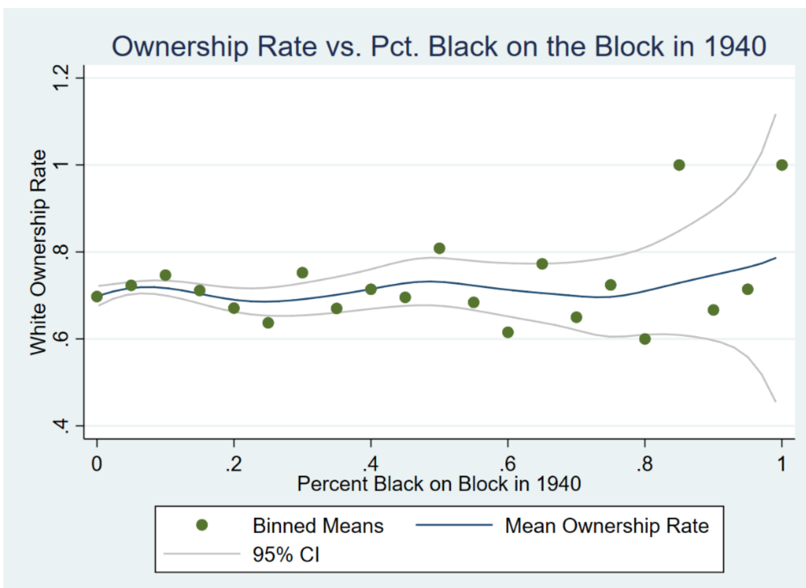
We now turn from rents to valuations of home prices. If racial market dynamics were driven solely by supply restrictions in the market for black housing related to the enforcement of segregated neighborhoods, we would expect the value of owner-occupied homes in black neighborhoods to experience similar increases in valuations upon racial transition. Yet, as is shown in Panel A of Figure 20, overall home values in fully transitioned neighborhoods declined by about 35 log points (about 40 percent). In Panel B, we decompose this relationship by the race of the owner. This figure suggests that the overall drop in home values was, in part, driven by the "pioneer" premium paid by black families buying a home on a mostly white block. We estimate that this premium is about 30 log points (35 percent). Further, homes purchased on transitioning blocks lost value throughout the transition process. By the time the block was mostly black, such homes had lost about 11 percent of their *original* value.

To better understand the impact of these price and rent dynamics, Figure 21 documents black homeownership rates over the range of transition. Panel A documents high home ownership rates (low rental rates) among the pioneering black families. Black ownership rates then decrease with transition level, plateauing when blocks become majority black. This pattern indicates that black families were most likely to buy homes when the purchase premium required from them was highest and most likely to rent when the rent premium was highest. Taken together, these results suggest that there was no escape from the disadvantageous housing market faced by black families. In contrast, there is no trend in ownership for white families (Panel B).

We now turn to a more parametrized analysis. Here, we have two primary goals. First, we wish to better understand the divergence between rents and owner-occupied housing values.



(A) Black ownership rate



(B) White ownership rate

Figure 21: The relationship between percent black and ownership rates

Note: These figures show the semiparametric relationship between percent black on the block in 1940 (independent variable) and log rent in 1940 (dependent variable) on our baseline sample of homes that were single family, owner occupied, and located on a block that had no blacks in 1930. Controls are included for 1930 price and occupancy at the address level, share renters and total number of addresses at the block level, and share black, share immigrant, share laborer, mean age, median home value, median rent, and median occupational score at the neighborhood level. The estimation method is Robinson's double residual method (1988). We also include binned residuals from the regression on each chart.

Second, we seek to better identify the relationships we document in the semi-parametric analysis and demonstrate that they are causal.

4.5 Capitalization Framework and Parametric Analysis

Our parametric framework models the relationship between rents, property values, and the racial composition of neighborhoods from the perspective of an arbitraging real estate investor. To fix ideas, we denote the price (rent or own) of an individual building as follows:

$$P_i = \begin{cases} annual\ rent_i & \text{if } tenure = r \\ sales\ value_i & \text{if } tenure = o \end{cases}$$

For a given owner occupied house, its price in year t is given by:

$$P_{it} = c_t * \rho_t * Q(Z_i) \tag{4.5.1}$$

where ρ_t is the city-specific price level at time t, Z_i is a vector fo housing and neighborhood characteristics that are particular to the given house, $Q(.)$ is a quantity function that maps these characteristics into a unidimensional measure of service flow, and c_t is a capitalization rate that captures the equilibrium relationship between sales price and annual rent.

Thus, we follow Poterba [1992] in conceptualizing the capitalization rate as follows:

$$rent_{it} = c_t * sale_{it} \tag{4.5.2}$$

The capitalization rate, c_t can be decomposed as follows:

$$c_t = i + \tau_p + risk + maintenance + depreciation - appreciation$$

where i is the risk-free interest. Intuitively, the real estate investor must receive a return on her investment equal to the risk-free interest rate available in the broader market place. This risk-free rate of return is adjusted for additional costs and benefits associated with owning the property. In particular: tax benefits or costs associated with owning a home (τ_p), a risk premium associated with housing price uncertainty ($risk$), costs for maintaining the property (*maintenance*), physical depreciation (*depreciation*), and appreciation of the home's value net of the overall inflation rate (*appreciation*) - with all of these terms expressed as percentages of the property's values. We also note that the results presented in Panel B of Figure 19 suggest augmenting the basic model to include an additional term to account for landlord preferences over the race of potential tenants (taste-based discrimination).

This no-arbitrage relationship is central to understanding Figures 19 and 20 that show racial transition being associated with lower sales values and higher rents. While perhaps surprising at first, this dichotomy can be rationalized by investors having exceedingly pessimistic expectations regarding the impact of racial transition on housing price appreciation (expectations of rapidly declining values), physical depreciation or maintenance costs.

To operationalize this relationship, we begin by combining equations (4.5.1) and (4.5.2) to derive a unified expression for P_{it}:

$$P_{it} = \rho_t * c_t^{I_{rent}} * Q(Z_i) \tag{4.5.3}$$

where I_{rent} is an indicator variable which equals 1 if the house is rented. Taking the log of both sides yields the following:

$$\ln P_{it} = \ln \rho_t + \ln c_t * I_{rent} + q(Z_i) \tag{4.5.4}$$

where $q(Z_i) = \ln Q(Z_i)$. In our application, we don't directly observe characteristics Z_i, but we do observe prices in both 1940 and 1930. As we detail below, we can use this information to effectively control for these unobserved characteristics.

Solving the 1930 iteration of equation (4.5.4) for $q(Z_i)$ gives: $q(Z_i) = \ln P_{it} - \ln \rho_t - \ln c_t * I_{rent}$. Assuming that Z_i is time invariant, limiting our sample to houses that were owner occupied in 1930 (we relax both of these restrictions later), and substituting this expression into the 1940 version of equation (4.5.4) yields the following expression for 1940 prices:

$$\ln P_{i40} = \ln \rho_{40} - \ln \rho_{30} + \ln P_{i30} + \ln c_{t40} * I_{rent40} \tag{4.5.5}$$

Thus, ignoring for the moment neighborhood racial transition, we have the following model:

$$\ln P_{i40} = \alpha + \beta * I_{rent40} + \gamma \ln P_{i30} + \epsilon_i \tag{4.5.6}$$

We can interpret the key coefficients in equation (4.5.6) as follows: α is the difference in the (logged) price levels between 1940 and 1930 and β is the logged capitalization rate in 1940. Further, inclusion of the 1930 house price effectively controls for all time-invariant house and neighborhood characteristics.[10]

To build on this basic empirical specification, we begin by limiting our sample to houses located on city blocks that were all white 1930. We then generate an indicator variable for racial transition (I_{trans_i}). Finally, we add the transition variable and its interaction with the rent indicator to equation (4.5.6) yielding our basic specification:

$$\ln P_{i40} = \alpha + \beta_{trans} * I_{trans_i} + \beta_{rent} * I_{rent_i} + \beta_{transXrent} * I_{transXrent_i} + \gamma \ln P_{i30} + \epsilon_i \tag{4.5.7}$$

In this specification, $\exp\left(\hat{\beta}_{trans}\right)$ provides an estimate of the percent difference in sales prices between blocks that transitioned and those that did not. Further, $\exp\left(\hat{\beta}_{trans} + \hat{\beta}_{transXrent}\right)$ provides an estimate of the percent difference in rental prices across transitioning and non-transitioning blocks.[11]

One potential concern is that certain characteristics of houses (or their neighborhoods) might change in systematic ways between 1930 and 1940. We control for this possibility in two separate ways. First, we directly include controls for a number of 1930 characteristics at the address, block, and neighborhood level that may be predictive of these systematic changes. Specifically, we control for the occupancy at the address level, share renters and total number of addresses at the city-block level, and at the neighborhood level we control for share black, share immigrant, share laborer, mean age, median home value, median rent, and median occupational score. Second, we drop the neighborhood-level controls (keeping the house and city-block-level controls) and instead include ED-level fixed effects. These fixed effects will absorb any time changing characteristics that are shared at the ED-level (recall that EDs in our sample are typically approximately four city blocks).

[10] One could restrict the coefficient γ to be equal to 1. However, not doing so allows for the possibility that price deflation between 1930 and 1940 varied across the distribution of housing quantities.

[11] We also note that $\hat{\beta}_{rent}$ and $\hat{\beta}_{transXrent}$ allow for the recovery of effective capitalization rates in transitioned and un-transitioned neighborhoods.

4.5.1 Baseline Results

We begin our parametric analysis by relating changes in block-level racial composition to changes in housing prices over the 1930s. For our baseline specification, we consider the impact of city block-level racial change as measured by a variable that equals 1 if a formerly white block became majority black by 1940 and 0 otherwise. Column (1) of Panel A in Table 13 reports the empirical estimate of equation (4.5.7), restricting the sample to single-family, owner-occupied homes and controlling only for price and occupancy in 1930. The second column adds neighborhood-level controls and the third incorporates both neighborhood fixed effects as well as block-level controls for share renters and number of households in 1930. While results are qualitatively consistent across specifications, the model presented in column (3) is the most robust in terms of controls. We therefore view it as our preferred specification.[12]

The coefficient on the rent indicator (-2.214) reflects the log of the capitalization rate for blocks that did not experience racial transition. It implies a baseline capitalization rate of 10.9 percent. Thus, in white neighborhoods the annual rent that a real estate investor should have expected to receive on a given property was roughly 11 percent of its sales value.[13] The coefficient on the racial transition variable (-.096) implies that houses on blocks that saw an influx of blacks lost 9.1 percent of their value relative to blocks that remained white. Meanwhile, in conjunction with the coefficient on the interaction between rented and transition (.503), this estimate implies that rents on these blocks increased by 50.2 percent relative to non-transitioning blocks. Finally, the estimated capitalization rate for transitioned neighborhoods is 18.1 percent (computed as the exponent of the sum of the rented coefficient and the interaction of transition and rented).

Although we prefer to restrict our attention to single-family, owner-occupied homes for the purpose of identification of the transition effect, we also present results for a larger sample

[12] Appendix Figures 32 and 33 demonstrate the general robustness of our analysis to different choices of baseline blocks (i.e. choosing as a baseline all city-blocks that were less than x% black in 1930) and different thresholds for racial transition (i.e. defining as transitioned all city-blocks that were more than x% black in 1940).

[13] The Great Depression was associated with substantial housing price deflation which outpaced the concomitant declines in rents, and thus we should expect capitalization rates that are in general larger than those from the current day, which tend to center around 6 percent (see for instance Davis et al., 2008).

Table 13: Main results: price and occupancy

Panel A: Log price	No Controls (1)	Controls (2)	ED FE (3)	All Obs. FE (4)	Rental FE (5)
Rented	-2.243***	-2.235***	-2.214***	-2.157***	-2.052***
	(0.003)	(0.003)	(0.003)	(0.002)	(0.004)
Racial Transition	-0.266***	-0.166***	-0.096**	-0.135***	-0.105
	(0.039)	(0.038)	(0.043)	(0.036)	(0.074)
Rented x Transition	0.460***	0.496***	0.503***	0.371***	0.272***
	(0.050)	(0.048)	(0.049)	(0.038)	(0.075)
Observations	242,441	241,793	242,441	399,964	151,501
R-squared	0.738	0.757	0.802	0.819	0.731

Panel B: Log occupancy	No Controls (1)	Controls (2)	ED FE (3)	All Obs. FE (4)	Only Rentals (5)
Rented	0.167***	0.182***	0.184***	0.185***	0.166***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.004)
Racial Transition	-0.020	-0.049*	-0.032	-0.033	0.068
	(0.030)	(0.027)	(0.033)	(0.029)	(0.063)
Rented x Transition	0.278***	0.279***	0.233***	0.163***	0.023
	(0.038)	(0.035)	(0.038)	(0.030)	(0.063)
Observations	252,781	246,234	247,169	407,954	154,626
R-squared	0.024	0.211	0.250	0.361	0.445

Note: The first three columns report the OLS estimation of equation (4.5.7) on our baseline sample of homes that were single family, owner occupied, and located on a block with no black residents in 1930. The first column controls only for price and occupancy of the address in 1930. The second column adds controls share renters and total number of addresses at the block level, and share black, share immigrant, share laborer, mean age, median home value, median rent, and median occupational score at the neighborhood level. The third column drops the neighborhood controls and includes ED fixed effects. The fourth column adds addresses that were rented in 1930 to the sample and uses the specification from column (3) with an additional control for tenure status in 1930. The fifth column uses only rented homes in 1930. The transition indicator is equal to one if the block became more than 50 percent black by 1940.

of addresses in column 4. Specifically, we also include buildings that were rented in 1930.[14] Our estimates are quantitatively similar. In column (5) we report results focusing solely on the sample of addresses that were rented in 1930, again finding similar results but with a smaller rental premium for homes on blocks that underwent racial transition and remained rented in 1940 as well. As we show below in Section 4.5.4, and in Appendix Figure 33, these results are robust to alternative definitions of racial transition.

In all specifications we find that racial transition was accompanied by falling home values, sharply increasing rents, and a substantially higher capitalization rate. As discussed above, the finding that rents and valuations diverged on transitioned blocks, can be rationalized by investors having exceedingly pessimistic expectations regarding housing prices, physical depreciation, or maintenance costs. We note that the channel through which racial preferences impact prices and rents is less direct here, where we are comparing average prices and rents across blocks at different stages of racial transition, than it was in Figure 19 Panel B where we compared differences in rent paid by black and white households on blocks at identical stages of transition. In the earlier comparison across the race of individual renters, differentials are likely driven by white landlords preferring to rent to white tenants and thus charging blacks higher rents than whites for identical properties. Here we are instead focused on how rents change with block-level transitions, independent of the race of a home's renter or owner. The primary channel through which racial preferences drive cross-block market dynamics on this dimension are more likely white flight and related expectations about future declines in price.

Independent of racial preferences or price expectations, contemporaneous narratives suggest that one channel through which capitalization rates (and thus rents) could have been higher for buildings on blocks undergoing racial transition is through higher occupancy rates, either due to subdividing single-family housing into multiple rental units or as a result of black families taking on boarders to help cover the steep rents that they faced. Managing contracts with multiple households could have imposed direct costs, while increased occupancy itself could have led to more rapid physical depreciation.

[14] This specification requires additional controls for tenure status in 1930. We do not include mixed-tenure or multiple owner addresses in this analysis because it is unclear how to aggregate a mix of valuations or valuations and rents into an address-level price.

We explore the impact of transition on occupancy rates in panel B of Table 13, which replicates panel A using log of aggregate occupancy as the outcome variable. Occupancy results are generally similar across all models. Houses on un-transitioned blocks that switched from being owned to rented saw increases in their average aggregate occupancy rate of approximately 20 percent. These occupancy rate increases were even larger when the move to rental status was associated with racial transition. The estimates from column (3) indicate that rental occupancy soared by 47 percent in such homes relative to homes that remained owned on blocks that did not transition.[15] For owner occupied housing, the main effect of racial transition is very small or negative in all specifications (-0.032 and statistically insignificant in our preferred specification). This finding is consistent with the narrative evidence that higher-socioeconomic-status black families, who would not need to bring on boarders or live in subdivided units to afford housing, were the first to arrive on a transitioning block and bought their homes rather than renting them (e.g. Massey and Denton, 1993).

Our occupancy results raise the possibility that the observed increase in capitalization rates on transitioned blocks, and the associated rent spikes, could simply be the direct result of increases in maintenance or physical depreciation costs arising from higher-density habitation. To examine this issue directly, in Table 14 we consider how capitalization rates varied with both occupancy and racial transition, augmenting our baseline log-price specification to consider multiple levels of racial transition and splitting the sample between houses that experienced increased occupancy rates and those that experienced decreased or unchanged occupancy rates. The results suggest that while occupancy rates had a small impact on capitalization rates on blocks that remained white, the magnitudes are too small to explain the bulk of the rent hikes experienced in transitioning blocks. In Table 15, we go further and focus on subsamples comprised only of addresses that gained between one and four members located on blocks that remained white between 1930 and 1940. Even for addresses that gained at least four members, a very large occupancy increase, the coefficient estimates imply capitalization rates that never exceed 11.5 percent. We thus reject the notion that our results are driven solely by occupation rates.

[15] That is, exp(.184-.032+.233)=1.47.

Table 14: Price shifts and capitalization rates by occupancy change

All Addresses			
Percent black on block in 1940	Sales	Rent	Cap. Rate
0	100.00%	100.00%	10.90%
0-10%	98.22%	107.36%	11.92%
10-50%	98.51%	110.08%	12.18%
50-100%	91.48%	151.74%	18.09%
Observations			242,441
Occupancy Increased			
Percent black on block in 1940	Sales	Rent	Cap. Rate
0	100.00%	100.00%	11.24%
0-10%	93.43%	111.18%	13.37%
10-50%	97.92%	116.53%	12.68%
50-100%	76.64%	129.30%	18.96%
Observations			71,943
Occupancy Decreased or Same			
Percent black on block in 1940	Sales	Rent	Cap. Rate
0	100.00%	100.00%	10.32%
0-10%	101.01%	101.82%	10.40%
10-50%	100.40%	100.20%	10.30%
50-100%	99.80%	151.29%	15.65%
Observations			170,498

Note: The table reports the implied capitalization rates from an OLS estimation of equation (4.5.7) on our baseline sample of homes that were single family, owner occupied, and located on a block with no black residents in 1930. Regressions include controls for price and occupancy of the address in 1930, share renters and total number of addresses at the block level, and ED fixed effects. See text for details on how to compute the capitalization rate from regression coefficients.

Table 15: Coefficient on rental indicator for addresses on blocks that remained white

	No Controls (1)	Controls (2)	ED FE (3)	All Obs FE (4)
All addresses	-2.244***	-2.237***	-2.216***	-2.160***
	(0.003)	(0.003)	(0.003)	(0.002)
Addresses that gained at least 2 members	-2.186***	-2.171***	-2.177***	-2.114***
	(0.009)	(0.009)	(0.010)	(0.008)
Addresses that gained at least 3 members	-2.164***	-2.153***	-2.179***	-2.106***
	(0.013)	(0.013)	(0.016)	(0.011)
Addresses that gained at least 4 members	-2.139***	-2.118***	-2.161***	-2.080***
	(0.019)	(0.018)	(0.025)	(0.017)

Note: The table reports the rental indicator from OLS estimation of equation (4.5.7) on our baseline sample of homes that were single family, owner occupied, and located on a block that had no blacks in both 1930 and 1940. The first column controls only for price and occupancy of the address in 1930. The second column adds controls share renters and total number of addresses at the block level, and share black, share immigrant, share laborer, mean age, median home value, median rent, and median occupational score at the neighborhood level. The third column drops the neighborhood controls and includes ED fixed effects. The last column adds addresses that were rented in 1930 to the sample and uses the specification from column (3) with an additional control for tenure status in 1930. The table reports the coefficient on the "rented" variable, which is an indicator for whether the house switched to being a rental in 1940.

4.5.2 Discriminatory Premiums in the Housing Market

We next seek to estimate the premiums required of black families in owned and rented housing markets suggested by the semiparametric results from Section 4.4. Recall that black families appeared to pay a premium to buy a house on a white block at the earliest stages of transition (Figure 20 Panel B). To estimate this premium, we modify our baseline specification (4.5.7) by adding an indicator for a black household and interacting this indicator with rental status. We also drop the indicator for racial transition and instead restrict analysis to blocks that experienced low levels of racial transition (black share in 1940). Column 1 (column 2) of Table 16 presents results for the sample of blocks that were all white in 1930 and less than five percent (ten percent) black in 1940. The highly significant point estimate on black household of 0.32 (0.25) translates to pioneering black families paying a 38 percent (28 percent) discriminatory premium. It is unlikely that these premiums reflect simple differences in perceptions since the black homebuyers would have just recently purchased their homes in white neighborhoods.

Turning to the rental market, Figure 19 Panel B suggests that white families received a large discount if they remained in their rental units during the racial transition process, particularly once the block experienced marked racial mixing. To estimate these premia, we again rerun our modified specification but for blocks where racial transition was well underway. Column 3 (column 4) shows the results for blocks that were at least 40 percent (60 percent) black in 1940. The coefficient estimates suggest that on such blocks black renters paid 34 percent (44 percent) more than white renters for identical housing. Again, the most direct explanation for these premiums is racial discrimination on the part of landlords. One potential concern is that, by construction, black households on newly transitioned blocks would have had a shorter tenure than white residents and that rental and sales premia are being driven by these differences. As we discuss below in section 4.5.4, we can rule out this concern by limiting our sample of white households to only include those whose 1940 tenure was less than five years. We discuss the implications of the rental and homeownership premiums faced by black households in Section 4.6.

Table 16: Discrimination in owned and rented housing

	Black < 5%	Black < 10%	Black > 40%	Black > 60%
	(1)	(2)	(3)	(4)
Rented	-2.216***	-2.215***	-2.093***	-2.033***
	(0.003)	(0.003)	(0.080)	(0.104)
Black Household	0.322***	0.250***	0.097	-0.023
	(0.106)	(0.074)	(0.079)	(0.095)
Rented x Black Household	0.213	0.133	0.295***	0.368***
	(0.182)	(0.128)	(0.111)	(0.133)
Black Pioneer Premium	0.38	0.28		
Black Rental Premium			0.34	0.44
Observations	239,397	240,450	837	533
R-squared	0.858	0.846	0.822	0.840

Note: The table reports the OLS estimation of the modified version of equation (4.5.7) that includes an indicator for black household interacted with the rental indicator. The racial transition indicator is dropped and the modified specification run on different parts of the black share distribution. All specifications include enumeration district fixed effects and are run on our baseline sample of homes that were single family, owner occupied, and located on a block with no black residents in 1930.

4.5.3 Selection

One potential concern with our empirical results is the possibility that neighborhoods that were already destined to experience declining values (or higher rents) were differentially targeted for racial expansion, even after controlling for price in 1930. Perhaps most concerning is the role played by proximity to existing black neighborhoods. Our data clearly document that proximity to an existing black neighborhood was a strong predictor of racial transition. If these proximate neighborhoods were also destined to see systematic departures from price trends, for instance because of reduced city services or other forms of disinvestment, our results could be biased. The inclusion of enumeration district (ED) fixed effects in our preferred specification is largely a response to this concern as they will control for all factors affecting prices that are constant over very small neighborhood definitions. However, it is still possible that even differences in black neighborhood proximity across a few city blocks could lead to selection problems.

As a first test of our fixed effects strategy we evaluate the effectiveness of using enumeration district fixed effects to absorb control for the correlation between 1930 demographic measures and racial transition over the following decade. Table 17 presents the results of a block-level estimation of the determinants of racial transition for blocks that had at least one owner-occupied single-family home and were all white in 1930. Columns (1) and (4) present regressions on the entire sample that include ED fixed effects in addition to controls for household head age, share laborer, foreign-born share, average rent per person and homeownership share. For ease of interpretation, all explanatory variables are expressed in terms of their standard deviations. Thus, the coefficient estimate of -.001 on average age of household head implies that, once one controls for enumeration district fixed effects, a one standard deviation decrease in average household head age in 1930 is on average associated with a one-tenth of a one percentage point increase in percent black on the block in 1940. While a number of demographic variables are statistically significant in columns 1 and 4, the coefficient estimates are all quite small, and from an economic perspective, they are precisely estimated zeros.

Omitted from these first two regressions are controls for proximity to existing black

Table 17: Predicting racial transition in baseline sample

	Percent Black in 1940			Percent Black in 1940 > 50%		
Block characteristics in 1930:	(1)	(2)	(3)	(4)	(5)	(6)
Average age of heads of HH	-0.001***	-0.001**	-0.001**	-0.001***	-0.001*	-0.001*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Share laborer heads of HH	0.001***	0.000	0.000	0.001***	0.001**	0.001**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Share foreign born heads of HH	0.001***	0.000	0.000	0.001*	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Average rent per person	-0.001**	-0.000	-0.000	-0.001	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Ownership share	-0.000	0.000	0.000	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Distance to nearest ghetto			-0.005*			-0.002
			(0.003)			(0.003)
Sample	All	Geo.	Geo.	All	Geo.	Geo.
Observations	51,859	43,819	43,819	53,478	43,819	43,819
R-squared	0.585	0.654	0.654	0.563	0.609	0.609

Note: This table reports OLS estimations of selection into racial transition using our baseline sample of blocks that had at least one owner-occupied, single-family home and no black residents in 1930.

neighborhoods, perhaps the most important potential confound (see Table 12). To address the possibility that distance to an existing black neighborhood is biasing our baseline results, we geocoded our sample of city blocks.[16] This geocoded subsample allows us to directly test the efficacy of our ED fixed effects in controlling for existing black neighborhood proximity. Appendix Figure 30 presents a visualization of our geocoded blocks for Detroit, which is typical of all of our sample cities. A limitation of our geocoding is that we were only able to geocode approximately 87 percent of our sample. One concern is that this subsample will vary systematically from our main sample as addresses that were targeted for urban renewal and demolition in the 1960s and 1970s may be overwhelmingly represented in the set of addresses that could not be geocoded.

Columns (2) and (5) of Table 17 replicate the regressions of columns 1 and 4 on the geocoded subsample; while columns (3) and (6) add distance to the nearest black neighborhood (ED $>$ 15 percent black in 1930) to the regressions (normalized by standard deviation). Consistent with expectations, such proximity is a stronger predictor of transition than were our demographic variables. Nonetheless, ED fixed effects are still effective in absorbing proximity's impact. Controlling for ED, on average, a one standard deviation decrease in proximity in 1930 is associated with only a one-half of a one percentage point increase in percent black on a block in 1940. These results suggest that our price and occupancy results are driven by racial transition and not by other factors.

As a final test on this dimension, we evaluate the impact of incorporating distance to existing black neighborhoods directly into our main specification. Columns (2) and (5) of Table 18 replicate our baseline results for the geocoded sample; for comparison, baseline results for the entire sample are repeated in Columns (1) and (4). While qualitatively similar to the full-sample estimates, the interaction between rented and majority black is smaller in the geocoded sample versus the full sample (.345 versus .503, respectively). Thus, it is important to focus within the geocoded subsample when assessing the impact of controls for distance to the nearest black neighborhood on our coefficients of interest. Columns (3) and (6) add a control for distance to the nearest black neighborhood (defined as miles to an enumeration district that was at least 15 percent black) to the model. Comparing these

[16] See the Appendix C.3 for a description of this process.

results to those in columns (2) and (5) demonstrates that while distance to the nearest black neighborhood is negatively associated with price, all other coefficient estimates are virtually unchanged by its inclusion in the regression, suggesting that enumeration district fixed effects provide sufficient controls for this source of selection bias. Additionally, distance to a black neighborhood is not associated with occupancy (column 6).

4.5.4 Further Robustness and Concordance with Non-Parametric Analysis

Our parametric results are based on a relatively granular characterization of the racial transition of city blocks: moving from all white in 1930 to majority black in 1940. To develop a richer understanding of the underlying process, we explore the impact of racial transition on prices and occupancy over the range of 1940 black share. This approach echoes our semiparametric analysis and provides insight into price dynamics on blocks that were at different stages of racial transition. Specifically, we partition our sample of blocks that were white in 1930 into four groups: those that remained white, those that had strictly between 0 and 10 percent black population in 1940, those that had between 10 and 50 percent black population in 1940, and those that had over 50 percent black population in 1940. The coefficient estimates from this analysis are presented in Appendix Table 27. For ease of interpretation, we also summarize the effects on prices, rents and capitalization rates for this specification in the top panel of Table 14.

Recall that our preferred specification includes neighborhood (ED) fixed effects along with block-level controls. Thus, identification comes from variation in block-level racial composition from within a very small neighborhood and beyond that which can be predicted by residential density and rental share. In terms of average prices and rents, our findings are robust to this disaggregation. The finding that transition impacts are muted below 50 percent black in our most robust specification (with ED fixed effects) is consistent with the non-parametric analysis of Figures 19 and 20 and the sensitivity analysis presented in Appendix Figure 33. Appendix Figure 33 also demonstrates our results' robustness to the choice of transition threshold. Additionally, we note here that our results are robust to alternate definitions of a white block in 1930 (see Appendix Figure 32).

Table 18: Results for racial transition and proximity to nearest black neighborhood

	Dependent variable = log price			Dependent variable = log occupancy		
	All blocks	Geocoded	Geocoded	All blocks	Geocoded	Geocoded
	(1)	(2)	(3)	(4)	(5)	(6)
Rented	-2.214***	-2.222***	-2.222***	0.186***	0.184***	0.184***
	(0.003)	(0.003)	(0.003)	(0.002)	(0.002)	(0.002)
Transition	-0.096**	-0.202***	-0.201***	-0.039	-0.042	-0.042
	(0.043)	(0.058)	(0.058)	(0.033)	(0.044)	(0.044)
Rented x Transition	0.503***	0.345***	0.345***	0.240***	0.120**	0.120**
	(0.049)	(0.066)	(0.066)	(0.037)	(0.050)	(0.050)
Distance to Ghetto			0.102***			-0.001
			(0.012)			(0.009)
Observations	242,441	211,964	211,964	252,781	221,054	221,054
R-squared	0.802	0.805	0.805	0.250	0.252	0.252

Note: The table reports the OLS estimation of equation (4.5.7) on our baseline sample of homes that were single family, owner occupied, and located on a block with no black residents in 1930. Regressions include controls for price and occupancy of the address in 1930, share renters and total number of addresses at the block level, and ED fixed effects. The second and third columns include only addresses that could be geocoded. Black neighborhoods are defined as EDs with at least 15 percent black population.

A final concern is that the differential prices faced by black and white households are driven by tenure bias, in particular the possibility that white households bought houses or signed rental contracts long before the Great Depression began. To address this concern, we replicate all of our main findings restricting our sample to white households that had resided in a different address in 1935 using the migration question first asked in the 1940 census. The semiparametric regressions from Figures 19 and 20 are reproduced for this sample of recent arrivers of both races in Appendix Figures 34 and 35, respectively. The main results from Tables 13 and 16 are similarly produced in Appendix Tables 28 and 29. There are no substantive differences, strong suggesting that our results are driven by race and not tenure.

4.6 Discussion

The housing market dynamics underlying our analysis arose under, and were shaped by, the Great Migration. During this period, black migrants were both pushed and pulled to the North by a myriad of factors; the opportunity for economic advancement playing a central role. In 1940, black men between the age of 18 and 60 working for wages in the states of the former Confederacy earned $475 per year. In contrast, their counterparts living in one of our ten sample cities earned on average $994 per year. Upon migrating North, these individuals fared slightly less well than longer-term black residents of the North, earning on average approximately 15 percent less than the extant work force ($839 per year), but they still experienced a greater than 75 percent increase in average wages.[17]

In contrast, our analysis demonstrates that this promise of higher wages was offset, at least partially, by forces at work in the North's segregated housing markets. At this time, the large majority of blacks living in our sample cities were renters, paying an average rent of $36.88 per month. At this level of rent, our estimated 50.2 percent rent premium translated to an annual cost of $147.97, or just over 40 percent of the income gain associated with northern migration. One way that black renters attempted to ameliorate these costs was

[17] Averages computed from the 100 percent sample of the 1940 US census accessed through IPUMS-USA (Ruggles et al., 2019). We restrict the sample to wage workers who reported working at least 50 weeks in the prior year.

to live more densely relative to white renters (on the order of 22 percent according to the estimates presented in Table 13 column 3). But of course this increase in density was not without costs, and our estimates assume that the transition from white block to black block was associated with no other changes in neighborhood quality, such as those that might be expected if the racial transition was associated with a reduction in the quality of city services provided to its residents (Derenoncourt, 2018).

Some migrants would have avoided these steep rent premiums by instead purchasing their home. As is shown in Panel A of Figure 21, by far the highest black ownership rates occurred on predominantly white blocks where black ownership rates were on the order of 70 percent (as opposed to black ownership rates of closer to 20 percent on predominantly black blocks). Blacks purchasing on these blocks were also disadvantaged by the segregated housing markets (see Figure 20 Panel B and Table 16). Black families who purchased homes on city blocks that were less than 10 percent white paid on average $4,166.74 for their home and bought at a premium of almost 28 percent relative to what white families would have paid on the same block. Further, the arrival of a few pioneering black families led to a significant racial transition, switching the block from white to black. Then, this transition would have on average eroded the home's value to roughly 10 percent its initial value (See Figure 20 Panel A and Table 13). The net effect of the initial race premium and ensuing price erosion on such a house represents a loss of $1,218.72, or nearly 3.5 years' worth of the migration-driven gain in wages for a typical black migrant.

Largely unanswered in this discussion is an identification of the specific role that racism played in underpinning the price dynamics of this period's segregated housing markets and the costs that these markets extracted from black families. The potential channels are numerous and interwoven. Clearly white flight from the arrival of pioneering black families is an important channel.[18] While such flight was likely at least partially driven by white attitudes about black families, flight could also be partially explained by expectations about how a block's racial transition could lead to a reduction in the quality of city services, with such reductions themselves being the result of racist city policies. Similarly, the price premium demanded of pioneering black families can be viewed as evidence of preference-based

[18]Shertzer and Walsh [2019], Boustan and Margo [2013].

discrimination by sellers or of concerns about sanctions that would be faced by either the selling agent or the selling family at the hands of remaining owners. Of course these sanctions reflected underlying racist attitudes or a fear of future price declines, which themselves were likely rooted in racist attitudes and city policies. To some degree, likely all of these channels were at work and served to reinforce themselves in an unfortunate circle of causality.

4.7 Conclusion

In this paper we constructed a novel dataset of rents, home values, and the racial composition of city blocks in interwar American cities to systematically investigate the housing market dynamics associated with black entry into white neighborhoods. We find that racial transition was associated with both increases in aggregate rental prices and decreases in property values. To our knowledge this is the first paper to demonstrate that black entry into a neighborhood caused the price of owned and rented housing to diverge, a finding that is consistent with much of the narrative history.

Impacts of racial transition were large. We find that rental prices soared by 50 percent in blocks that transitioned from all white to majority black. In contrast, home values fell by 10 percent relative to blocks that remained all white. The impact of these market dynamics for racial wealth inequality were further exacerbated by our finding that pioneering black families paid a significant premium for homes on majority white blocks at the early stages of transition. Similarly, rent discounts to white families that remained on transitioning blocks later into the process also further eroded black wealth relative to that of whites. Our conservative calculation suggests that the rental premium required of black families was roughly 40 percent of the wage gain for the average unskilled laborer of moving North relative to remaining in the South. Our findings strongly indicate that segregated housing markets eroded a large fraction of the potential return to migrating to higher-paying labor markets for African Americans.

The dramatic decline in property values had important implications for city budgets and real estate investors alike. Rental property owners, faced with the costs of creating and maintaining rental units that were going to depreciate in value and with a ready supply of black households desperate for housing outside of the already underserved ghetto, were able to charge high enough rental prices to make their investment worthwhile. These processes overlapped and reinforced each other, during which entire sections of cities transitioned from being all white to majority black over a relatively short period, with devastating results for black household wealth. Our results highlight the importance of private market dynamics that occurred at the block level prior to the heyday of the FHA and suggest that racial disparities in wealth accumulation would likely have emerged absent discriminatory federal policies. Government at all levels missed the opportunity to change the trajectory of private housing markets.

Appendix A Who Benefits from Faster Public Transit?

A.1 Defining and Simulating Trips on Google Maps

This section describes how I sample trip origin-destination pairs and query them on Google Maps for travel times. These travel times are then used to estimate census tract-specific travel speeds by each mode as described in Section A.2. To do so credibly, there needs to be enough trips going through each census tract and the speeds on these trips need to be representative of trips actually taken (and not just speeds on infrequently travelled routes). In addition, because transit networks can be sparse, the trips need to be geographically spread out so that I am not just looking at areas within a tract far away from (or close to) transit routes.

To that end, a subset of trips are defined to be between the origins and destinations on trips reported in the 2017 National Household Travel Survey (NHTS). The confidential version of the NHTS (U.S. Department of Transportation) identifies locations at the block group level, and I define my trips to be between the population-weighted centroids of these block groups. I ignore round trips and unrepresentative trips (such as trips by air). NHTS trips span only a few thousand in total across all cities and they are missing for a sizeable share of my urban block groups. So, I generate additional origin-destination pairs myself.

For the remainder of my trips, I set the trip origins to be the population-weighted centroids of each block group with a non-zero residential population within the extent of my CBSAs. Since block groups are geographically smaller than tracts, I always guarantee a few trips originating in every tract. Trip destinations are of two types: (1) centroids of tracts that are popular commuting destinations as observed in the CTPP and (2) popular non-residential amenities nearby (such as restaurants and shopping malls). Popular commuting tract destinations include the 5 most popular destinations from the trip's tract of origin and the 5 most popular destinations from the trip's county of origin.

For trips to amenities, I first gather a dataset of popular amenities (also from Google). I categorize non-residential amenities into 19 types, each corresponding to a different Google "place type" on Google's Places API. These amenity types include banks, cafes, churches, city hall, convenience stores, doctors, gyms, hospitals, libraries, mosques, movie theaters, parks, pharmacies, post offices, restaurants, schools, shopping malls, stadiums, and train stations. I use each of these as search terms to query Google's Places API for the most popular destinations of each type within a fixed radius of (the centroid of) each block group. On any search Google returns upto 20 places in order of "prominence", as determined "by a place's ranking in Google's index, global popularity, and other factors." The search radius determines the average proximity to the returned destinations. I let the radius vary with the place type being searched since some types may be sparser across space than others (such as restaurants are typically more common than stadiums). In setting the search radii, I also try to mimic the distribution of trip distances observed in the NHTS. For each place, Google returns geographical coordinates (as well as other data not used in this paper), which I then use to define trips between each block group centroid and the closest of the (twenty) returned destinations around it. Sometimes, Google may find no destination of a particular type around a block group, in which case I choose the closest destination from the pool of places of that type returned on queries from other block groups in the city. In total, I defined roughly 2 million origin-destination (O-D) pairs across all cities to query on Google Maps for travel times. I defined more trips in cities with more block groups (as per the trip sampling strategy outlined above), which also translates to more trips in more populated cities.

All trips were queried on weekdays in the middle of June 2018. Google's travel time predictions for driving and walking trips are based on its own historical and real-time data. I only scrape the travel times that are based on historical averages (as opposed to real-time predictions by Google). These averages do not vary much over time and should be less susceptible to idiosyncratic shocks at the time of the data collection. On the other hand, Google's travel time predictions for transit are based on transit schedules shared by transit authorities and the GTFS. While the transit schedule variation is also small across weekdays, they are still sensitive to the trip's departure time. So, I repeat each transit trip at roughly 5 different hours of the day and take a weighted average where the weights are constructed from the distribution of trip departure times observed in the NHTS.

Not all queries to Google Maps return route results. A small share of driving queries (less than 1%) and walking queries (less than 2%) return null results, but roughly a fifth of transit queries return null results. Transit networks are sparse, so this is unsurprising. In fact, the share of null results would be higher if not for Google returning the walking routes in most (but not all) of the cases where the trip does not overlap with any transit route. The rate of queries with non-zero returns varies across and within cities, with more null results farther away from city centers. I impute travel times on missing trips by assuming people walk the entire trip (straight-line) distance at a speed that is the 90th percentile of 'effective' walking speeds across successful trips in the surrounding tracts. The 'effective' speed is the straight-line distance covered per minute and by penalizing the missing trips with a slow walking speed, I implicitly assume there are obstructions and long detours along the way (that are also leading Google to not return these as viable travel routes).

A.2 Estimating Tract Speeds and Commuting Times

The goal of this exercise is to estimate travel times by driving, transit and walking between all possible pairings of residential and work tracts within a city. I compute this matrix of travel times in three steps. First, I identify the shortest routes between all O-D pairs (including for the non-commuting trips queried on Google Maps) along major road networks and their overlap with the city's tracts. Second, using the trips for which I also have travel times from Google Maps, I estimate tract-level speeds on each travel mode using a series of OLS regressions. Third, I use the estimated speeds together with route overlaps with tracts to predict travel times on the remaining (commuting) trips.

I download the network of major streets in each city from OpenStreetMap (OSM), a crowd-sourced mapping platform. The street networks cover a 1% buffer zone around the geographic bounds of trips and includes the following OSM street types: motorways, trunks, primary, secondary, tertiary and unclassified. To improve the speed of (and memory constraints from) the millions of shortest route searches, I exclude smaller residential streets and driveways. As such, my 'shortest routes' are only along major streets and may not be the actual shortest route along the entire road network. This is not a major concern because residential streets tend to be slower and even when they make up a large portion of the shortest route, they are less likely to be part of the fastest route (or to be traveled). As such, my routes may even be more representative of actual traveled routes.

Then I map each trip origin and destination to their nearest point on the street network and project the entire network as a directional graph of edges along streets and nodes at street intersections and trip endpoints. Shortest paths between trip endpoints are computed using NetworkX, a python package. Having identified the shortest routes, I intersect them at tract boundaries and compute the lengths of the intersections with each tract that is within a 1% buffer around the convex hull of the set of tracts in the CBSA. I ignore a small share of trips with less than 50% overlap with these tracts. Note that commuting trips are defined to be between the centroids of tracts within the CBSA and are, hence, always within the convex hull of these tracts. The total distance along the shortest path on commuting trips is the trip distance measure used in subsequent analysis from Section 2.3 onwards.

For estimating tract speeds, I specify a trip's total travel time as the sum of travel times through each tract that its route overlaps. As shown in (2.2.1), I further decompose each travel time segment into a route distance divided by travel speed. When I know both the total travel time and the distances traveled through each tract, I can use an OLS regression to uncover the coefficients on distances which are also the travel speeds in the corresponding tracts. So, using my set of non-commuting trips for which I have the Google Maps travel times, I run separate regressions for each city and travel mode to estimate the tract-specific speeds.

With the large number of tracts to estimate speeds for, the OLS regression faces a multi-colinearity problem that is more prominent among tracts with limited variation in trip routes. For example, if two tracts share a large fraction of the trips passing through them, then it is difficult to isolate the effect that going through each tract has on the trips' travel times. In the worst case, some tracts have to be dropped from the estimation due to perfect colinearity. I assign each dropped tract the median of estimated speeds of their surrounding tracts. The OLS regression may also estimate extremely high or low speeds for some less central tracts in the city. So, I truncate the top and bottom 5% of estimated speeds in each city.

Finally, to predict total travel times on commuting trips, I plug in the estimated tract speeds along with each trip's route (length) overlaps with tracts into (2.2.1).

A.3 Housing Demand Estimation

I observe annual household incomes and annual housing expenditures in the publicly available census microdata from IPUMS but not their census tract of residence. The smallest identifiable geography of residence in the microdata are PUMAs, which are usually larger than tracts. In order to combine the housing expenditure data with tract-level standardized housing prices from Davis et al. [2020] to the microdata, I rely on aggregate tract-level data from NHGIS. In the aggregate data, I observe household counts by census tract across 16 income brackets, so I can determine the median housing prices experienced by households in each bracket. To aggregate the tract level prices for each income group to the PUMA level, I use a crosswalk from the website of Missouri Census Data Center that returns the population-weighted overlaps between PUMAs and tracts. I use these as weights to compute the median housing prices experienced by households in each income bracket within a PUMA. I merge these PUMA-income-level average prices to the micro-data to use in the housing demand estimation. As such, these are not the actual housing prices corresponding to the housing expenditures but the housing prices likely to be experienced by the median household in the same income bracket and PUMA.

Once I have incomes, housing expenditures and housing prices for my sample of individual housesholds, I run the OLS regression in (2.4.5) separately for each CBSA: I regress the log share of income spent on housing expenditures (on the left) on log income and log housing price (on the right). Observations are weighted by survey weights for households and excludes households with zero housing expenditure and households at the top and bottome percentiles of the sample's income distribution. Sample sizes for the regressions range from around 15,000 households in the smallest cities to over 700,000 in the largest ones.

Estimated price elasticities of housing demand (α_h) range from -0.66 (in Syracuse, NY) to -0.82 (in San Francisco, CA). Estimated income elasticities of housing demand (α_w)

range from 0.4 (in Provo-Orem, UT) to 0.6 (in San Francisco, CA). Figure 22 compares the predicted ("fitted") and the observed housing expenditures as a function of household income, pooling together all cities. My predicted housing expenditures are too high for household incomes below $15,000 (an artifact of the log-log functional form) and slightly smaller than those observed for incomes above.

A.4 Mode and Neighborhood Choice Estimation

Estimation requires numerically searching over parameters α^S_{my} and α^D_y and fixed effects δ_{mny} to maximize the sum of log likelihoods L from (2.4.6). To aid the search process, I exploit a contraction mapping approach popularized by Berry et al. [1995]. More specifically, given any realization of the vector of parameters α^S and α^D, a contraction mapping is used to calculate the matrix of fixed effects δ that solves the first order conditions $\frac{\partial L}{\partial \delta} = 0$.

Consider the following first-order Taylor approximation of L as a function of the fixed effects:

$$L(\alpha^S, \alpha^D, \delta^{t+1}) = L(\alpha^S, \alpha^D, \delta^t) + (\delta^{t+1} - \delta^t)' \frac{\partial L(\alpha^S, \alpha^D, \delta^t)}{\partial \delta}$$

The first order condition to solve for the δ^{t+1} that maximizes this approximation is

$$\frac{\partial L(\delta^{t+1})}{\partial \delta^{t+1}} = 0$$

which, following some algebraic manipulation, evaluates to

$$\delta^{t+1}_{mny} = \delta^t_{mny} - \ln \left[\sum_j \left(\sum_m \sum_n \sum_y P_{jmny} \right) \pi_{mn|jy} \Big/ \left(\sum_j P_{jmny} \right) \right]$$

Updating the values of δ as above until convergence maximizes L conditional on parameters α^S and α^D. I update parameters α^S and α^D by the (weighted) gradient of the log likelihood with respect to each:

$$\frac{\partial L}{\partial \alpha^D_y} = \sum_j \sum_n \sum_{m \in M} \left[P_{jmny} - \pi_{mn|jy} \left(\sum_m \sum_n P_{jmny} \right) \right] \cdot D_{jn}$$

$$\frac{\partial L}{\partial \alpha^S_{my}} = \sum_j \sum_n \left[P_{jmny} - \pi_{mn|jy} \left(\sum_m \sum_n P_{jmny} \right) \right] \cdot S_{jmn}$$

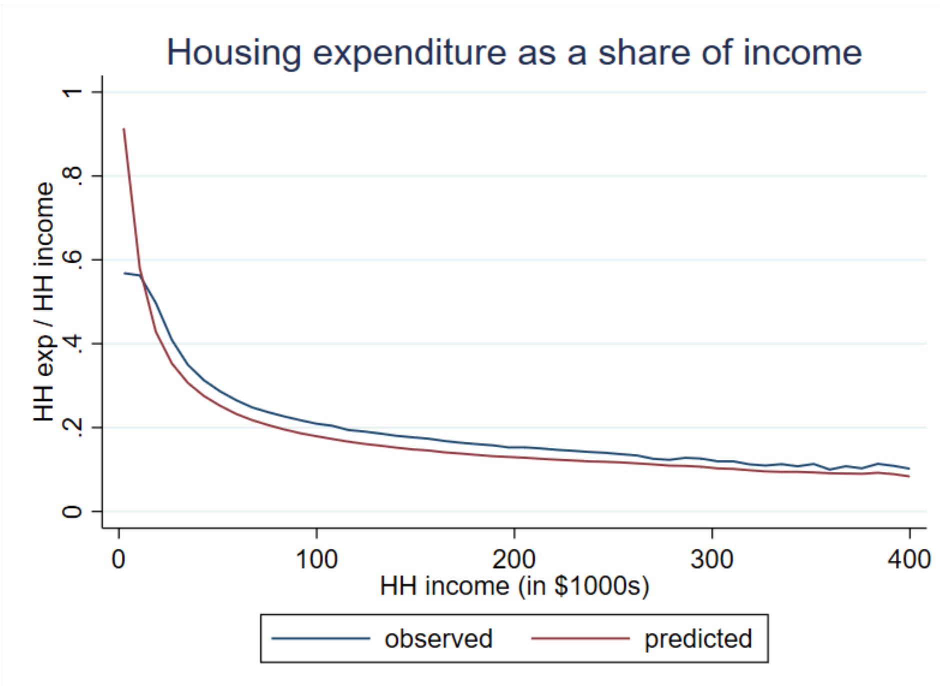


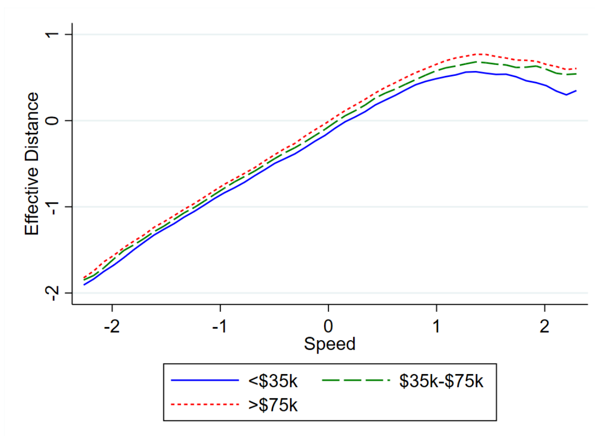
Figure 22: Predicted vs observed housing expenditures in the microdata

Note: The fitted regression line is based on the OLS estimation of (2.4.5). The figure pools together households across all cities.

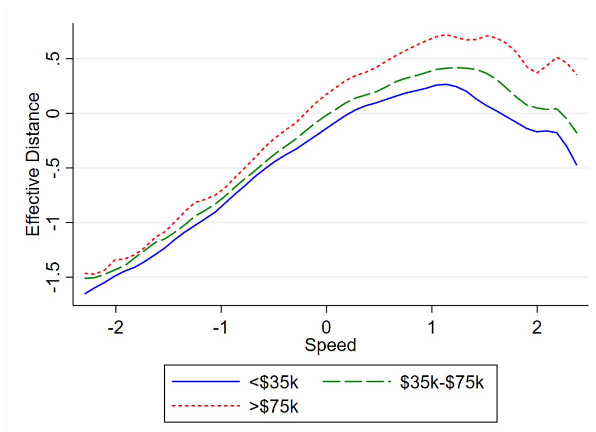
A.5 Additional Tables and Figures

A.5.1 Travel Distances vs. Speeds

Figure 23 shows that average travel distance is increasing with travel speed, suggesting commuters (on average) travel farther when they can travel faster. Alternatively, longer trips tend to be faster. This is true for both drivers and transit riders and across all income groups. However, even conditional on speed, higher income groups appear to commute slightly longer.



Drivers



Transit riders

Figure 23: Average commuting distances by speed

Note: Distances and speeds are in logs and standardized across commutes within each CBSA and travel mode. The figures pool together commutes across all cities in my sample.

Table 19: Full ranking of cities by commuting speeds on transit

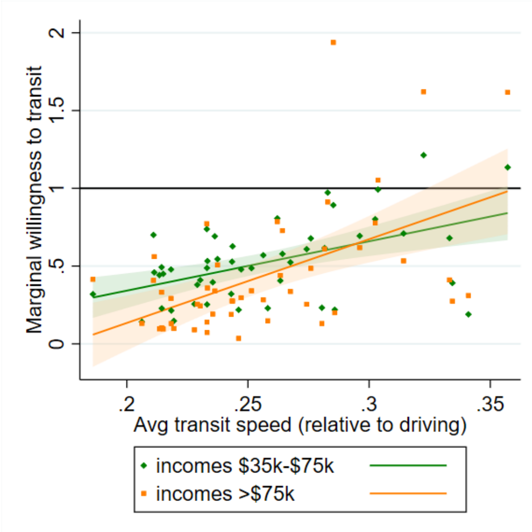
Rank	City	Transit speed (in km/h)	Ratio of transit to driving speed	% commuters riding transit	Rail share of transit riders
1	New York-Newark-Jersey City, NY-NJ-PA	20.2	0.35	30.7%	86.7%
2	San Francisco-Oakland-Hayward, CA	18.9	0.31	15.5%	51.6%
3	Seattle-Tacoma-Bellevue, WA	17.8	0.30	8.6%	5.2%
4	Chicago-Naperville-Elgin, IL-IN-WI	17.7	0.28	11.9%	69.8%
5	Philadelphia-Camden-Wilmington, PA-NJ-DE-MD	17.1	0.30	9.7%	46.0%
6	Washington-Arlington-Alexandria, DC-VA-MD-WV	17.0	0.30	14.5%	82.3%
7	Houston-The Woodlands-Sugar Land, TX	16.5	0.21	2.7%	2.5%
8	Denver-Aurora-Lakewood, CO	15.9	0.28	4.9%	16.2%
9	Urban Honolulu, HI	15.8	0.33	8.2%	0.3%
10	Atlanta-Sandy Springs-Roswell, GA	15.7	0.21	3.5%	30.8%
11	Santa Maria-Santa Barbara, CA	15.7	0.28	4.0%	1.3%
12	Los Angeles-Long Beach-Anaheim, CA	15.5	0.27	6.4%	10.9%
13	Boston-Cambridge-Newton, MA-NH	15.5	0.28	12.4%	78.4%
14	St. Louis, MO-IL	15.4	0.23	2.7%	19.5%
15	Minneapolis-St. Paul-Bloomington, MN-WI	15.1	0.20	4.8%	5.8%
16	Portland-Vancouver-Hillsboro, OR-WA	14.9	0.29	6.6%	12.2%
17	Sacramento–Roseville–Arden-Arcade, CA	14.8	0.23	2.8%	18.4%
18	Miami-Fort Lauderdale-West Palm Beach, FL	14.7	0.26	3.8%	14.2%
19	Cleveland-Elyria, OH	14.6	0.21	4.0%	8.3%
20	San Antonio-New Braunfels, TX	14.5	0.23	2.3%	0.3%
21	Milwaukee-Waukesha-West Allis, WI	14.4	0.23	3.8%	1.5%
22	Phoenix-Mesa-Scottsdale, AZ	14.4	0.23	2.3%	2.8%
23	Pittsburgh, PA	14.3	0.25	6.0%	3.0%
24	Boulder, CO	14.2	0.32	5.9%	0.2%
25	Hartford-West Hartford-East Hartford, CT	14.0	0.23	2.9%	6.6%
26	San Diego-Carlsbad, CA	13.9	0.24	3.5%	11.0%
27	Salt Lake City, UT	13.9	0.26	3.5%	16.3%
28	Providence-Warwick, RI-MA	13.8	0.24	2.7%	45.6%
29	Baltimore-Columbia-Towson, MD	13.7	0.25	6.5%	36.0%
30	Eugene, OR	13.7	0.28	4.1%	0.3%
31	Albany-Schenectady-Troy, NY	13.4	0.25	3.2%	6.2%
32	Las Vegas-Henderson-Paradise, NV	13.3	0.27	3.8%	0.2%
33	Buffalo-Cheektowaga-Niagara Falls, NY	13.1	0.23	3.8%	7.2%
34	Bridgeport-Stamford-Norwalk, CT	13.1	0.23	9.7%	83.6%
35	Rochester, NY	13.1	0.19	2.1%	3.5%
36	Madison, WI	13.0	0.23	4.0%	1.1%
37	Austin-Round Rock, TX	12.8	0.21	2.8%	1.1%
38	Tucson, AZ	12.8	0.28	2.6%	0.4%
39	Durham-Chapel Hill, NC	12.6	0.24	4.0%	1.4%
40	Lansing-East Lansing, MI	12.5	0.21	2.4%	0.8%
41	Provo-Orem, UT	12.5	0.26	2.2%	2.0%
42	Syracuse, NY	11.8	0.21	2.2%	1.0%
43	San Jose-Sunnyvale-Santa Clara, CA	11.7	0.24	3.4%	36.9%
44	Trenton, NJ	11.1	0.24	7.6%	73.9%
45	New Haven-Milford, CT	11.1	0.24	3.8%	35.8%
46	Ann Arbor, MI	10.8	0.23	4.1%	1.7%
47	Springfield, MA	10.7	0.21	2.1%	3.2%
48	Savannah, GA	9.9	0.21	2.1%	0.9%
49	Vallejo-Fairfield, CA	8.8	0.18	2.7%	33.3%

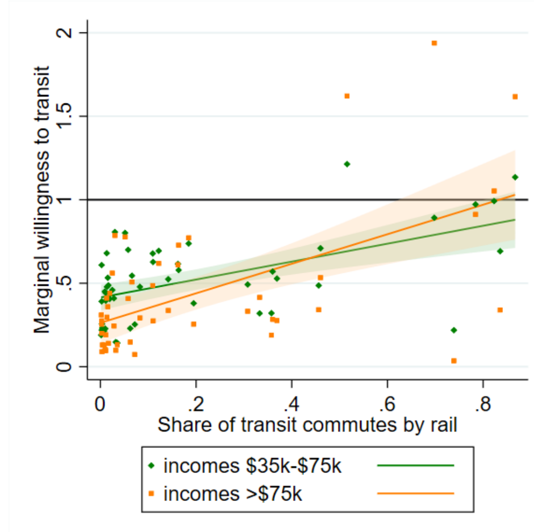
Note: Speeds are relative to shortest road distance. Speeds and ratios of travel times are means across all trips between observed work-residence location pairs (unconditional on travel mode choice) ignoring the top and bottom 5% of outliers. Rail share is the fraction of transit commutes via rail transit in the city.

Table 20: Estimated coefficients α_y^D and α_{my}^S on commuting distance and speed

Variable	**Mode**	**Income**	**Mean**	**p5**	**p25**	**Median**	**p75**	**p95**
Distance	all	< \$35k	1.518	0.971	1.260	1.601	1.686	2.006
		\$35k-\$\$50k	1.501	0.911	1.260	1.555	1.700	1.991
		\$50k-\$75k	1.453	0.864	1.142	1.514	1.649	1.947
		> \$75k	1.421	0.851	1.155	1.465	1.624	1.891
Speed	driving	< \$35k	0.301	0.156	0.218	0.293	0.370	0.471
		\$35k-\$\$50k	0.310	0.131	0.247	0.303	0.376	0.494
		\$50k-\$75k	0.293	0.083	0.211	0.297	0.380	0.487
		> \$75k	0.272	0.091	0.201	0.273	0.337	0.484
	transit	< \$35k	0.271	0.140	0.210	0.271	0.313	0.387
		\$35k-\$\$50k	0.241	0.119	0.197	0.220	0.257	0.374
		\$50k-\$75k	0.243	0.087	0.200	0.248	0.282	0.377
		> \$75k	0.276	0.097	0.225	0.274	0.319	0.478
	walking	< \$35k	-0.155	-0.303	-0.212	-0.153	-0.103	0.010
		\$35k-\$\$50k	-0.146	-0.364	-0.189	-0.146	-0.086	0.054
		\$50k-\$75k	-0.177	-0.408	-0.219	-0.148	-0.115	-0.039
		> \$75k	-0.265	-0.435	-0.321	-0.265	-0.208	-0.137

Note: Table reports the mean, 5th percentile, 25th percentile, median, 75th percentile and 95th percentile (in that order) of coefficient estimates across all 49 cities. Standard errors on all estimated coefficients are less than 0.00001.





by mean (relative) transit speeds | by rail share of transit commutes

Figure 24: Mean MWTT from 1% increase in transit speed (relative to lowest income group)

Note: Each observation corresponds to a city. Vertical axis depicts the MWTT for faster transit as a fraction of the MWTT of commuters with incomes less than $35,000 (indicated by solid black line at 1). Horizontal axis depicts either (a) the ratio of driving to transit travel times (across all observed commutes) in the city or (b) the share of transit riders in the city who commute by rail transit. Confidence intervals for each linear fit are shaded in corresponding color. For commuters with incomes $35k-$75k, figures plot population-weighted means of the MWTT estimates for the two middle-income groups in my data.

Table 21: Cities ranked by mean MWTP for faster transit commutes

Rank	City	MWTP for faster transit	MWTP for faster driving
1	San Francisco-Oakland-Hayward, CA	$ 374	$ 302
2	Seattle-Tacoma-Bellevue, WA	$ 188	$ 179
3	New York-Newark-Jersey City, NY-NJ-PA	$ 178	$ 345
4	San Jose-Sunnyvale-Santa Clara, CA	$ 169	$ 139
5	Boston-Cambridge-Newton, MA-NH	$ 148	$ 189
6	Washington-Arlington-Alexandria, DC-VA-MD-WV	$ 129	$ 156
7	Vallejo-Fairfield, CA	$ 119	$ 69
8	Chicago-Naperville-Elgin, IL-IN-WI	$ 116	$ 179
9	Los Angeles-Long Beach-Anaheim, CA	$ 114	$ 102
10	Sacramento–Roseville–Arden-Arcade, CA	$ 101	$ 95
11	Portland-Vancouver-Hillsboro, OR-WA	$ 97	$ 94
12	Denver-Aurora-Lakewood, CO	$ 94	$ 67
13	San Diego-Carlsbad, CA	$ 87	$ 92
14	Boulder, CO	$ 85	$ 48
15	Minneapolis-St. Paul-Bloomington, MN-WI	$ 78	$ 129
16	Providence-Warwick, RI-MA	$ 78	$ 134
17	Philadelphia-Camden-Wilmington, PA-NJ-DE-MD	$ 77	$ 123
18	Pittsburgh, PA	$ 73	$ 90
19	Houston-The Woodlands-Sugar Land, TX	$ 70	$ 70
20	Miami-Fort Lauderdale-West Palm Beach, FL	$ 64	$ 75
21	Bridgeport-Stamford-Norwalk, CT	$ 64	$ 80
22	Hartford-West Hartford-East Hartford, CT	$ 61	$ 74
23	Santa Maria-Santa Barbara, CA	$ 61	$ 78
24	Atlanta-Sandy Springs-Roswell, GA	$ 59	$ 78
25	Baltimore-Columbia-Towson, MD	$ 59	$ 76
26	Savannah, GA	$ 52	$ 19
27	New Haven-Milford, CT	$ 47	$ 54
28	San Antonio-New Braunfels, TX	$ 47	$ 34
29	Phoenix-Mesa-Scottsdale, AZ	$ 44	$ 47
30	St. Louis, MO-IL	$ 43	$ 47
31	Ann Arbor, MI	$ 42	$ 27
32	Albany-Schenectady-Troy, NY	$ 41	$ 55
33	Austin-Round Rock, TX	$ 39	$ 65
34	Eugene, OR	$ 38	$ 26
35	Milwaukee-Waukesha-West Allis, WI	$ 35	$ 39
36	Urban Honolulu, HI	$ 32	$ 19
37	Durham-Chapel Hill, NC	$ 32	$ 56
38	Springfield, MA	$ 32	$ 43
39	Madison, WI	$ 31	$ 42
40	Trenton, NJ	$ 31	$ 45
41	Lansing-East Lansing, MI	$ 30	$ 30
42	Cleveland-Elyria, OH	$ 30	$ 57
43	Tucson, AZ	$ 29	$ 35
44	Salt Lake City, UT	$ 28	$ 19
45	Syracuse, NY	$ 26	$ 38
46	Provo-Orem, UT	$ 22	$ 17
47	Rochester, NY	$ 21	$ 50
48	Buffalo-Cheektowaga-Niagara Falls, NY	$ 17	$ 36
49	Las Vegas-Henderson-Paradise, NV	$ 9	$ 17

Note: Cities are ranked by the mean MWTP for faster transit. MWTP values are means across all commuters for 1% change in travel speed on their observed commutes (i.e. conditional on commuters choosing their observed modes and neighborhoods).

Table 22: Cities ranked by MWTT from 1% increase in commuting speed

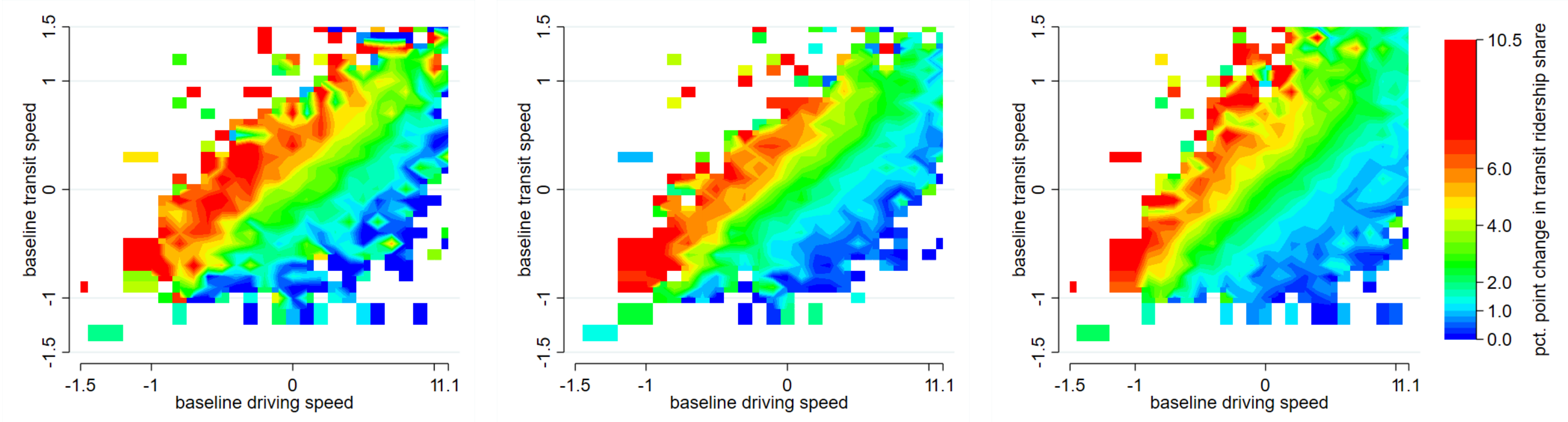
Rank	City	%age pt change in transit ridership	Baseline transit ridership (in %)
1	San Francisco-Oakland-Hayward, CA	3.52	15.45
2	Chicago-Naperville-Elgin, IL-IN-WI	2.97	11.87
3	Washington-Arlington-Alexandria, DC-VA-MD-WV	2.97	14.46
4	Seattle-Tacoma-Bellevue, WA	2.88	8.63
5	Boston-Cambridge-Newton, MA-NH	2.76	12.43
6	Portland-Vancouver-Hillsboro, OR-WA	2.22	6.57
7	New York-Newark-Jersey City, NY-NJ-PA	2.22	30.74
8	Philadelphia-Camden-Wilmington, PA-NJ-DE-MD	1.81	9.66
9	Pittsburgh, PA	1.77	5.97
10	Boulder, CO	1.73	5.93
11	Denver-Aurora-Lakewood, CO	1.57	4.92
12	Baltimore-Columbia-Towson, MD	1.16	6.51
13	Los Angeles-Long Beach-Anaheim, CA	1.11	6.38
14	Minneapolis-St. Paul-Bloomington, MN-WI	1.07	4.76
15	Eugene, OR	1.05	4.11
16	Atlanta-Sandy Springs-Roswell, GA	0.97	3.54
17	Houston-The Woodlands-Sugar Land, TX	0.85	2.66
18	Miami-Fort Lauderdale-West Palm Beach, FL	0.80	3.84
19	Durham-Chapel Hill, NC	0.79	4.02
20	Savannah, GA	0.79	2.14
21	Madison, WI	0.78	4.01
22	Bridgeport-Stamford-Norwalk, CT	0.76	9.73
23	San Antonio-New Braunfels, TX	0.76	2.32
24	Salt Lake City, UT	0.75	3.46
25	Urban Honolulu, HI	0.71	8.18
26	Ann Arbor, MI	0.70	4.06
27	New Haven-Milford, CT	0.69	3.78
28	Sacramento–Roseville–Arden-Arcade, CA	0.69	2.83
29	San Jose-Sunnyvale-Santa Clara, CA	0.66	3.44
30	Tucson, AZ	0.65	2.63
31	Santa Maria-Santa Barbara, CA	0.56	4.01
32	Austin-Round Rock, TX	0.55	2.78
33	St. Louis, MO-IL	0.55	2.69
34	Phoenix-Mesa-Scottsdale, AZ	0.55	2.33
35	San Diego-Carlsbad, CA	0.54	3.52
36	Albany-Schenectady-Troy, NY	0.51	3.24
37	Hartford-West Hartford-East Hartford, CT	0.45	2.86
38	Lansing-East Lansing, MI	0.45	2.40
39	Trenton, NJ	0.39	7.57
40	Vallejo-Fairfield, CA	0.38	2.71
41	Buffalo-Cheektowaga-Niagara Falls, NY	0.38	3.77
42	Provo-Orem, UT	0.36	2.22
43	Milwaukee-Waukesha-West Allis, WI	0.35	3.77
44	Cleveland-Elyria, OH	0.34	4.03
45	Providence-Warwick, RI-MA	0.33	2.72
46	Springfield, MA	0.33	2.08
47	Syracuse, NY	0.26	2.16
48	Las Vegas-Henderson-Paradise, NV	0.21	3.75
49	Rochester, NY	0.13	2.08

Note: Cities are ranked by the MWTT in response to a 1% increase in transit speed along all observed commutes (i.e. conditional on commuters choosing their observed neighborhoods).

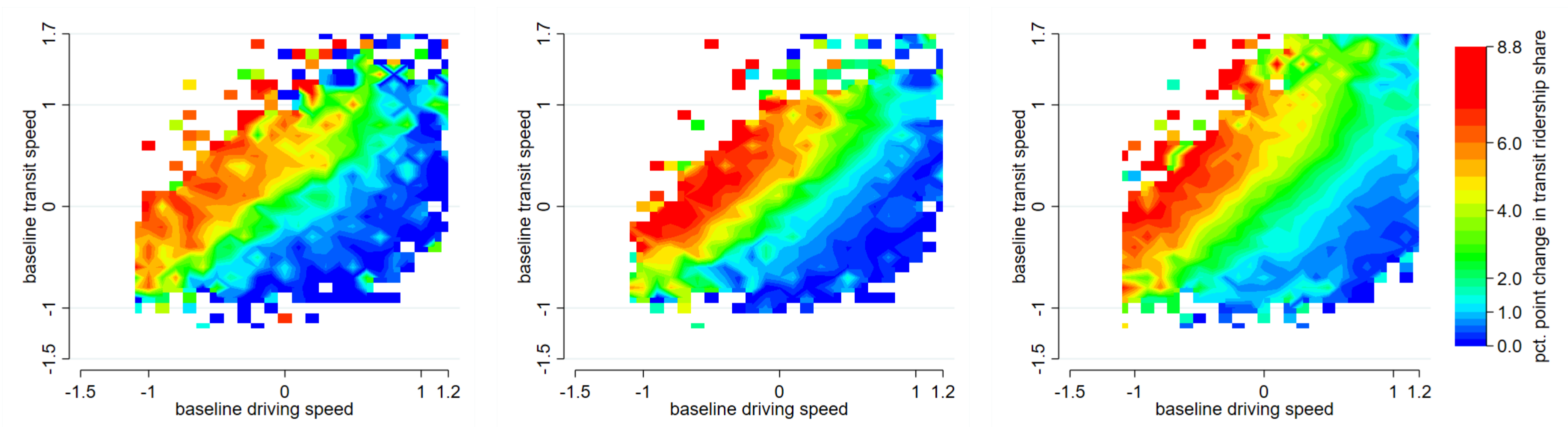
Table 23: Cities ranked by unconditional MWTP for faster transit

Rank	**City**	**uMWTP for faster transit**			**Relative to driving**
		all commuters	**incomes ¡$35k**	**incomes ¿$75k**	**all commuters**
1	San Francisco-Oakland-Hayward, CA	$ 39.82	$ 17.24	$ 46.26	0.1179
2	New York-Newark-Jersey City, NY-NJ-PA	$ 38.75	$ 18.22	$ 44.21	0.0954
3	Boston-Cambridge-Newton, MA-NH	$ 16.19	$ 12.90	$ 16.04	0.0750
4	Washington-Arlington-Alexandria, DC-VA-MD-WV	$ 14.81	$ 13.86	$ 14.31	0.0868
5	Chicago-Naperville-Elgin, IL-IN-WI	$ 11.44	$ 4.81	$ 16.29	0.0534
6	Seattle-Tacoma-Bellevue, WA	$ 7.87	$ 9.33	$ 6.96	0.0379
7	Philadelphia-Camden-Wilmington, PA-NJ-DE-MD	$ 5.69	$ 8.20	$ 4.49	0.0379
8	Portland-Vancouver-Hillsboro, OR-WA	$ 2.49	$ 4.26	$ 1.67	0.0230
9	Pittsburgh, PA	$ 2.01	$ 3.51	$ 1.52	0.0181
10	Minneapolis-St. Paul-Bloomington, MN-WI	$ 1.59	$ 3.38	$ 0.92	0.0103
11	Los Angeles-Long Beach-Anaheim, CA	$ 1.56	$ 2.91	$ 0.89	0.0121
12	Baltimore-Columbia-Towson, MD	$ 1.37	$ 4.11	$ 0.55	0.0158
13	Atlanta-Sandy Springs-Roswell, GA	$ 0.97	$ 2.37	$ 0.51	0.0101
14	Denver-Aurora-Lakewood, CO	$ 0.79	$ 1.75	$ 0.37	0.0104
15	Miami-Fort Lauderdale-West Palm Beach, FL	$ 0.72	$ 1.51	$ 0.37	0.0078
16	Boulder, CO	$ 0.60	$ 2.75	$ 0.05	0.0120
17	San Jose-Sunnyvale-Santa Clara, CA	$ 0.60	$ 2.10	$ 0.15	0.0039
18	Santa Maria-Santa Barbara, CA	$ 0.56	$ 1.19	$ 0.26	0.0064
19	Urban Honolulu, HI	$ 0.54	$ 3.13	$ 0.24	0.0253
20	Durham-Chapel Hill, NC	$ 0.52	$ 1.41	$ 0.11	0.0084
21	San Diego-Carlsbad, CA	$ 0.51	$ 1.37	$ 0.18	0.0049
22	Ann Arbor, MI	$ 0.50	$ 1.42	$ 0.02	0.0179
23	Bridgeport-Stamford-Norwalk, CT	$ 0.50	$ 1.52	$ 0.18	0.0054
24	Sacramento–Roseville–Arden-Arcade, CA	$ 0.46	$ 0.90	$ 0.27	0.0042
25	Albany-Schenectady-Troy, NY	$ 0.39	$ 2.38	$ 0.04	0.0063
26	Austin-Round Rock, TX	$ 0.38	$ 1.24	$ 0.05	0.0052
27	Providence-Warwick, RI-MA	$ 0.35	$ 0.87	$ 0.18	0.0022
28	Madison, WI	$ 0.35	$ 1.32	$ 0.05	0.0073
29	Houston-The Woodlands-Sugar Land, TX	$ 0.35	$ 0.74	$ 0.22	0.0041
30	New Haven-Milford, CT	$ 0.34	$ 1.54	$ 0.06	0.0056
31	Hartford-West Hartford-East Hartford, CT	$ 0.28	$ 0.86	$ 0.17	0.0032
32	Springfield, MA	$ 0.27	$ 1.41	$ 0.02	0.0056
33	Trenton, NJ	$ 0.26	$ 1.93	$ 0.00	0.0054
34	Eugene, OR	$ 0.25	$ 1.05	$ 0.02	0.0090
35	Phoenix-Mesa-Scottsdale, AZ	$ 0.24	$ 0.65	$ 0.10	0.0044
36	Cleveland-Elyria, OH	$ 0.22	$ 0.79	$ 0.07	0.0032
37	St. Louis, MO-IL	$ 0.21	$ 0.76	$ 0.07	0.0038
38	Buffalo-Cheektowaga-Niagara Falls, NY	$ 0.21	$ 0.97	$ 0.02	0.0051
39	San Antonio-New Braunfels, TX	$ 0.17	$ 0.51	$ 0.01	0.0044
40	Lansing-East Lansing, MI	$ 0.14	$ 0.26	$ 0.14	0.0044
41	Salt Lake City, UT	$ 0.09	$ 0.35	$ 0.03	0.0046
42	Savannah, GA	$ 0.09	$ 0.23	$ 0.00	0.0045
43	Rochester, NY	$ 0.09	$ 0.59	$ 0.01	0.0015
44	Tucson, AZ	$ 0.08	$ 0.24	$ 0.01	0.0022
45	Vallejo-Fairfield, CA	$ 0.06	$ 0.14	$ 0.01	0.0008
46	Syracuse, NY	$ 0.04	$ 0.20	$ 0.00	0.0009
47	Milwaukee-Waukesha-West Allis, WI	$ 0.03	$ 0.13	$ 0.01	0.0008
48	Las Vegas-Henderson-Paradise, NV	$ 0.03	$ 0.12	$ 0.00	0.0019
49	Provo-Orem, UT	$ 0.02	$ 0.06	$ 0.00	0.0012

Note: Cities are ranked by their mean uMWTP (across all commuters) for 1% increase in transit speeds. Reported uMWTP values are estimates of mean MWTP across all commuters unconditional on their choices of mode and neighborhood. Ratio in column 6 divides uMWTP estimates in column 3 by estimates of the city's mean uMWTP for 1% increase in driving speeds.



Seattle, Incomes<\$35k Seattle, Incomes \$35k-\$75k Seattle, Incomes>\$75k



Boston, Incomes<\$35k Boston, Incomes \$35k-\$75k Boston, Incomes>\$75k

Figure 25: Mean MWTT by location of transit improvement

Note: The x- and y-axes depict standardized driving and transit speeds (resp.) on the commuting route. The z-axis depicts the percantage point change in transit ridership in response to a 1% increase in transit speed along the commuting route. The z-axis colours are fixed across all graphs. Speeds are standardized (to mean 0 and std. dev. 1) across trips between observed work-residence pairs within each CBSA.. Trips at the top and bottom percentiles of speeds are ignored. White spaces in the graphs correspond to 0.1-by-0.1 cells with fewer than 20 commutes.

Appendix B Public Transit Access and Income Segregation

B.1 Additional Results and Details

B.1.1 Income Differences in Transit Ridership Across Cities

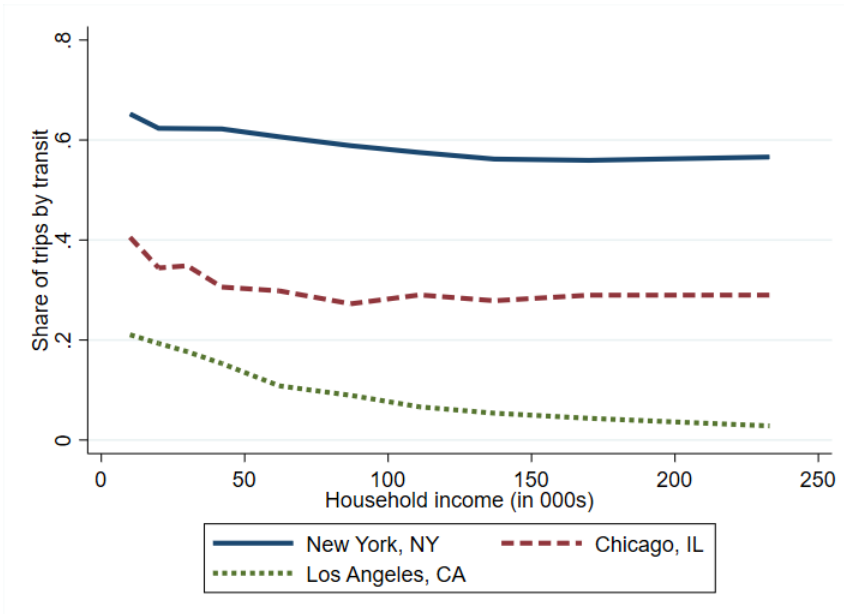


Figure 26: Share of commuting trips using mass transit by household income in the 3 largest US cities

Note: Figure uses data from the 2013-17 American Community Survey. Household income is discretized into 10 bins and and the graph connects points at the median income of each bin.

Figure 26 shows overall transit ridership separately for the three largest U.S. cities. The city of New York, ranked the most transit friendly large city in the US by walkscore.com (with a Transit Score of 84 out of 100), has a dense enough subway network that it is the most popular means of transportation for both high and low income commuters.[1] Public transportation in Los Angeles (with a Transit Score of 53), on the other hand, is mostly made up of a sparse network of buses. Ridership is a lot lower in general, but is also mostly made up of low-income commuters. Chicago (with a Transit Score of 65) is somewhere in

[1]The methodology behind Transit Scores is described in more details at this link: https://www.walkscore.com/transit-score-methodology.shtml.

between with a dense bus network and a sparse rail transit network. Transit ridership is again decreasing with income more steeply than in New York but less steeply than in Los Angeles.

B.1.2 Income $DISS$imilarity

This section characterizes a closed form solution for income $DISS$imilarity as a function of *transit* ridership, travel times and exogenous parameters of the model. The results incorporate the generalization of the model from Section 3.6.1 with income specific preferences over amenities A_{gn} and different travel times by *car* across neighborhoods. I continue to assume that there is non-zero high and low *transit* ridership in both neighborhoods ($\tilde{\gamma}_{gn} \in [-\Gamma, \Gamma]\ \forall g \in \{L, H\}$ and $\forall n \in \{1, 2\}$).

Proposition B.1. *$DISS$ is proportional to $|\bar{\xi}_L - \bar{\xi}_H|$ where*

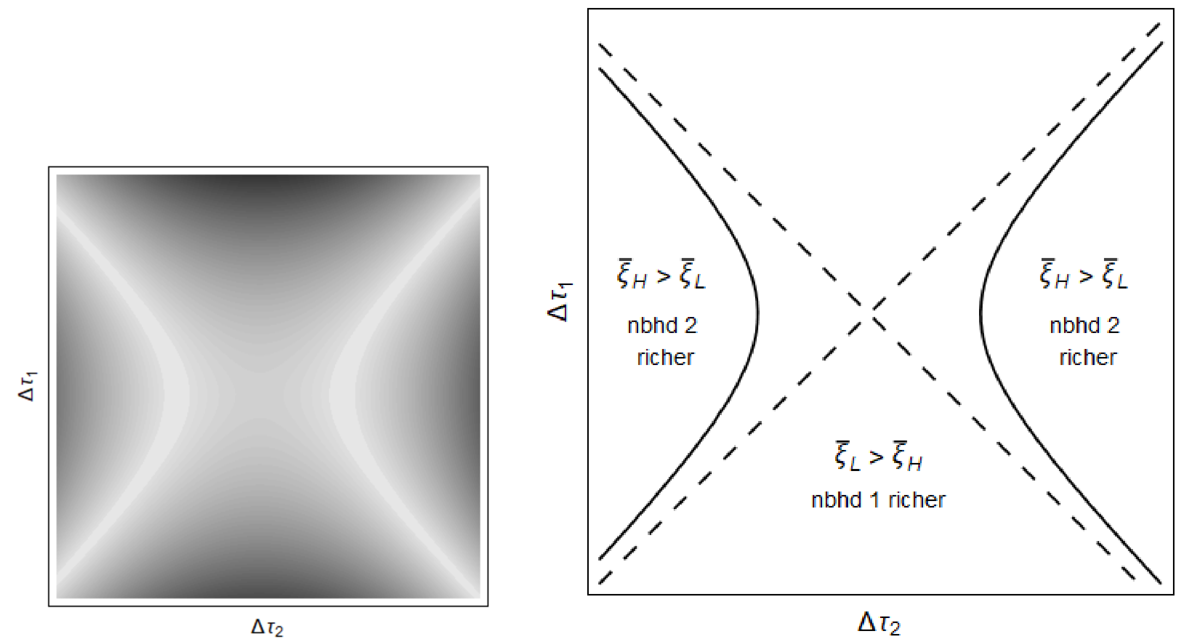
$$\bar{\xi}_L - \bar{\xi}_H = \frac{1}{2\psi} \cdot \left(\Psi\big(\tilde{\gamma}_{L2}\big)^2 - \Psi\big(\tilde{\gamma}_{H2}\big)^2 - \Psi\big(\tilde{\gamma}_{L1}\big)^2 + \Psi\big(\tilde{\gamma}_{H1}\big)^2 \right) + K \tag{B.1.1}$$

$$= Q \cdot \big(\Delta\tau_1 - \Delta\tau_2\big) \cdot \big(\Delta\tau_1 + \Delta\tau_2 - 2\bar{\tau}\big) + K \tag{B.1.2}$$

where $K \equiv A_{H1} - A_{H2} - A_{L1} + A_{L2} + \beta \cdot (w_H - w_L) \cdot (\tau_2^c - \tau_1^c)$ and $Q \equiv \frac{1}{2}\beta \cdot \psi \cdot (w_H^2 - w_L^2)$ are constants.

The proof follows in Appendix B.2.2.2.

That $DISS$ is proportional to $|\bar{\xi}_L - \bar{\xi}_H|$ follows trivially from its definition in (3.4.3). The first equality, (B.1.1), characterizes income sorting across neighborhoods as a function of differences in high and low income *transit* ridership (squared) between the two neighborhoods. Greater differences across neighborhoods in the income sorting into travel mode choices translates to greater income sorting across the residential neighborhoods themselves. In other words, $DISS$ is higher when the difference in *transit* ridership between high and low income households is much larger in one neighborhood than the other. The second equality, (B.1.2), of Proposition B.1 substitutes in households' optimal mode choices to rewrite $DISS$ purely as a function of travel time differences (between *transit* and *car*) and other exogenous parameters of the model.



(A) Contour plot of $DISS$

(B) How to minimize $DISS$?

Figure 27: Income dissimilarity as a function of travel times, when $\mathbf{K} > \mathbf{0}$

Note: Darker shades in Panel A correspond to larger $DISS$imilarity. Solid lines in Panel B show travel time combinations with zero dissimilarity (where $\bar{\xi}_L = \bar{\xi}_H$), which corresponds to either $\Delta\tau_1 = \Delta\tau_2$ or $\Delta\tau_1 + \Delta\tau_2 = 2\bar{\tau}$. Dashed lines are asymptotes, which correspond to either $\Delta\tau_1 = \Delta\tau_2$ or $\Delta\tau_1 + \Delta\tau_2 = 2\bar{\tau}$. Arrows indicate where to reduce transit travel times to minimize $DISS$.

In section 3.4, I illustrated a special case of $K = 0$ where the income sorting is driven solely by differences in travel times by *transit*. When $K \neq 0$, there is a baseline level of income segregation that arises even when *transit* is the same in both neighborhoods ($\tau_1^t = \tau_2^t$): high-income households find neighborhood 1 more attractive when $K > 0$ and neighborhood 2 more attractive when $K < 0$. Assume, without loss of generality, that $K > 0$. In other words, neighborhood 1 offers better high-income amenities and shorter travel times by *car*.[2] As shown in Figure 27, equalizing travel costs across neighborhoods (as in along the lines $\Delta\tau_1 = \Delta\tau_2$ and $\Delta\tau_1 + \Delta\tau_2 = 2\bar{\tau}$ and nearby) is no longer the optimal solution for minimizing income segregation. Minimizing $DISS$ now involves attracting some more high-income households to 2 or some more low-income households to 1 in order to offset the baseline level of income segregation. The former requires *transit* to be faster in 2 (i.e. a lower $\Delta\tau_2$) than before when *transit* is generally fast ($\Delta\tau_1 + \Delta\tau_2 < 2\bar{\tau}$ and *transit* riders are relatively high-income) while the latter requires *transit* to be slower in 2 (i.e. a higher $\Delta\tau_2$) than before when *transit* is generally slow ($\Delta\tau_1 + \Delta\tau_2 > 2\bar{\tau}$ and *transit* riders are relatively low-income). The opposite would be true for $K < 0$.

When $K < 0$, neighborhood 2 offers better high-income amenities and shorter travel times by *car*. As shown in Figure 28, even when *car* and *transit* cost differences are the same across neighborhoods (as in along the dashed lines $\Delta\tau_1 = \Delta\tau_2$ and $\Delta\tau_1 + \Delta\tau_2 = 2\bar{\tau}$ and nearby), minimizing $DISS$ involves attracting some more high-income households to 1 or some more low-income households to 2 (rellative to when $K = 0$) in order to offset the baseline level of income segregation. The former requires *transit* to be faster in 1 (i.e. a lower $\Delta\tau_1$) than before when *transit* is generally fast ($\Delta\tau_1 + \Delta\tau_2 < 2\bar{\tau}$) and *transit* riders are relatively high-income while the latter requires *transit* to be slower in 1 (i.e. a higher $\Delta\tau_1$) than before when *transit* is generally slow ($\Delta\tau_1 + \Delta\tau_2 > 2\bar{\tau}$) and *transit* riders are relatively low-income.

[2] In a monocentric city, neighborhood 1 might correspond to the central business district.

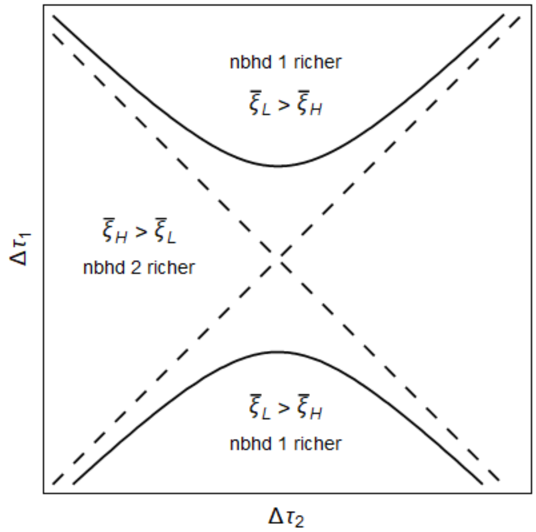


Figure 28: Transit travel time combinations with $DISS = 0$ for $K < 0$

Note: Solid lines correspond to $\bar{\xi}_L = \bar{\xi}_H$. Dashed lines are asymptotes of $\bar{\xi}_L = \bar{\xi}_H$, which corresponds to either $\Delta\tau_1 = \Delta\tau_2$ or $\Delta\tau_1 + \Delta\tau_2 = 2\bar{\tau}$.

B.1.3 Transit *R*idership

Recall that r_g is the total *transit* ridership among households of type g, as in (3.5.2), and R denotes the total *transit* ridership across all households, as in (3.5.1). The marginal effect on this total *transit* ridership of a *transit* time change in neighborhood n is given by:

$$\frac{dR}{d\Delta\tau_n} = \mathbf{E}\left[\frac{dr_g}{d\Delta\tau_n}\right] = \underbrace{\mathbf{E}\left[\frac{d\Psi\left(\tilde{\gamma}_{gn}\right)}{d\Delta\tau_n} \cdot \left(\mathbf{I}_{n=2} \cdot F\left(\bar{\xi}_g\right) + \mathbf{I}_{n=1} \cdot \left[1 - F\left(\bar{\xi}_g\right)\right]\right)\right]}_{\text{change in } transit \text{ ridership among stayers, } S_n}$$
$$+ \underbrace{\mathbf{E}\left[\frac{dF\left(\bar{\xi}_g\right)}{d\Delta\tau_n} \cdot \left(\Psi\left(\tilde{\gamma}_{g2}\right) - \Psi\left(\tilde{\gamma}_{g1}\right)\right)\right]}_{\text{change in } transit \text{ ridership among movers, } M_n} \quad \text{(B.1.3)}$$

where $\mathbf{E}[\cdot]$ denotes the expectation over the distribution of w. The first additive component of $\frac{dR}{d\Delta\tau_n}$ in (B.1.3) is the marginal change in *transit* ridership in neighborhood n among households that continue to stay in the same neighborhood or the change in overall *transit* ridership assuming no households move ($\frac{\partial F\left(\bar{\xi}_g\right)}{\partial\Delta\tau_n} = 0$). Let S_n denote this “short-run” change in *transit* ridership. The second additive component, denoted M_n, is the net change in *transit* ridership among households moving neighborhoods in response to changing travel costs and housing prices. Together, they sum up to the total "long-run" change in *transit* ridership in the city. In this section, I identify when the marginal effect on *transit* ridership is larger from *transit* time reductions in neighborhood 1 rather than in neighborhood 2. In other words, when is $\frac{dR}{d\Delta\tau_2} > \frac{dR}{d\Delta\tau_1}$? Alternatively, when is the following expression positive?

$$\frac{dR}{d\Delta\tau_2} - \frac{dR}{d\Delta\tau_1} = \underbrace{\mathbf{E}\Big[\frac{d\Psi\big(\tilde{\gamma}_{g2}\big)}{d\Delta\tau_2} \cdot F\big(\bar{\xi}_g\big) - \frac{d\Psi\big(\tilde{\gamma}_{g1}\big)}{d\Delta\tau_1} \cdot \big[1 - F\big(\bar{\xi}_g\big)\big]\Big]}_{S_2 - S_1} + \underbrace{\mathbf{E}\Big[\Big(\frac{dF\big(\bar{\xi}_g\big)}{d\Delta\tau_2} - \frac{dF\big(\bar{\xi}_g\big)}{d\Delta\tau_1}\Big) \cdot \Big(\Psi\big(\tilde{\gamma}_{g2}\big) - \Psi\big(\tilde{\gamma}_{g1}\big)\Big)\Big]}_{M_2 - M_1} \quad \text{(B.1.4)}$$

B.1.3.1 Maximizing Short-Term Transit Ridership (Proof of Proposition 3.2)

Proposition 3.2 claims $S_2 > S_1$ (i.e. *transit* ridership among non-movers is maximized from a *transit* time reduction in neighborhood 1) if and only if neighborhood 1 has higher residential incomes than neighborhood 2.

Proof. Since $\tilde{\gamma}_{gn}$ lie in the support $[-\Gamma, \Gamma]$ of the distribution of γ for both g and both n, the marginal effect of *transit* times on *transit* ridership of households of a given type is the same across neighborhoods:

$$\frac{d\Psi\big(\tilde{\gamma}_{g1}\big)}{d\Delta\tau_1} = \frac{d\Psi\big(\tilde{\gamma}_{g2}\big)}{d\Delta\tau_2} = -\psi \cdot \beta \cdot w_g \quad \text{(B.1.5)}$$

Plug this into $S_2 - S_1$ from (B.1.4) to get

$$S_2 - S_1 = \psi \cdot \beta \cdot \mathbf{E}\Big[w_g \cdot \Big(1 - 2F\big(\bar{\xi}_g\big)\Big)\Big] \quad \text{(B.1.6)}$$

We can expand the expectation over the two possible household types to get $S_2 > S_1$ if and only if

$$\Lambda \cdot w_L \cdot \Big(1 - 2F\big(\bar{\xi}_L\big)\Big) + (1 - \Lambda) \cdot w_H \cdot \Big(1 - 2F\big(\bar{\xi}_H\big)\Big) > 0$$

$$\Leftrightarrow F\big(\bar{\xi}_L\big) \cdot w_L \cdot \Lambda + F\big(\bar{\xi}_H\big) \cdot w_H \cdot (1 - \Lambda) < \frac{1}{2} \cdot \Big(w_H \cdot (1 - \Lambda) + w_L \cdot \Lambda\Big)$$

In the inequality above, on the left is the total income of households in neighborhood 2, and on the right is half the total income of households in the city. In other words, when the aggregate income of residents of neighborhood 2 is smaller than that of the residents of neighborhood 1, it is optimal for the transit provider to to reduce *transit* times in neighborhood 1 (and vice versa). □

B.1.3.2 Maximizing Long-Term Transit Ridership

Let us now identify the optimal location of marginal *transit* time reductions in order to maximize overall 'long-term' *transit* ridership R. Households that stay in the same neighborhood in response to marginal changes in *transit* face the same changes in long-term *transit* ridership as in the short-term. I evaluate this change in Appendix B.2.3.1. What about the change in ridership among households that move?

Lemma. *A marginal reduction in transit travel times τ_n^t maximizes transit ridership among households that move (between neighborhoods) if n is the neighborhood with smaller relative transit travel time $\Delta\tau_n$.*

This is because high-income households are more likely to switch to *transit* and move in to the neighborhood when *transit* is fast. Low-income households are more likely to move out but retain high *transit* ridership even when *transit* is slow. The formal proof follows in Appendix B.2.3.2. Finally, comparing the sum of the change in ridership among households that stay S_n and the change in ridership among households that move M_n lets me solve for the values of $\Delta\tau_1$ and $\Delta\tau_2$ for which $\frac{dR}{d\Delta\tau_2} - \frac{dR}{d\Delta\tau_1}$ is positive. In other words, I can characterize when lower *transit* times from neighborhood 1 increases the city's 'long-term' *transit* ridership more than lower *transit* times from neighborhood 2.

Proposition B.2. *A marginal reduction in transit travel times from neighborhood 1 increases transit ridership more than a marginal reduction in transit travel times from neighborhood 2 ($\frac{dR}{d\Delta\tau_1} < \frac{dR}{d\Delta\tau_2}$) if and only if*

$$\bar{\xi}_L - \bar{\xi}_H > \frac{K}{2}$$

where $K \equiv A_{H1} - A_{H2} - A_{L1} + A_{L2} + \beta \cdot (w_H - w_L) \cdot ({\tau_2}^c - {\tau_1}^c)$ is as defined in Proposition B.1. The proof follows in Appendix B.2.3.3. Note that $K = 0$ in the baseline model (and differences in amenities and *car* travel times do not affect income sorting), where long-term *transit* ridership is always maximized by improving *transit* access from the richer neighborhood, just as in the short-term and as discussed in Section 3.5.2.

Besides what is covered in the main text of the paper, it is worth briefly considering what happens when $K \neq 0$ and income sorting also depends on preferences over amenities and differences in *car* travel times (the generalization described in Section 3.6.1). There are now two additional possible income sorting scenarios to the ones listed in Section 3.5.2. Either:

(a) *transit* is faster from the richer neighborhood and more attractive to low-income households, so improving *transit* access from the richer neighborhood would decrease *transit* ridership among the (primarily) high-inccome households that move out, OR

(d) *transit* is faster from the poorer neighborhood and more attractive to high-income households, so improving *transit* access from the richer neighborhood would decrease *transit* ridership for the high-income households that move in.

In both cases, the policy that maximizes long-term *transit* ridership depends on how the change in ridership among households that move compare to that of households that stay in their original neighborhood. Whether or not a household moves depends not just on differences in *transit* access (as in the baseline model) but also on differences in *car* access and preferences over residential amenities.

B.1.4 Model Generalizations

B.1.4.1 Price-Elastic Housing Demand

Let us relax the assumption of fixed housing consumption and fixed neighborhood populations in the baseline model. Suppose households now gain utility from consuming more housing and choose their housing consumption h to maximize the following utility function

$$U_{gn}(x, h, m^\star; \xi) \equiv x + h^{\sigma/(1+\sigma)} + A_{ng} + \xi \cdot \mathbf{I}_{n=1} + \int_\gamma \gamma \mathbf{I}_{[m^\star_{gn}(\gamma)=c]} \cdot \partial\Psi(\gamma) \qquad \text{(B.1.7)}$$

subject to budget constraint

$$x = w_g - hp_n - \int_\gamma \tilde{C}_{gn}^{m^\star_{gn}(\gamma)} \cdot \partial\Psi(\gamma) \tag{B.1.8}$$

In this specification, $\sigma > 0$ determines the constant price elasticity of housing demand.[3] First order condition w.r.t. h lets us solve for the optimal housing consumption as a function of housing price:

$$\begin{aligned} 0 &= \frac{\sigma}{1+\sigma} h^{-1/(1+\sigma)} - p_n \\ \implies h^\star &= \left(\frac{(1+\sigma)p_n}{\sigma}\right)^{-(1+\sigma)} \end{aligned}$$

After substituting in optimal numerarire consumption and mode chocies, the indirect utility from choosing to reside in neighborhood n is

$$V_{gn} \equiv w_g + \sigma^\sigma(1+\sigma)^{-(1+\sigma)} p_n^{-\sigma} - C_{gn} + A_{gn} + \xi \mathbf{I}_{n=1} \tag{B.1.9}$$

Households are indifferent between the two neighborhoods when their taste ξ for neighborhood 1 is equal to

$$\bar{\xi}_g \equiv V_{g2} - V_{g1} = \Delta_\sigma p + C_{g1} - C_{g2} + A_{g2} - A_{g1}$$

where $\Delta_\sigma p \equiv \sigma^\sigma(1+\sigma)^{-(1+\sigma)}(p_2^{-\sigma} - p_1^{-\sigma})$ is the difference in the utility from housing prices in each neighborhood. The baseline scenario corresponds to $\Delta_\sigma p = \Delta p$.

We will also drop the assumption of equally sized neighborhoods, and assume the housing stock in neighborhood n is fixed at H_n. For the housing market to clear in each neighborhood, aggregate housing demand needs to equal equal the fixed housing supply:

$$h^\star(p_1) \cdot \Big(\Lambda \cdot \big(1 - F(\bar{\xi}_L)\big) + (1-\Lambda) \cdot \big(1 - F(\bar{\xi}_H)\big)\Big) = H_1$$

$$h^\star(p_2) \cdot \Big(\Lambda \cdot F(\bar{\xi}_L) + (1-\Lambda) \cdot F(\bar{\xi}_H)\Big) = H_2$$

The clearing conditions for the two housing markets are equivalent since the total population of the city is still fixed at 1, so that

$$\frac{H_2}{h^\star(p_2)} + \frac{H_1}{h^\star(p_1)} = 1$$

[3]The price elasticity of housing demand is $-(1+\sigma)$.

The population in each neighborhood is now a function of the housing price. Our dissimilarity measure (the fraction of population that needs to move to achieve perfect income mixing) is:

$$DISS \equiv \Lambda \cdot \left| F\big(\bar{\xi}_L\big) - \frac{H_2}{h^{\star}(p_2)} \right| + (1-\Lambda) \cdot \left| F\big(\bar{\xi}_H\big) - \frac{H_2}{h^{\star}(p_2)} \right|$$

We can substitute in $\frac{H_2}{h^{\star}(p_2)}$ from the housing market clearing condition and solve for the same dissimilarity measure as before:

$$\begin{aligned} DISS &= \Lambda \cdot \left| F\big(\bar{\xi}_L\big) - \Lambda \cdot F(\bar{\xi}_L) - (1-\Lambda) \cdot F(\bar{\xi}_H) \right| + (1-\Lambda) \cdot \left| F\big(\bar{\xi}_H\big) - \Lambda \cdot F(\bar{\xi}_L) - (1-\Lambda) \cdot F(\bar{\xi}_H) \right| \\ &= 2\Lambda \cdot (1-\Lambda) \cdot \left| F\big(\bar{\xi}_L\big) - F\big(\bar{\xi}_H\big) \right| \end{aligned}$$

Given $\bar{\xi}_g$ are always in the support of ξ, income dissimilarity

$$DISS = 2\Lambda \cdot (1-\Lambda) \cdot f \cdot \left| \bar{\xi}_L - \bar{\xi}_H \right|$$

is, as before, no longer a function of housing prices. We can substitute Δp with $\Delta_\sigma p$ in the proofs and results on transit's effect on income segregation and they still hold. Income segregation does not depend on neighborhood population (density) or housing prices in this model.

B.1.4.2 Destination-Specific Travel Times

In this section, I extend the model proposed in Section 3.6.3. High and low income households have different trip destinations, and τ_{ng}^{m} denotes the travel time to destinations of type g from neighborhood n using mode m. There are now four possible *transit* travel times that can be changed and, for now, assume each travel time can be changed independent of the other three. Planners choose to improve travel times not just from particular neighborhoods but also for particular income groups. Improving travel times to low-income destinations attracts more low-income households to the neighborhood, whereas improving travel times to high-income destinations attracts more high-income households. It is then straightforward to extend Proposition 3.1 to this *transit* network with four travel times.

Proposition B.3. *A marginal reduction in travel time* τ_{ng}^{m}

- ***increases income segregation*** *($\frac{dDISS}{d\tau^t_{ng}} < 0$) if and only if income group g is more likely to reside in neighborhood n*
- ***decreases income segregation*** *($\frac{dDISS}{d\tau^t_{ng}} > 0$) if and only if income group $k \neq g$ is more likely to reside in neighborhood n*

In other words, improving travel times from either the poorer neighborhood to low-income destinations or the richer neighborhood to high-income destinations increases income segregation by attracting more low-income households to the poorer neighborhood or more high-income households to the richer neighborhood. On the other hand, improving travel times from either the poorer neighborhood to high-income destinations or the richer neighborhood to low-income destinations decreases income segregation. Note that, unlike the results in section 3.4, the outcome for income segregation does not depend on the level of *transit* ridership (as long as it is positive) or the *transit* travel time. In the baseline model, the speed of *transit* travel relative to *car* determined who benefited more from reductions in *transit* travel times and who were more likely to move in response. Now that travel time improvements can be targeted directly at a particular income group, the effect on income segregation depends only on who are being targeted.

Of course, this is a highly stylized scenario. In reality, extending a transit route to a neighborhood usually improves connection to the rest of the transit network for everyone in the neighborhood. The following section accounts for these positive spillover effects from network connectivity.

B.1.4.3 Travel Network Externalities

Building off of the scenario with income-specific trip destinations, suppose travel times were not independent and expanding the *transit* network from neighborhood n to destination type g has positive spillovers for all *transit* riders residing in n. More precisely, suppose *transit* travel times from any residential neighborhood n are related such that

$$\frac{d\tau^t_{nk}}{d\tau^t_{ng}} = \theta_k \geq 0 \text{ for } k \neq g \;\forall g \;\forall n \tag{B.1.10}$$

where θ_k measures how additionally accessible group k destinations are following a marginal reduction in *transit* travel times to other destinations from the same neighborhood.

Intuitively, θ_k captures how well the existing transit network connects the routes between neighborhood n and group g destinations also to group k destinations.[4] For example, if low-income jobs are more dispersed than high-income jobs (as in Tsivanidis, 2019) and have relatively smaller travel time gains from improved *transit* connectivity to a particular neighborhood, θ_L must be smaller than θ_H.[5]

What is the marginal effect of lower *transit* travel times to type g destinations on income segregation?

$$\frac{dDISS}{d\tau_{ng}^t} = \frac{\partial DISS}{\partial \tau_{ng}^t} + \theta_k \cdot \frac{\partial DISS}{\partial \tau_{nk}^t} \text{ where } k \neq g$$

For small enough travel time complementarities θ_k, the first additive component (the direct effect of lower τ_{ng}^t) dominates the expression above and the effect on $DISS$imilarity is qualitatively the same as in Section B.1.4.2. When $\theta_k = 1$, the effect on $DISS$imilarity is exactly the same as in Section 3.4 (the baseline model). For high θ_k, the spillover effect from lower τ_{nk}^t dominates the direct effect of lower τ_{ng}^t.

Proposition B.4. *Given non-negative travel time complementarities θ_H and θ_L, a marginal reduction in travel time τ_{ng}^t to destinations of type $g \neq k$*

- ***increases income segregation*** *($\frac{dDISS}{d\tau_{ng}^t} < 0$) if and only if either:*
  - *(a) income group g is more likely to reside in neighborhood n and benefits more from the shorter transit times: $w_g \Psi\big(\tilde{\gamma}_{gn}\big) > \theta_k w_k \Psi\big(\tilde{\gamma}_{kn}\big)$, OR*
  - *(b) income group k is more likely to reside in neighborhood n and benefits more from the shorter transit times: $w_g \Psi\big(\tilde{\gamma}_{gn}\big) < \theta_k w_k \Psi\big(\tilde{\gamma}_{kn}\big)$*
- ***decreases income segregation*** *($\frac{dDISS}{d\tau_{ng}^t} > 0$) if and only if either:*
  - *(a) income group k is more likely to reside in neighborhood n but income group g benefits more from the shorter transit times: $w_g \Psi\big(\tilde{\gamma}_{gn}\big) > \theta_k w_k \Psi\big(\tilde{\gamma}_{kn}\big)$ OR*

[4] θ_k could also be interpreted as the outcome of some underlying trip destination choice model. For instance, conditional on residence and travel mode, each income group can choose their destination to maximize some destination-specific utility shifter net of any additional destination-specific travel cost, where θ_k captures how costly it is (in terms of travel) to switch trip destinations.

[5] Note that in (B.1.10) θ_k does not depend on the destination types g that are getting shorter transit times. As such, high and low income destinations are symmetrically distributed with respect to each other. This assumption is simply for notational convenience. One could easily accommodate a different parameter θ_{kg} for each destination type g.

(b) income group g is more likely to reside in neighborhood n but income group k benefits more from the shorter transit times: $w_g \Psi\big(\tilde{\gamma}_{gn}\big) < \theta_k w_k \Psi\big(\tilde{\gamma}_{kn}\big)$

In other words, suppose high (low) income households have higher *transit* ridership, *transit* connectivity and/or value of travel time so that they benefit more from shorter *transit* times. Then, improving *transit* access from the high (low) income neighborhood increases income segregation by disproportionately attracting more high (low) income households to the neighborhood. In contrast, improving *transit* from the low (high) income neighborhood decreases income segregation by disproportionately attracting more high (low) income households. Note that, qualitatively, this effect of lower *transit* travel times on income segregation is the same as in the baseline model, as depicted in Lemma 3.1. Quantitatively, the outcome depends on the destinations being connected and the magnitude of the network spillover effects.

Corollary. *Given non-negative travel time complementarities θ_H and θ_L, a marginal reduction in travel time τ^t_{ng} to destinations of type $g \neq k$ minimizes $DISSimilarity$ more from the residential neighborhood*

- *with a larger share of income group k when $w_g\big[\Psi(\tilde{\gamma}_{1g})+\Psi(\tilde{\gamma}_{2g})\big] > \theta_k w_k\big[\Psi(\tilde{\gamma}_{1k})+\Psi(\tilde{\gamma}_{2k})\big]$*
- *with a larger share of income group g when $w_g\big[\Psi(\tilde{\gamma}_{1g})+\Psi(\tilde{\gamma}_{2g})\big] < \theta_k w_k\big[\Psi(\tilde{\gamma}_{1k})+\Psi(\tilde{\gamma}_{2k})\big]$*

In other words, to minimize income segregation, a transit planner would reduce travel times from the high (low) income neighborhood when overall *transit* ridership in the city is sufficiently large among low (high) income households. Once again, this result reinforces that of Corollary 3.1.

B.2 Mathematical Derivations and Proofs

B.2.1 Marginal Effect of Transit Times on Income Segregation

B.2.1.1 Proof of Lemma 3.1

Proof. First, let us determine the marginal effect of *transit* times on overall travel costs C_{gn} from (3.3.5):

$$\frac{dC_{gn}}{d\Delta\tau_n} = \beta \cdot w_g \cdot \Big[\psi\big(\tilde{\gamma}_{gn}\big) \cdot \tilde{C}^c_{gn} - \psi\big(\tilde{\gamma}_{gn}\big) \cdot \tilde{C}^t_{gn} + \Psi\big(\tilde{\gamma}_{gn}\big) - \tilde{\gamma}_{gn} \cdot \psi\big(\tilde{\gamma}_{gn}\big)\Big]$$

where the last component follows from the Fundamental Theorem of Calculus.

$$\implies \frac{dC_{gn}}{d\Delta\tau_n} = \beta \cdot w_g \cdot \Big[\psi\big(\tilde{\gamma}_{gn}\big) \cdot \Big(\tilde{C}^c_{gn} - \tilde{C}^t_{gn} - \tilde{\gamma}_{gn}\Big) + \Psi\big(\tilde{\gamma}_{gn}\big)\Big]$$

Then, plugging in $\tilde{\gamma}_{gn}$ from (3.3.2) yields

$$\frac{dC_{gn}}{d\Delta\tau_n} = \beta \cdot w_g \cdot \Psi\big(\tilde{\gamma}_{gn}\big) \tag{B.2.1}$$

Now, we can take the derivative of $DISS$ from (3.4.3) with respect to $\Delta\tau_n$:

$$\begin{aligned}\frac{dDISS}{d\Delta\tau_n} &= 2\Lambda \cdot (1-\Lambda) \cdot (1 - 2\mathbf{I}[\bar{\xi}_L < \bar{\xi}_H]) \\ &\quad \cdot \Big[(1 - 2\mathbf{I}_{n=2}) \cdot \Big(f \cdot \frac{dC_{Ln}}{d\Delta\tau_n} - f \cdot \frac{dC_{Hn}}{\Delta d\tau_n}\Big) + \Big(f - f\Big) \cdot \frac{d\Delta p}{d\tau^t_n}\Big]\end{aligned} \tag{B.2.2}$$

$$= 2\Lambda \cdot (1-\Lambda) \cdot f \cdot (1 - 2\mathbf{I}_{n=2}) \cdot (1 - 2\mathbf{I}[\bar{\xi}_L < \bar{\xi}_H]) \cdot \Big(\frac{dC_{Ln}}{d\Delta\tau_n} - \frac{dC_{Hn}}{d\Delta\tau_n}\Big) \tag{B.2.3}$$

where

$$\frac{dC_{Ln}}{d\Delta\tau_n} - \frac{dC_{Hn}}{d\Delta\tau_n} = \beta \cdot \Big(\Psi\big(\tilde{\gamma}_{Ln}\big) \cdot w_L - \Psi\big(\tilde{\gamma}_{Hn}\big) \cdot w_H\Big) \tag{B.2.4}$$

In (B.2.3), $\frac{dDISS}{d\tau^t_n} < 0$ if and only if one of the following holds true:

(a) $n = 2$, $\bar{\xi}_L < \bar{\xi}_H$ and $\Psi\big(\tilde{\gamma}_{Ln}\big) \cdot w_L < \Psi\big(\tilde{\gamma}_{Hn}\big) \cdot w_H$

(b) $n = 1$, $\bar{\xi}_L > \bar{\xi}_H$ and $\Psi\big(\tilde{\gamma}_{Ln}\big) \cdot w_L < \Psi\big(\tilde{\gamma}_{Hn}\big) \cdot w_H$

(c) $n = 2$, $\bar{\xi}_L > \bar{\xi}_H$ and $\Psi\big(\tilde{\gamma}_{Ln}\big) \cdot w_L > \Psi\big(\tilde{\gamma}_{Hn}\big) \cdot w_H$

(d) $n = 1$, $\bar{\xi}_L < \bar{\xi}_H$ and $\Psi\big(\tilde{\gamma}_{Ln}\big) \cdot w_L > \Psi\big(\tilde{\gamma}_{Hn}\big) \cdot w_H$

Recall that $F(\bar{\xi}_g)$ is the fraction of type g households that live in neighborhood 2. Since there are only two residential neighborhoods, a larger fraction of high-income households in neighborhood 2 (i.e., $F(\bar{\xi}_H) > F(\bar{\xi}_L)$ or $\bar{\xi}_H > \bar{\xi}_L$) automatically implies a larger fraction of low-income households in neighborhood 1 (i.e., $1 - F(\bar{\xi}_L) > 1 - F(\bar{\xi}_H)$). So, the first two conditions correspond to n being the richer neighborhood and the last two conditions correspond to n being the poorer neighborhood. Lumping them together, $\frac{dDISS}{d\Delta\tau_n} < 0$ if and only if either:

- n is the richer neighborhood and $\Psi(\tilde{\gamma}_{Ln}) \cdot w_L < \Psi(\tilde{\gamma}_{Hn}) \cdot w_H$ OR
- n is the poorer neighborhood and $\Psi(\tilde{\gamma}_{Ln}) \cdot w_L > \Psi(\tilde{\gamma}_{Hn}) \cdot w_H$

Similarly, $\frac{dDISS}{d\tau_n^t} > 0$ if and only if either:

- n is the richer neighborhood and $\Psi(\tilde{\gamma}_{Ln}) \cdot w_L > \Psi(\tilde{\gamma}_{Hn}) \cdot w_H$ OR
- n is the poorer neighborhood and $\Psi(\tilde{\gamma}_{Ln}) \cdot w_L < \Psi(\tilde{\gamma}_{Hn}) \cdot w_H$

□

B.2.1.2 Proof of Proposition 3.1

Proof. Note that $\Psi(\tilde{\gamma}_{Ln}) \cdot w_L < \Psi(\tilde{\gamma}_{Hn}) \cdot w_H$ is equivalent to

$$\psi \cdot \left(\kappa - \beta \cdot w_L \cdot \Delta\tau_n + \Gamma\right) \cdot w_L < \psi \cdot \left(\kappa - \beta \cdot w_H \cdot \Delta\tau_n + \Gamma\right) \cdot w_H$$

$$\Leftrightarrow \beta \cdot \Delta\tau_n \cdot \left(w_H - w_L\right) \cdot \left(w_H + w_L\right) < (w_H - w_L) \cdot \left(\kappa + \Gamma\right)$$

$$\Leftrightarrow \Delta\tau_n < \frac{\kappa + \Gamma}{\beta \cdot (w_H + w_L)}$$

Conversely, $\Psi(\tilde{\gamma}_{Ln}) \cdot w_L > \Psi(\tilde{\gamma}_{Hn}) \cdot w_H$ is equivalent to

$$\Delta\tau_n > \frac{\kappa + \Gamma}{\beta \cdot (w_H + w_L)}$$

Letting $\bar{\tau} \equiv \frac{\kappa+\Gamma}{\beta \cdot (w_H + w_L)}$, Lemma 3.1 can be re-stated as follows.

Improved *transit* access increases income segregation ($\frac{dDISS}{d\Delta\tau_n} < 0$) if and only if either:

- n is the richer neighborhood and $\Delta\tau_n < \bar{\tau}$ OR
- n is the poorer neighborhood and $\Delta\tau_n > \bar{\tau}$

Whereas, improved *transit* access decreases income segregation ($\frac{dDISS}{d\Delta\tau_n} > 0$) if and only if either:

- n is the richer neighborhood and $\Delta\tau_n > \bar{\tau}$ OR
- n is the poorer neighborhood and $\Delta\tau_n < \bar{\tau}$

□

B.2.1.3 Proof of Corollary 3.1

Proof. Take the derivative of $DISS$ w.r.t. $\Delta\tau_n$ and compare it for the two neighborhoods:

$$\frac{dDISS}{d\Delta\tau_1} - \frac{dDISS}{d\Delta\tau_2} = 2\Lambda \cdot (1-\Lambda) \cdot f \cdot (1 - 2\mathbf{I}[\bar{\xi}_L < \bar{\xi}_H]) \cdot G \tag{B.2.5}$$

$$\text{where } G \equiv \frac{dC_{L1}}{d\Delta\tau_1} - \frac{dC_{H1}}{d\Delta\tau_1} + \frac{dC_{L2}}{d\Delta\tau_2} - \frac{dC_{H2}}{d\Delta\tau_2}$$

Improving *transit* times in neighborhood 1 would induce more income mixing (or less income segregation) than doing so in neighborhood 2 if and only if $\frac{dDISS}{d\Delta\tau_1} - \frac{dDISS}{d\Delta\tau_2}$ is positive. The sign depends on G. If we plug in $\frac{dC_{gn}}{d\Delta\tau_n}$ from (B.2.1),

$$G = \beta \cdot w_L \cdot \Big(\Psi\big(\tilde{\gamma}_{L1}\big) + \Psi\big(\tilde{\gamma}_{L2}\big)\Big) - \beta \cdot w_H \cdot \Big(\Psi\big(\tilde{\gamma}_{H1}\big) + \Psi\big(\tilde{\gamma}_{H2}\big)\Big)$$

Since $\tilde{\gamma}_{gn} \in [-\Gamma, \Gamma]\ \forall n, g$, we can plug in $\Psi\big(\tilde{\gamma}_{gn}\big) = \psi \cdot \big(\tilde{\gamma}_{gn} + \Gamma\big)$ into G:

$$G = \beta \cdot \psi \cdot \Big[w_L \cdot \Big(\tilde{\gamma}_{L1} + \tilde{\gamma}_{L2} + 2\Gamma\Big) - w_H \cdot \Big(\tilde{\gamma}_{H1} + \tilde{\gamma}_{H2} + 2\Gamma\Big)\Big]$$

Plug in $\tilde{\gamma}_{gn} \equiv \kappa - \beta \cdot w_g \cdot \Delta\tau_n$:

$$\implies G = \beta \cdot \psi \cdot \Big[\beta \cdot (\Delta\tau_1 + \Delta\tau_2) \cdot (w_H^2 - w_L^2) - 2(\kappa + \Gamma) \cdot (w_H - w_L)\Big]$$

$$= \beta \cdot \psi \cdot (w_H - w_L) \cdot \Big[\beta \cdot (\Delta\tau_1 + \Delta\tau_2) \cdot (w_H + w_L) - 2(\kappa + \Gamma)\Big]$$

Finally, on plugging this expression for G back into (B.2.5), we get that $\frac{dDISS}{d\Delta\tau_1} - \frac{dDISS}{d\Delta\tau_2}$ is positive if and only if either:

- neighborhood 2 is poorer ($\bar{\xi}_L > \bar{\xi}_H$) and *transit* is sufficiently slow

$$\Delta\tau_1 + \Delta\tau_2 > \frac{2(\kappa + \Gamma)}{\beta \cdot (w_H + w_L)} = 2\bar{\tau}$$

- OR neighborhood 2 is richer ($\bar{\xi}_L < \bar{\xi}_H$) and *transit* is sufficiently fast

$$\Delta\tau_1 + \Delta\tau_2 < \frac{2(\kappa + \Gamma)}{\beta \cdot (w_H + w_L)} = 2\bar{\tau}$$

$\square$

B.2.2 Income *DISS*imilarity as a Function of Travel Times

In this section, I derive a closed-form solution of income *DISS*imilarity in the city purely in terms of travel times and exogenous parameters of the model. Income segregation is driven by the difference in travel costs between the neighborhoods, and how it differs between high and low income households. First, I characterize how this difference in travel costs varies with *transit* ridership and travel times (section B.2.2.1). Then, I show how neighborhood differences in travel costs and independent amenities affect endogenously determined housing prices and ultimately the level of income *DISS*imilarity in a competitive equilibrium (section B.2.2.2). Throughout this section, assume that $\tilde{\gamma}_{gn}$ lies within the support of the distribution of γ for all n, g.

B.2.2.1 Aggregate Travel Cost

Based on the travel cost function specified in (3.3.5), we have

$$C_{g1} - C_{g2} = \sum_n (1 - 2\mathbf{I}_{n=2}) \cdot \left[\tilde{C}^c_{gn} + \Psi\big(\tilde{\gamma}_{gn}\big) \cdot \big(\tilde{C}^t_{gn} - \tilde{C}^c_{gn}\big)\right] + \int_{\tilde{\gamma}_{g2}}^{\tilde{\gamma}_{g1}} \gamma \cdot d\Psi(\gamma)$$

Substitute $\tilde{C}^c_{gn} \equiv \kappa + \beta \cdot w_g \cdot \tau^c_n$ from (3.3.1) and $\tilde{\gamma}_{gn} \equiv \tilde{C}^c_{gn} - \tilde{C}^t_{gn}$ from (3.3.2) into $C_{g1} - C_{g2}$

$$= \sum_n (1 - 2\mathbf{I}_{n=2}) \cdot \left[\beta \cdot w_g \cdot \tau^c_n - \Psi\big(\tilde{\gamma}_{gn}\big) \cdot \tilde{\gamma}_{gn}\right] + \int_{\tilde{\gamma}_{g2}}^{\tilde{\gamma}_{g1}} \gamma \cdot d\Psi(\gamma) \tag{B.2.6}$$

Because γ is uniformly distributed with constant density ψ and $\tilde{\gamma}_{gn}$ lie within the support $[-\Gamma, \Gamma]$, we know $\Psi\big(\tilde{\gamma}_{gn}\big) = \psi \cdot \big[\tilde{\gamma}_{gn} + \Gamma\big]$ and we can substitute $d\Psi(\gamma) = \psi \cdot d\gamma$ into the integral to get

$$\int_{\tilde{\gamma}_{g2}}^{\tilde{\gamma}_{g1}} \gamma \cdot d\Psi(\gamma) = \frac{\psi}{2} \cdot \left[\big(\tilde{\gamma}_{g1}\big)^2 - \big(\tilde{\gamma}_{g2}\big)^2\right]$$

Now plug them into (B.2.6) to get

$$C_{g1} - C_{g2} = \sum_n (1 - 2\mathbf{I}_{n=2}) \cdot \Big[\beta \cdot w_g \cdot \tau_n^c - \psi \cdot \big(\tilde{\gamma}_{gn} + \Gamma\big) \cdot \tilde{\gamma}_{gn} + \frac{\psi}{2} \cdot \big(\tilde{\gamma}_{gn}\big)^2\Big] \tag{B.2.7}$$

Add $0 = \frac{\psi}{2} \cdot \Big(3\Gamma^2 - 3\Gamma^2 + \sum_n (1 - 2\mathbf{I}_{n=2}) \cdot 2\tilde{\gamma}_{gn} \cdot \big(\Gamma - \Gamma\big)\Big) = \sum_n (1 - 2\mathbf{I}_{n=2}) \cdot \Big[- \psi \cdot \Gamma \cdot \big(\tilde{\gamma}_{gn} + \Gamma\big) + \frac{\psi}{2} \cdot \Big(\Gamma^2 + 2\tilde{\gamma}_{gn} \cdot \Gamma\Big)\Big]$:

$$C_{g1} - C_{g2} = \sum_n (1 - 2\mathbf{I}_{n=2}) \cdot \Big[\beta \cdot w_g \cdot \tau_n^c - \psi \cdot \big(\tilde{\gamma}_{gn} + \Gamma\big) \cdot \big(\tilde{\gamma}_{gn} + \Gamma\big) + \frac{\psi}{2} \cdot \big(\tilde{\gamma}_{g1} + \Gamma\big)^2\Big]$$

$$= \sum_n (1 - 2\mathbf{I}_{n=2}) \cdot \Big[\beta \cdot w_g \cdot \tau_n^c - \frac{1}{2\psi} \cdot \Psi\big(\tilde{\gamma}_{gn}\big)^2\Big] \tag{B.2.8}$$

B.2.2.2 Income Sorting (Proof of Proposition B.1)

Proof. Recall that $\bar{A} \equiv A_{H1} - A_{H2} - A_{L1} + A_{L2}$. Then

$$\bar{\xi}_L - \bar{\xi}_H = C_{L1} - C_{L2} - C_{H1} + C_{H2} + \bar{A}$$

Plug in $C_{g1} - C_{g2}$ from (B.2.8) to get

$$\bar{\xi}_L - \bar{\xi}_H = \sum_g \sum_n (1 - 2\mathbf{I}_{g=H}) \cdot (1 - 2\mathbf{I}_{n=2}) \cdot \Big[\beta \cdot w_g \cdot \tau_n^c - \frac{1}{2\psi} \cdot \Psi\big(\tilde{\gamma}_{gn}\big)^2\Big] + \bar{A}$$

and substitute in $K \equiv \beta \cdot (w_H - w_L) \cdot (\tau_2^c - \tau_1^c) + \bar{A}$:

$$= K - \frac{1}{2\psi} \cdot \sum_g \sum_n (1 - 2\mathbf{I}_{g=H}) \cdot (1 - 2\mathbf{I}_{n=2}) \cdot \Psi\big(\tilde{\gamma}_{gn}\big)^2 \tag{B.2.9}$$

which can be rewritten as

$$\bar{\xi}_L - \bar{\xi}_H = \frac{1}{2\psi} \cdot \Big(\Psi\big(\tilde{\gamma}_{L2}\big)^2 - \Psi\big(\tilde{\gamma}_{H2}\big)^2 - \Psi\big(\tilde{\gamma}_{L1}\big)^2 + \Psi\big(\tilde{\gamma}_{H1}\big)^2\Big) + K$$

Thus, we have (B.1.1), the first equality of Proposition B.1. Now plug in $\tilde{\gamma}_{gn}$ from (3.3.2) into (B.2.9) to get $\bar{\xi}_L - \bar{\xi}_H$

$$= K - \sum_g (1 - 2\mathbf{I}_{g=H}) \cdot \sum_n (1 - 2\mathbf{I}_{n=2}) \cdot \Big[\frac{\psi}{2} \cdot \big(\kappa - \beta \cdot w_g \cdot \Delta\tau_n + \Gamma\big)^2\Big]$$

and expand the square:

$$= K - \sum_g (1 - 2\mathbf{I}_{g=H}) \cdot \sum_n (1 - 2\mathbf{I}_{n=2}) \cdot \frac{\psi}{2} \cdot \Big[2(\kappa + \Gamma) \cdot (\beta \cdot w_g \cdot \Delta\tau_n) - \big(\beta \cdot w_g \cdot \Delta\tau_n\big)^2 \Big]$$

where $\sum_g (1 - 2\mathbf{I}_{g=H}) \cdot \sum_n (1 - 2\mathbf{I}_{n=2}) \cdot (\kappa + \Gamma)^2 = 0$.

$$= \beta \cdot \frac{\psi}{2} \cdot \Big[\beta \cdot (w_H^2 - w_L^2) \cdot \big[(\Delta\tau_1)^2 - (\Delta\tau_2)^2\big] - 2(\kappa + \Gamma) \cdot (w_H - w_L) \cdot (\Delta\tau_1 - \Delta\tau_2) \Big] + K$$

$$= \beta \cdot \frac{\psi}{2} \cdot (w_H - w_L) \cdot (\Delta\tau_1 - \Delta\tau_2) \cdot \Big(\beta \cdot (w_H + w_L) \cdot (\Delta\tau_1 + \Delta\tau_2) - 2(\kappa + \Gamma) \Big) + K$$

Substitute in $\bar{\tau} \equiv \frac{\kappa + \Gamma}{\beta \cdot (w_H + w_L)}$ to get

$$= \beta \cdot \frac{\psi}{2} \cdot (w_H - w_L) \cdot (\Delta\tau_1 - \Delta\tau_2) \cdot \beta \cdot (w_H + w_L) \cdot \big(\Delta\tau_1 + \Delta\tau_2 - 2\bar{\tau} \big) + K$$

Substitute in $Q \equiv \frac{1}{2}\beta \cdot \psi \cdot (w_H^2 - w_L^2) = \frac{1}{2}\beta \cdot \psi \cdot (w_H - w_L) \cdot (w_H + w_L)$ to derive our second equality, (B.1.2), from Proposition B.1:

$$\bar{\xi}_L - \bar{\xi}_H = Q \cdot \big(\Delta\tau_1 - \Delta\tau_2 \big) \cdot \big(\Delta\tau_1 + \Delta\tau_2 - 2\bar{\tau} \big) + K$$

□

Then, based on our definition of income $DISS$imilarity from (3.4.1),

$$DISS = 2\Lambda \cdot (1 - \Lambda) \cdot f \cdot \Big| Q \cdot \big(\Delta\tau_1 - \Delta\tau_2 \big) \cdot \big(\Delta\tau_1 + \Delta\tau_2 - 2\bar{\tau} \big) + K \Big|$$

B.2.3 Marginal Effect of Transit Times on Long-Term Transit Ridership

B.2.3.1 Change in Transit Ridership Among Stayers

Since the distribution of incomes across neighborhoods are an endogenous function of the distribution of travel times, we can continue to develop the expression in (B.1.6) to re-write it as a function of exogenous parameters of the model. This will be useful when characterizing changes in *transit* ridership in the long-run. So, plug in $\bar{\xi}_g$ from (3.3.7):

$$S_2 - S_1 = \psi \cdot \beta \cdot \mathbf{E}\Bigg[w \cdot \bigg(1 - 2f \cdot \big(C_{g1} - C_{g2} - A_{g1} + A_{g2} + \Delta p + \Xi\big)\bigg)\Bigg]$$

$$= \psi \cdot \beta \cdot \mathbf{E}\Bigg[w \cdot \bigg(1 - 2f \cdot \big(C_{g1} - C_{g2} - A_{g1} + A_{g2} + \Delta p + \Xi\big)\bigg)\Bigg] \tag{B.2.10}$$

From the housing market clearing condition in (3.3.8), we have

$$\Delta p = \frac{1}{2f} - \Xi - \mathbf{E}\big[C_{g1} - C_{g2} - A_{g1} + A_{g2}\big] \tag{B.2.11}$$

Plug in this Δp into (B.2.10) to get

$$S_2 - S_1 = \psi \cdot \beta \cdot \mathbf{E}\Bigg[w_g \cdot \bigg(1 - 2f \cdot \big(C_{g1} - C_{g2} - A_{g1} + A_{g2} + \frac{1}{2f} - \mathbf{E}\big[C_{g1} - C_{g2} - A_{g1} + A_{g2}\big]\big)\bigg)\Bigg]$$

$$= 2f \cdot \psi \cdot \beta \cdot \Bigg[\mathbf{E}\big[w_g \cdot \big(C_{g1} - C_{g2} - A_{g1} + A_{g2}\big)\big] - \mathbf{E}[w_g] \cdot \mathbf{E}\big[C_{g1} - C_{g2} - A_{g1} + A_{g2}\big]\Bigg]$$

We can simplify the expectation over incomes to get

$$S_2 - S_1 = 2f \cdot \psi \cdot \beta \cdot \Lambda \cdot (1 - \Lambda) \cdot (w_H - w_L) \cdot \big[C_{H1} - C_{H2} - C_{L1} + C_{L2} + \bar{A}\big] \tag{B.2.12}$$

$$\text{where } \bar{A} \equiv A_{H1} - A_{H2} - A_{L1} + A_{L2}$$

To be concise, I use $\bar{A}$ to denote the effect of exogenously distributed amenities in the city. Note that $S_2 - S_1$ is proportional to income $DISS$imilarity as defined in (3.4.1):

$$S_2 - S_1 = 2f \cdot \psi \cdot \beta \cdot \Lambda \cdot (1 - \Lambda) \cdot (w_H + w_L) \cdot \big(\bar{\xi}_L - \bar{\xi}_H\big) \tag{B.2.13}$$

In words, the greater the difference in incomes across residential neighborhoods, the larger are the gains in ('short-term') *transit* ridership from improving *transit* in the richer neighborhood.

B.2.3.2 Change in Transit Ridership Among Movers (Proof of Lemma B.1.3.2)

What is the change in *transit* ridership M_n among households that move?

Proof. Plug in $\bar{\xi}_g$ from (3.3.7) into $M_2 - M_1$ from (B.1.4) and take its derivative w.r.t τ_1^t and τ_2^t to get

$$M_2 - M_1 = f \cdot \mathbf{E}\Bigg[\Bigg(\frac{d\Delta p}{d\Delta\tau_2} - \frac{dC_{g2}}{d\Delta\tau_2} - \frac{d\Delta p}{d\Delta\tau_1} - \frac{dC_{g1}}{d\Delta\tau_1}\Bigg) \cdot \Bigg(\Psi\big(\tilde{\gamma}_{g2}\big) - \Psi\big(\tilde{\gamma}_{g1}\big)\Bigg)\Bigg]$$

The derivative of Δp from (B.2.11) w.r.t. $\Delta\tau_n$ is

$$\frac{d\Delta p}{d\Delta\tau_n} = -\mathbf{E}\big[\frac{dC_{gn}}{d\Delta\tau_n} \cdot (1 - 2\mathbf{I}_{n=2})\big]$$

which we can plug into $M_2 - M_1$

$$= f \cdot \mathbf{E}\Bigg[\Bigg(\mathbf{E}\big[\frac{dC_{g2}}{d\Delta\tau_2} + \frac{dC_{g1}}{d\Delta\tau_1}\big] - \frac{dC_{g2}}{d\Delta\tau_2} - \frac{dC_{g1}}{d\Delta\tau_1}\Bigg) \cdot \Bigg(\Psi\big(\tilde{\gamma}_{g2}\big) - \Psi\big(\tilde{\gamma}_{g1}\big)\Bigg)\Bigg]$$

Substitute in $\frac{dC_{gn}}{d\Delta\tau_n} = \beta \cdot w_g \cdot \Psi\big(\tilde{\gamma}_{gn}\big)$ from (B.2.1) and plug in $\Psi\big(\tilde{\gamma}_{gn}\big) = \psi \cdot \big(\kappa - \beta \cdot w_g \cdot \Delta\tau_n + \Gamma\big)$ to get

$$\begin{aligned} M_2 - M_1 = f \cdot \beta \cdot \mathbf{E}\Big[\psi \cdot \beta \cdot w_g^2 \cdot (\Delta\tau_1 + \Delta\tau_2)\Big] \cdot \mathbf{E}\Big[\psi \cdot \beta \cdot w_g \cdot (\Delta\tau_1 - \Delta\tau_2)\Big] \\ - f \cdot \beta \cdot \mathbf{E}\Big[w_g \cdot \big[\psi \cdot \beta \cdot w_g \cdot (\Delta\tau_1 + \Delta\tau_2)\big] \cdot \big[\psi \cdot \beta \cdot w_g \cdot (\Delta\tau_1 - \Delta\tau_2)\big]\Big] \\ = f \cdot \psi^2 \cdot \beta^3 \cdot \Bigg(\mathbf{E}[w_g^3] - \mathbf{E}[w_g^2] \cdot \mathbf{E}[w_g]\Bigg) \cdot \big[(\Delta\tau_2)^2 - (\Delta\tau_1)^2\big] \end{aligned}$$

Finally, simplify the expectation over the two possible incomes:

$$M_2 - M_1 = f \cdot \beta^3 \cdot \psi^2 \cdot \Lambda \cdot (1 - \Lambda) \cdot (w_H^2 - w_L^2) \cdot (w_H - w_L) \cdot \big[(\Delta\tau_2)^2 - (\Delta\tau_1)^2\big] \quad \text{(B.2.14)}$$

$M_2 > M_1$ if and only if $\Delta\tau_1 < \Delta\tau_2$. In other words, ridership among households that move increases more from *transit* improvements in neighborhood 1 (as opposed to 2) if and only if *transit* is relatively faster from neighborhood 1 than from 2. This is because movers increase their *transit* usage when they move in to a neighborhood with relatively shorter *transit* times, but decrease their *transit* usage when they move to a neighborhood with longer *transit* times. Similarly, households that move out of the neighborhood with faster *transit* had relatively lower *transit* usage (and lower willingness to pay the higher housing prices for it) to begin with. So, overall *transit* ridership among the city's movers is maximized by marginal improvements in *transit* from the neighborhood that has the relatively shorter *transit* travel time. □

B.2.3.3 Maximizing Long-Term Transit Ridership (Proof of Proposition B.2)

Let me finally compare the change in *transit* ridership among all households in the city.

Proof. Recall from (B.1.4) that $\frac{dR}{d\Delta\tau_2} - \frac{dR}{d\Delta\tau_1}$ equals the sum of $S_2 - S_1$ and $M_2 - M_1$. So, plug in $\bar{\xi}_L - \bar{\xi}_H$ from (B.1.2) into $S_2 - S_1$from (B.2.13) and add them to $M_2 - M_1$ from (B.2.14) to get $\frac{dR}{d\Delta\tau_2} - \frac{dR}{d\Delta\tau_1}$

$$= 2f \cdot \psi \cdot \beta \cdot \Lambda \cdot (1-\Lambda) \cdot (w_H - w_L) \cdot \Bigg[\beta \cdot (w_H - w_L) \cdot \big[\psi \cdot (\kappa + \Gamma) \cdot (\Delta\tau_1 - \Delta\tau_2)\big] - \psi \cdot \beta^2 \cdot (w_H^2 - w_L^2) \cdot \big[(\Delta\tau_1)^2 - (\Delta\tau_2)^2\big] + K\Bigg]$$

which is positive if and only if

$$\beta \cdot (w_H - w_L) \cdot \psi \cdot (\Delta\tau_1 - \Delta\tau_2) \cdot \Bigg(\kappa + \Gamma - \beta \cdot (w_H + w_L) \cdot (\Delta\tau_1 + \Delta\tau_2)\Bigg) + K > 0$$

$$\Leftrightarrow 2Q \cdot (\Delta\tau_1 - \Delta\tau_2) \cdot \Bigg(\bar{\tau} - (\Delta\tau_1 + \Delta\tau_2)\Bigg) + K > 0$$

$$2(\bar{\xi}_L - \bar{\xi}_H - K) + K > 0$$

where I substituted in Q, K and $\bar{\xi}_L - \bar{\xi}_H$ from Proposition B.1. So, improving *transit* travel times from neighborhood 1 increases *transit* ridership more than improving *transit* times from neighborhood 2 if and only if

$$\bar{\xi}_L - \bar{\xi}_H > \frac{K}{2}$$

□

B.2.4 Generalization: Travel Times to Income-Specific Destinations

Suppose the travel network is characterized by travel times τ_{ng}^m to destinations of type g (for income group g). What is the marginal effect of transit travel times on income segregation? When is $\frac{dDISS}{d\tau_{ng}^t} < 0$? There are four marginal *transit* travel time changes to evaluate. Let $\Delta\tau_{ng} \equiv \tau_{ng}^c - \tau_{ng}^t$ denote the travel time difference between *car* and *transit* for each commute ng. Households are indifferent between *car* and *transit* on trips with γ equal to

$$\tilde{\gamma}_{ng} = \kappa - \beta w_g \Delta\tau_{ng}$$

B.2.4.1 Zero Network Spillovers (Proof of Proposition B.3)

Proof. To compute $\frac{dDISS}{d\tau_{ng}^t}$, first, derive the marginal effect of travel times on travel costs:

$$\frac{dC_{ng}}{d\tau_{ng}^t} = \beta \cdot w_g \cdot \left[\psi\big(\tilde{\gamma}_{ng}\big) \cdot \tilde{C}_{ng}^c - \psi\big(\tilde{\gamma}_{ng}\big) \cdot \tilde{C}_{ng}^t + \Psi\big(\tilde{\gamma}_{ng}\big) - \tilde{\gamma}_{ng} \cdot \psi\big(\tilde{\gamma}_{ng}\big)\right]$$

where the last component follows from the Fundamental Theorem of Calculus.

$$\implies \frac{dC_{ng}}{d\tau_{ng}^t} = \beta \cdot w_g \cdot \left[\psi\big(\tilde{\gamma}_{ng}\big) \cdot \left(\tilde{C}_{ng}^c - \tilde{C}_{ng}^t - \tilde{\gamma}_{ng}\right) + \Psi\big(\tilde{\gamma}_{ng}\big)\right]$$

Then, plugging in $\tilde{\gamma}_{ng}$ from (3.3.2) yields

$$\frac{dC_{ng}}{d\tau_{ng}^t} = \beta \cdot w_g \cdot \Psi\big(\tilde{\gamma}_{ng}\big) \tag{B.2.15}$$

Now, we can take the derivative of $DISS$ from (3.4.3) with respect to τ_{ng}^t:

$$\frac{dDISS}{d\tau_{ng}^t} = 2\Lambda \cdot (1-\Lambda) \cdot (1 - 2\mathbf{I}[\bar{\xi}_L < \bar{\xi}_H]) \cdot \\ \left[(1-2\mathbf{I}_{n=2}) \cdot (1-2\mathbf{I}_{g=H}) \cdot f \cdot \frac{dC_{ng}}{d\tau_{ng}^t} + \left(f - f\right) \cdot \frac{d\Delta p}{d\tau_{ng}^t}\right] \tag{B.2.16}$$

$$\implies \frac{dDISS}{d\tau_{ng}^t} = 2\Lambda \cdot (1-\Lambda) \cdot f \cdot (1-2\mathbf{I}_{n=2}) \cdot (1-2\mathbf{I}_{g=H}) \cdot (1 - 2\mathbf{I}[\bar{\xi}_L < \bar{\xi}_H]) \cdot \frac{dC_{ng}}{d\tau_{ng}^t} \tag{B.2.17}$$

In (B.2.17), $\frac{dDISS}{d\tau_{ng}^t} < 0$ if and only if there is non-zero *transit* ridership among the target group ($\Psi(\tilde{\gamma}_{ng}) > 0$) and one of the following holds true:

- $n = 2$, $\bar{\xi}_L < \bar{\xi}_H$ and $g = H$
- $n = 1$, $\bar{\xi}_L > \bar{\xi}_H$ and $g = H$
- $n = 2$, $\bar{\xi}_L > \bar{\xi}_H$ and $g = L$
- $n = 1$, $\bar{\xi}_L < \bar{\xi}_H$ and $g = L$

Recall that $F(\bar{\xi}_g)$ is the fraction of group g households that live in neighborhood 2. Since there are only two residential neighborhoods, a larger fraction of high-income households in neighborhood 2 (i.e., $F(\bar{\xi}_H) > F(\bar{\xi}_L)$ or $\bar{\xi}_H > \bar{\xi}_L$) automatically implies a larger fraction of low-income households in neighborhood 1 (i.e., $1 - F(\bar{\xi}_L) > 1 - F(\bar{\xi}_H)$). So, the first two conditions correspond to n being the richer neighborhood and the last two conditions correspond to n being the poorer neighborhood. Lumping them together, $\frac{dDISS}{d\tau^t_{ng}} < 0$ if and only if either:

- n is the richer neighborhood and $g = H$ OR
- n is the poorer neighborhood and $g = L$

Similarly, $\frac{dDISS}{d\tau^t_{ng}} > 0$ if and only if either:

- n is the richer neighborhood and $g = L$ OR
- n is the poorer neighborhood and $g = H$

□

B.2.4.2 Positive Network Spillovers (Proof of Proposition B.4)

Proof. When is $\frac{dDISS}{d\tau^t_{ng}} < 0$?

$$\frac{dDISS}{d\tau^t_{ng}} = \frac{\partial DISS}{\partial \tau^t_{ng}} + \theta_k \cdot \frac{\partial DISS}{\partial \tau^t_{nk}} \text{ where } k \neq g$$

where we can plug in the derivative from (B.2.17) to get

$$\frac{dDISS}{d\tau^t_{ng}} = 2\Lambda \cdot (1 - \Lambda) \cdot f \cdot (1 - 2\mathbf{I}_{n=2}) \cdot (1 - 2\mathbf{I}[\bar{\xi}_L < \bar{\xi}_H]) \cdot (1 - 2\mathbf{I}_{g=H}) \cdot \left(\frac{dC_{ng}}{d\tau^t_{ng}} - \theta_k \frac{dC_{nk}}{d\tau^t_{nk}} \right)$$

$$= 2\Lambda \cdot (1 - \Lambda) \cdot f \cdot (1 - 2\mathbf{I}_{n=2}) \cdot (1 - 2\mathbf{I}[\bar{\xi}_L < \bar{\xi}_H]) \cdot (1 - 2\mathbf{I}_{g=H})\beta \cdot \Big(w_g \Psi(\tilde{\gamma}_{ng}) - \theta_k w_k \Psi(\tilde{\gamma}_{nk}) \Big)$$

Then $\frac{dDISS}{d\tau^t_{ng}} < 0$ if and only if one of the following holds true:

(a) n is the richer neighborhood and $g = H$ and $w_g \Psi(\tilde{\gamma}_{gn}) > \theta_k w_k \Psi(\tilde{\gamma}_{kn})$

(b) n is the poorer neighborhood and $g = L$ and $w_g \Psi(\tilde{\gamma}_{gn}) > \theta_k w_k \Psi(\tilde{\gamma}_{kn})$

(c) n is the richer neighborhood and $g = L$ and $w_g \Psi(\tilde{\gamma}_{gn}) < \theta_k w_k \Psi(\tilde{\gamma}_{kn})$

(d) n is the poorer neighborhood and $g = H$ and $w_g \Psi(\tilde{\gamma}_{gn}) < \theta_k w_k \Psi(\tilde{\gamma}_{kn})$

The first two conditions are consistent with the results of Lemma 3.1. They state that improving travel times from the high (low) income neighborhood to high (low) income destinations increases income segregation when there is large enough high (low) income transit ridership in the neighborhood and sufficiently small θ_k. The last two conditions state that improving travel times from the high (low) income neighborhood even to low (high) income destinations increase income segregation when there is large enough high (low) income transit ridership and sufficiently large θ_k.

Similarly, $\frac{dDISS}{d\tau_{ng}^t} > 0$ if and only if one of the following holds true:

(a) n is the richer neighborhood and $g = L$ and $w_L \Psi(\tilde{\gamma}_{Ln}) > \theta_H w_H \Psi(\tilde{\gamma}_{Hn})$

(b) n is the poorer neighborhood and $g = H$ and $w_H \Psi(\tilde{\gamma}_{Hn}) > \theta_L w_L \Psi(\tilde{\gamma}_{Ln})$

(c) n is the richer neighborhood and $g = H$ and $w_H \Psi(\tilde{\gamma}_{Hn}) < \theta_L w_L \Psi(\tilde{\gamma}_{Ln})$

(d) n is the poorer neighborhood and $g = L$ and $w_L \Psi(\tilde{\gamma}_{Ln}) < \theta_H w_H \Psi(\tilde{\gamma}_{Hn})$

□

B.2.4.3 Positive Network Spillovers (Proof of Corollary B.1.4.3)

Proof. Take the derivative of $DISS$ w.r.t. τ_{gn}^t and compare $n = 1$ to $n = 2$:

$$\frac{dDISS}{d\tau_{g1}^t} - \frac{dDISS}{d\tau_{g2}^t} = 2\Lambda \cdot (1 - \Lambda) \cdot f \cdot (1 - 2\mathbf{I}[\bar{\xi}_L < \bar{\xi}_H]) \cdot (1 - 2\mathbf{I}_{g=H}) \cdot G_1 \tag{B.2.18}$$

$$\text{where } G_1 \equiv \frac{dC_{g1}}{d\tau_{g1}^t} - \theta_k \frac{dC_{k1}}{d\tau_{k1}^t} + \frac{dC_{g2}}{d\tau_{g2}^t} - \theta_k \frac{dC_{k2}}{d\tau_{k2}^t} \text{ where } k \neq g$$

Improving *transit* times in neighborhood 1 would induce more income mixing (or less income segregation) than doing so in neighborhood 2 if and only if $\frac{dDISS}{d\tau_{g1}^t} - \frac{dDISS}{d\tau_{g2}^t}$ is positive. The sign depends on G_1. Based on (B.2.1),

$$G_1 = w_g \Psi(\tilde{\gamma}_{1g}) - \theta_k w_k \Psi(\tilde{\gamma}_{1k}) + w_g \Psi(\tilde{\gamma}_{2g}) - \theta_k w_k \Psi(\tilde{\gamma}_{2k})$$

$$= w_g\Bigg(\Psi\big(\tilde{\gamma}_{1g}\big) + \Psi\big(\tilde{\gamma}_{2g}\big)\Bigg) - \theta_k w_k\Bigg(\Psi\big(\tilde{\gamma}_{1k}\big) + \Psi\big(\tilde{\gamma}_{2k}\big)\Bigg)$$

$G_1 < 0$ implies that the non-targeted benefits from expanding the transit network outweighs the direct benefits from shorter travel times to targeted destinations. So, $\frac{dDISS}{d\tau^t_{1g}} > \frac{dDISS}{d\tau^t_{2g}}$ if and only if either

(a) neighborhood 1 is richer, $g = L$ and sufficiently large low-income *transit* ridership such that $G_1 > 0$, OR

(b) neighborhood 1 is poorer, $g = H$ and sufficiently large high-income *transit* ridership such that $G_1 > 0$, OR

(c) neighborhood 1 is richer, $g = H$ and sufficiently large low-income *transit* ridership such that $G_1 < 0$, OR

(d) neighborhood 1 is poorer, $g = L$ and sufficiently large high-income *transit* ridership such that $G_1 < 0$

The cases for improving *transit* times in neighborhood 2 follow the same reasoning. □

Qualitatively, we get lower income segregation on improving *transit* access between the high (low) income neighborhood and

- low (high) income destinations when *transit* ridership is sufficiently large among low (high) income households
- high (low) income destinations when *transit* ridership is sufficiently large among low (high) income households

More concisely, we get lower income segregation on improving *transit* access from the high (low) income neighborhood when *transit* ridership is sufficiently large among low (high) income households, just like in the baseline model.

B.2.5 Perfect Income Segregation

The paper's main results focus on cases where both $\bar{\xi}_L$ and $\bar{\xi}_H$ lie in the support $[-\Xi, \Xi]$ of the distribution of ξ. In this section, I consider the alternative where $\bar{\xi}_g \notin [-\Xi, \Xi]$ for some $g \in \{L, H\}$. In other words, all households in one of the income groups sort perfectly into one neighborhood. Let $f(\xi)$ denote the probability density of ξ such that $f(\xi)=0$ for $\xi \notin [-\Xi,\Xi]$ and $f(\xi)=\frac{1}{2\Xi}$ for $\xi \in [-\Xi,\Xi]$.

Proposition B.5. *Suppose $\bar{\xi}_g \notin [-\Xi,\Xi]$ for some $g \in \{L,H\}$. Then*

$$\frac{dDISS}{d\tau_n^m} = 0 \ \forall m \in \{t,c\},\ \forall n \in \{1,2\}$$

Proof. Take the derivative of our measure of $DISS$ in (3.4.2) with respect to travel time τ_n^m to get

$$\frac{dDISS}{d\tau_n^m} = 2\Lambda \cdot (1-\Lambda) \cdot (1-2\mathbf{I}[\bar{\xi}_L < \bar{\xi}_H]) \cdot \left[(1-2\mathbf{I}_{n=2}) \cdot \left(f\big(\bar{\xi}_L\big) \cdot \frac{dC_{Ln}}{d\tau_n^m} - f\big(\bar{\xi}_H\big) \cdot \frac{dC_{Hn}}{d\tau_n^m}\right) + \left(f\big(\bar{\xi}_L\big) - f\big(\bar{\xi}_H\big)\right) \cdot \frac{d\Delta p}{d\tau_n^m}\right]$$

When $\bar{\xi}_g \notin [-\Xi,\Xi]$ for both $g \in \{L,H\}$, $f\big(\bar{\xi}_g\big) = 0\ \forall g$. So none of the households move in response to marginal changes (in $\bar{\xi}$) and $\frac{dDISS}{d\tau_n^m} = 0$.

Let us then consider the case where at least one of $\bar{\xi}_L$ or $\bar{\xi}_H$ lie in the support. Suppose $\bar{\xi}_g \in [-\Xi,\Xi]$ and $\bar{\xi}_k \notin [-\Xi,\Xi]$ for $g \neq k$. The housing market clearing condition in (3.3.8) boils down to

$$\frac{1}{2} = \Lambda \cdot \mathbf{I}[\bar{\xi}_k > \Xi] + (1-\Lambda) \cdot \frac{\bar{\xi}_g + \Xi}{2\Xi}$$

and we can decompose $\bar{\xi}_g$ to solve for the equilibrium housing price difference across neighborhoods:

$$\Leftrightarrow \Delta p = -\Xi + \big(1 - 2\Lambda \cdot \mathbf{I}[\bar{\xi}_k > \Xi]\big) \cdot \frac{2\Xi}{2(1-\Lambda)} - \big[C_{g1} - C_{g2} - A_{g1} + A_{g2}\big]$$

Take the derivative with respect to τ_n^m to get

$$\frac{d\Delta p}{d\tau_n^m} = -(1-2\mathbf{I}_{n=2}) \cdot \frac{dC_{gn}}{d\tau_n^m}$$

$$\implies \frac{dDISS}{d\tau_n^m} = -\frac{2\Lambda \cdot (1-\Lambda)}{2\Xi} \cdot \left[(1-2\mathbf{I}_{n=2}) \cdot \frac{dC_{gn}}{d\tau_n^m} + \frac{d\Delta p}{d\tau_n^m}\right] = 0$$

Since only households in income group g relocate in response to travel time changes and since the number of group g households that move out is the same as the number of group g households that move in (given fixed housing supply), the income compositions of the neighborhoods remain the same in equilibrium.

Thus, marginal changes in travel times do not affect $DISS$ when either $\bar{\xi}_L$ or $\bar{\xi}_H$ (or both) does not lie in the support $[-\Xi,\Xi]$ of the distribution of ξ. □

Appendix C Racial Segregation in Housing Markets and the Erosion of Black Wealth

C.1 Constructing the Matched Address Sample

Each record in the census data represents an individual in a household. Each household has a head and related members who share the same address. An address is the combination of a house number and a street name. In an ideal world, we would know the number of individuals and households residing at a given address. However, either the house number or the street name entry for an individual could have been mis-recorded by the census enumerators or mis-digitized by the contemporary census digitization workers. Therefore, some households have incorrect or incomplete addresses, possibly leading to inaccurate counts of households in any building. This appendix describes the algorithm we used to construct a representative set of households for our sample cities in 1930 and 1940, focusing in particular on the challenge of assigning all individuals to the correct address.

We first need to make sure that no household is either missing an address or assigned more than one. We assume that the enumeration districts (EDs) and tracts reported in the census data were transcribed correctly. A tiny fraction of EDs and tracts from the census do not coincide with the list of EDs that we use to define our cities. We drop those EDs or tracts, as they are likely to be institutions that were given a separate ED number.

We have digitized 1930 enumeration district boundaries (Shertzer et al., 2016) and obtained census tract boundary files from the National Historical Geographic Information System (NHGIS). We cross-check census address data by "fuzzy" matching each census street name to a list of street names from the corresponding ED/tract obtained from the spatial datasets. We exclude addresses on streets that have either no reasonable match or too many potential matches among the digitized streets.

Census enumerators were instructed to survey households as they moved along a street, and thus we do not expect to see house numbers within a street jump around. Thus, the order in which households appear on the manuscripts should generally reflect their location within the ED relative to neighboring households.[1] To ensure that we have all the households living in each address in our sample, we also drop any address that shares a street-block (or the entire street-ED when the block cannot be identified) with an address that is potentially out of order on the manuscript. We provide further details of the process below.

C.2 Details on Matching Methodology

We make sure that every household has exactly one address composed of a street name and house number. To begin, we assign the address information from the household head to everyone in his/her household. When the household head has partial (e.g. only a street name or only the house number) or no information on address, we fill in information from the household's non-head member. We perform a series of quality checks on these imputed addresses that are described below. If the household head is missing an address and household members disagree on either street name or house number, we impute the missing address information from those of households listed just before this one in the census manuscripts and flag these households.

In the case of multiple households sharing the same dwelling unit, we will have more than one household head. When these household heads disagree on the address, we compare each component of the addresses (the street names and house numbers) to those of adjacent households and keep the one(s) that matches that of the most number of neighbors. We flag all addresses imputed from adjacent households. A very small number of dwellings from the 1940 Census seem to have members belonging to different EDs/tracts. As with street names and house numbers, we assume the household head's ED/tract is the correct one. In the case of multi-family households, we compare each candidate ED/tract with those of households appearing immediately before and after on the census manuscripts, and only retain the EDs/tracts with the highest number of matches. We have a few households located at the intersection of EDs/tracts, and we flag these as well.

[1] Our indicators of manuscript page and line numbers are not very reliable, so we use the household IDs assigned by IPUMS as proxy for the order in which households appear in the original census manuscripts.

Then we standardize street names in the census, which are noisy and frequently riddled with typos. We first standardize all the directional prefix and street suffix, convert ordinal street numbers to their cardinal text forms, and remove any redundant information from street name (such as “Block A”). We then match these formatted street names to our digitized 1930 city streets to standardize further the names. We create a crosswalk of digitized street names, 1930 EDs, and 1940 tracts and fuzzy match them with the set of unique census street names by ED/tract (allowing some margin of error in the string match). We use STATA’s reclink2 command for this task. If a census street matches to more than one digitized street (a “one-to-many” match) within an ED/tract, then we flag all the digitized streets that were a match. Eventually we drop all Census records where the street does not match a digitized street or matches one that is flagged as part of a one-to-many match. Note that the process is sensitive to the margin of error that we allow in our string match. A wide error margin means we will have more one-to-many matches and fewer non-matches, whereas with a narrow error margin, we will have more non-matches and fewer one-to-many matches. The former introduces false one-to-one matches that might otherwise stay unmatched, whereas the latter introduces false one-to-one matches that might otherwise be matched to many. Thus, a conservative approach is to allow a wide margin of error, but narrow enough that we are still left with a reasonably sized sample after dropping one-to-many and non-matches.

House numbers, like street names, are also prone to errors and typos. The next step is to standardize house numbers as best as we can across ED/tracts and census years. When the house number variable is just one clear number, we leave it as it is. When it is not (e.g., “945/6”, “4531 667” or “1??2”), we try to identify a minimum and a maximum possible house number. For instance, when the reported house number is “4531 667”, we treat it as ranging from 667 to 4531 and flag all addresses on the same street block and ED with house numbers in that range.[2] We assume a “?” can range from 0 to 9, so that house number “1??2” ranges from 1002 to 1992. We treat separators like “/”, “-“, “&”, “+”, “ ” and

[2]There are alternative ways of interpreting a reported house number of “4531 467”. The second number might be an apartment number within the building, or the building might span house numbers 4531 to 4667. However, given that we eventually drop all street blocks intersecting this range of numbers, we believe our range assignment is the most conservative in dealing with such ambiguity. The street block is defined by the street name and the hundreds of the house number.

"," as spaces when identifying the range, while we ignore alphabets (treating "5a" as "5") and other non-alphanumeric characters (e.g. parentheses and brackets). All problematic addresses are flagged.

We do not have digitized historical house numbers as with street names to validate our cleaning process. Instead, we perform a number of quality checks based on the ordering of households in the census manuscripts and flag households that fail to satisfy these checks. Failing one or more of these reality checks implies that the re-formatted and standardized addresses are unlikely to be correct. These flagged households include cases where:

(a) the address differs from that of adjacent households on the manuscript when adjacent households share an address,

(b) only the house number matches that of one adjacent household, and only the street name matches that of the other adjacent household,

(c) the house number differs from adjacent house numbers by more than 10 along the same street,

(d) the house number changes non-monotonically (and differs from adjacent house numbers by at least 4) along the same street, and

(e) the address is (either partially or completely) imputed from that of the preceding household when adjacent street names differ.

We drop households in all addresses that were flagged in any of the previous steps. If a household's address is flagged, the correct address is likely to be that of adjacent households on the manuscript, given our assumption on the path of the enumerators. To avoid undercounting the individuals in these adjacent addresses, we also drop all addresses adjacent to flagged addresses on the manuscript. Thus, we generate a sample of addresses that are correct with a reasonable degree of accuracy that is our baseline.[3]

Finally, from each sample, we retain only the addresses that appear in both the 1930 and the 1940 Census. Since we have digitized 1930 ED boundaries and 1940 tract boundaries,

[3]If the street block of a flagged address cannot be identified credibly (e.g. when the house number is completely non-numeric or the range of house numbers is unrealistically large), we drop all addresses on the same street and ED.

we further make sure that the reported EDs (in 1930) and tracts (in 1940) corresponding to each address overlap spatially.

C.3 Geocoding Addresses

We geocode all formatted address strings on Google Maps' Directions API. We include all 1930 and 1940 addresses with non-missing street names and house numbers, including those we have flagged as potentially erroneous. The Directions API does a fuzzy name match of our input strings with addresses on Google's database and returns none, one or multiple location matches. For each location match, the API returns the geographic coordinates, the level of precision of the geocoding (e.g. "street address", "route", "intersection", "ward", etc.), and any administrative/political areas that the geocoded location falls within (e.g. the county, city, state, postal code or other well-defined "neighborhoods"). We drop any matches where the precision of the geocoding is an administrative area (e.g. a ward, a neighborhood, a city, etc.) or if the state differs from that of our city.

We then map each geocoded location to our 1930 ED and 1940 tract boundaries, and drop any location matches that do not coincide with either the ED or the tract associated with the input address. From each remaining geocoded location matches, we compute straight-line distances to the nearest black neighborhood. If there are still multiple location matches for an address, we keep the location match whose distance to the nearest black neighborhood is closest to the average distance from all location matches of addresses in the same block. Finally, in a small number of cases, when location matches for an address are tied in their deviation from the average distance to the nearest black neighborhood in the block, we pick the location match that appears first in the Directions API's sorting of results.[4]

To compute block-level distances to the nearest black neighborhood, we take the average of distances from each address in the block. As long as a block includes at least one address that is not flagged as problematic, we exclude distances from flagged addresses.

[4]The sorting reflects the "prominence" of the location, which is Google's measure of how likely the location is to be the result of a search.

C.4 Additional Tables and Figures

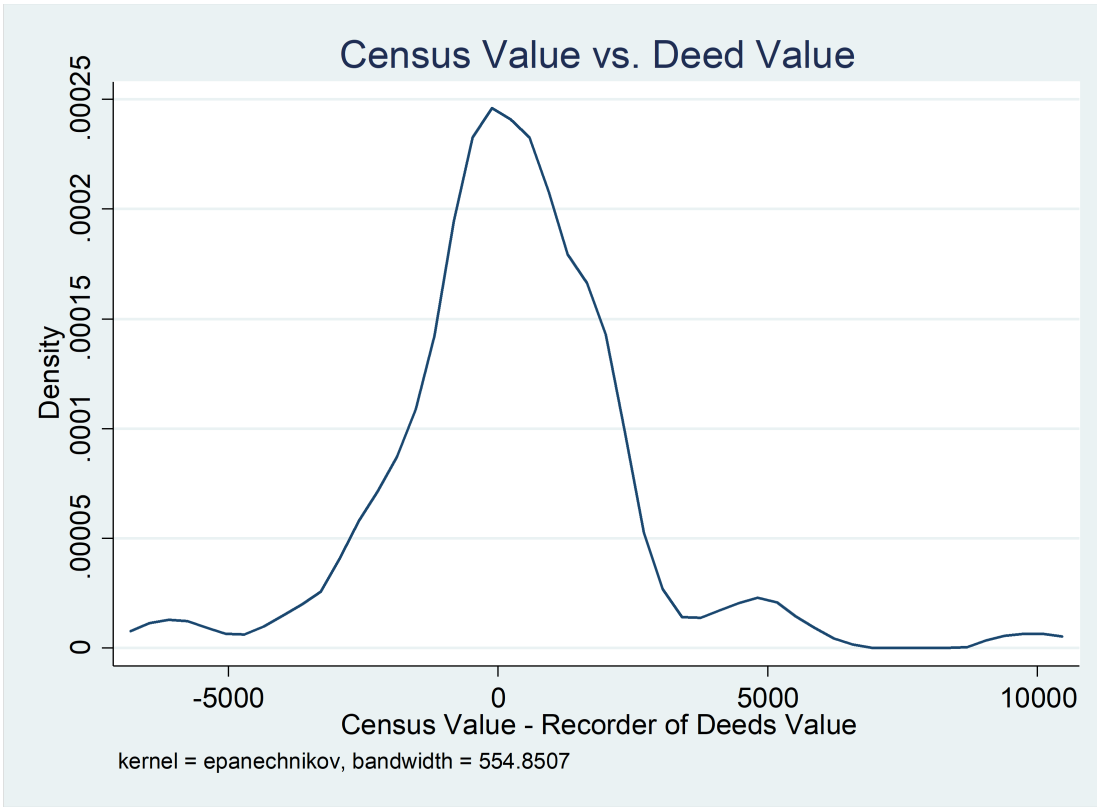


Figure 29: Self-reported value vs. deed value from county records

Note: The figure presents a Kernel Density Estimate of the PDF of differences between self-reported home valuations as recorded in the decennial census and sales amounts as recorded by the Allegheny County Recorder of Deeds for a sample of 404 owner-occupied homes in the city of Pittsburgh. The data were constructed by identifying homes in the recorder of deed's records that were sold in either 1930 or 1940 and then hand matching them to the appropriate individual census record based on the home's address.

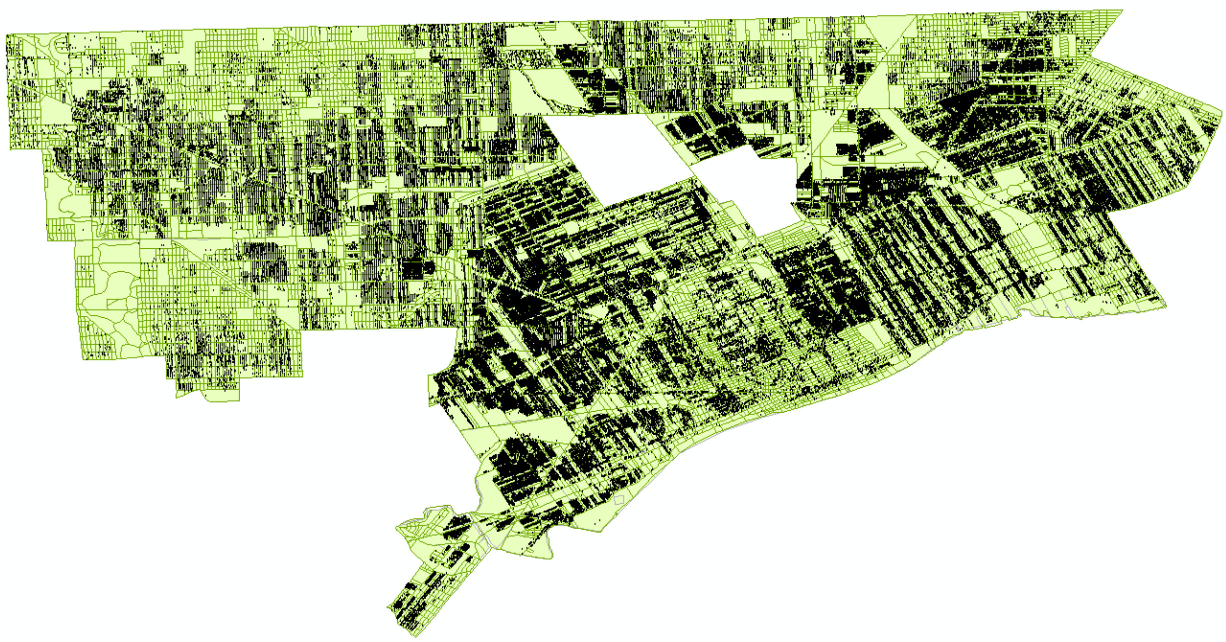


Figure 30: Geocoded Detroit addresses

Note: The figure shows the addresses in our sample for the city of Detroit that could be geocoded against a map of 1940 enumeration districts produced by Logan and Zhang (2017).

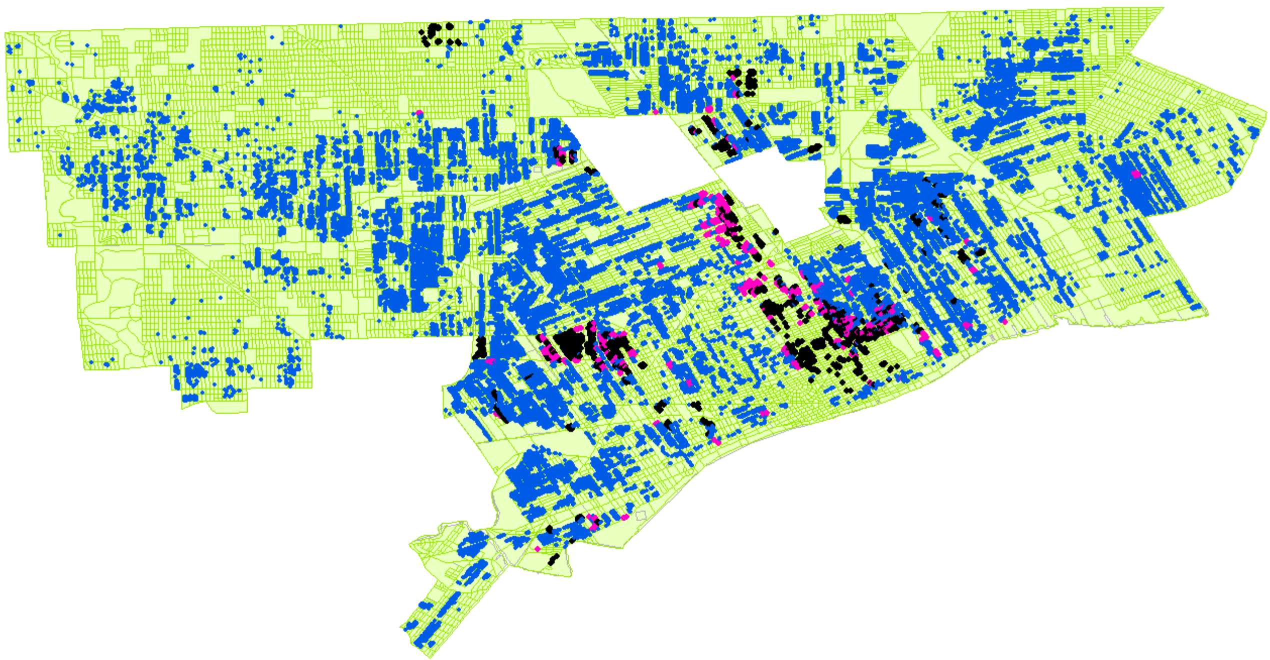
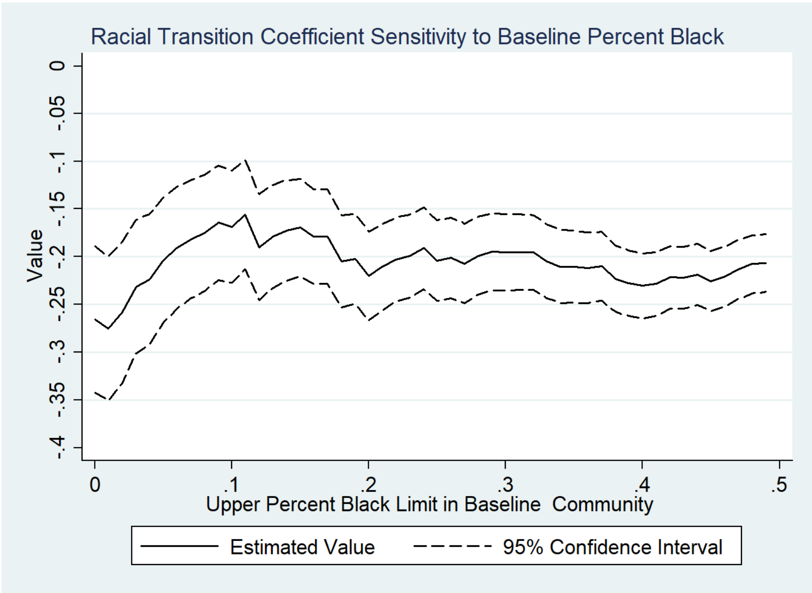
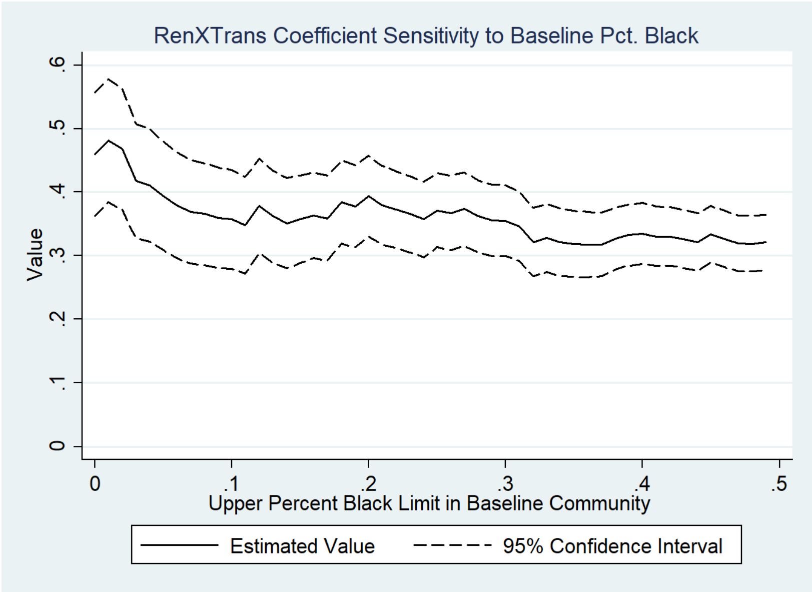


Figure 31: Racial transition in geocoded blocks in Detroit

Note: The figure shows the addresses in our sample for the city of Detroit that could be geocoded against a map of 1940 enumeration districts produced by Logan and Zhang (2017). Blocks are color-coded as follows: blue blocks were less than 5 percent black in both 1930 and 1940, pink blocks were less than 5 percent black in 1930 and more than 5 percent black in 1940, and black blocks were over 5 percent black in both 1930 and 1940.



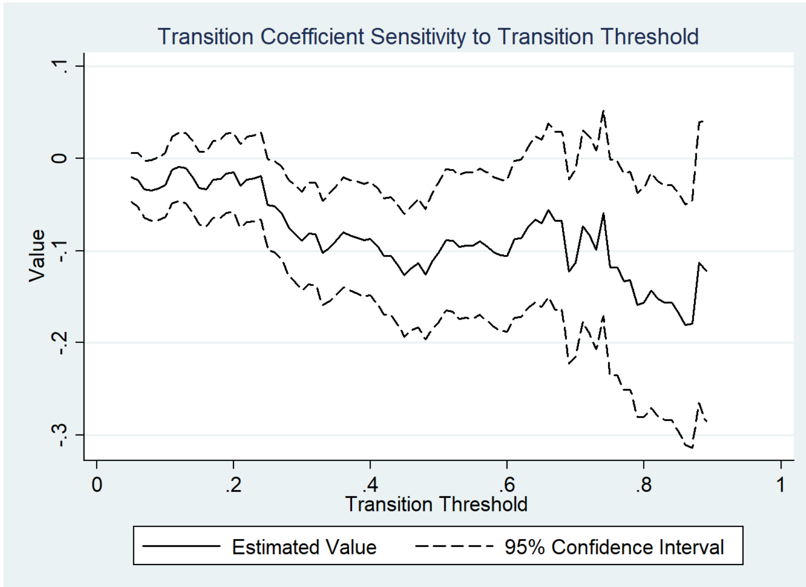
Racial Transition Coefficient



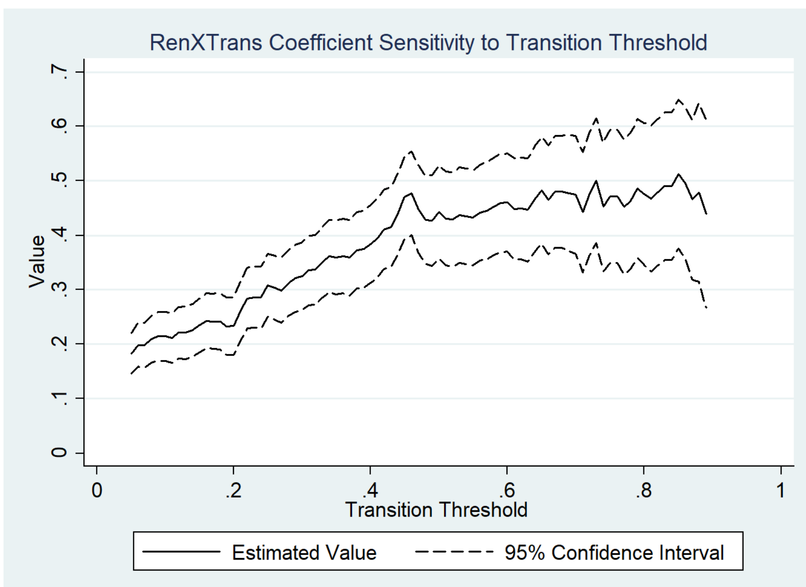
Racial Transition Rent Interaction Coefficient

Figure 32: Robustness to definition of a white block in 1930

Note: These figures present parameter estimates consistent with those presented in Column 3 of Table 13, Panel A under different definitions of a baseline block (in Table 13, only blocks with pct. black = 0 in 1930 were included in the analsyis).



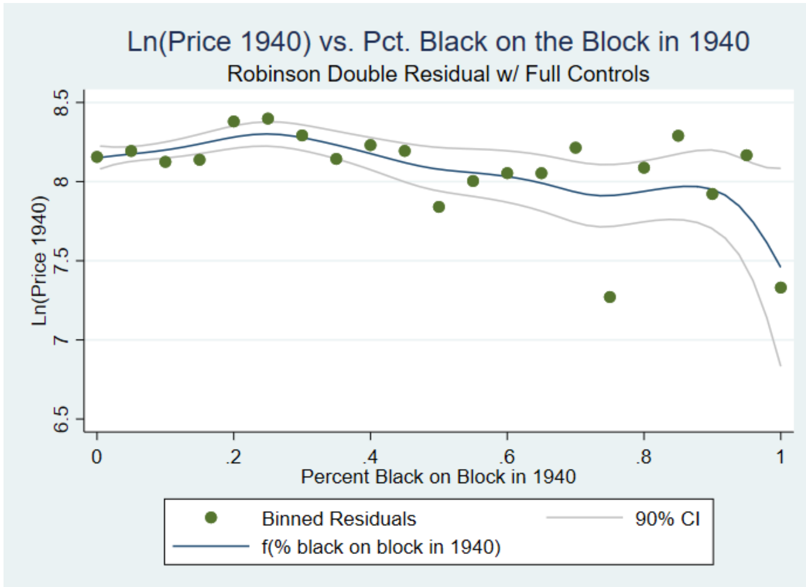
Racial Transition Coefficient



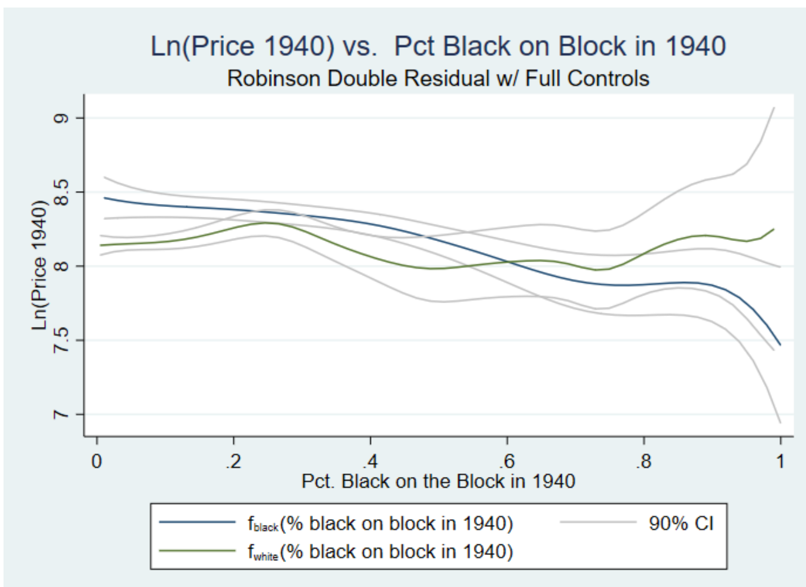
Racial Transition Rent Interaction Coefficient

Figure 33: Robustness to definition of racial transition

Note: These figures present parameter estimates consistent with those presented in Column 3 of Table 13, Panel A under different definitions of a racial transition (in Table 13, transition was defined as all city-blocks that were > 50% black in 1940).



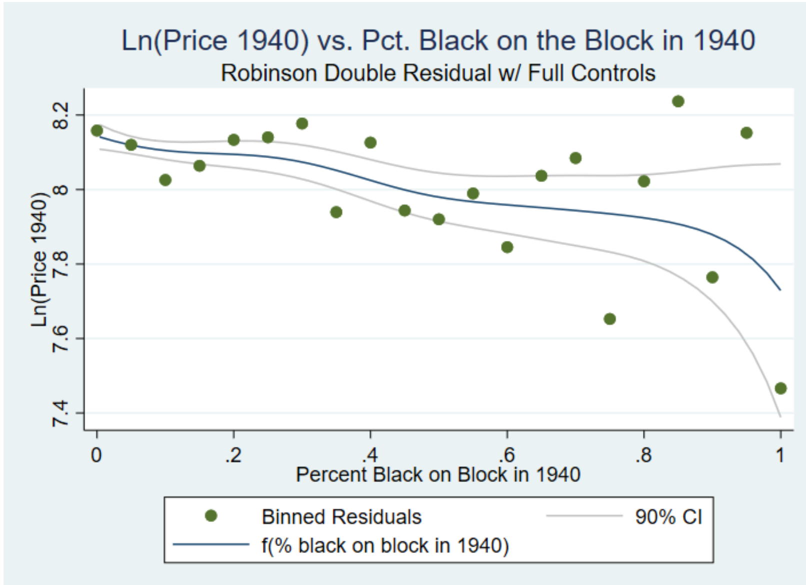
Baseline Sample



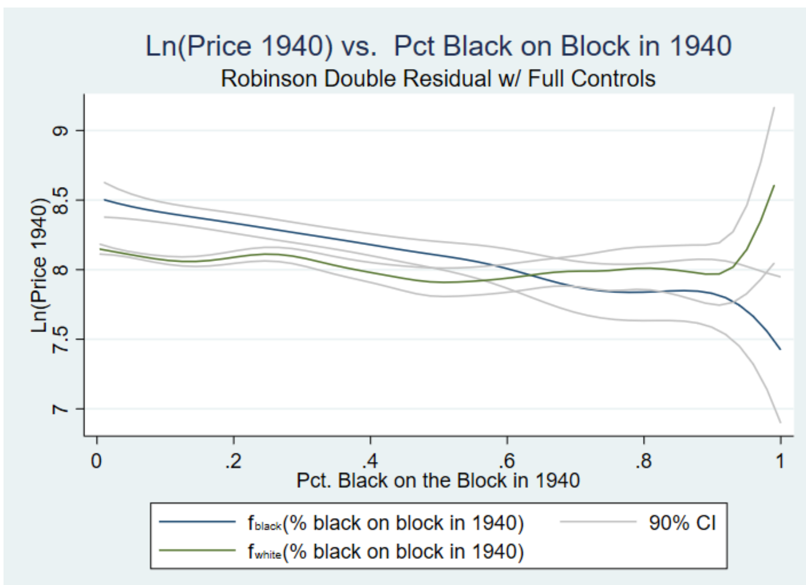
Black and White Households Separately

Figure 34: Semiparametric relationship between percent black and rents, excluding longstanding white residents

Note: This figure replicates Figure 19 except for dropping white households that had lived in the same address in 1935 from the sample.



Baseline Sample



Black and White Households Separately

Figure 35: Semiparametric relationship between percent black and home values, excluding longstanding white residents

Note: This figure replicates Figure 20 except for dropping white households that had lived in the same address in 1935 from the sample.

Table 24: Address statistics for block sample

	All Households				Addresses		Blocks		Addresses per Block	
	Total Households		Quality Address		Unique Addresses		Unique Blocks			
	1930	1940	1930	1940	1930	1940	1930	1940	1930	1940
Baltimore	193,979	245,862	147,962	132,680	118,741	97,264	8,249	7,831	14.4	12.4
Boston	182,090	211,731	132,944	135,944	62,913	61,052	4,090	4,051	15.4	15.1
Brooklyn	614,082	752,606	390,826	358,432	157,005	125,803	8,935	7,450	17.6	16.9
Chicago	845,436	1,025,731	545,383	437,973	278,694	198,297	20,530	17,766	13.6	11.2
Cincinnati	124,321	143,864	87,188	65,169	51,436	38,384	4,898	4,009	10.5	9.6
Cleveland	222,856	247,713	129,774	99,907	86,588	65,744	10,991	8,745	7.9	7.5
Detroit	370,556	451,198	225,457	219,961	168,955	163,406	18,380	18,169	9.2	9.0
Manhattan	470,552	614,786	188,258	191,471	25,178	20,876	1,854	1,856	13.6	11.2
Philadelphia	459,749	515,472	338,928	254,737	291,919	211,705	15,054	12,033	19.4	17.6
Pittsburgh	153,628	185,039	107,276	102,587	78,809	66,712	7,878	7,134	10.0	9.4
St. Louis	216,133	225,794	116,945	111,305	77,551	72,166	7,117	6,560	10.9	11.0
Total/Average	3,853,382	4,619,796	2,410,941	2,110,166	1,397,789	1,121,409	107,976	95,604	12.9	11.9

Note: The first two columns report the number of households reported in the census in each city. “Quality addresses” are the households for which we were able to assign an address that passed all quality checks described in the Data Appendix. “Unique addresses” are addresses that both pass the quality checks and are unique with a street name, street number, and 1930 enumeration district. We use postal service convention and assign house numbers to blocks using hundreds within a given street name. “Unique blocks” are the number of unique blocks represented by our sample of unique addresses. The last column of the table reports the number of unique addresses per unique block. This is the sample of addresses we used to construct our block sample.

Table 25: Address sample statistics

	Households with address found in both census years						Addresses		Households per Address	
	Total		Restricted Sample		Quality Address		Unique Addresses			
	1930	1940	1930	1940	1930	1940	1930	1940	1930	1940
Baltimore	110,312	125,598	98,780	111,757	67,925	75,888	57,287	57,287	1.2	1.3
Boston	122,353	136,230	100,785	109,334	67,008	71,343	33,267	33,267	2.0	2.1
Brooklyn	365,589	413,796	254,723	286,483	144,116	159,787	62,108	62,108	2.3	2.6
Chicago	443,948	497,700	355,109	389,081	190,802	207,627	104,553	104,553	1.8	2.0
Cincinnati	78,245	85,719	67,293	72,601	33,132	35,112	20,967	20,967	1.6	1.7
Cleveland	124,151	135,182	111,170	118,948	48,676	51,126	34,843	34,843	1.4	1.5
Detroit	212,211	228,290	184,660	194,112	95,309	98,560	76,845	76,845	1.2	1.3
Manhattan	235,841	299,774	95,304	119,594	29,369	36,001	3,913	3,913	7.5	9.2
Philadelphia	227,479	244,202	206,716	218,856	145,313	152,650	131,469	131,469	1.1	1.2
Pittsburgh	84,028	94,428	73,731	81,806	43,172	47,767	32,289	32,289	1.3	1.5
St. Louis	141,183	148,756	124,771	130,522	48,185	50,361	34,239	34,239	1.4	1.5
Total/Average	2,145,340	2,409,675	1,673,042	1,833,094	913,007	986,222	591,780	591,780	2.1	2.3

Note: The "Total" columns report the number of households with addresses we were able to locate in both the 1930 and 1940 censuses. We trimmed this sample to eliminate transcription errors and institutions (we drop any households with more than 10 members, any household with more than three heads, any addresses with monthly rent greater than \$100, and finally any addresses with a value greater than \$20,000). The "Trimmed Sample" columns report the number of households without problematic census values in both 1930 and 1940. The "Quality Address" columns report the number of households without problematic census values that passed the address quality checks described in the Data Appendix. The "Unique Addresses" columns report the number of addresses represented by this sample of households. This is the sample of addresses we used in our address-level analysis.

Table 26: Selection into sample

	Year	All	Clean Address	Matched Address
Individuals	1930	15,591,308	9,894,466	4,495,743
	1940	15,729,224	7,560,898	4,345,911
Households	1930	3,845,617	2,406,975	1,082,691
	1940	4,610,562	2,106,438	1,180,009
Addresses	1930	2,077,442	1,407,878	659,688
	1940	2,217,640	1,125,845	659,688
Households per address	1930	1.85	1.71	1.64
	1940	2.08	1.87	1.79
Individuals per address	1930	7.51	7.03	6.81
	1940	7.09	6.72	6.59
Average household size	1930	4.40	4.39	4.39
	1940	3.87	3.96	3.99
Distance to CBD (tract centroid)	1930	4.43	4.32	4.30
	1940	4.61	4.47	4.30
Population density (tract)	1930	0.013	0.013	0.013
	1940	0.012	0.012	0.013
Percent black (tract)	1930	0.076	0.073	0.066
	1940	0.084	0.078	0.078

Note: The "All" column reports statistics for the full sample of census records across all ten cities. The "Quality Address" column reports statistics for census records that had an address that passed our quality checks as described in the Data Appendix. The "Matched Address" column reports statistics for the sample of quality addresses that could be matched across the 1930 and 1940 census. The distance to CBD is defined as the distance from the central business district to the centroid of the 1940 tract. All tract variables refer to the 1940 census tract.

Table 27: Decomposing transition

	Log Price			Log Occupancy		
	No Controls	Controls	ED FE	No Controls	Controls	ED FE
	(1)	(2)	(3)	(4)	(5)	(6)
Rented	-2.244***	-2.238***	-2.216***	0.184***	0.181***	0.183***
	(0.003)	(0.003)	(0.003)	(0.002)	(0.002)	(0.002)
Transition < 10%	0.005	-0.007	-0.018	0.022***	0.017*	-0.008
	(0.012)	(0.012)	(0.013)	(0.009)	(0.009)	(0.010)
Rented < 10%	0.071***	0.087***	0.089***	0.066***	0.065***	0.053***
	(0.023)	(0.022)	(0.021)	(0.016)	(0.016)	(0.017)
Transition 10-50%	-0.142***	-0.080***	-0.015	-0.000	-0.012	-0.025
	(0.020)	(0.020)	(0.022)	(0.014)	(0.014)	(0.017)
Rented x 10-50%	0.105***	0.141***	0.111***	0.152***	0.153***	0.137***
	(0.034)	(0.033)	(0.032)	(0.024)	(0.024)	(0.025)
Transition 50-100%	-0.266***	-0.166***	-0.089**	-0.042	-0.046*	-0.028
	(0.039)	(0.038)	(0.043)	(0.027)	(0.027)	(0.033)
Rented x 50-100%	0.461***	0.499***	0.506***	0.290***	0.286***	0.238***
	(0.050)	(0.048)	(0.049)	(0.035)	(0.035)	(0.038)
Observations	242,441	241,793	242,441	247,169	246,234	247,169
R-squared	0.738	0.757	0.802	0.202	0.212	0.251

Note: The first three columns report the OLS estimation of equation (4.5.7) on our baseline sample of homes that were single family, owner occupied, and located on a block with no black residents in 1930 with racial transition disaggregated to black share strictly between zero and ten percent, black share between ten and fifty percent, and black share strictly above 50 percent. The first and fourth columns controls only for price and occupancy of the address in 1930. The second and fifth columns add controls share renters and total number of addresses at the block level, and share black, share immigrant, share laborer, mean age, median home value, median rent, and median occupational score at the neighborhood level. The third and sixth columns drop the neighborhood controls and includes ED fixed effects.

Table 28: Main results excluding longstanding white residents

Panel A: Log price	No Controls (1)	Controls (2)	ED FE (3)	All Obs. FE (4)	Rental FE (5)
Rented	-2.217***	-2.214***	-2.191***	-2.136***	-2.049***
	(0.003)	(0.003)	(0.003)	(0.002)	(0.005)
Racial Transition	-0.264***	-0.150***	-0.090**	-0.124***	-0.084
	(0.039)	(0.038)	(0.043)	(0.036)	(0.078)
Rented x Transition	0.460***	0.496***	0.503***	0.371***	0.272***
	(0.050)	(0.048)	(0.049)	(0.038)	(0.075)
Observations	242,441	241,793	242,441	399,964	151,501
R-squared	0.738	0.757	0.802	0.819	0.731

Panel B: Log occupancy	No Controls (1)	Controls (2)	ED FE (3)	All Obs. FE (4)	Only Rentals (5)
Rented	0.167***	0.187***	0.188***	0.181***	0.150***
	(0.003)	(0.002)	(0.002)	(0.002)	(0.004)
Racial Transition	-0.020	-0.046*	-0.012	-0.043	0.044
	(0.030)	(0.027)	(0.033)	(0.029)	(0.063)
Rented x Transition	0.298***	0.293***	0.240***	0.185***	0.046
	(0.038)	(0.035)	(0.038)	(0.030)	(0.063)
Observations	233,053	227,347	228,221	335,343	101,671
R-squared	0.020	0.221	0.261	0.296	0.373

Note: This table replicates Table 13 except for dropping white households that had lived in the same address in 1935 from the sample.

Table 29: Housing market discrimination excluding longstanding white residents

	Black < 5% (1)	Black < 10% (2)	Black > 40% (3)	Black > 60% (4)
Rented	-2.193***	-2.192***	-2.114***	-1.991***
	(0.003)	(0.003)	(0.091)	(0.116)
Black Household	0.322***	0.250***	0.085	-0.030
	(0.104)	(0.072)	(0.079)	(0.096)
Rented x Black Household	0.199	0.054	0.328***	0.325**
	(0.183)	(0.132)	(0.120)	(0.144)
Black Pioneer Premium	0.38	0.28		
Black Rental Premium			0.39	0.38
Observations	220,674	221,629	808	520
R-squared	0.775	0.775	0.822	0.838

Note: This table replicates Table 16 except for dropping white households that had lived in the same address in 1935 from the sample.

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