(Sub)Urbanization of Commercial Real Estate Development from 1980 to 2020

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Abstract

We describe the spatial evolution of commercial real estate development from 1980 to 2020. Using geolocated construction year data, we identify trends in within-city development locations and potential drivers of urban versus suburban development decisions in major US cities. We find substantial suburbanization trends in CRE development up to the turn of the last century, with a shift towards the re-urbanization of multifamily, office, and retail beginning in the 2000s. The suburbanization trend is strongest for large and medium-sized car-oriented cities, whereas later urbanization is more prominent in large transit-oriented cities. The location of new multifamily and office development is highly sensitive to changes in the suburbanization of residential population, within-city travel speeds, and the migration of college-educated workers to central cities.

1 Introduction

The spatial organization of American metropolitan areas has undergone profound shifts over the past several decades. Households and jobs have moved between urban cores and suburban peripheries in response to economic, demographic, and infrastructural changes. The latter part of the 20th century saw significant suburbanization of both households and employment; however, by the early 2000s, many central cities regained their primacy as people and jobs returned to city centers. These shifts have had significant implications for real estate development and investment. And yet, a full accounting of commercial real estate (CRE) development location trends during these decades of suburbanization and urbanization does not exist nor is there a quantitative exploration of channels and mechanisms for these trends. We seek to fill in these knowledge gaps by examining how CRE development patterns have evolved over the past 40 years, with a special focus on the relationship between shifting residential preferences and employment opportunities across central cities and suburban areas.

Extant literature has identified a number of contributors to the rapid suburbanization of the population within American cities during the last century. One such contributor was the improvements in transportation technology and infrastructure, which increased travel speeds and reduced commuting costs, making it easier for households to live further from central cities (Baum-Snow, 2007). The expansion of the interstate highway system played a crucial role, enabling decentralization of households by lowering the cost of accessing urban job centers from suburban locations (Glaeser and Kahn, 2001). In addition to transportation improvements, suburbanization was influenced by shifting amenity values, as many households sought larger homes, better schools, and lower crime rates compared to central city neighborhoods (Brueckner and Rosenthal, 2009). Racial preferences and discriminatory housing policies, such as redlining and exclusionary zoning, also facilitated white flight and reinforced suburban expansion patterns (Massey, 1993). As households moved to the suburbs, jobs followed, reflecting firms' strategic location decisions based on lower land costs, access to suburban workers, and transportation cost savings for inputs and outputs (Glaeser and Kahn, 2001).

More recent re-urbanization trends appear to be driven by rising commuting costs and changing preferences among young, college-educated workers. Couture and Handbury (2020) document a significant increase in the share of young professionals living in city centers since 2000, linked to their demand for urban amenities such as restaurants, nightlife, and cultural institutions. This shift correlates with broader societal changes, including delayed family formation and rising top-income growth among educated workers, which have increased their willingness to pay for downtown living (Gyourko et al., 2013). Additionally, the growing appeal of urban life has encouraged similar households to remain in central cities rather than relocating to the suburbs (Baum-Snow and Hartley, 2020). The resulting transformation has contributed to gentrification and neighborhood reinvestment, often displacing lower-income and less-educated residents, though out-migration is also linked to improved suburban employment opportunities. As higher-income households returned to urban cores, reinvestment in the built environment followed, fueling new residential and commercial developments that cater to an urban workforce.

In our initial exploration, we document suburbanization and urbanization trends in the location of new or substantially redeveloped commercial real estate from 1980-2020 and begin analyzing the drivers of these trends. We consider multiple methods of urban vs suburban categorization, including distance and relative distance to the central business district, categorization based on residential population density and building density, and whether a tract is within or outside the central city of a metropolitan area. Three stylized facts emerge: (1) substantial suburbanization trends in CRE development were evident well up to the turn of the last century. (2) the mid-2000s marked a shift towards increased central city development with a greater share of multifamily, office, and retail development occurring in the core of cities by the mid-2010s than had occurred in the 1980s. This is especially true for multifamily housing, which began an urbanization trend potentially earlier than other property classes. Industrial is the outlier, where new developments continued a steady movement away from central business districts from 1980 to 2020. (3) the suburbanization trend is strongest for large and medium-sized car-oriented cities, whereas later urbanization is more prominent in large transit-oriented cities.

Next, we explore the city-level correlates of the activity of the CRE development location. These results inform the subsequent development of a theoretical model and causal analysis—, which will be forthcoming. Three groups of correlates are considered that align with existing literature on drivers of household, job, and firm suburbanization as well as more recent observations of urban revitalization: overall patterns of household location within a city related to patterns of segregation, centrality, and suburbanization; variables related to travel speed within a city; share of college educated workers in the central city.

Taken together, we find that the location of new multifamily and office development, in particular, is highly sensitive to changing patterns in the suburbanization of residential populations, the decline of within-city travel speeds, and the migration of college-educated workers to central cities between 1980 and 2020. As the proportion of city-level population living in the suburbs increased over the sample period, multifamily and office development significantly shifted to lower density tracts, further from the CBD and outside central cities in general. In contrast, the increase in average car commute times observed is associated with large declines in the proportion of multifamily and office development taking place in decentralized/suburban locations. Perhaps the most significant effect in terms of explaining the later period urbanization of multifamily and office developments is the increase in the share of central city (or urban neighborhood) population with a college degree or more. The 13 percentage point increase in the share from 1980 to 2020 is associated with a roughly 15 percentage point drop in the proportion of multifamily and office development taking place in decentralized/suburban locations.

These results will inform our next steps, which include developing a theoretical model for CRE development location and causally analyzing the potential mechanisms identified here. Work on these next steps is well underway.

2 Data and Stylized Facts

2.1 Data

Tract-level demographic and socioeconomic data is retrieved from the 1980, 1990, and 2000 Decennial Census as well as the 2005-2009, 2015-2019 American Community Survey (ACS) waves. Commuting zone level transit share and commute time variables are constructed using the IPUMS microdata. We use 1990 commuting zone boundaries based on Public Use Microdata Areas (Autor and Dorn, 2013; Autor et al., 2018). We combine five pairs of commuting zones to reflect larger metropolitan areas: New York City and Newark; Dallas and Fort Worth; Philadelphia and Wilmington, DE; Charlotte and Gastonia-Rock Hill, NC; and Hickory and Morganton, NC. Most regressions contain 216 commuting zones.

For distance to central business district (CBD) calculations for both tracts and buildings, we rely on longitude and latitudes derived from Google Maps (Manduca, 2021). Tract centroids are used to calculate the distance to the CBD for each tract.

We classify Census tracts as 'suburban' using two different measures. The first is a HUD classification based on an American Housing Survey question asked in 2017 and extrapolated to Census tracts within the 2013-2017 5-year ACS using regional and neighborhood characteristics and machine learning techniques (HUD GIS Helpdesk, 2025). Note that this measure is likely biased as the classification is based on 2017 observations of the built environment. Thus, tracts classified as urban (suburban) may have been more suburban (rural) in earlier decades. For our second measure, we follow (Baum-Snow, 2020). Census tracts within the *central city*—as defined by Census places[1]—are considered urban, with tracts outside the central place boundaries considered suburban.

The data for CRE development is provided to us by MSCI. More specifically, we use the MSCI Real Capital Analytics (RCA) data and data from Dodge Construction Company. The RCA data contains geotagged transactions of properties (plus building characteristics, such as property type) between 2000 and 2021. Each transaction has a construction year associated with it. We use this year per unique building (i.e., we drop repeated observations) to identify the amount of development during pre-specified construction year cohorts. On average, buildings in the CRE market are sold once every 5 to 7 years. Therefore, we additionally used Dodge data (starting in 2015) to ensure that we did not miss developments near the end of the sample (because the property was not sold at completion). Dodge provides data on all properties in the pipeline, plus the year of expected completion. We can link Dodge and RCA data via a unique identifier to ensure that we do not double-count properties that were under development *and* also transacted. Note that the MSCI datasets only include investment-grade commercial real estate. More specifically, properties must have sold for at least $2.5 million in their history once.

A forthcoming analysis, not currently in this draft, will construct ZIP code-level market access measures from both the worker and firm perspectives. We use ZIP Code Business Pattern Data from 1994, 2000, 2010, and 2019. Market access ratios for whites and non-whites will also be constructed to identify differential trends in accessibility. Details of the construction of the market access measure are found in the appendix.

2.2 Trends in decentralization and centralization

We start with a simple analysis of the location of new development relative to the central business district (CBD)—i.e mean log distance to the CBD in kilometers, conditional on commuting zone, for development within a given time period conditional on commuting zone. We group building years as follows, given subsequent merging with Census data: 1970 = 1965-1974, 1980 = 1975-1984, 1990=1985-1994, 1990 = 1985-1994, 2000 = 1995-2004, 2010 = 2005-2013, 2019=2014-2019.

Heterogeneity across city type and building type is considered; a number of observations emerge. From Figure 1, we see decentralization was the dominant trend for new CRE

[1] We use year 2000 Census places but will consider the 1970 definition of central city in future drafts.

development location over the past 40 years. However, by the mid-2000s, the average distance from the CBD for new multifamily development significantly declined and continued to do so over the next decade, which coincided with urban revitalization that began in many cities in the early 2000s. Office development also shows signs of centralization but not until the mid-2010s. Figure 2, Panel (a) reveals that declines in distance to the CBD are most pronounced in large transit-oriented cities.[2]

Distance from the CBD does not fully capture variation in development density of a given location—nonconcentric patterns of urban and suburban development; thus, we also include a nonparametric measurement of urban vs suburban development for comparison in Panels (b) and (c). We calculate the proportion of development taking place in suburban tracts (or outside the central city) within a given commuting zone within a given year and plot the average across the commuting zones. Overall, the results are qualitatively similar to the pattern found using the log distance from the CBD.

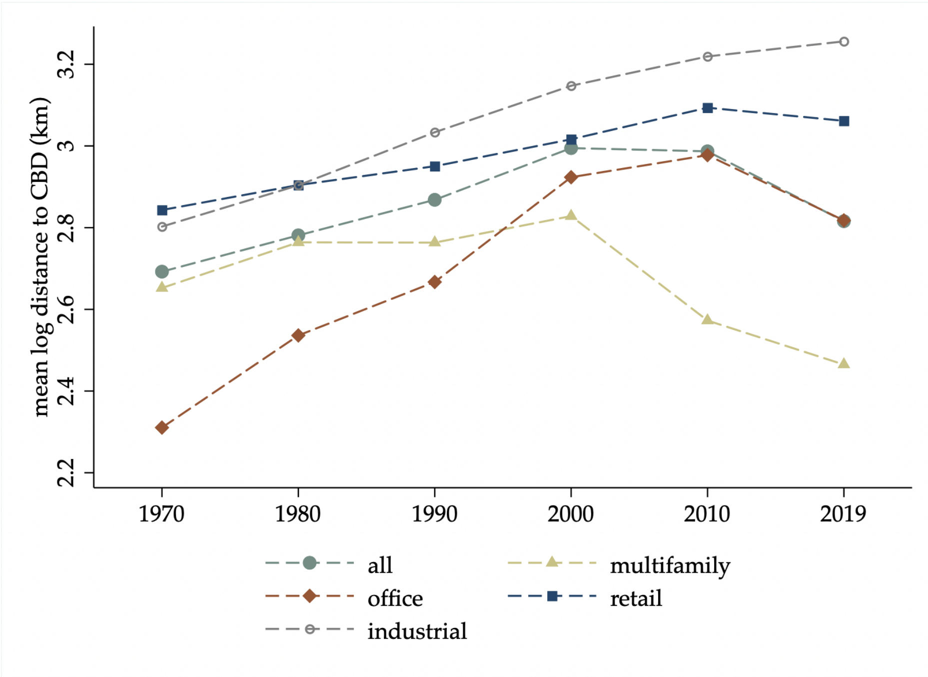
Looking across both city type and property class (Figure 3), we see that regardless of city type, industrial development maintains a steady increasing trend of decentralization. Multifamily residential in both large car and transit cities shows signs of decentralization but the trend begins a decade earlier in transit cities. For transit cities, the mean distance tumbles from a high of 22 kms during 1975-1984 to a low of 13 kms by the end of the 2010s. Strong centralization trends show up strongly for smaller cities ("other") by the mid-2000s after 40 years of significant decentralization. By the end of the 2010s, mean distance returns to 1965-1974 levels. Office and retail within transit cities displays the clearest shift away from decentralization trends by the mid-2010s—average distance of new development returns to the 1965-1974 average.

Turning to city type and property class figures using the HUD measure (Figure 4): from 1965-2004, the proportion of multifamily development within suburban areas of large transit oriented commuting zones oscillated between about 54% and 58%. However, after 2004, the vast majority of development within these cities was no longer in suburban low-density tracts. By 2015-2019, less than 35% of development within large transit cities was in suburban tracts. In these same cities, an initial suburbanization trend for office development reverses beginning in the mid-2000s. Retail and industrial properties show steady suburbanization trends; however, retail in large transit cities is incredibly stable, with about 70% of development within a city taking place in suburban areas on average.

[2]We include Boston, Chicago, Philadelphia, DC, San Francisco, Atlanta, Los Angeles and "big transit" cities. Big Car cities include Dallas/Fort Worth, Houston, Miami, Seattle, Detroit, San Diego, Minneapolis/St. Paul. The other category includes the remaining cities over a population of 250,000.

Figure 5 shows similar patterns to the pure distance and density-based measures. Namely, an increasing proportion of development was outside of the central city for the early decades (1970s-1990s), with centralizing trends in multifamily and office in more recent decades, especially within large transit-oriented cities.

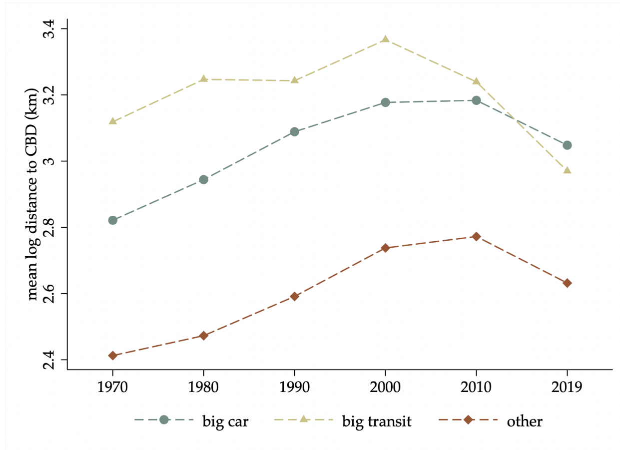
Figure 1: Mean log distance of new development to CBD conditional on commuting zone



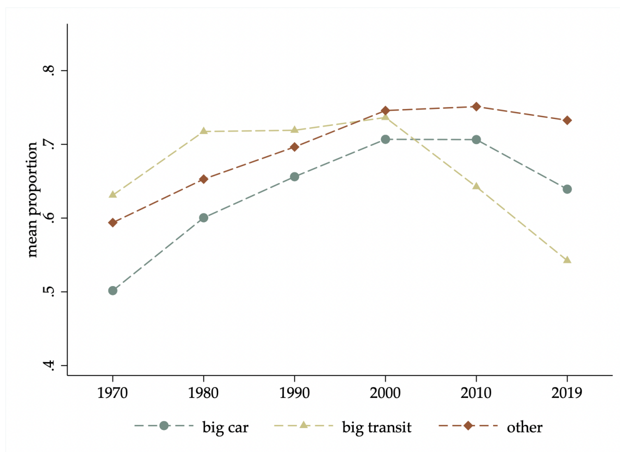
Next, we present a figure similar to (Baum-Snow, 2020)'s Figure 1 showing the CDF of commercial development with respect to the distance from the CBD (see Figure 6). The plots of the CDF with respect to central city boundaries highlight the decentralizing-to-centralizing trend as well. Here, we assign a distance of one to the census tract within the central city that is furthest from the CBD. We plot only 1980 (1975-1984), 2000 (1995-2004), and 2019 (2015-2019) for ease of visual comparison. Subfigure (a) plots a CDF for all developments (within and outside the central city), subfigures (b) and (c) present the CDFs for developments within the central city and outside the central city separately. Note that developments outside the central city may have a relative distance less than one given central city boundaries are nonconvex. Combined, these figures show a strong trend towards *highly* central urban development by the end of the 2010s, with the relative location of suburban development remaining fairly consistent from the 2000s into the 2010s.

We additionally present the central city CDFs by property class in Figures 7 - 9. Similar to other findings, the CDFs for all developments hint towards a centralization of multifamily and office at the very core of central cities by the end of the 2010s (Figure 7). Focusing on the CDFs for just the central city, multifamily, office, and even retail display greater central masses of development in the late 2010s as compared to 1975-1984. This is most pronounced for multifamily development. The location of industrial urban development remains stable from 2000 to 2019 in terms of relative distance within the central city. The location of suburban development for each property type also remains stable from 2000 to 2019.

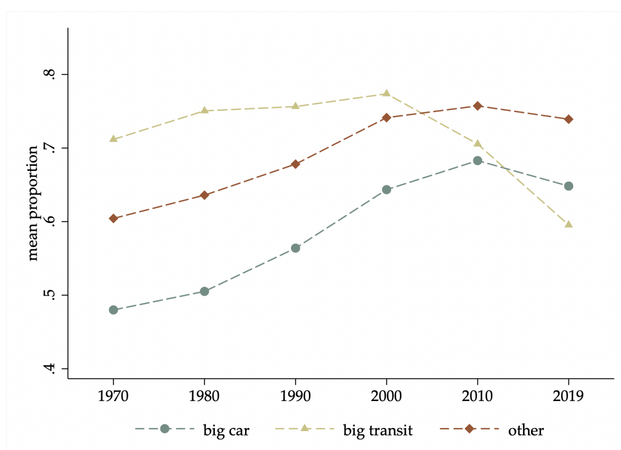
Figure 2: Average decentralization/suburbanization by city type, all building classes



(a) log distance

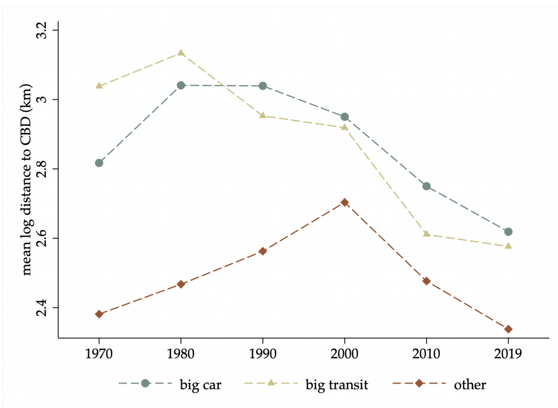


(b) HUD measure of suburban development

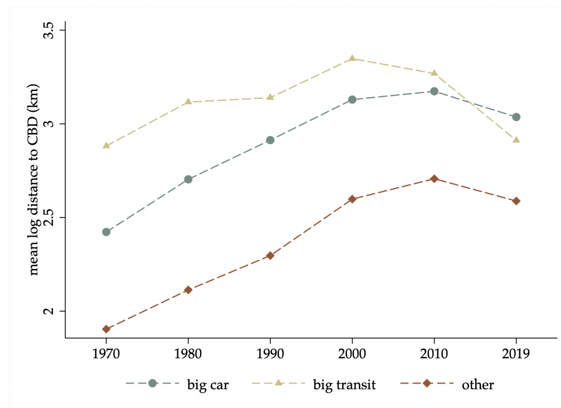


(c) Central City measure of suburban development

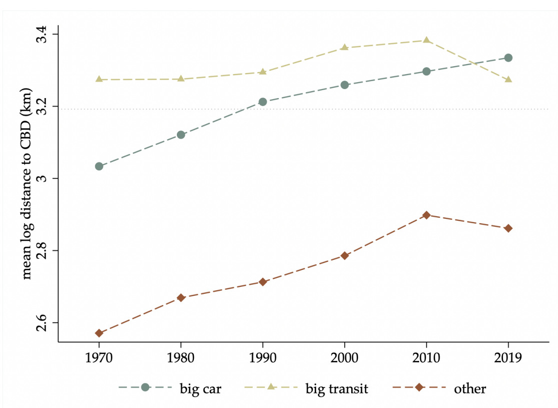
Figure 3: City heterogeneity of mean log distance to CBD, by building type



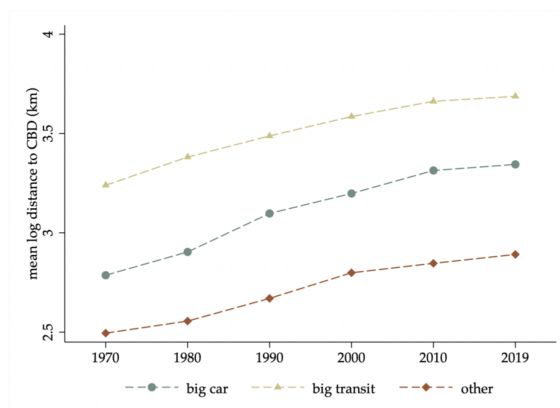
(a) multifamily



(b) office

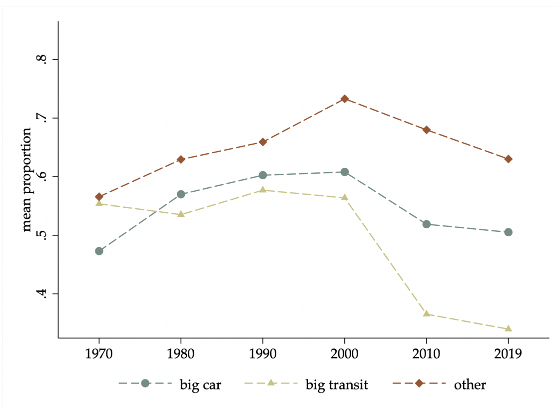


(c) retail

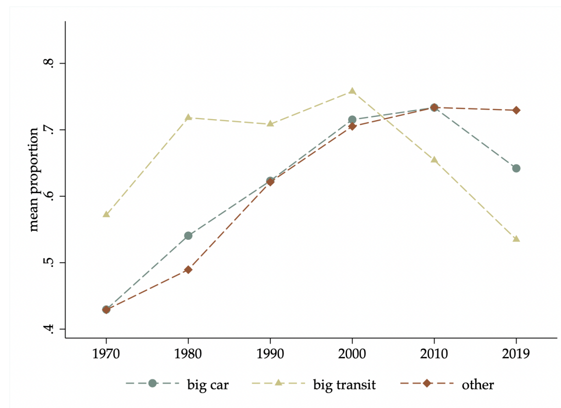


(d) industrial

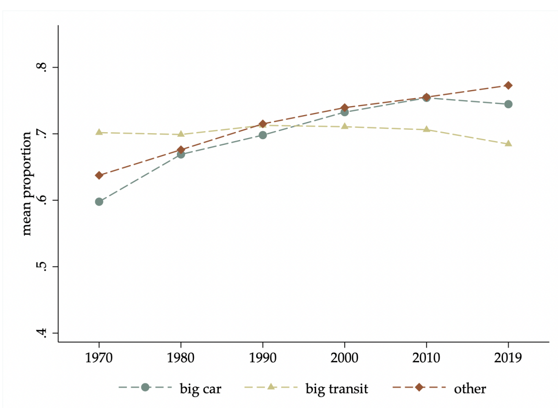
Figure 4: Mean proportion suburban development by building and city type



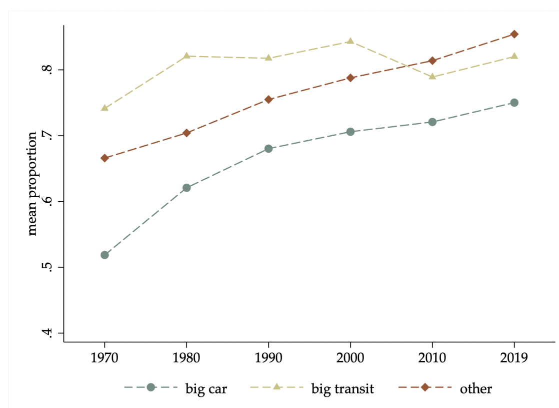
(a) multifamily



(b) office

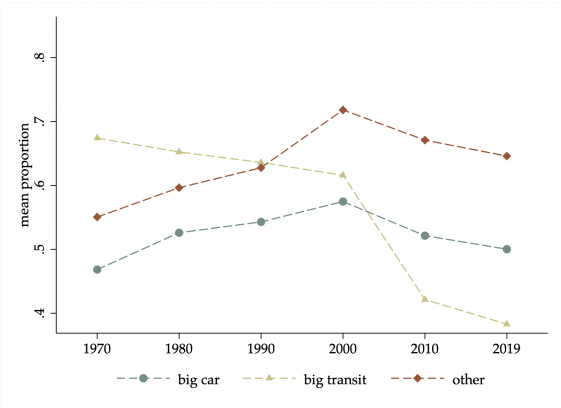


(c) retail

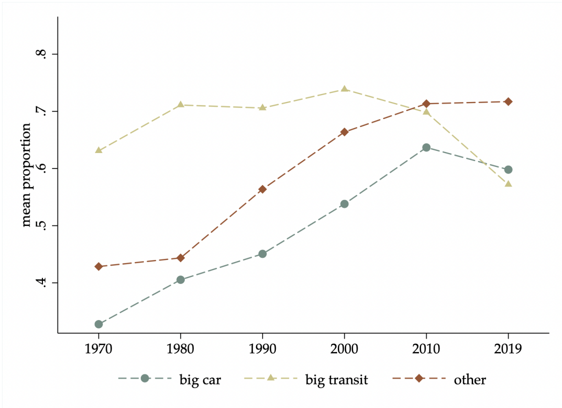


(d) industrial

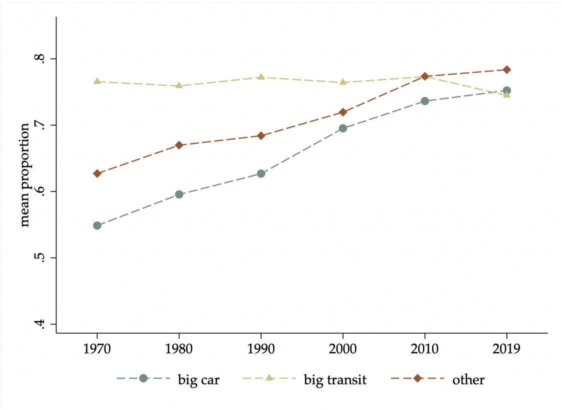
Figure 5: Mean proportion of development outside the central city by building and city type



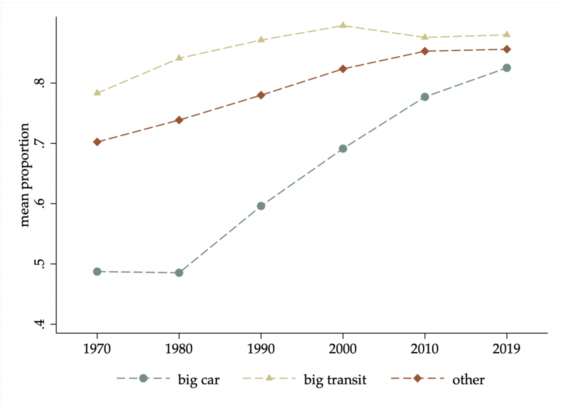
(a) multifamily



(b) office

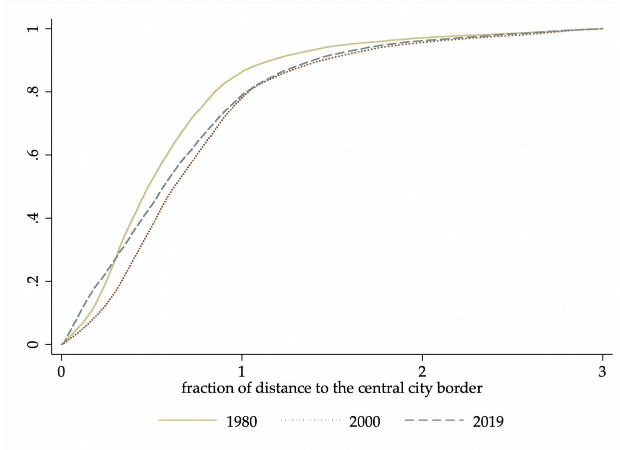


(c) retail

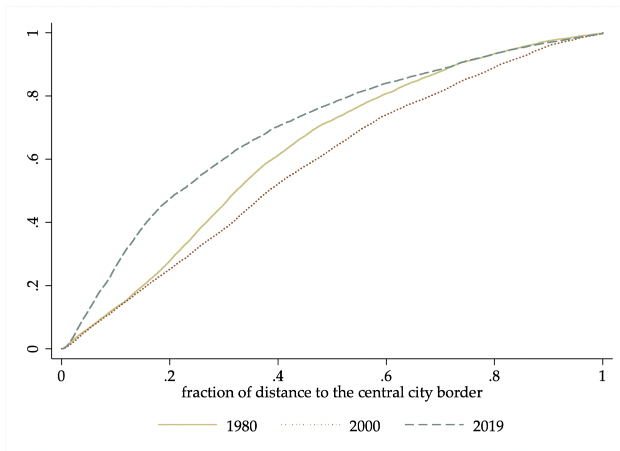


(d) industrial

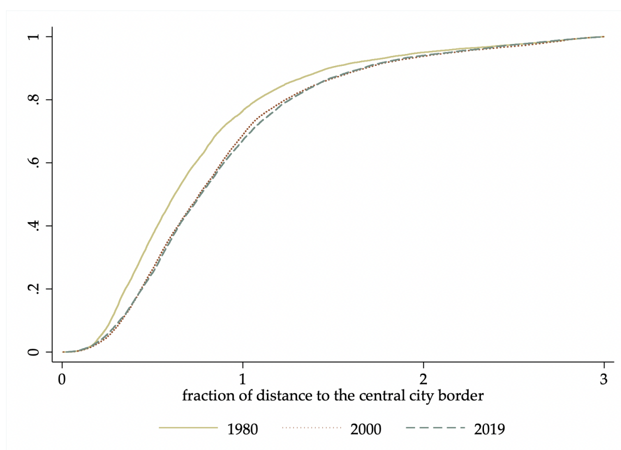
Figure 6: CDF wrt relative distance to central city boundary, all building types



(a) all



(b) within central city



(c) outside central city

Figure 7: CDF wrt relative distance to central city boundary, by property type

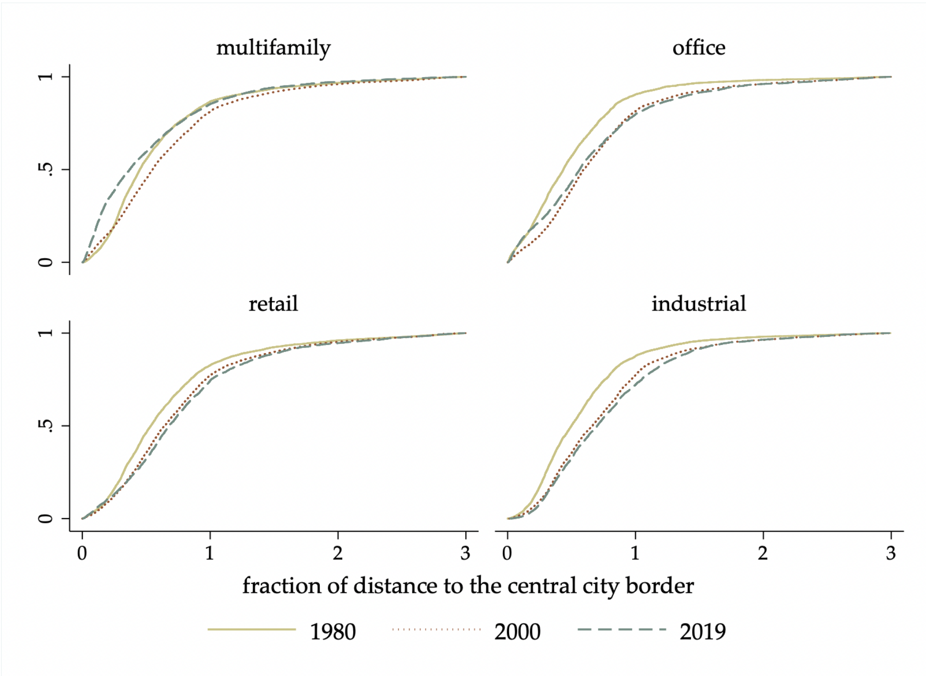


Figure 8: CDF for developments w/in central city by building types

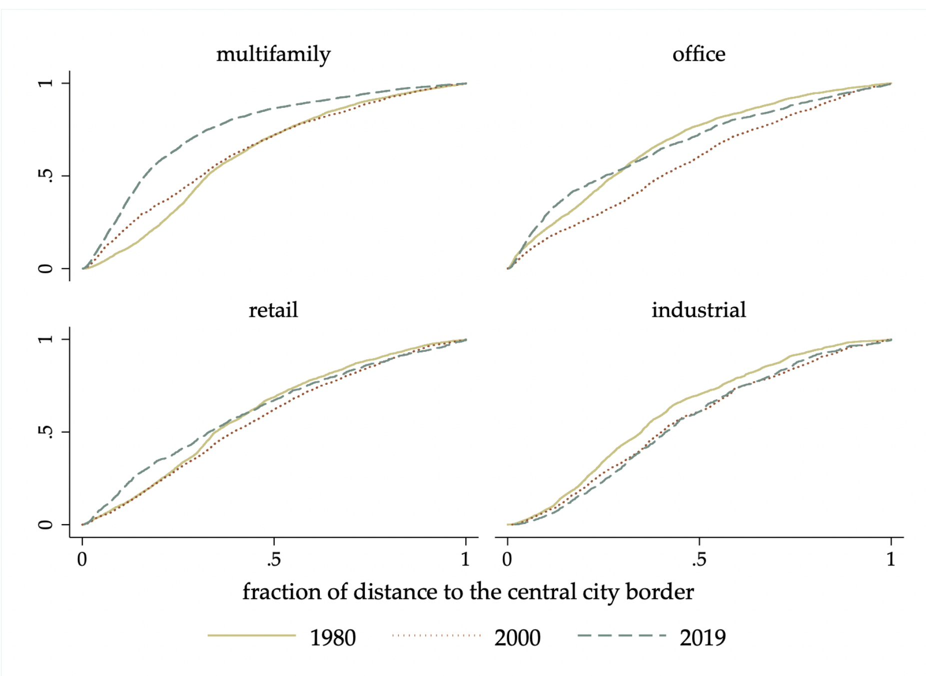
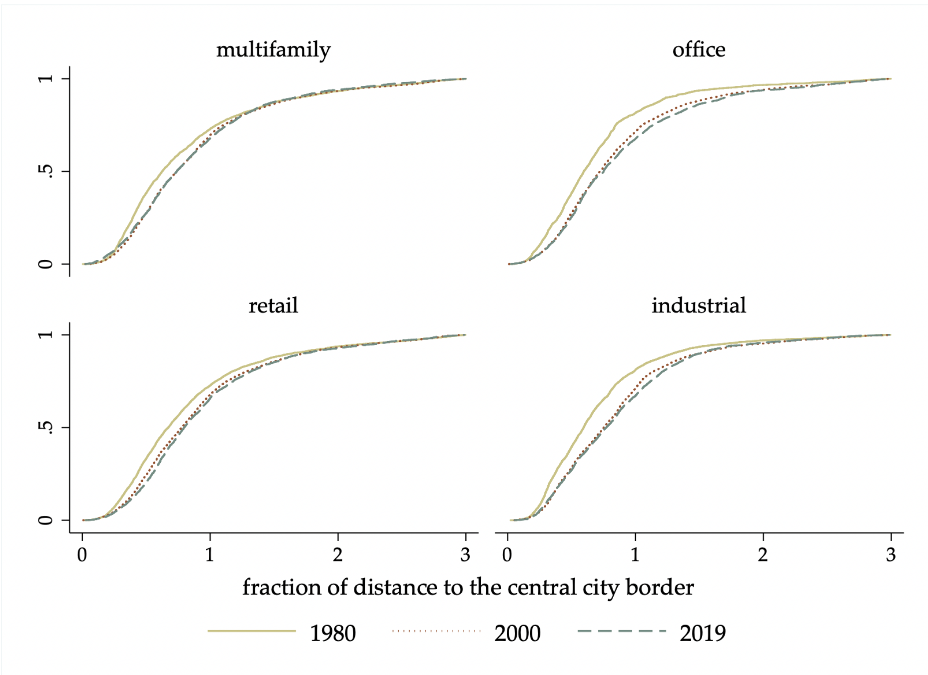


Figure 9: CDF for developments outside the central city by building types



3 Methods

3.1 Tract-level Analysis

Our first specification is a tract level analysis that explores the relationship between development location and city- and tract-level characteristics over time. Our dependent variable of interest is the proportion of development within a given commuting zone taking place in a given Census tract. We revert this variable to a count variable in order to model the count within a poisson setting with the inclusion of the total count of development within the commuting zone as a control. Coefficients are interpreted as incidence risk ratio for new tract-level development.

$$Bld_{ict} = \beta_t \mathbb{1}[suburb_i] + TotBld_{ct} + \gamma_t + \epsilon_{ict} \tag{1}$$

where Bld_{ict} is the count of new developments in tract i in city c in time period t. $\mathbb{1}[suburb_{ic}]$ is an indicator for whether tract i is outside the central city. $TotBld_{ct}$ is the total amount of new development within city c during time period t. We restrict the coefficient to one. Time period fixed effects are included, γ_t.

Analysis begins with a baseline version of Equation 1 omitting tract-level controls and retaining only the time period fixed effects. To this baseline model, we add the following sequentially and plot the β_t coefficients:

- commuting zone by year fixed effects
- share white, share college educated, log mean household income
- lagged count of development

Forthcoming work will consider decomposition analysis along with the location choice model for new development.

3.2 Market Access Analysis

Forthcoming. Goal is to understand how the location of new CRE developments maps to firm market access to employees and residential market access to employment over the time period considered. See Appendix for market access variable construction.

3.3 Commuting Zone-level Analysis

We construct commuting zone×year measures of the proportion of development taking place in the suburbs (HUD and central city classifications both considered) as well as average log distance of development from CBD. Based on previous literature, we select a number of commuting zone-level characteristics that may be be associated with within-city development location choice.

Our first set of measures considers the variation of within-city location by racial groups; we employ a dissimilarity index (white vs non-white households), and a white-centrality measure. The dissimilarity index for a given commuting zone is constructed as follows:

$$Dissimilarity = \frac{1}{2}\sum_{i=1}^{N}\left|\frac{w_i}{W} - \frac{nw_i}{NW}\right| \tag{2}$$

where w_i and nw_i represent the White and non-White population count in tract i. W and NW represent the total White and non-White population in the commuting zone. Larger values indicate more White and non-White separation. Population counts from the Decennial Census and ACS are used to construct both indexes.

Centrality measures the white-population weighted average distance from census tract centroid to the commuting zone central business district (CBD). Given the variation in the commuting zone total area, the population-weighted average distance is standardized with respect to the average distance from all census tracts to the center. The centrality of a commuting zone is calculated as follows:

$$Ctr = \frac{\sum_{i=1}^{N} d(i, CBD)/N}{\sum_{i=1}^{N}(w_i/W)\cdot d(i, CBD)} - 1 \tag{3}$$

where $d(i, CBD)$ is the distance from the centroid of census tract i to the CBD and w_i/W is the weight assigned to tract n based on the white population share in tract i with respect to the total white population within a given commuting zone. A number larger than zero indicates a population is more centrally located than would be expected on average.

The next two correlates relate to travel mode and commuting time—share of commuters taking transit, commute time for automobile commuters—and provide slightly different measures of within-city travel time. Decennial Census and ACS surveys are used to construct commuting zone level measures for each period considered.

Lastly, we construct a commuting zone level measure of the share of population in the suburbs and the share of urban (or central city) residents with a college degree or more.

We regress the share of our three measures of decentralization and suburbanization on each correlate separately and include two-way commuting zones and year-fixed effects. We additionally control for the log of commuting zone-level population.

$$Y_{ct} = \beta X_{ct} + \eta Pop_{ct} + \lambda_c + \gamma_t + \epsilon_{ct} \tag{4}$$

where Y is the suburban development share or average log distance of new development from CBD, X is the city-level correlate dissimilarity, centrality, transit share, car commute time, suburban pop. share, central average tract share college grads, Pop is the log of city-level population in commuting zone i in period t, λ is the commuting zone fixed effect, and γ is the period fixed effect.

4 Results

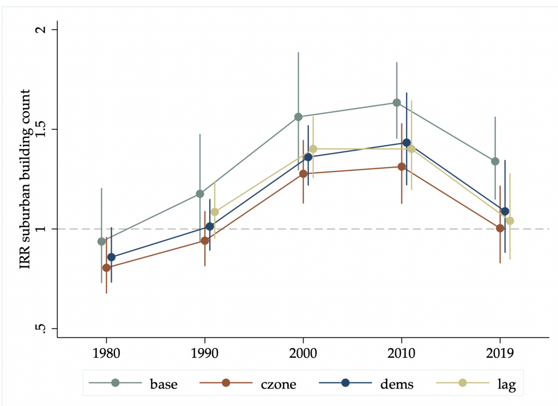
4.1 Role of demographics in centralization/decentralization

In this section, we explore patterns of new development at the Census tract level to identify the role of neighbourhood demographics/socioeconomics in the development patterns found in Section 2.2. Figure 10 presents coefficients from Equation 1. We first consider all property types combined to get a sense of the overall CRE development activity. In Figure 11 we consider multifamily and office buildings, and in Figure 12 we focus on retail and industrial properties.

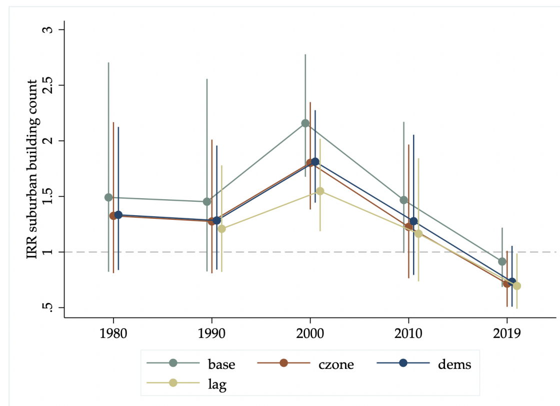
Panel A in Figure 10 shows the incidence risk ratio (IRR) for the new suburban development activity across all cities in our sample. Estimates of the baseline regression shown in Equation 1 show an increase in the likelihood of suburban development (IRR being greater than one) across all property types starting in the 1980s all the way to the 2010s, with a marked decline in 2019. While the likelihood of suburban development (relative to urban) has been higher across this time period, it exhibits an inverse U-shape. The inclusion of the local demographic variables (share white, share college educated, log mean household income) explains little of the observed patterns, while the inclusion of the commuting zone by year fixed effects seems to explain a great deal of the observed variation. This suggests that the observed pattern of lower likelihood of new suburban development in the late 2010s is, to a large extent, driven by city-level trends.

Panel B in Figure 10 shows the incidence risk ratio (IRR) for the new suburban development activity in large predominantely transit-oriented cities. We see that in the case of large transit-oriented cities, the trend in the de-suburbanisation of the new development started in the early 2000s, leading to a significantly lower likelihood of new suburban development in 2019 (estimated IRR is below one). Panel C, on the other hand, shows that in the case of large, predominantly car-oriented cities, we see an increasing trend in the likelihood of new suburban development starting in the 1980s and going all the way to 2019. These results point to markedly different patterns in suburban development depending on the predominant mode of transport across cities.

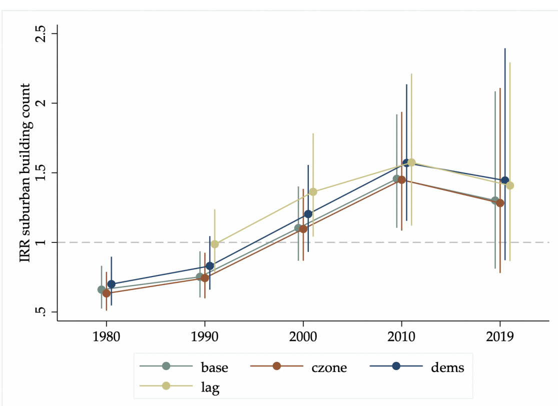
Figure 10: Suburban tract IRR of tract-level building count, central city measure



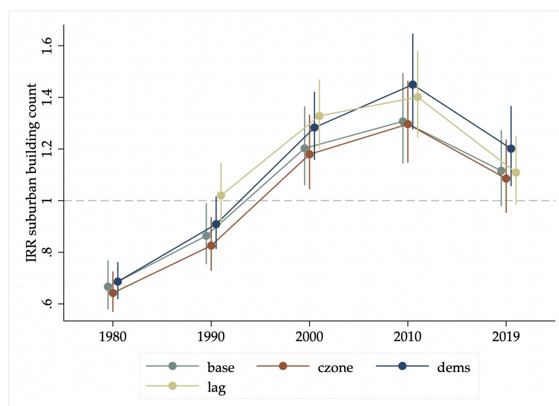
(a) All Cities



(b) Big Transit

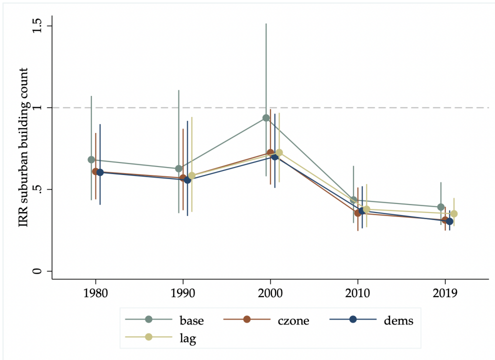


(c) Big Car

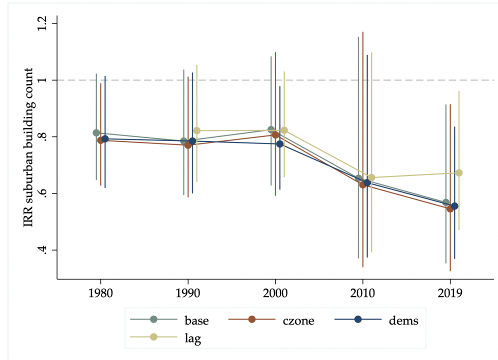


(d) Other

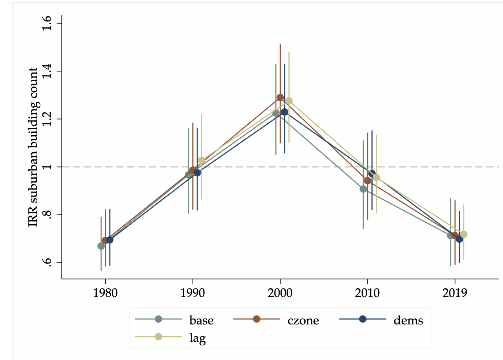
Figure 11: Suburban tract IRR: Multifamily and Office



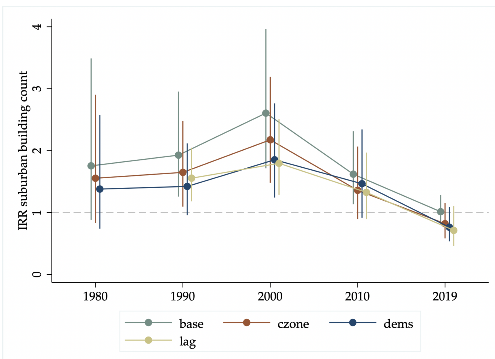
(a) multifamily: big transit



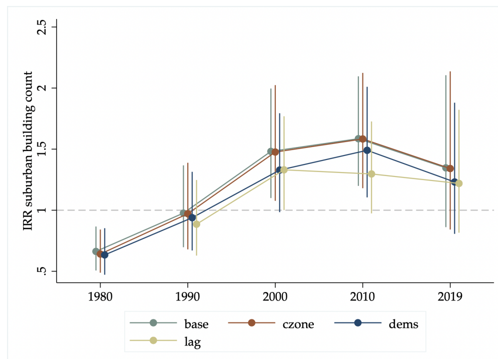
(b) multifamily: big car



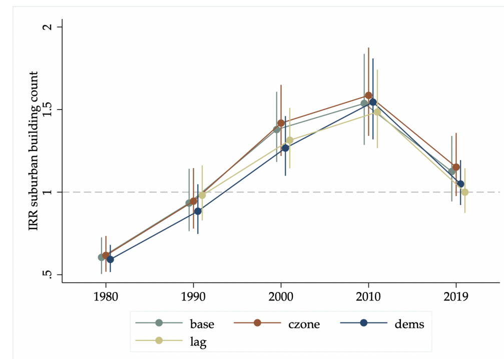
(c) multifamily: other



(d) office: big transit

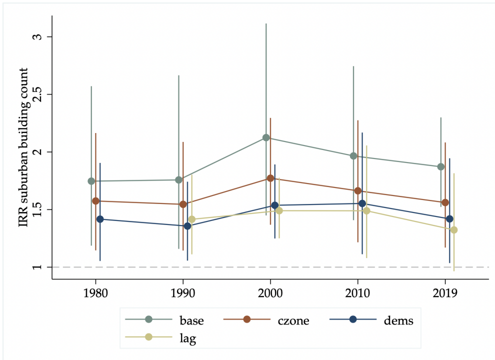


(e) office: big car

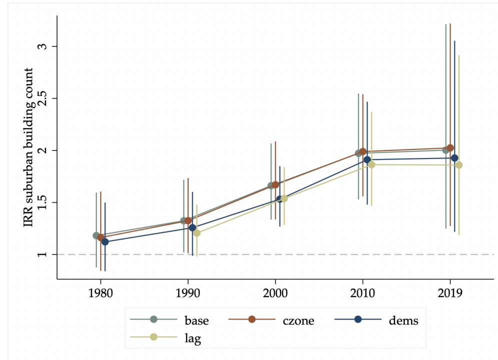


(f) office: other

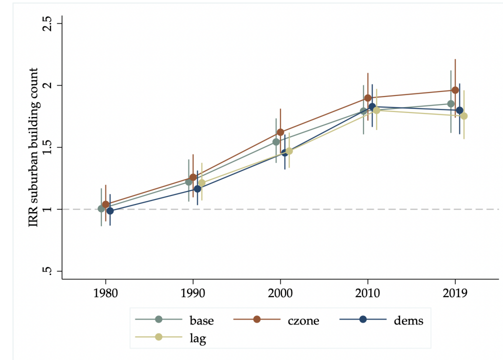
Figure 12: Suburban tract IRR: Retail and Industrial



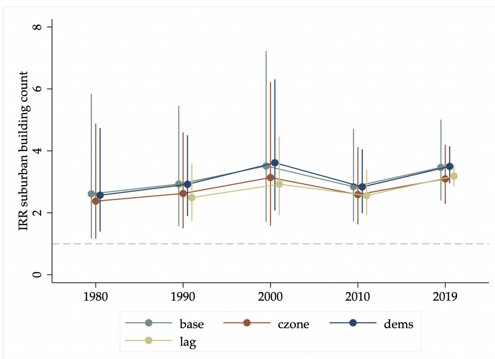
(a) retail: big transit



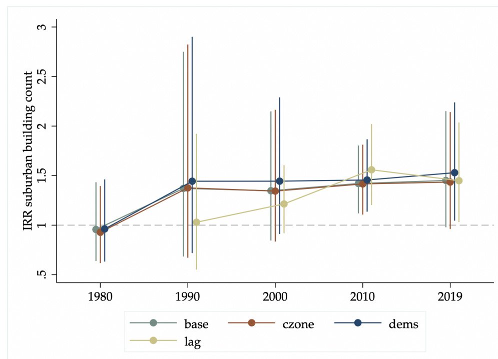
(b) retail: big car



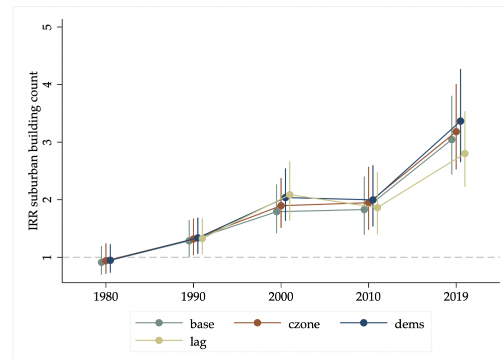
(c) retail: other



(d) industrial: big transit



(e) industrial: big car



(f) industrial: other

4.2 Commuting Zone-Level Analysis

Tables 1-3 present the coefficients for the commuting zone level analysis. We pull out multifamily and office samples for separate specifications. Commuting zone level means of each variable for each time period are presented at the bottom of the tables.

Starting with the full sample of buildings, which includes multifamily, office, retail, and industrial (Table 1), how the residential population is distributed across a city shows some correlation with decentralization/suburbanization. The dissimilarity index has declined over time, implying a decline in city-level segregation patterns (on average). With a positive and somewhat significant coefficient for the central city suburb classification (Panel C) this implies an increase in the proportion of development outside of the central city. The centrality of white residents shows less of a trend over time, but the somewhat significant negative coefficients for Panel (b) and (c) imply that as white households become more (less) centrally located, we expect a decline (increase) in the proportion of development taking place in suburban neighborhoods. The effect size is small, however. Not surprisingly,the suburban population proportion is strongly positively correlated with decentralization/suburbanization. The increase in suburban population proportion from 1980 to 2019 implies a 7.7% increase in the distance a development is from the CBD on average or a 5.8 or 7.8 percentage point increase in the proportion of development occurring in the suburbs (with respect to Panel (b) and (c) measures). However, over this same time period, the share of people over 25 with college degrees or more within urban neighborhoods—i.e. in the central city or within dense tracts—increases from 0.18 to 0.30 and this increase is associated with a large decline in the share of development occurring in the suburbs. From Panel (b), we find a 10-percentage-point decline in the suburban share of development over this time period; from Panel (c), we find a 6.5-percentage-point decline in the share of development taking place outside the central city.

Coefficients for variables related to travel speed display intuitive signs. In the first few decades of the sample, transit share declines but then rebounds by 2010. The significant negative coefficient on transit share in each panel implies that the initial decline in the share is associated with an increase in decentralized/suburban development and a decline after the mid-2000s. The average commute time by car increases by about 3.5 mins during our sample period; this is associated with a 7% decline in the average development distance from the CBD, a 6.8 percentage point decline in the proportion of development occurring in suburban tracts, and a 8.9 percentage point decline in the proportion of development occurring outside the central city. Together, these results provide evidence that declining travel speeds are associated with more central development.

Focusing on multifamily development (Table 2), we see strong correlations with urban college share, suburban population share, and car commute time. Signs and magnitudes are qualitatively similar to the full sample. The largest and most significant effect for the travel speed variables is found in Panel (c), where the increase in car commuting time from 1980 to 2019 of 3.5 minutes is associated with a decline in the proportion of development outside the central city by 12 percentage points. We find the 0.13 percentage point increase in the urban (or central city) college share is associated with a 20% decline in the average development distance from the CBD, a 12 percentage point decline in the proportion of development occurring in suburban tracts, and a 15 percentage point decline in the proportion of development occurring outside the central city. These magnitudes are nearly double that of the full sample.

The effect of urban college share on the location of office development is also large and significant for the measures used in Panels (b) and (c). Specifically, we find a 15-percentage-point decline in the proportion of development occurring in suburban tracts and an 11-percentage-point decline in the proportion of development occurring outside the central city. Increasing share of suburban population also has an outsized effect on office location—as compared to the full sample. The 13 percentage point increase in the share of suburban population is associated with a 25% increase in the distance an office development is from the CBD and a 12 percentage point increase in the share of development taking place in suburban tracts within a city. These findings imply that office development is quite sensitive to suburban population growth. Travel speed variables show some significant and moderately large effect sizes. Namely, a one percentage point increase in the transit share is associated with a 4-percentage-point decline in the average office development distance from the CBD. The 3.5-minute increase in car commuting time over the time period considered results in a 12% decline in the average development distance from the CBD, a 12-percentage-point decline in the proportion of development occurring in suburban tracts, and an 8-percentage-point decline in the proportion of development occurring outside the central city. Lastly, we note a suggestive 2.7 percentage point decline in the proportion of office development outside the city center as white segregation levels declined over the time period considered.

Taken together, we find that the location of new multifamily or office development is highly sensitive to changing patterns in residential population location and travel speed within cities.

Table 1: Correlates of Decentralization/Suburbanization: All property types

	(1) diss. index	(2) white centrality	(3) transit share	(4) commute time	(5) suburban pop. prop.	(6) college prop.
Panel (a): log distance to CBD						
var	0.0296	-0.0146	-2.4747**	-0.0211**	0.6789***	-0.3819
	(0.1642)	(0.2073)	(1.1790)	(0.0107)	(0.2514)	(0.2323)
lpop	0.2175***	0.2158***	0.2401***	0.2624***	0.1744**	0.1874**
	(0.0812)	(0.0782)	(0.0844)	(0.0821)	(0.0810)	(0.0847)
R^2	0.889	0.889	0.889	0.889	0.889	0.888
Panel (b): HUD measure of suburban development proportion						
var	-0.0602	-0.0973*	-1.2289*	-0.0198***	0.5283***	-0.8462***
	(0.0855)	(0.0509)	(0.7395)	(0.0055)	(0.1292)	(0.1388)
lpop	0.2193***	0.2090***	0.2307***	0.2615***	0.1735***	0.2384***
	(0.0313)	(0.0308)	(0.0330)	(0.0319)	(0.0323)	(0.0290)
R^2	0.685	0.686	0.687	0.693	0.706	0.718
Panel (c): proportion of development outside central city						
var	0.1356+	-0.1075+	-1.8723*	-0.0257***	0.7078***	-0.5493***
	(0.0743)	(0.0614)	(0.7304)	(0.0056)	(0.1305)	(0.1257)
lpop	0.1975***	0.1856***	0.2143***	0.2517***	0.1775***	0.2247***
	(0.0354)	(0.0370)	(0.0379)	(0.0366)	(0.0309)	(0.0359)
R^2	0.8651	0.8652	0.8668	0.8708	0.8753	0.8678
Observations	1063	1063	1063	1063	1057	1039
mean 1980	0.6029	-0.0450	0.0262	19.8283	0.6807	0.1840
mean 1990	0.5671	-0.0115	0.0191	20.3450	0.7520	0.2187
mean 2000	0.5430	-0.0496	0.0172	22.3685	0.7687	0.2492
mean 2010	0.5646	-0.0564	0.0185	22.4407	0.7823	0.2535
mean 2019	0.5384	-0.0544	0.0190	23.2861	0.7903	0.3071

Standard errors in parentheses

+ $p<0.10$, * $p<0.05$, ** $p<0.01$, *** $p<0.001$

Note:

5 Conclusion

In this paper we document suburbanization and urbanization trends in commercial real estate (CRE) development from 1980-2020 and analyze the drivers behind these trends. We use various methods to categorize urban vs. suburban, including proximity to the central business district and building density. Three key findings emerge: (1) significant suburbanization in CRE development persisted until the early 2000s. (2) The mid-2000s marked a shift towards increased development in central cities, particularly for multifamily housing, which began urbanizing earlier than other property types. Industrial development, however,

Table 2: Correlates of Decentralization/Suburbanization: Multifamily

	(1) diss. index	(2) white centrality	(3) transit share	(4) commute time	(5) suburban pop. prop.	(6) college prop.
Panel (a): log distance to CBD						
var	-0.1232	0.0861	-1.8962	-0.0259	0.4286	-1.5675***
	(0.3505)	(0.2964)	(1.4843)	(0.0184)	(0.4445)	(0.4091)
lpop	0.4084***	0.4176***	0.4284***	0.4671***	0.3526***	0.3896***
	(0.1225)	(0.1215)	(0.1243)	(0.1350)	(0.1189)	(0.1204)
R^2	0.768	0.768	0.768	0.768	0.778	0.780
Panel (b): HUD measure of suburban development proportion						
var	0.0444	-0.0795	-0.1302	-0.0122	0.3854**	-0.8804***
	(0.1563)	(0.1267)	(0.7665)	(0.0076)	(0.1889)	(0.2314)
lpop	0.2904***	0.2818***	0.2918***	0.3181***	0.2491***	0.2933***
	(0.0528)	(0.0519)	(0.0527)	(0.0544)	(0.0542)	(0.0511)
R^2	0.569	0.570	0.569	0.571	0.581	0.590
Panel (c): proportion of development outside central city						
var	0.1895	-0.0435	-0.0914	-0.0352***	0.7055***	-1.1074***
	(0.1740)	(0.1359)	(0.8820)	(0.0088)	(0.1825)	(0.1875)
lpop	0.1789**	0.1744**	0.1801**	0.2591***	0.1707**	0.2145***
	(0.0561)	(0.0585)	(0.0578)	(0.0582)	(0.0513)	(0.0539)
R^2	0.721	0.720	0.720	0.728	0.727	0.731
Observations	949	949	949	949	943	943
mean 1980	0.6102	-0.0461	0.0271	19.8059	0.6755	0.1813
mean 1990	0.5694	-0.0103	0.0209	20.4636	0.7437	0.2251
mean 2000	0.5421	-0.0517	0.0180	22.4694	0.7582	0.2550
mean 2010	0.5585	-0.0605	0.0201	22.5000	0.7643	0.2635
mean 2019	0.5349	-0.0564	0.0197	23.3358	0.7849	0.3130

Standard errors in parentheses

+ $p<0.10$, * $p<0.05$, ** $p<0.01$, *** $p<0.001$

Note:

continued to decline in city centers. (3) Suburbanization is strongest in large, car-oriented cities, while urbanization is more prominent in large, transit-oriented ones.

We then examine city-level correlates of CRE development activity. These results inform the subsequent development of a theoretical model and causal analysis—which is forthcoming. Three correlates align with existing literature on suburbanization drivers and urban revitalization: patterns of household location, travel speed within the city, and the share of college-educated workers in the central city.

Table 3: Correlates of Decentralization/Suburbanization: Office

	(1) diss. index	(2) white centrality	(3) transit share	(4) commute time	(5) suburban pop. prop.	(6) college prop.
Panel (a): log distance to CBD						
var	0.5243	-0.3765	-4.0354*	-0.0344*	1.8145***	-0.4759
	(0.3450)	(0.3047)	(2.2196)	(0.0208)	(0.6484)	(0.5058)
lpop	0.0461	-0.0009	0.1020	0.1219	-0.0206	0.0346
	(0.1594)	(0.1581)	(0.1683)	(0.1729)	(0.1582)	(0.1687)
R^2	0.777	0.777	0.777	0.777	0.781	0.775
Panel (b): HUD measure of suburban development proportion						
var	0.1360	0.0478	-0.5192	-0.0337***	0.3047	-1.1466***
	(0.1584)	(0.1012)	(1.3624)	(0.0086)	(0.2517)	(0.2645)
lpop	0.2015***	0.2064***	0.2083***	0.2776***	0.1707***	0.1949***
	(0.0577)	(0.0610)	(0.0645)	(0.0606)	(0.0651)	(0.0524)
R^2	0.571	0.570	0.570	0.581	0.571	0.588
Panel (c): proportion of development outside central city						
var	0.3142+	-0.1732	-2.0559	-0.0243*	0.9054***	-0.8975***
	(0.1744)	(0.1287)	(1.4187)	(0.0108)	(0.2372)	(0.2070)
lpop	0.2038**	0.1819**	0.2321**	0.2577***	0.1703**	0.2242***
	(0.0612)	(0.0668)	(0.0702)	(0.0656)	(0.0592)	(0.0599)
R^2	0.7623	0.7613	0.7618	0.7633	0.7691	0.7660
Observations	874	874	874	874	874	862
mean 1980	0.6228	-0.0508	0.0316	20.1083	0.6433	0.1886
mean 1990	0.5743	-0.0134	0.0219	20.5223	0.7292	0.2300
mean 2000	0.5418	-0.0542	0.0184	22.5102	0.7557	0.2525
mean 2010	0.5630	-0.0639	0.0200	22.5982	0.7673	0.2583
mean 2019	0.5378	-0.0600	0.0206	23.3949	0.7796	0.3164

Standard errors in parentheses

+ $p<0.10$, * $p<0.05$, ** $p<0.01$, *** $p<0.001$

Note:

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Appendix

Market Access

In this section we outline the construction of our zip code-level differential market access term. Our focus is on the firm's perspective, i.e. for a given location within the city (zip code), what is the differential access to white workers vs non-white workers. From the residential perspective, we consider market access to all jobs for a given location. We do not differentiate jobs by group.[3]

We begin by defining the target market access terms. Commuting zones are indexed by c while market access to jobs from a residential neighbourhood $i \in c$ is denoted as ϕ_{Ri} and market access to workers from employment area $j \in c$ is denoted as ϕ_{Fj}. Specifically, we define residential market access as $\phi_{Ri} = \sum_s w_s^\theta \tau_{is}^{-\kappa\theta}$ and firm market access as $\phi_{Fj} = \sum_r b_r^\theta \tau_{rj}^{-\kappa\theta}$ for wages w, residential characteristics b, travel times τ, labor supply elasticity θ, and commuting elasticity κ. We later construct group-specific ϕ_{Fj} terms—$\phi_{F_j^k}$ and $\phi_{F_j^{k'}}$.

For the construction of the market access terms, consider neighbourhoods (zip codes) indexed by i and j that reside within some c with commute flows L_{ij}, total residential population $L_{Ri} = \sum_j L_{ij}$, white residential population $L_{R_i^k} = \sum_j L_{ij}^k$, non-white residential population $L_{R^{k\prime}{}_i} = \sum_j L_{ij}^{k'}$, workplace population as $L_{Fj} = \sum_i L_{ij}$, and distances between locations as $d_{ij} \geq 1$. We require that $d_{ij} \geq 1$ in order to ensure $d_{ij}^{-\kappa} \in (0, 1]$ for $\kappa > 0$. Here κ is the marginal disutility of travel distance. We additionally let θ denote the elasticity of labor supply.[4] Lastly, let $\bar{s}_c$, $\bar{\tau}_c$, and $\bar{w}_c$ be CZ-specific average speed, average travel time, and average wage, respectively.

Proposition 1. *Consider a standard gravity model of commuting with the form* $L_{ij} \propto \gamma_i \delta_j k_{ij}$, $\forall i, j \in c$. *Given data* $\{L_{Ri}, L_{Fj}, d_{ij}\}_{i,j\in c}$, $\bar{\tau}_c$, $\bar{w}_c$, *and parameters* θ *and* κ, *there exist market access terms* $\{\phi_{Ri}, \phi_{Fj}\}_{i,j\in c}$ *and average speed* $\bar{s}_c$ *that are uniquely consistent with the data.*

Proof. Denote travel time as distance divided by speed: $\tau_{ij} = \frac{d_{ij}}{\bar{s}_c}$. The standard gravity model of commuting yields

$$\frac{L_{ij}}{L} = \pi_{ij} = \frac{b_i^\theta w_j^\theta \tau_{ij}^{-\kappa\theta}}{\sum_r \sum_s b_r^\theta w_s^\theta \tau_{rs}^{-\kappa\theta}} = \frac{b_i^\theta \tilde{w}_j^\theta d_{ij}^{-\kappa\theta}}{\sum_r \sum_s b_r^\theta \tilde{w}_s^\theta d_{rs}^{-\kappa\theta}}, \tag{5}$$

where $\gamma_i = b_i^\theta = (u_i r_i^\beta)^\theta$ for some amenity u_i, housing price r_i, and housing expenditure

[3] Note that publicly available zip code-level employment data does not differentiate employment counts by race or ethnicity. Details on data used to construct the market access variable follow within this section.

[4] Similar to bunten et. al (2023), we use a travel time elasticity rather than semi-elasticity.

share β; and where $\delta_j = \tilde{w}_j^\theta = (\varsigma w_j)^\theta$ for wages w_j. The third equality in Equation 5 holds because commute shares are invariant to speed and the level of wages (π_{ij} is homogeneous of degree zero in $\bar{s}_c$ and ς).

Aggregating Equation 5 by residence and workplace respectively yields:

$$\frac{L_{Ri}}{L} = \pi_{Ri} = \frac{b_i^\theta \tilde{\phi}_{Ri}}{\sum_r b_r^\theta \tilde{\phi}_{Rr}}, \quad \text{and} \quad \frac{L_{Fj}}{L} = \pi_{Fj} = \frac{\tilde{w}_j^\theta \tilde{\phi}_{F_j}}{\sum_s \tilde{w}_s^\theta \tilde{\phi}_{Fs}}, \tag{6}$$

where $\tilde{\phi}_{Ri} = \sum_s \tilde{w}_s^\theta d_{is}^{-\kappa\theta}$ and $\tilde{\phi}_{Fj} = \sum_r b_r^\theta d_{rj}^{-\kappa\theta}$ are modified market access terms. These are level transformations of the true market access shares: Substitution yields $\phi_{Ri} = \frac{\tilde{\phi}_{Ri}}{\varsigma^\theta \bar{s}_c^{-\kappa\theta}}$ and $\phi_{Fj} = \frac{\tilde{\phi}_{Fj}}{\bar{s}_c^{-\kappa\theta}}$.

Proposition 1 in Tsivanidis (2023) establishes that $\{\tilde{\phi}_{Ri}, \tilde{\phi}_{Fj}\}_{i,j\in c}$ are the unique-to-scale solutions of the system:

$$\tilde{\phi}_{Ri} = \sum_s d_{is}^{-\kappa\theta} \frac{L_{Fs}}{\tilde{\phi}_{Fs}} \quad \text{and} \quad \tilde{\phi}_{Fj} = \sum_r d_{rj}^{-\kappa\theta} \frac{L_{Rr}}{\tilde{\phi}_{Rr}}, \tag{7}$$

given $\{L_{Ri}, L_{Fj}, d_{ij}\}$, θ, and κ. Given these data, parameters, and values of $\{\tilde{\phi}_{Ri}, \tilde{\phi}_{Fj}\}_{i,j\in c}$, we only need values of ς and $\bar{s}_c$ to recover $\{\phi_{Ri}, \phi_{Fj}\}_{i,j\in c}$.

Given that $L_{Rr} = L_{R_r^k} + L_{R_r^{k'}}$, i.e. total residential population in r is the sum of white and non-white populations in r, we can rewrite $\tilde{\phi}_{Fj}$ as:

$$\begin{aligned} \tilde{\phi}_{Fj} &= \sum_r d_{rj}^{-\kappa\theta} \frac{(L_{R_r^k} + L_{R_r^{k'}})}{\tilde{\phi}_{Rr}} \\ &= \sum_r d_{rj}^{-\kappa\theta} \frac{L_{R_r^k}}{\tilde{\phi}_{Rr}} + \sum_r d_{rj}^{-\kappa\theta} \frac{L_{R_r^{k'}}}{\tilde{\phi}_{Rr}} \\ &= \tilde{\phi}_{F_j^k} + \tilde{\phi}_{F_j^{k'}} \end{aligned} \tag{8}$$

Note the remainder of the derivation follows from bunten et al. (2024). We proceed by defining $\pi_{ij|i} \equiv L_{ij}/L_{Ri}$, and note that average time is

$$\bar{\tau}_c = \sum_{r\in c} \sum_{s\in c} \pi_{rs} \tau_{rs} = \sum_{r\in c} \pi_{Rr} \sum_{s\in c} \pi_{rs|r} \frac{d_{rs}}{\bar{s}_c} \tag{9}$$

and that $\sum_{r\in c} \pi_{Rr} \sum_{s\in c} \pi_{rs|r} = 1$. Because $\pi_{ij} = \pi_{ij|i}\pi_{Ri}$, it follows that $\pi_{ij|i} = \tilde{w}_j^\theta d_{ij}^{-\kappa\theta}/\tilde{\phi}_{Ri}$.

From Equation 6, $\tilde{w}_j^\theta = \frac{L_{Fj} \sum_s \tilde{w}_s^\theta \tilde{\phi}_{Fs}}{\tilde{\phi}_{Fj} L}$. Note that after some derivation

$$\sum_s \tilde{w}_s^\theta \tilde{\phi}_{Fs} = L \sum_r \pi_{Rr} \frac{\sum_s \tilde{w}_s^\theta d_{rs}^{-\kappa\theta}}{\sum_{s'} \tilde{w}_{s'}^\theta d_{rs'}^{-\kappa\theta}}$$

and so $\sum_s \tilde{w}_s^\theta \tilde{\phi}_{Fs} = L$. Thus, we can express $\tilde{w}_j^\theta = L_{Fj}/\tilde{\phi}_{Fj}$.

Substituting these derivations into Equation 9 gives:

$$\bar{\tau}_c = \sum_{r \in c} \pi_{Rr} \sum_{s \in c} \frac{L_{Fs} d_{rs}^{-\kappa\theta}}{\tilde{\phi}_{Rr} \tilde{\phi}_{Fs}} \frac{d_{rs}}{\bar{s}_c} = \bar{s}_c^{-1} \sum_{r \in c} \pi_{Rr} \sum_{s \in c} \frac{L_{Fs} d_{rs}^{1-\kappa\theta}}{\tilde{\phi}_{Rr} \tilde{\phi}_{Fs}}$$

And so $\bar{s}$ is

$$\bar{s}_c = \bar{\tau}_c^{-1} \sum_{r \in c} \pi_{Rr} \sum_{s \in c} \frac{L_{Fs} d_{rs}^{1-\theta}}{\tilde{\phi}_{Rr} \tilde{\phi}_{Fs}}.$$

To recover ς, note that average wage is

$$\bar{w}_c = \sum_s \pi_{Fs} w_s = \sum_s \pi_{Fs} \frac{\tilde{w}_s}{\varsigma} = \varsigma^{-1} \sum_s \pi_{Fs} \left(\frac{L_{Fs}}{\tilde{\phi}_{Fs}} \right)^{1/\theta} \tag{10}$$

And so ς is

$$\varsigma = \bar{w}_c^{-1} \sum_s \pi_{Fs} \left(\frac{L_{Fs}}{\tilde{\phi}_{Fs}} \right)^{1/\theta}. \tag{11}$$

$\square$

One implementation note: It is standard to use κ as a semi-elasticity of commute time. To simplify Theorem 1, we instead define κ as an elasticity of commute time. To help facilitate cross-city comparison, we develop an adjusted local elasticity κ_c where we define

$$\kappa_c = \frac{\%\Delta U}{\%\Delta \tau_c} = \frac{\%\Delta U}{\Delta \tau / \bar{\tau}_c} = \bar{\tau}_c \frac{\%\Delta U}{\Delta \tau}.$$

The term $\frac{\%\Delta U}{\Delta \tau}$ is the semi-elasticity more frequently estimated in the quantitative spatial literature. The new elasticity κ_c will this be a bit higher in cities with longer average commutes.

The construction of the market access term requires granular employment and non-White/White employed population counts. For employment counts, we use ZIP Code Business Patterns data (ZCBP) for 1994, 2000, 2010, and 2018. Unfortunately data for 1980 and 1990 are unavailable. We thus match 1994 ZCBP to 1990 Census data. ZIP Code level Decennial Census (1990, 2000) and ACS (2006–2010, 2014–2018) data provide population counts. Note that the annual ZCBP data are produced using ZIP Codes, where as Census data rely on ZIP Codes for 1990 then uses ZIP Code Tabulation Areas (ZCTAs) for remaining years. ZCTAs are generalized representations of ZIP Code boundaries constructed by the Census Bureau.