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# Tracking and Explaining Neighborhood Socioeconomic Change in U.S. Metropolitan Areas Between 1990 and 2010

John D. Landis*

*Department of City and Regional Planning, University of Pennsylvania, Philadelphia, USA*

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This article addresses four fundamental questions about neighborhood change processes and outcomes among large U.S. metropolitan areas between 1990 and 2010: (a) Is it possible using census data and other secondary sources to come up with a consistent and robust method to measure gentrification and other forms of substantial neighborhood socioeconomic change (SNSEC) across all U.S. metropolitan areas? (b) To what degree are gentrification and other forms of SNSEC the result of metropolitan-scale economic and demographic forces versus more bottom-up and neighborhood-specific forces and dynamics? (c) To what degree are gentrification and other forms of SNSEC shaped by the actions of individual, and groups of, property owners, developers, and speculators versus the neighborhood service and location preferences of households? (d) To what extent are gentrification and other forms of substantial neighborhood change always accompanied by the displacement of existing residents?

**Keywords:** neighborhood change; gentrification

Cities and urban living are back. After half a century of relentless population decline and several false starts at revitalization, residential investment in America's urban centers began to pick up in the mid-1990s. In the 10 years between the 2000 and 2010 decennial censuses, the housing stock in America's 50 largest central cities grew by 1.5 million dwelling units, or 8.3%.[1] As Ramsey (2012) of the Environmental Protection Agency reports, this back-to-the-city construction trend continued even through the Great Recession. Of course, not all residential investment took the form of new construction. There were also sizable increases in residential rehabilitation and upgrading.

Multiple factors underlie this construction boomlet. Members of the millennial generation (born between 1982 and 2004) proved themselves less interested than prior generations in getting married, having children, and moving to the suburbs. Urban crime rates fell significantly. Suburban highways became as congested as their urban counterparts. Pushed by successive presidential administrations and Congress, low-cost mortgage money grew more available to moderate-income and minority residents of older neighborhoods, enabling many of them to become homeowners. Between 2000 and 2008, the number of homeowners in America's 50 largest central cities rose by 0.6 million, pushing the central city homeownership rate to an all-time high of just under 50%.

Not everyone greeted these changes favorably. Newspaper articles appeared in city after city citing the rising incidence of gentrification—a form of neighborhood change

*Email: jlan@design.upenn.edu

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wherein developers and higher-income households buy up residential properties in low-income neighborhoods for the purpose of inhabiting them, upgrading them, renting them out at a higher rent, or, in some cases, just flipping them.[2] The purported end result is the displacement of long-time and usually poorer residents.

Residential upgrading was hardly limited to urban cores. Homebuilders were also hard at work in suburban communities and at the peri-urban edge, building millions of large single-family homes. These McMansions, as they were known, were typically larger than 3,000 square feet and included garage space for three cars. Marketed toward move-up buyers who could afford their higher prices, McMansion demand was fueled by the same low interest rates and permissive lending standards that enabled moderate-income households to buy homes in older urban neighborhoods. Likewise, just as urban upgrading was drawing popular criticism as gentrification, suburban upgrading was drawing comparable attacks for being unsustainable and contributing to sprawl.

Of course, not everyone was lucky enough to live in an improving or even stable neighborhood. Behind the newspaper headlines and websites protesting gentrification and McMansion development, large numbers of urban and suburban residents continued living in neighborhoods where public and private investment had failed to keep pace with the ravages of time, depopulation, or economic decline. Not until the subprime mortgage bubble finally popped in 2008 did the vulnerability of both urban and suburban neighborhoods to macroeconomic forces and financial policies finally become clear.

Planners and urban analysts have had a tough time understanding these changes. With a few exceptions (Berube & Kneebone, 2009; Kneebone & Berube, 2013; Lucy & Phillips, 2006), planners' understanding of the nature, extent, and beneficiaries of neighborhood change has occurred in the absence of a comprehensive analysis that includes cities *and* suburbs *and* neighborhood upgrading *and* neighborhood decline. This is understandable: with 360+ metropolitan areas, each with its own core areas and suburbs, and most experiencing some combination of upgrading and decline, the set of neighborhood change possibilities is mind-boggling.

The format in which the U.S. Census Bureau publishes its data also presents challenges. Census tracts are a good approximation of neighborhoods but they are only an approximation and do not map particularly well onto how residents perceive their actual neighborhoods. This is especially true in suburban areas, where neighborhoods are often subdivision-based rather than street- and block-based. Published census data provide good 10-year snapshot views, but because it they do not track individual households or housing units over time, they provide a less accurate view of how change actually occurs. Last, how planners summarize neighborhood change—usually after the fact using census definitions and data—is different than how local residents actually experience such changes in real time. This is especially true in the case of gentrification, where the visible replacement of one set of residents or dwelling units by another is usually perceived as onerous regardless of how many residents are actually displaced.

This article takes up the challenge of trying to consistently identify the extent and spatial incidence of gentrification and other forms of substantial neighborhood socioeconomic change (SNSEC) among large U.S. metropolitan areas between 1990 and 2010. Along the way, it seeks to answer four related questions about neighborhood change processes and outcomes:

1. Is it possible, using census data and other secondary sources, to come up with a consistent and robust method to measure gentrification and other forms of SNSEC across all U.S. metropolitan areas?

2. To what degree are gentrification and other forms of SNSEC the result of metropolitan-scale economic and demographic forces versus more bottom-up and neighborhood-specific forces and dynamics?
3. To what degree are gentrification and other forms of SNSEC shaped by the actions of individual, and groups of, property owners, developers, and speculators versus the neighborhood service and location preferences of households?
4. To what extent are gentrification and other forms of substantial neighborhood change always accompanied by the displacement of existing residents?

This article addresses each of these questions in turn. I start, in Section 1, by introducing the double-decile difference (3-D) method for identifying SNSEC, and apply it to all census tracts in the nation's 70 largest metropolitan areas between 1990 and 2010. Next, in Section 2, I investigate whether, and to what degree, metropolitan-scale population and economic changes trickle down to drive neighborhood-level upgrading and decline. In Section 3, I investigate the local determinants of neighborhood change. In Section 4, I use census-based turnover rates as a partial proxy for displacement, and investigate whether 2010 turnover rates are systematically higher or lower in upgrading and/or declining census tracts. Finally, in Section 5, I reiterate the strengths and weaknesses of my approach before offering a limited set of policy observations and conclusions. With four topics to consider instead of the usual one, the format of this article is a little unusual. Rather than reviewing the relevant literatures en masse and up front, I discuss them in their appropriate sections.

## 1. Identifying Gentrification and Other Forms of SNSEC

There are essentially four ways to measure and categorize neighborhood change. The first is to observe changes in the aggregate sociodemographic and economic characteristics of neighborhood residents and businesses over an extended period of time, typically 10 years. This approach is most consistent with available data from the U.S. Census Bureau, which are heavily oriented toward the population and household characteristics of residents, and which arrive spatially preorganized in the form of census tracts which serve as a reasonable approximation of neighborhoods.[3]

A second approach focuses on observing changes in the physical, occupancy, and financial characteristics of the building stock, and, to a lesser extent, on the physical condition of public infrastructure such as streets, parks, and schools. This approach also makes good use of available census data, particularly with regard to housing.

A third approach focuses on the specific number and characteristics of neighborhood newcomers—whether people, households, or businesses—and compares them with the characteristics of existing residents or businesses. This usually requires original survey work and is not easily done with census data, which, for reasons of confidentiality, do not track individuals or household respondents at the municipal or neighborhood scales.[4]

A final approach tracks the balance of physical and capital investment flows into and out of particular neighborhoods by monitoring building permits and real estate prices. These data are typically not available from federal or state government agencies at the neighborhood scale, but may occasionally be cobbled together from local building permit data and industry real estate databases.[5]

A quick review of landmark studies of neighborhood change reveals how diverse the field truly is. Park and Burgess's pioneering work on the neighborhood succession process (Burgess, 1929; Park, Burgess, & McKenzie, 1925) made use of neighborhood population profiles (Method 1) and individual surveys (Method 3). Hoover and Vernon's (1959) study identifying the dynamics of neighborhood growth and decline in the New York metropolitan area compared static profiles of population and business data (Method 1) and economic investment or flow data (Method 4). Glass's (1964) study of the Islington neighborhood of London, which gave birth to the term *gentrification*, compared the characteristics of newcomers and existing residents, making use of Method 3. In seeking to develop a formal model of the neighborhood change process, Downs (1981) and his colleagues at the Brookings Institution and the Real Estate Research Corporation made use of all four approaches. Later work by Wilson (1987) and Jargowsky (1997) on the reinforcing effects of declining work opportunities and social isolation made extensive use of detailed census data (Method 1). Turning their attention from decline to gentrification, Wyly and Holloway (1999) and Freeman and Braconi (2004) creatively coupled census-based household and housing data (Methods 1 and 2) with information on neighborhood investment flows (Method 4). Perhaps the most comprehensive work on neighborhood change to date is by Lucy and Phillips (2000, 2006). Their work covers neighborhood trends in cities and suburbs across all major U.S. metropolitan areas, and makes extensive use of census population and housing data (Methods 1 and 2). Most recently, Sampson (2012), in his exhaustive study of neighborhood change processes and outcomes in Chicago, Illinois, creatively combined the results of household and community surveys (Method 3) with census population and housing data (Methods 1 and 2).

### *The 3-D Method*

This work follows Lucy and Phillips's (2006) example of emphasizing spatial comprehensiveness over dynamic detail. Specifically, it seeks to categorize all urban and suburban census tracts in the 70 largest U.S. metropolitan areas according to whether they experienced SNSEC between 1990 and 2010. I define *SNSEC* as a two or more decile changes in the median household income level of a census tract over an extended period of time. A two or more decile upward shift constitutes substantial neighborhood upgrading. A two or more decile downward shift constitutes substantial neighborhood decline. By considering only population and household socioeconomic change, this approach is firmly located in Method 1. It does not explicitly consider corresponding changes in the building stock (Method 2), the specific characteristics of neighborhood newcomers as compared with long-time residents (Method 3), or levels and rates of physical, capital or financial investment (Method 4).

This 3-D method has both pros and cons. It is easy to operationalize across many metropolitan areas using readily available census data. By identifying substantial neighborhood change as a two-decile change rather than a one-decile change, it avoids overinterpreting small changes in household incomes as indicative of more substantial neighborhood-level change. And, by using deciles (which are calculated separately for each metropolitan area and year) to compare neighborhood income levels at earlier and later points in time, it avoids the problem of having to determine precisely how much household income change constitutes substantial change.

On the downside, the 3-D method is extremely partial and lacks subtlety. It identifies neighborhoods solely as census tracts. As implemented here, it only considers income changes as the basis for identifying neighborhood change. Like any quantile-based method, it is overly relative. If, for example, median household incomes in every census tract in a particular metropolitan area rose by $40,000 between 1990 and 2010, there would be no shift among decile ranks even though everyone had grown materially wealthier. Finally, the method simplistically identifies neighborhood upgrading and decline solely as a socioeconomic process rather than as a process that involves simultaneous demographic, physical, social, and financial change. In addition to socioeconomic change, neighborhood upgrading involves investments in new and existing housing, rising rent or housing price levels, and a reorientation of existing and new businesses to a wealthier clientele. Likewise, the process of neighborhood decline typically involves cumulative disinvestment in the local housing and commercial building stock, falling reals estate values, declining public service quality, rising residential and commercial vacancies, and, in the worst case, wholesale neighborhood blight and abandonment.

These two broad categories of SNSEC, upgrading and decline, can be further differentiated in terms of their income levels and location. In terms of income, I henceforth identify gentrifying tracts as those that experienced substantial socioeconomic upgrading starting from an initial (1990) income level that put them within the first four income deciles of their respective metropolitan area. This four-tenths threshold more or less corresponds to the 80% of median income criteria used by the U.S. Department of Housing and Urban Development to distinguish low - and moderate-income neighborhoods from middle-income ones.

My use of the word *gentrifying* as an adjective modifying socioeconomic upgrading differs from the usual use of the word as a noun or verb. As commonly used, the term *gentrification* marries any level of socioeconomic upgrading with some amount of physical upgrading and some degree of displacement of the poor or the prior population. That is, when talking about gentrification, the combination of these three outcomes is usually regarded as being more important than their individual magnitudes.[6] Here, however, I use the term *gentrifying* just to identify those low-income census tracts undergoing significant socioeconomic upgrading without having also investigated the extent of housing stock improvement or displacement. Compared with how existing residents actually experience a neighborhood, my use of the term *gentrifying* will tend to underestimate the number of neighborhoods in which gentrification is perceived as occurring.

In terms of location, I distinguish core area census tracts from suburban area census tracts based on their distance from the central business district (CBD) and the age and density of their housing stock. I identify core area tracts as those located 10 km or less from a CBD or downtown city hall. Tracts located more than 10 km from the CBD are identified as suburban. This 10-km threshold is correspondingly reduced (to 8, 6, and 5 km) for smaller metro areas and for metro areas in which closer-in tracts had a lower population density or a younger housing stock, and is increased (to 12 and 15 km) for larger metro areas or those with older suburban neighborhoods. Appendix A indicates which distance thresholds are applied to which metropolitan areas.

A final measurement issue concerns changing census tract boundaries. A small but not insignificant number of census tracts changed either names or boundaries between 1990 and 2010. This complicates comparing income deciles (or any other measure) over time. As a workaround to this problem, I used ArcGIS (Esri, Redlands, CA) to first convert both 1990 and 2010 census tracts into a common raster of 500-meter grid cells. Each cell was then assigned its 1990 and 2010 income decile values. Next, I subtracted the 1990 cell values from the 2010 cell values to yield a decile-difference raster. Finally, I used ArcGIS's zonal statistics by table procedure to pour each difference cell back into its corresponding 1990 census tract, thereby yielding a consistent measurement of change amidst inconsistent spatial boundaries. This procedure is illustrated graphically in Appendix B.[7]

Although it is easy to imagine what core area upgrading or decline might look like, it is harder to visualize similar changes when they occur in the suburbs. Suburban upgrading occurs through the construction of new homes for move-up and custom buyers in locations near existing neighborhoods, or when rising home prices encourage existing residents to cash out, or when nearby job growth brings sudden and concentrated wealth. Suburban gentrification, like core area gentrification, may occur in older suburban neighborhoods when certain types of homes or neighborhood services start attracting wealthier households. It can also occur when previously passed-by lots are finally built out or redeveloped to a higher quality level. Suburban decline, like core area decline, can occur when existing residents leave one neighborhood for another; through overdevelopment and rapid filtering, which may encourage residents to leave older established neighborhoods in search of new housing elsewhere; or when the residents of particular suburban neighborhoods disproportionately experience sudden job and/or income losses.

### *Summarizing Substantial Neighborhood-Level Socioeconomic Change, 1990 to 2010*

These income and locational criteria can be used to identify six types of SNSEC: upgrading occurring in core area census tracts, gentrification occurring in core area census tracts, decline occurring in core area census tracts, upgrading occurring in suburban census tracts, gentrification occurring in suburban census tracts, and decline occurring in suburban census tracts. As noted previously, tracts identified as upgrading experienced a two-or-more-decile increase in median household income between 1990 and 2010, whereas tracts identified as declining experienced a two-or-more-decile decline. Gentrifying tracts, which are a subset of upgrading tracts, were those that experienced a two-or-more-decile increase in median household income and had a 1990 median income level that was 80% or less of the 1990 metropolitan average, making them relatively poor.

Table 1 summarizes the share of census tracts falling within each neighborhood change category, as well as their population shares and median household income levels. It also offers additional socioeconomic comparisons across the six neighborhood categories. To make it easier to compare characteristics across different categories, I first compare each tract-type characteristic with the same characteristic for its metropolitan area. For example, the average 1990 median household income among the 31 core upgrading tracts in New York City, New York was $31,003. When divided by the comparable average median income of $35,368 for *all* New York metropolitan area tracts, the resulting relative income measure is .88. This indicates that median household incomes in New York's upgrading core tracts in 1990 were 12% lower than for the metropolitan region as a whole. New York's relative income measure is then combined with those for all other large metropolitan areas, resulting in an overall relative median household income measure for all core upgrading tracts of .74. Last, in the far right columns, Table 1 summarizes the average difference (and significance levels) between core area and suburban areas values; in all cases, the differences are statistically significant at the .01 level.[8]

Popular fascination with gentrification notwithstanding, the dominant form of SNSEC continues to be decline, not upgrading. Of the roughly 32,000 metropolitan census tracts included in this analysis, just 6.9% experienced substantial upgrading between 1990 and 2010, whereas 18% experienced substantial decline. In terms of population percentages, the residents of upgrading tracts accounted for 6.1% of metropolitan populations as of

Table 1. Selected characteristics of urban and suburban upgrading, gentrifying, and declining census tracts.

| Characteristic | All census tracts | Core | | | Suburb | | | t test: Core vs. suburban | |
|---|---|---|---|---|---|---|---|---|---|
| | | Upgrading | Gentrifying | Declining | Upgrading | Gentrifying | Declining | Mean difference | Significance |
| Number of tracts per category | 32,463 | 951 | 635 | 1,344 | 1,289 | 591 | 4,503 | | |
| Share of total tracts | 100% | 2.9% | 2.0% | 4.1% | 4.0% | 1.8% | 13.9% | | |
| 1990 population per category (millions) | 141.6 | 3.2 | 2.0 | 5.4 | 5.4 | 2.2 | 22.4 | | |
| Share of total metropolitan population | 100% | 2.3% | 1.4% | 3.8% | 3.8% | 1.6% | 15.8% | | |
| Share of urban population | 100% | 7.2% | 4.6% | 12.1% | na | na | na | | |
| Share of suburban population | 100% | — | — | — | 5.6% | 2.3% | 23.1% | | |
| Standardized tract averages (from 1990, except as noted) | | | | | | | | | |
| Median income (1990 dollars) | $34,377 | $25,746 | $20,888 | $30,867 | $29,546 | $22,331 | $38,121 | −$12,191 | 0.00 |
| Median income (normalized) | 1.00 | 0.74 | 0.60 | 0.96 | 0.86 | 0.66 | 1.15 | | |
| In poverty (%) | 1.00 | 1.50 | 1.87 | 0.97 | 0.90 | 1.26 | 0.58 | 10.8% | 0.00 |
| White (%) | 1.00 | 0.88 | 0.75 | 0.89 | 1.09 | 0.96 | 1.09 | −20.4% | 0.00 |
| African American (%) | 1.00 | 1.45 | 1.88 | 1.41 | 0.53 | 0.78 | 0.73 | 15.8% | 0.00 |
| Hispanic (%) | 1.00 | 1.44 | 1.67 | 1.15 | 0.79 | 0.98 | 0.82 | 4.7% | 0.00 |
| College graduate (%) | 1.00 | 0.96 | 0.82 | 1.01 | 0.87 | 0.71 | 1.11 | −7.7% | 0.00 |
| One-family home (%) | 1.00 | 0.74 | 0.68 | 0.93 | 0.99 | 0.84 | 1.10 | −16.4% | 0.00 |
| Multi family home (%) | 1.00 | 1.50 | 1.59 | 1.23 | 0.71 | 0.84 | 0.89 | 18.3% | 0.00 |
| Median gross rent | 1.00 | 0.90 | 0.82 | 1.00 | 0.89 | 0.77 | 1.10 | −$112 | 0.00 |
| Median (self-reported) home value | 1.00 | 0.92 | 0.74 | 0.93 | 0.91 | 0.72 | 1.04 | −$34,757 | 0.00 |
| Home 40+years old (%) | 1.00 | 2.10 | 2.14 | 1.08 | 0.94 | 1.06 | 0.47 | 20.8% | 0.00 |
| Home 20–40 years old (%) | 1.00 | 0.79 | 0.76 | 1.26 | 0.87 | 0.84 | 1.08 | −2.3% | 0.00 |
| Home 0–20 years old (%) | 1.00 | 0.49 | 0.47 | 0.69 | 1.10 | 0.95 | 1.27 | 19.5% | 0.00 |
| Population density (per mile)$^2$ | 1.00 | 1.73 | 1.76 | 1.32 | 0.45 | 0.58 | 0.77 | 2,737 | 0.00 |
| Distance to metro center | 0.99 | 0.29 | 0.25 | 0.36 | 1.78 | 1.94 | 1.16 | | |

1990, whereas the residents of declining tracts accounted for another 19.6%. Overall, the population of declining tracts exceeded the population of upgrading tracts by a ratio of 3 to 1. Looking at each neighborhood category type in greater detail, we find the following.

- *Core area upgrading:* There were 951 census tracts (of a total of 32,463) identified as core area upgrading. These tracts were home to 3.2 million residents in 1990 and accounted for 2.3% of their metropolitan populations. Compared with their respective metropolitan areas, these tracts were notably poorer (with an average median household income in 1990 of $25,746 vs. $34,377 for their metropolitan areas), and had 50% higher poverty rates. They included proportionately fewer white residents and proportionately more African Americans and Hispanics; had a much older housing stock with proportionately fewer single-family homes and more apartments; and were more affordable in terms of apartment rents and home values. They were also 75% denser. The proportion of college-educated workers residing in core upgrading tracts was slightly less than the comparable metropolitan proportion.
- *Core area gentrifying:* The 635 census tracts identified as core area gentrifying were home to just over 2 million residents in 1990, and accounted for just 1.4% of their metropolitan populations. Compared with their metropolitan areas, these core-area gentrifying tracts were 40% poorer (with an average median household income in 1990 of $20,888 vs. $34,377 for their metropolitan areas) and included 25% fewer white residents, 88% more African Americans, and 67% more Hispanics. They included 18% fewer college-educated adults, 32% fewer single-family homes, and 59% more apartments. Rents in these core gentrifying tracts were 18% lower, on average, than rents in their metropolitan areas, while home values were 26% lower. The housing stock was considerably older than that of their metropolitan areas, and the average density was considerably higher.
- *Core area declining:* The 1,344 census tracts identified as core area declining were home to 5.3 million residents in 1990, and accounted for 3.8% of the population of their metropolitan areas. These core area declining tracts were fairly typical of their metropolitan areas in terms of income and poverty levels, rents, and home values. Demographically, their populations were considerably more diverse, while their educational achievement levels paralleled those of their metropolitan areas. Their housing stocks were somewhat more tilted to apartments, and also somewhat older. They were also considerably denser than their metropolitan areas, although not as dense as nearby upgrading and gentrifying tracts.
- *Suburban upgrading:* Turning to the set of suburban census tracts, there were 1,289 tracts identified as suburban upgrading. Home to roughly 5.4 million people in 1990, these tracts accounted for just less than 4% of their metropolitan populations. Demographically, these tracts were less racially and ethnically diverse than their respective metropolitan areas. They were also home to proportionately fewer college graduates. In terms of median income, they were less well off than their metropolitan areas; however, their incidence of poverty was lower. Their housing values and rent levels were also lower. They included the same proportion of single-family homes as their metropolitan areas, but substantially fewer apartments. Their housing stocks were newer, and their population densities were much lower.
- *Suburban gentrifying:* Gentrification is usually considered an urban phenomena rather than a suburban one, but the 591 census tracts identified as suburban gentrifying were actually home to more residents in 1990 (2.2 million) than the

tracts identified as core area gentrifying (2 million). Compared with their metropolitan areas, these core area gentrifying tracts were 34% poorer (with an average median household income in 1990 of $22,331 vs. $34,377 for their metropolitan areas) and included 26% more poverty households, and nearly 30% fewer college graduates. Demographically, they included 22% fewer African American residents than their metropolitan areas, but about the same proportions of white and Hispanic residents. Compared with their metropolitan areas, they included proportionately fewer single-family homes and multi family dwelling units, but were also more affordable in terms of rents and home values. The housing stock was very slightly older than that of their metropolitan areas, their average densities were lower, and they were much more likely to be located at the suburban edge.

- *Suburban declining:* The majority form of SNSEC in metropolitan America between 1990 and 2010 was suburban decline. Indeed, in terms of both census tracts (4,503) and 1990 residents (22.4 million), the number of suburban declining tracts outnumbered all five other tract types combined. Collectively, these suburban declining tracts were fairly typical of their metropolitan areas in terms of income levels, college graduation rates, housing stock composition and affordability, and their proportion of white residents. Where they most differed was in their lower proportions of African American and Hispanic residents, and the comparative newness of their housing stocks. Compared with other suburban tracts, they had slightly higher densities and were more likely to be located closer to the CBD.

This group-based categorical comparison tends to minimize the huge amount of variation among individual metropolitan areas. To make such differences more explicit, Figures 1 and 2 list the top 10 metropolitan areas in each neighborhood change category. Metros area are ranked both by the number of residents living within each neighborhood category (see Figure 1) and by the share of residents in each category (see Figure 2). Note that these totals are all ex ante, not ex post. That is, they estimate the number of 1990 residents in each metropolitan area and neighborhood category who will subsequently be affected by future neighborhood change, not the number of residents living in the affected census tracts in 2010 after such changes have occurred.

The raw number rankings in Figure 1 are dominated by a few large metropolitan areas: Los Angeles, California; the San Francisco Bay Area, California; and Chicago. As of 1990, Los Angeles was home to the largest number of core area residents of future upgrading, future gentrifying, and future declining census tracts. It was also home to the largest number of suburban residents of future upgrading and gentrifying tracts. The San Francisco Bay area came in second, behind Los Angeles, in the number of residents of future core area and suburban upgrading tracts, second in the number of residents of future gentrifying suburban tracts, third in the number of residents of gentrifying core area tracts, and fourth in the number of residents of declining core area tracts. Chicago topped the rankings in the number of residents of declining suburban tracts, came in second in the number of residents of core area gentrifying tracts, and was third in the number of residents of core area upgrading tracts. There were relatively few suburban Chicago residents, by contrast, living in suburban tracts which would undergo upgrading or gentrification.

Size isn't everything: The nation's largest metro area, New York City, came in only sixth in terms of the number of core area residents of future upgrading neighborhoods (behind Washington, DC, and Seattle, Washington) and in 10th place in its number of core

Figure 1. Top 10 metropolitan areas by number of 1990 core area and suburban residents of upgrading, gentrifying, and declining census tracts.

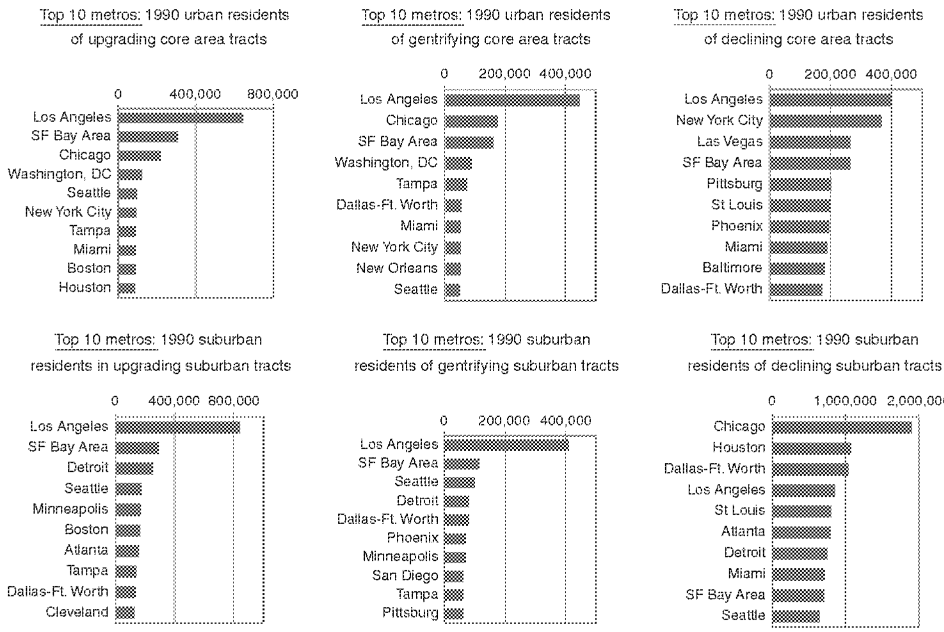
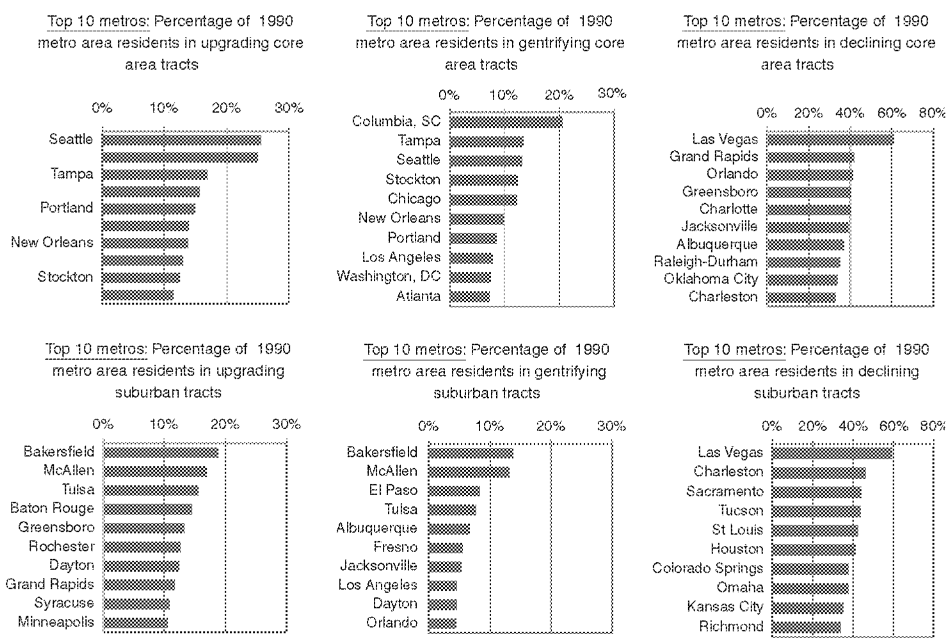



Figure 2. Top 10 metropolitan areas by share of 1990 urban and suburban residents of upgrading, gentrifying, and declining census tracts.



area residents of gentrifying neighborhoods. It was second, however (after Los Angeles), in the number of core area residents of future declining neighborhoods. New York's suburban areas were more stable than its core areas: it does not appear among any of the three top-10 lists of suburban neighborhood change. Washington, DC, is similar to New York City in this regard. It was among the nation's leaders in terms of core area upgrading and gentrification, while its suburban tracts proved remarkably stable.

Seattle, despite being smaller than New York City, Los Angeles, and Chicago, was among the most active metro areas in terms of neighborhood upgrading and gentrification. In raw-number terms, Seattle was third in the number of suburban residents of gentrifying census tracts, fourth in suburban upgrading, fifth in core area upgrading, and 10th in core area gentrification. Tampa, Florida, and, to a lesser extent, Miami–Ft. Lauderdale, Florida, had comparable upgrading experiences to Seattle, although Miami–Ft. Lauderdale also experienced substantial core area and suburban decline.

Other metro areas that experienced substantial absolute levels of core area upgrading and gentrification included Boston, Massachusetts; Houston, Texas; and Dallas–Ft. Worth, Texas. Among the metropolitan areas whose core experienced significant decline were three Rust Belt metros area (Pittsburgh, Pennsylvania; St. Louis, Missouri; and Baltimore, Maryland), and two Sun Belt metros area (Las Vegas, Nevada; Orlando, Florida) whose economies were hard hit by the collapse of the housing market in 2008. Metros area whose suburban neighborhoods prospered at the apparent expense of their core areas included Detroit, Michigan; Atlanta, Georgia; Cleveland, Ohio; and Pittsburgh. Atlanta was also among the leading suburban decliners, along with St. Louis, Dallas–Ft. Worth, and Houston.

Figure 2, which scales absolute change levels by total population, offers a number of surprises. In addition to the usual suspects like Seattle, the San Francisco Bay Area, and Los Angeles, the list of top metros in terms of core area upgrading and gentrification includes several less-talked-about metros area such as Columbia, South Carolina; Tampa, Portland, Oregon, and Atlanta. Similarly surprising is the fact that the list of top core area decliners is dominated not by Rust Belt metros area like Detroit or St. Louis, but by Sun Belt metros area including Las Vegas; Orlando, Florida; Charlotte, North Carolina; and Albuquerque, New Mexico. Turning to relative changes among suburban neighborhoods, with a few notable exceptions (Minneapolis, Minnesota for upgrading, Los Angeles for gentrification, and St. Louis for decline) the lists of top upgraders and decliners are dominated by midsized and smaller metros area. Appendix C includes tabulations of the amounts and shares of neighborhood change by core and suburban areas for all 68 metros area.

### *Caveats*

Before using the results of the 3-D method in any further analysis, it is worth repeating the method's limitations. Foremost among these are that its results are statistically derived rather than formally observed or measured, or otherwise captured from resident perceptions and experiences. Second, the method accounts only for changes in resident incomes, and not for changes in resident composition, or any physical changes to the housing stock or neighborhood. Although it is true that socioeconomic upgrading is usually accompanied by substantial physical upgrading—especially over longer periods—the two change processes do not necessarily move in sync. Especially when it comes to gentrification, small socioeconomic changes may either trigger or follow substantial physical changes. The same is also true for socioeconomic and physical decline. Nor does this method measure changing occupancy, or housing price and rent levels. Vacancy rates, rents, and housing prices respond first and foremost to the local balance between housing supply and demand. An influx of new residents—even those at or just above current neighborhood income levels—will cause vacancy rates to fall and rents or prices to rise, often disproportionately.

## 2. Metropolitan-Scale Drivers of Neighborhood Change and Gentrification

Having developed what I hope are robust procedures for categorizing neighborhood change trajectories, I now turn to the task of explaining those trajectories. Urban researchers are somewhat divided over the degree to which the forces driving neighborhood change are primarily exogenous or endogenous.[9] By *exogenous*, I mean processes that occur at the regional or metropolitan level, and which affect the status of individual neighborhoods through a sort of trickle-down mechanism. By *endogenous*, I mean processes and opportunities arising at the neighborhood scale.

Economists Hoover and Vernon (1959) were the first to empirically link inter- and intra-metropolitan growth trajectories, and, although they did not see the relationship as entirely one-way, the idea that neighborhood-scale changes mostly follow metropolitan-scale trends quickly became the mainstream view. This top-down approach of distributing metropolitan growth to local neighborhoods was codified in the Penn-Jersey Regional Transportation Study (Herbert & Stevens, 1960), and in work at the RAND Corporation that became known as the Lowry Model (Lowry, 1964). Although the Penn-Jersey and Lowry Models were later the subject of considerable criticism for their lack of a strong theoretical or empirical basis, the view that "a rising tide lifts all boats"—to use a phrase coined by President John F. Kennedy in 1963—soon established itself as the default model of intra-metropolitan growth.

What of metropolitan-scale decline, or, to use Kennedy's tides metaphor, a receding tide? The first to sound the alarm over the neighborhood impacts of regional economic disinvestment were Bluestone and Harrison (1980, 1982), who, in two volumes in the early 1980s, *Capital and communities: The Causes and Consequences of Private Disinvestment*, and *The Deindustrialization of America: Plant Closings, Community Abandonment, and the Dismantling of Basic Industry*, chronicled the impact of manufacturing plant closings on both regional and neighborhood economies. In *The Truly Disadvantaged: The Inner City, the Underclass, and Public Policy*, sociologist Wilson (1987) broadened the argument by exploring how deindustrialization and the loss of well-paying jobs interacted with racial discrimination to create a widening gyre of concentrated poverty and racial isolation. More recently, other scholars have traced the macroeffects of falling housing prices and increasing foreclosure rates on neighborhood outcomes (Baxter & Lauria, 2000; Immergluck & Smith 2006; Schuetz, Been, & Ellen, 2008; Voicu & Been, 2008).

I explore the effects of exogenous versus endogenous factors on neighborhood upgrading and decline in two parts. I start this section by using ordinary least squares regression to compare each of the six neighborhood change percentages calculated previously (the 1990 shares of core and suburban populations living in census tracts which would experience substantial neighborhood upgrading, gentrification, and decline) with a variety of population, economic, density, social, and policy indicators measured at the metropolitan scale. The assumption behind these regressions is that certain metropolitan-scale characteristics and dynamics might predispose a metro area toward more or less neighborhood change, or to neighborhood change of a particular type. Unless otherwise indicated, and to insure the proper time order, these indicators are based on 1990 census estimates, or on change estimates spanning the 1990 to 2010 period. The various metro-scale independent variables are:

- *Metropolitan area size, as indicated by 1990 population (Pop_1990):* Because the number and diversity of residential neighborhoods usually increase with population, I would expect opportunities for neighborhood change to also increase with metro area population.
- *Metropolitan population growth, as indicated by the percentage change in metro area population between 1990 and 2010 (Pct_Pop_Chng):* Because population growth fuels development, I would expect higher rates of metropolitan population growth to be positively correlated with more neighborhood upgrading and gentrification activity, and negatively correlated with neighborhood decline.
- *Income and income change, as measured by 1990 median household income (MHHInc_1990) and the percentage change in real median household income between 1990 and 2010 (Pct_Chng_MHHInc):* Neighborhood upgrading usually accompanies and is accompanied by gains in resident wealth, so I expect wealthier metro areas and/or those that gained disproportionate wealth between 1990 and 2010 to have experienced more neighborhood upgrading and gentrification, and perhaps less neighborhood decline.
- *Housing price levels, as measured by the average median housing value across all census tracts in 1990 (Avg_Med_HmeValu_90), and the change in housing prices between 1990 and 2007 as measured using the Federal Housing Finance Agency's House Price Index series (HmPrice_Indx_2007):* As with income and income change, I would expect the financial returns to real estate investment to be greater in metros area with higher initial home prices and higher rates of price appreciation, creating positive correlations between housing price levels and neighborhood upgrading.
- *Average housing stock age, as measured by the share of homes built prior to 1950 (Pct_Hms_b1950):* With gentrification opportunities typically concentrated in older neighborhoods, I would expect the share of a metro area's homes built before 1950 to be positively correlated with upgrading and gentrification activity and negatively associated with suburban upgrading. A surplus of older homes may also be correlated with neighborhood decline.
- *Racial composition, as measured by the average share of whites in each census tract in 1990 (Pct_White_1990):* Race can cut several ways. On the one hand, gentrification is sometimes characterized as a process by which wealthier whites invade lower-income minority neighborhoods. If this is indeed the case, we might expect upgrading and gentrification activity to be greater in metropolitan areas with a higher average percentage of white residents. On the other hand, to the degree that minority neighborhoods offer more upgrading opportunities, it could well be that upgrading and gentrification are more common in metro areas with fewer white residents. The a priori nature of the relationship between racial composition and neighborhood decline is less obvious.
- *Percentage of family households, as measured by the share of households in a metropolitan area with children ages 18 and younger living at home (Pct_FamHH_w/children_2000):* The conventional image of suburbia is of a place that is most attractive to families with children. If this is indeed the case, I would expect the percentage of family-with-children households in a metropolitan area to be positively correlated with suburban upgrading. Note that this indicator, like the two that follow, is measured in the year 2000, not 1990.

- *Education levels, as measured by the share of adults with bachelor's degrees as of 2000 (Pct_Bach_2000):* The common stereotype of gentrifiers is that of an educated population highly interested in urban amenities. If this generalization is accurate, I would expect the share of adult residents with a bachelor's degree to be positively correlated with upgrading and gentrification activity.
- *Nativity, as measured by the share of the population born outside the United States (Pct_Foreign-born_2000):* Much has been made of foreign-born residents' greater openness to living in higher-density core neighborhoods (Myers & Gearin, 2001). To the degree that this openness to urban living extends to older and more established neighborhoods, I expect to observe a positive correlation between the share of foreign-born residents and core upgrading and gentrification activity.
- *Residential density, as measured using the intercept and slope coefficients for the residential density gradient for each metropolitan area*: These coefficients were estimated by regressing each tract's average distance to its city center against its 1990 residential density (in dwelling units per square mile). The resulting slope coefficient, which measures the steepness with which densities decline with distance, is designated DenSlope_90. The intercept coefficient, which imputes the average housing density at the city center, is designated DenMax_90. With higher densities come more opportunities for gentrification, so I would expect higher positive values of DenMax_90 to be associated with greater upgrading and gentrification activity. For the same reason, I would expect higher negative values of DenSlope_90 to be associated with increased neighborhood upgrading. Since most suburban development occurs at the urban fringe, where average densities are lower, I might also expect suburban upgrading to be associated with lower positive values of DenMax_90, and lower negative values of DenSlope_90. Appendix D summarizes the 1990 density gradient regression results and the values of DenSlope_90 and DenMax_90 for each metropolitan area.
- *Immigration gateway status:* Immigration is a powerful engine for economic and physical development. Although immigration activity and nativity status often go hand in hand, many immigrants arrive in one place but ultimately settle in another. To investigate the particular role of immigration gateways on neighborhood upgrading and decline, I used the Brookings Institution's immigrant gateway classification system (Singer, 2004), which identifies particular metro areas as continuous, post–War, or emerging immigration gateways.[10] All else being equal, I would expect metropolitan areas which function as immigration gateways to have experienced more core and suburban neighborhood upgrading and less decline.
- *Presence of urban containment programs:* One of the principal reasons why growing communities enact urban containment programs is to redirect growth from suburban areas inward toward established neighborhoods. Thus, the establishment of an urban containment program should have the effect of encouraging core area upgrading and gentrification, and discouraging neighborhood decline. Leaving aside the question of whether urban containment programs actually work as advertised—that is, whether they really do contain and redirect urban growth—is there an empirical relationship between the adoption of urban containment programs and core area upgrading and gentrification? Prior work by Pendall, Puentes, and Martin (2006) has identified the extent and stringency of urban containment programs among the country's 50 largest metro areas. Using their *high* and *very high* categories, I created a 0/1 dummy variable indicating which metros area had previously enacted urban containment programs.[11]
- *Presence of infrastructure capacity limits:* Urban growth boundaries and other containment programs are not the only ways communities limit growth or redirect

development. Similar to their urban containment categories discussed above, Pendall et al. (2006) also developed measures of how stringently metropolitan areas use infrastructure capacity limits to constrain and redirect growth. Using Pendall, Puentes, and Martin's *high* and *very high* categories, I created a 0/1 dummy variable indicating which metros area had enacted such limits. As with the urban containment dummy variable discussed above, I would expect metros area with infrastructure capacity limits in place to have experienced more gentrification activity, and less degentrification.[12]

These hypotheses are summarized in Table 2, along with descriptive statistics for each measure.

### *Regression Results*

Tables 3 and 4 present the regression results. Table 3 presents the results of neighborhood change activity in core area census tracts, whereas Table 4 presents comparable results for suburban census tracts. In each case, I tested a neighborhood upgrading model, a neighborhood gentrification model, and a neighborhood decline model, bringing the total number of models tested to six.

Since I am less interested in formal hypothesis testing than in identifying robust correlations, I used stepwise regression to eliminate those measures whose correlations with neighborhood change activity fell below the .05 probability level. The results are a set of lean models which, judging from their low $R^2$ values, do not fit the data all that well. This suggests that the determinants of neighborhood change are more local than metropolitan in origin.

Among the independent variables that do not enter any model are metro area size (Pop_1990), metro area income growth (Pct_Chng_MHHInc), education levels (Pct_Bach_2000), housing stock age (Pct_Hms_b1950), the slope of the density gradient (DenSlope_90), the presence of infrastructure constraints, and immigrant gateway status. Among the variables that do enter, only the percentage of families with children (Pct_FamHH_w/children_2000) and core area density (DenMax_90) enter more than one model. The share of families with children in a metro area is positively associated with suburban upgrading and gentrification activity, whereas core area density is negatively associated with these same outcomes.

#### *Metropolitan-Level Models of Core Area Neighborhood Change*

Turning first to the three core-area models of neighborhood change (see Table 3), metro-scale factors explain 44% of the variation in the share of each metro's area 1990 population living in declining tracts, but just 19% of the shares of those living in subsequently upgraded or gentrified census tract. Metro-scale factors, it seems, do a better job of explaining core decline than core upgrading.

The only metro-scale independent variable to enter the Core Upgrading Model is DV_UrbContain, a dummy variable indicating the presence of an urban containment program. Even though such programs are usually targeted toward suburban areas, the positive coefficient value suggests that they may also serve to promote urban reinvestment, possibly by channeling foregone fringe development into existing urban neighborhoods.

The urban containment dummy variable also enters the Core Gentrification Model, where it has a similar effect. The other metro-scale variable entering this model is Avg_WhiteShare_1990, the white population share averaged across all tracts. Its coefficient is negative, indicating that core gentrification was less prevalent in metro areas

Table 2. Metropolitan drivers of neighborhood change activity: Descriptive statistics and summary of expected relationships.

| | | Expected relationships between metropolitan driver variables and core area or suburban population shares (by type of neighborhood change) | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | | Core area | | | Suburban | | | | | |
| Measure | Variable name | Upgrading tracts | Gentrifying tracts | Declining tracts | Upgrading tracts | Gentrifying tracts | Declining tracts | Mean values | Standard deviation | Data source |
| *Dependent variables (1990 population shares)* | | | | | | | | | | |
| Core area population share in upgrading tracts | | | | | | | | 5.8% | 4.0% | |
| Core area population share in gentrifying tracts | | | | | | | | 3.9% | 4.0% | |
| Core area population share in declining tracts | | | | | | | | 20.3% | 11.9% | |
| Suburban population share in upgrading tracts | | | | | | | | 6.4% | 4.0% | |
| Suburban population share in gentrifying tracts | | | | | | | | 2.8% | 2.6% | |
| Suburban population share in declining tracts | | | | | | | | 23.4% | 11.6% | |
| *Independent variables (drivers)* | | | | | | | | | | |
| Metropolitan population (1990)[a] | Pop_1990 | + | + | + | + | + | + | 2,183,900 | 2,791,373 | 1990 census |
| Population growth (%; 1990–2010)[a] | Pct_Pop_Chng | + | + | − | + | + | ? | 34% | 30% | 1990 census |
| Median household income (1990)[a] | MHHInc_1990 | + | + | − | + | + | − | $31,350 | $5,434 | 1990 census |
| Change in real median household income (%; 1990–2010)[a] | Pct_Chng_MHHInc | + | + | − | + | + | − | −5.8% | 8.3% | 1990 census |
| Median home value (averaged across all tracts, 1990)[a] | Avg_Med_HmeValue_1990 | + | + | − | + | + | − | $93,132 | $44,848 | 1990 census |
| Federal Housing Finance Agency Housing Price Index (2007, 1990 = 100)[b] | HmPrice_Indx_2007 | + | + | − | + | + | − | 2.34 | 0.51 | Federal Housing Finance Agency |
| Homes built prior to 1950 (%; 1990 tract average)[a] | Pct_Hms_b1950 | + | + | − | − | − | + | 26.4% | 12.9% | 1990 census |
| White residents (%; averaged across all tracts, 1990)[a] | Pct_White_1990 | + | + | ? | + | + | ? | 76.5% | 9.1% | 1990 census |
| Family households with children (%; 2000)[c] | Pct_HamHH_w/children_2000 | ? | ? | ? | + | + | ? | 37.0% | 4.4% | 1998 census |
| Adults with bachelor's degrees (%; 2000)[d] | Pct_Bach_2000 | + | + | ? | ? | ? | ? | 26.4% | 5.6% | 1999 census |
| Foreign-born population (%; 2000)[e] | Pct_Foreign-born_2000 | + | + | ? | ? | ? | ? | 10.7% | 8.4% | 2000 census |
| Estimated density gradient slope (1990)[f] | DenSlope_90 | − | − | ? | − | − | ? | −0.03 | 0.01 | See Appendix D. |
| Estimated density gradient intercept (1990)[f] | DenMax_90 | + | + | ? | − | − | ? | 3.42 | 0.27 | See Appendix D. |
| Status as immigration gateway[g] | DV_Imm_Gateway | + | + | − | + | + | − | 0.19 | 0.40 | Singer, 2004 |
| Presence of urban containment program (0/1)[h] | DV_UrbContain | + | + | − | + | + | − | 0.16 | 0.37 | Pendall, Puentes, & Martin, 2006 |
| Presence of infrastructure capacity limits (0/1)[h] | DV_InfraLimits | + | + | − | + | + | − | 0.24 | 0.43 | Pendall, Puentes, & Martin, 2006 |

Table 3. Stepwise regression results comparing core area neighborhood change activity between 1990 and 2010 with selected metro-scale population, size, economic, housing market, and density characteristics.

| Dependent variable | Share of 1990 metro core area population in upgraded core area census tracts | | Share of 1990 metro core area population in gentrified core area census tracts | | Share of 1990 metro core area population in declining core area census tracts | |
|---|---|---|---|---|---|---|
| Independent variable | Standardized coefficient | Significance | Standardized coefficient | Significance | Standardized coefficient | Significance |
| Constant | 4.77 | 0.00 | 11.29 | 0.00 | 80.87 | 0.00 |
| Pop_%Ch | DNE | | DNE | | 0.31 | 0.00 |
| AvgWhiteSh_1990 | DNE | | −0.24 | 0.04 | DNE | |
| Average median income | DNE | | DNE | | −0.28 | 0.01 |
| DenMax_90 | DNE | | DNE | | −0.30 | 0.01 |
| DV_UrbContain | 0.43 | 0.00 | 0.34 | 0.00 | DNE | |
| $R^2$ | 0.19 | | 0.19 | | 0.44 | |
| Number of observations | 68 | | 68 | | 68 | |

*Note*. AvgWhiteSh_1990 = white population share averaged across all tracts; DenMax_90 = population density at city center; DNE = did not enter; DV_UrbContain = dummy variable indicating presence of an urban containment program; Pop_%Ch = percentage population change.

Table 4. Stepwise regression results comparing suburban neighborhood change activity between 1990 and 2010 with selected metro-scale population, size, economic, housing market, and density characteristics.

| Dependent variable | Share of 1990 metro suburban population in upgraded suburban census tracts | | Share of 1990 metro suburban population in gentrified suburban census tracts | | Share of 1990 metro suburban population in declining suburban census tracts | |
|---|---|---|---|---|---|---|
| Independent variable | Standardized coefficient | Significance | Standardized coefficient | Significance | Standardized coefficient | Significance |
| Constant | 17.05 | 0.02 | −1.30 | 0.00 | 19.54 | 0.00 |
| Population change (%; 1990–2010) | DNE | | DNE | | 0.57 | 0.00 |
| Households with children (%) | 0.29 | 0.10 | 0.57 | 0.00 | DNE | |
| Foreign-born (%) | DNE | | DNE | | −0.24 | 0.03 |
| DenMax_90 | −0.40 | 0.00 | −0.25 | 0.01 | DNE | |
| $R^2$ | 0.28 | | 0.44 | | 0.31 | |
| Number of observations | 68 | | 68 | | 68 | |

*Note.* DenMax_90 = population density at city center; DNE = did not enter.

with higher proportions of white residents. In terms of magnitudes, the urban containment effect slightly dominates the white population effect.

Three metro-scale variables enter the Core Decline Model: percentage population change (Pct_Pop_Chng), median household income averaged across all census tracts (Avg_MedInc), and population density at the city center (DenMax_90). The positive coefficient sign for Pct_Pop_Chng indicates that faster rates of metropolitan population growth between 1990 and 2010 were associated with higher levels of core neighborhood decline. The negative sign for the (average) median income variable Avg_MedInc indicates that metro areas with higher income levels experienced proportionately less core neighborhood decline. Likewise, the negative sign for the CBD density variable DenMax_90 indicates that metropolitan areas with higher downtown residential densities experienced proportionately less neighborhood decline among their core neighborhoods.

*Metropolitan-Level Models of Suburban Neighborhood Change*

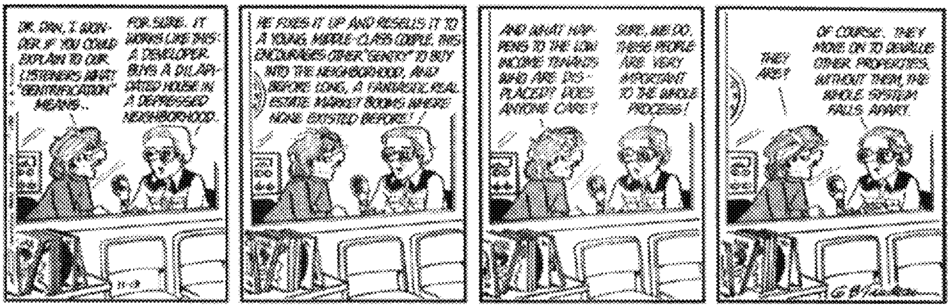
Compared with the previous set of core area models, the set of suburban models (see Table 4) does a slightly better job relating metro-scale factors to neighborhood upgrading, but a slightly worse job relating them to neighborhood decline. Looking first at the suburban upgrading models, two metro-scale factors, downtown densities (DenMax_90) and the share of households with children (Pct_FamHH_w/children_2000), explain 28% of the variation in suburban upgrading activity between 1990 and 2000. The share of households with children is positively associated with suburban upgrading, while downtown densities are negatively associated with such activity. The same two factors—downtown densities and the share of households with children—explain 44% of the variation in suburban gentrification. Given the suburbs' lower densities and traditional attraction to families, none of these results is particular surprising. Whereas the density effect dominates the families-with-children effect for suburban upgrading, in the case of suburban gentrification, the families-with-children effect dominates the density effect.

Two different metro-scale factors, percentage population growth and nativity, are associated with suburban neighborhood decline, which explains 31% of the variation in suburban decline between 1990 and 2010. As in the core decline model presented above, higher rates of metropolitan population growth are associated with higher levels of suburban decline. The opposite is true for nativity, however; metro areas with higher percentages of foreign-born residents experienced reduced rates of suburban neighborhood decline. Immigrants, it seems, are not only good for cities; they are also good for suburbs.

## 3. Gentrification and Neighborhood Change Drivers at the Census-Tract Scale

Having explored the effects of exogenous or metropolitan-scale factors on neighborhood change activity, I now turn to the role of possible endogenous factors. By *endogenous*, I mean those neighborhood-scale conditions or circumstances which give rise to individual investment or disinvestment opportunities. The complex nature of these factors was the subject of a very funny but also very insightful 1980 Doonesbury comic strip that purported to explain gentrification (see Figure 3).Interest in neighborhood change and gentrification certainly precedes Doonesbury. Observing the process of neighborhood growth and change in Chicago during the 1920s, Park, Burgess, and McKenzie (1925) wrote of how competition for limited housing supplies between different income and immigrant groups led to large-scale processes of neighborhood invasion and succession. Hoyt (1939) and Grigsby (1963) expanded Park and Burgess's succession idea into a

Figure 3.



*Source.* Copyright 1980 Garry Trudeau.

model of residential filtering, whereby households would continually adjust their housing and location choices in response to changing quality-adjusted housing prices. Neighborhoods in which the combination of housing and community services was perceived to be a relative bargain would attract new households, while those in which the package of housing and services was perceived as a poor economic value would decline. Downs (1981) and his colleagues at Brookings subsequently tried to extend Grigsby's filtering framework into a predictive model of neighborhood stability and change. Taking a more theoretical approach, Anas (1978), Arnott (1980), Braid (2001), Capozza and Helsley (1990), Wheaton (1982), and Brueckner and Rosenthal (2009) incorporated neighborhood change into the standard monocentric bid-rent model of urban spatial structure by introducing formal assumptions about physical depreciation and replacement rates, uncertainty, landowner expectations, and income sorting.

All of these models take the invisible hand of the marketplace as implicit, and ignore the actions of individual actors and agents. Among scholars who have focused on how individual or group actions contribute to neighborhood change are Schelling (1969) and, more recently, in his articulation of rent gap theory, Smith (1979, 1982, 1996). Rent gap theory posits that gentrification is a special case of neighborhood change, and that the primary force behind it is the intentional and manipulative redirection of speculative capital into rundown neighborhoods, based on the difference between the ground rent of land in its current (depreciated) use, and what that same land could earn in a potentially higher and better use. Just as in the Doonesbury comic strip (see Figure 3), the existence of potential rent gaps creates an incentive for external speculators to try to gain control of local real estate markets to push out poor residents and replace them with higher-income gentrifiers. In Smith's view, most of the action is on the supply side; demand-side forces and household preferences are assumed to be largely incidental. A few researchers, notably Bostic and Martin (2003), Edel (1971), and Lees, Slater, and Wyly (2008), have tried to bridge Smith's supply-side view with a more traditional demand-based perspective. Most recently, several scholars have pointed out the roles of anchor institutions such as universities and hospitals in encouraging nearby neighborhood upgrading.

To better understand the role of neighborhood-level conditions in shaping neighborhood change, I model such changes as a series of three tract-level binary outcomes: upgraded versus not upgraded, gentrifying versus not gentrifying, and declining versus not declining.[13] This use of binary-dependent variables frees us to consider each form of neighborhood change as a potentially different phenomenon.

Because ordinary least squares regression cannot be reliably used to model categorical variables, I turn instead to logistical regression, better known as logit. In its most basic binary or binomial form, logistical regression approximates a categorical response or outcome as a continuous S-shaped probability function that varies between 0 and 1.[14] What is modeled statistically is the probability of a particular outcome occurring, and not the outcome itself. The general form of the binary logit model is as follows:

$$\text{Probability (Outcome } i \text{ of } i, j) = \frac{(e^{a+b1X1+b2X2+\ldots bnXn})}{(1 + e^{a+b1X1+b2X2+\ldots bnXn})}$$

where $i$ is one outcome of two possible outcomes, $i$ and $j$—in this case, neighborhood change versus no change; X1 though Xn are the values of the independent variables; a and b1 through bn are parameters to be estimated; and $e$ is the base of the natural logarithm.

Logit models are generally more robust than regression models, meaning that they do not require as many observations to yield statistically reliable results. This makes them particularly useful in situations like this where one set of outcomes (e.g., gentrification) may be vastly more infrequent than another (e.g., non gentrification).[15]

Altogether, I tested six different binary logit models, each with its own dependent or outcome variable: upgrading (or not) of a core area tract, core area tract gentrification, core area tract decline, suburban tract upgrading, suburban tract gentrification, and suburban tract decline. While the dependent variable in a logit model *must* be categorical, the independent variables can take any form. In the six logit models that follow, I include four different types of tract-level independent variables: those measuring initial demographic and economic characteristics; those measuring the physical characteristics of the housing stock and neighborhood location; those measuring apartment rents, housing values, and the estimated price gap; and a single variable measuring any metropolitan-scale effects.

### *Tract-Level Socioeconomic Characteristics*

In Doonesbury's stereotypical cartoon model (see Figure 3), it is only the initial presence of poor tenants that makes gentrification possible. Likewise, in many models of neighborhood decline and abandonment, it is the initial socioeconomic status of the residents that largely determines the future trajectory of the neighborhood.

To what degree does the initial presence of certain populations—be they poor or rich, white or nonwhite, college-educated or not—determine whether a particular neighborhood prospers or declines? To find out, I compared the six categorical neighborhood change outcomes identified above with six measures of initial neighborhood socioeconomic status: median household income, percentage white, percentage African American, percentage Hispanic, percentage of families in poverty, and percentage of workers with a college education. To facilitate robust comparisons across metropolitan areas as well as within them, I first divided each tract-level measure by its corresponding metropolitan average to create relative measures of income, race, poverty, and education level. As an example, suppose that the 1990 median income in both tracts X and Y was \$50,000, but that tract X is located in a metro area with a median household income of \$40,000, whereas tract Y is located in a metro area with a median income of just \$25,000. In this example, the relative median income for tract X would be 1.25 (e.g., \$50,000 divided by \$40,0000), whereas for tract Y it would be 2.0, or \$50,000 divided by \$25,000.

Neighborhood upgrading is usually accompanied by an increase in the consumption of housing and neighborhood services, so, as with any income-normal good, we would expect upgrading to be positively associated with income. That is, the higher the initial neighborhood income and the lower the poverty rate, the higher the probability of tract-level upgrading or gentrification. By contrast, we would expect higher initial incomes and lower poverty rates to be negatively associated with neighborhood decline.

The relationships between initial racial composition and neighborhood change are not quite so obvious, particularly if income and poverty are held constant. To the degree that residents of all or most racial backgrounds might prefer to live in white-majority neighborhoods—and there is some empirical research indicating this is the case—then the higher the initial share of white residents in a neighborhood, the greater its likelihood of being upgraded or gentrified, and the lower the likelihood of it declining. By the same logic, to the degree that some potential in-movers might wish to avoid minority or diverse neighborhoods, census tracts with proportionately more African American or Hispanic residents might be less likely to gentrify or be upgraded. I keep using the words *some* and *might* to indicate that racial location preferences are hardly monolithic and that they have become even less so in recent years.

As for education levels, recent work by Murray (2012) and others has demonstrated that most highly educated people strongly prefer to live near or among other highly educated people. If this is indeed true, we would expect neighborhoods with proportionately more college-educated residents to attract even more such residents, thereby increasing the likelihood that they might prosper or gentrify, and decreasing the likelihood that they might decline. All of these relationships are presumed to apply in both core area and suburban tracts, albeit perhaps to different degrees.

To allow for the possibility that neighborhood change might also be a function of neighborhood population size and absolute household income—rather than relative income, as suggested above—I also included tract-level population counts and median household income in each logit model.

### *Tract-Level Built-Form, and Location Characteristics*

When it comes to explaining neighborhood change, location and the presence of a malleable and upgradable housing stock matter as much as favorable demographics. No matter how strong the demand, unless there is also a ready supply of existing housing available for upgrading, or available land for new construction, the market will not be able to respond. To determine how important physical and locational characteristics are to neighborhood change, I compared the six categorical neighborhood change variables with nine location and housing built-form measures: (a) the percentage of one-family homes in each census tract, (b) the percentage of multi-family dwelling units, (c) the percentage of dwelling units built prior to 1950, (d) the percentage of homes built between 1950 and 1970, (e) the percentage of homes built between 1970 and 1990, (f) the straight-line distance from the census tract centroid to the city center, (g) the census tract density in people per square mile, and (h and j) the $x$ and $y$ coordinates of each census tract centroid.

That built-form and location characteristics should matter is obvious; less obvious is how they should matter. I do have a few hypotheses in this regard, starting with dwelling unit type. Because multi-family dwellings are less physically malleable than single-family dwellings—and thus harder and more expensive to upgrade—I expect to observe a negative relationship between the proportion of multi family homes in a neighborhood (particularly a suburban neighborhood) and the likelihood of upgrading or gentrification. In terms of age, older homes, particularly those built prior to World War II, are likely to be more architecturally and historically distinguished than newer homes, and this should mitigate in favor of upgrading, especially in older neighborhoods. Similarly, newer homes—those built after 1970—are likely to be in better physical condition than older homes, or to be located in newer and more desirable neighborhoods. This should mitigate against neighborhood change of any type. To the degree that regional access, walkability, and proximity to neighborhood services are highly valued, there may also be a positive relationship between proximity to the city center and the likelihood of upgrading. Or, to put it more simply, I would expect to observe a negative relationship between distance to the CBD and the probability of upgrading. Likewise, to the degree that higher density neighborhoods are more walkable than lower density ones, there may also be a positive relationship between population density and the likelihood of upgrading. Whether these same relationships also apply to neighborhood decline, albeit in the opposite direction (i.e., close-in neighborhoods are less likely to decline), is an open question.

### *Tract-Level Housing Market Characteristics*

Housing markets, like most markets, clear on price. This means that it is prices that adjust upward and downward, not the supply of houses or number of residents. Prices will go up if buyers' willingness to pay exceed sellers' reservation prices, and down if buyers are unwilling to meet sellers' reservation prices. This does not mean that the housing market clears at a uniform price. Because housing is a heterogeneous good and not a commodity, different homes with different characteristics in different locations will sell for different prices. Indeed, similar houses in similar locations can sell for different prices depending on when and how they sell. Even the most efficient market does not function perfectly—and the housing market is far from efficient or perfect—so, to the degree that homes in a particular neighborhood are systematically overvalued or undervalued, such differentials may serve to promote neighborhood change.

The easiest way to understand where a particular census tract fits into the broader housing market is to compare its relative rents and home values. On the one hand, supply-side, the availability of less expensive houses or apartments signals the possibility of greater bargains, and this should tend to mitigate in favor of neighborhood upgrading and against neighborhood decline. On the other hand, demand-side, inexpensive houses and apartments are usually inexpensive for a reason—the reason being that they are of lower quality or are located in less desirable areas. In such cases, I might expect such deficiencies to mitigate against upgrading and gentrification and in favor of neighborhood decline. In weak housing markets (those with low demand and high vacancy rates), I would expect the demand-side view to prevail, and for higher prices and rents to be associated with reduced upgrading and greater decline. Conversely, in strong housing markets (those with lower vacancy rates), I would expect the supply-side perspective to dominate, and for neighborhood upgrading to favor higher priced tracts.

What of Smith's rent gap hypothesis? Thus far, the rent gap hypothesis has proven extremely resilient to empirical testing. Rent gaps cannot be observed in the marketplace, nor can they be properly constructed from census data or statistically estimated from transaction data. These operational difficulties have led to continuing disagreements over whether gentrification is primarily demand driven, or is instead the result of rent-seeking behavior on the part of landowners.

Rather than trying to operationalize rent-gap theory per se, I look at the related concept of speculative price gaps, or the difference between current market rents and expected market rents pursuant to possible neighborhood change. To estimate these speculative price gaps (henceforth referred to just as price gaps), I first use hedonic price theory and linear regression to compare census tract-level housing stock and locational characteristics with median rent levels. The resulting regression models, one for each metro area, are summarized in Appendix E. Depending on the particular metro area, these models explain between 35% and 70% of the variation in tract-level median rents for 1990.

Despite their so-so explanatory power, I used each metro-specific regression model to calculate an estimated 1990 median rent level for each census tract in that metro area. I then compared the regression-estimated median rent with the observed median rent, creating the price gap measure. Last, to make these price gap measures easier to interpret and compare, I then scaled them by the observed median rent.[16] The resulting price gap measure is positive for census tracts where observed rents exceed estimated rents, and negative where observed rents fall short of estimated rents.

In terms of market behavior, a negative price gap indicates that local properties are selling or renting at a discount compared with similar properties elsewhere in the city, and, therefore, that the neighborhood is comparatively undervalued. A positive price gap indicates that properties are selling or renting at a comparative premium and that the neighborhood is comparatively overvalued. Systematically undervalued neighborhoods should attract speculative land purchasers and developers, resulting in gentrification. Conversely, the pervasive presence of overvalued properties should lead owners and investors to withhold additional investment, resulting in a gradual decline in building quality. The key word in both situations is *may*, as it is investors' expectations about the future, and not the actual or estimated price gap amount that ultimately determines investor behavior. By this logic, we would expect negative price gaps (indicating properties are systematically undervalued) to be associated with a higher probability of upgrading and gentrification, and positive price gaps (indicating properties are systematically overvalued) to be associated with a higher probability of neighborhood decline.

Price gaps, as operationalized above, are not the same as rent gaps, as defined by Smith. The latter measure expectations as capitalized into underlying land values, while the former measure mismatches between current and potential housing prices. Similarly, because price gaps are generated from regression models, they operationalize average price differences, not the differences perceived by unique actors such as housing and community development organizations or private-sector pioneers. Nor do they accurately measure the upgrading potential of unique properties.

### *Metropolitan Effects*

Last but not least, we need to account for any metropolitan effects. All else being equal, a census tract located in a metropolitan area in which upgrading and gentrification are common is itself more likely to be upgraded or to gentrify than an otherwise identical tract in a metropolitan area where upgrading or gentrification are rare. A similar logic applies to census-tract decline. Even though I hypothesize that all three neighborhood change processes are principally bottom up—that is, they emerge out of local preferences and supply-side differentials—there is still the possibility of some level of top-down, or metropolitan-scale effects. To identify these effects, I used the regression models presented in Section 2 to estimate upgrading, gentrification, and decline proportions for each major metropolitan area. I next joined each of these estimated proportions to its corresponding census tract. To the degree that these proportions are found to be associated with systematically higher or lower probabilities that individual census tracts experience significant neighborhood change, we may conclude that metropolitan effects do in fact matter. In statistical terms, these proportions serve the function of what are commonly known as fixed-effect variables, since they incorporate (observed and unobserved) effects that are unique to each metropolitan area but common to all the census tract observations within each metro area.

Tables 5 and 6 present the various logit model results. Table 5 presents the results for core area tracts, and Table 6 presents the suburban tract results. Except for population size, the estimated price gap, and the predicted metro-level effect, the independent variables are all expressed in relative terms, which is to say that census tract and neighborhood values are first compared with their respective metropolitan areas before being compared across metropolitan areas. Note that among the independent variables, the metro-level effect is listed first to indicate that it is held constant.

### *Core Area Logit Model Results*

As is typical for categorical models in which the status quo is the dominant outcome, the three core area models do a better job explaining the no-change outcome (that is, the absence of any form of neighborhood upgrading or decline) than explaining the change outcome. Model C3, the core area decline model, correctly identified 41% of the 797 census tracts that experienced substantial socioeconomic decline between 1990 and 2010 (of a total of 9,269 core area census tracts).[17] Model C1, the core area upgrading model, correctly identified 11.7% of upgraded census tracts, whereas Model C2, the gentrification model, properly identified just 3% of gentrification outcomes. The Nagelkerke $R^2$ estimates, which are roughly comparable to $R^2$ estimates in traditional linear regression, are also quite low. Thus, when it comes to fully explaining the sources of SNSEC in core area neighborhoods, these models leave out as much as they include.

Notwithstanding their lack of overall predictive power, the three core area models do a pretty good job of identifying which local factors contributed most to neighborhood socioeconomic change between 1990 and 2010. Looking first at the results of the core area upgrading model (Model C1), and based on the reported odds ratios, the five factors that most determined whether a particular census tract upgraded between 1990 and 2010 were its initial income level, its initial rent level, the percentage of college-educated workers initially residing in the tract, the initial percentage of white residents, and the presence of an older housing stock. All five measures are expressed in relative terms, meaning that they are first compared with their respective metropolitan averages.

Higher relative incomes reduced the likelihood that a tract would be upgraded, while higher relative rents, higher proportions of college-educated residents, higher proportions of white residents, and higher proportions of homes built before 1950 all increased the likelihood of upgrading. Smaller census tracts were slightly more prone to upgrading than larger ones, as were census tracts with higher median incomes. Higher-density census tracts or those with higher poverty rates were slightly less likely to experience upgrading by 2010. Tracts with higher home values were also slightly less likely to upgrade. Among the factors that had no significant effect on the likelihood of upgrading were the initial proportion of African Americans or Hispanics, the type of housing stock, distance to the CBD, and the estimated price gap. Finally, and not unexpectedly, census tracts located in more upgrading-prone metropolitan areas (as indicated by the metro-wide effect variable) were slightly more likely to have upgraded.

The pattern is similar although not identical for gentrifying tracts. Holding constant any metro-level tendencies, core area tracts with higher income levels in 1990 were less likely to have gentrified, just as tracts with higher rents were more likely to have gentrified. Tracts with higher proportions of white residents, college-educated residents,

Table 5. Stepwise binomial logit results comparing core area tract outcomes with initial tract characteristics and metro-scale drivers between 1990 and 2010.

| | | Model C1: Probability of a core tract upgrading | | Model C2: Probability of a core tract gentrifying | | Model C3: Probability of a core tract declining | |
|---|---|---|---|---|---|---|---|
| Independent variable type | Independent variable | Odds ratio | Significance level | Odds ratio | Significance level | Odds ratio | Significance level |
| Metro-scale effect | | 1.09 | 0.00 | 1.12 | 0.00 | 1.04 | 0.00 |
| Tract demographic and economic characteristics | Population | 0.95 | 0.01 | 0.94 | 0.01 | 1.05 | 0.00 |
| | Median household income (000) | 1.03 | 0.00 | 1.03 | 0.01 | 0.96 | 0.00 |
| | Relative household income | 0.02 | 0.00 | 0.01 | 0.00 | 7.98 | 0.00 |
| | White (relative %) | 1.81 | 0.00 | 1.88 | 0.00 | 0.62 | 0.00 |
| | African American (relative %) | DNE | | DNE | | DNE | |
| | Hispanic (relative %) | DNE | | DNE | | 1.05 | 0.01 |
| | In poverty (relative %) | 0.83 | 0.00 | 0.86 | 0.00 | 0.59 | 0.00 |
| | College-educated (relative %) | 2.12 | 0.00 | 1.49 | 0.00 | | 0.00 |
| Tract physical characteristics | One-family housing (relative %) | DNE | | DNE | | 1.64 | 0.00 |
| | Multi family housing (relative %) | DNE | | DNE | | 1.50 | 0.00 |
| | DUs > 40 years (relative %) | 1.49 | 0.00 | 1.48 | 0.00 | 0.74 | 0.00 |
| | DUs 20–40 years (relative %) | 0.83 | 0.01 | DNE | | 1.19 | 0.00 |
| | DUs < 20 years (relative %) | DNE | | DNE | | DNE | |
| | Relative distance to center | DNE | | DNE | | 5.61 | 0.00 |
| | Relative population density | 0.92 | 0.00 | DNE | | 0.93 | 0.02 |
| | Relative centroid $x$-coordinate | DNE | | DNE | | 0.72 | 0.04 |
| | Relative centroid $y$-coordinate | DNE | | DNE | | 0.57 | 0.00 |
| Tract housing market characteristics | Relative median rent | 4.22 | 0.00 | 4.57 | 0.00 | DNE | |
| | Relative median home value | 1.19 | 0.02 | DNE | | 0.63 | 0.00 |
| | Estimated price gap | DNE | | DNE | | DNE | |
| Constant | | 0.03 | 0.00 | 0.044 | 0.00 | 0.04 | 0.00 |
| Nagelkerke $R^2$ | | 0.112 | | 0.108 | | 0.198 | |
| Total observations | | 10,408 | | 10,596 | | 9,269 | |
| Observations this category | | 760 | | 583 | | 797 | |
| Correct predictions (%) | | 11.7 | | 3.0 | | 40.7 | |

*Note.* DNE = Did not enter; DUs = (Please ask the author for the definition of DUs.)

Table 6. Stepwise binomial logit results comparing suburban tract outcomes with initial tract characteristics and metro-scale drivers between 1990 and 2010.

| Dependent variable | | Model S1: Probability of a suburban tract upgrading | | Model S2: Probability of a suburban tract gentrifying | | Model S3: Probability of a suburban tract declining | |
|---|---|---|---|---|---|---|---|
| Independent variable type | Independent variable | Odds ratio | Significance level | Odds ratio | Significance level | Odds ratio | Significance level |
| Metro-scale effect | | 1.20 | 0.00 | 1.26 | 0.00 | 1.04 | 0.00 |
| Tract demographic and economic characteristics | Population | DNE | | DNE | | DNE | |
| | Median household income (000) | DNE | | DNE | | 0.97 | 0.00 |
| | Relative household income | 0.01 | 0.00 | 0.00 | 0.00 | 5.30 | 0.00 |
| | White (relative %) | 2.63 | 0.00 | 3.09 | 0.00 | 0.69 | 0.00 |
| | African American (relative %) | DNE | | DNE | | 1.16 | 0.00 |
| | Hispanic (relative %) | DNE | | DNE | | 1.08 | 0.00 |
| | In poverty (relative %) | 0.82 | 0.00 | DNE | | 0.53 | 0.00 |
| | College-educated (relative %) | DNE | | DNE | | DNE | |
| Tract physical characteristics | One-family housing (relative %) | DNE | | 1.40 | 0.03 | DNE | |
| | Multi family housing (relative %) | 0.69 | 0.00 | 0.67 | 0.00 | 1.61 | 0.00 |
| | DUs > 40 years (relative %) | 1.39 | 0.00 | 1.22 | 0.00 | 0.62 | 0.00 |
| | DUs 20–40 years (relative %) | DNE | | DNE | | 1.23 | 0.00 |
| | DUs > 20 years (relative %) | 1.25 | 0.00 | 1.30 | 0.00 | DNE | |
| | Relative distance to center | 1.14 | 0.00 | 1.195 | 0.00 | 0.84 | 0.00 |
| | Relative population density | 0.61 | 0.00 | DNE | | 1.04 | 0.01 |
| | Relative centroid *x*-coordinate | 1.07 | 0.04 | 1.12 | 0.01 | DNE | |
| | Relative centroid *y*-coordinate | DNE | | DNE | | 1.21 | 0.00 |
| Tract housing market characteristics | Relative median rent | DNE | | DNE | | 2.35 | 0.00 |
| | Relative median home value | 2.65 | 0.00 | 1.76 | 0.00 | 0.35 | 0.00 |
| | Estimated price gap | DNE | | 1.00 | 0.00 | 1.00 | 0.00 |
| Constant | | 0.12 | 0.00 | 0.171 | 0.00 | 0.11 | 0.00 |
| Nagelkerke $R^2$ | | 0.165 | | 0.234 | | 0.149 | |
| Total observations | | 20,904 | | 20,650 | | 14,946 | |
| Observations this category | | 1,129 | | 529 | | 1,882 | |
| Correct predictions (%) | | 10.7 | | 10.5 | | 57.7 | |

*Note.* DNE = Did not enter; DUs = (Please ask the author for the definition of DUs.)

and pre–War housing were also more likely to have gentrified. More populous tracts or those with greater proportions of residents below the poverty line were less likely to have gentrified. As in the upgrading model, the initial proportions of African Americans or Hispanics had little effect one way or another on whether a tract gentrified between 1990 and 2000, nor did the estimated price gap, distance from the CBD, median home values, or the prevalence of single-family homes versus apartments.

Factors that facilitated core area upgrading and gentrification mostly served to slow neighborhood decline, and vice versa. Whereas tracts with higher relative incomes as of 1990 were less likely to be upgraded or to gentrify by 2010, they were more likely to decline. Tracts with higher percentages of whites were less likely to decline, while larger tracts and tracts with proportionately more Hispanic residents were slightly more likely to decline. Holding relative incomes constant, poorer tracts and those with a higher percentage of residents in poverty were less likely to decline, as were tracts with more college-educated residents. Tracts with more pre-1950 housing were less likely to decline, whereas tracts with more homes built between 1950 and 1970 were more likely to decline. Proximity to downtown helped slow neighborhood decline: Tracts close to the CBD were far less likely to experience socioeconomic decline between 1990 and 2010 than more distant tracts. Higher density tracts were also less likely to decline. Tracts with higher initial home values were far less likely to decline. Median rent levels and the estimated price gap had no effect one way or another on the likelihood of decline, nor did the initial proportion of African American residents.

### *Suburban Logit Model Results*

In terms of overall explanatory power, the three suburban models do a notably better job of identifying neighborhood upgrading and decline than do their core area counterparts. Compared with the core area decline model, which correctly identifies 41% of declining tracts, the corresponding suburban model (Model S3) properly identifies 58% of declining tract outcomes. Likewise, whereas the core area gentrification model correctly classified only 3% of gentrifying urban tracts, the suburban model (Model S2) correctly classified 11%. Only in the case of upgrading tracts does the core area model outperform the suburban model (Model S1), and then only by the narrowest of margins: 12% correct predictions to 11%. Except for the metro area variable, all of the independent variables in the suburban models measure the same things as in the core area models.

Suburban upgrading—defined as a two or more decile increase in median household income between 1990 and 2010—is relatively rare. Out of 20,650 suburban tracts, only 1,129 suburban tracts upgraded between 1990 and 2010. Five tract-level factors had major roles in facilitating or impeding suburban upgrading, including (in order of importance): initial (household) income levels, initial home values, the initial proportion of residents who were white, population density, and the share of multi family housing units. Wealthier suburban tracts (i.e., those with higher relative incomes) were far less likely to upgrade, as were those with lower median home values. Suburban tracts with higher initial proportions of white residents (relative to their metro areas) were more likely to upgrade. Higher density suburban tracts were less likely to upgrade, as were tracts with proportionately more apartment units. Tracts with larger proportions of homes and apartments built prior to 1940 were also more likely to upgrade. As with the core neighborhoods, the initial proportion of African American and/or Hispanic residents had no evident effect on the probability of a suburban tract being subsequently upgraded. Neither did a neighborhood's size, absolute income level, relative rent level, or estimated price gap.

Suburban gentrification—defined here as socioeconomic upgrading that occurs among tracts with 80% or less of metro-area median income—is even rarer than suburban upgrading. Of the more than 20,000 suburban tracts included in the sample, only 529 gentrified between 1990 and 2010. Not surprisingly, the factors associated with suburban gentrification were mostly the same as those associated with suburban upgrading, and, judging from the estimated odds ratios, in much the same fashion. Suburban tracts with lower initial incomes and proportionately more whites were far more likely to gentrify by 2010, as were tracts with higher home values and fewer apartment units. Tracts with larger proportions of homes built prior to 1940 or between 1970 and 1990 were also more likely to gentrify. Suburban tracts more distant from the CBD were slightly more likely to gentrify. The few differences between suburban upgrading and suburban gentrification centered on the presence of single-family homes—those with proportionately more one-family homes were more likely to gentrify—and housing unit density, which did not affect the likelihood of gentrification one way or another. Suburban tracts with higher estimated price gaps were more likely to gentrify, although the effect was not very strong: For every $10 increase in its estimated price gap, the probability of a tract gentrifying rose by only 0.01%.

In suburban areas, as in core areas, neighborhood decline is generally the flip side of neighborhood upgrading. It is also somewhat more prevalent. Of the more than 20,000 suburban tracts in the sample, 1,882 declined—meaning their median income declined by two or more deciles between 1990 and 2010. The six tract-level factors that most affected whether a suburban tract would decline or not between 1990 and 2010 were, in order of importance: its initial median income level, prevailing rent levels, prevailing home values, its proportion of poor residents, its pre–War housing share, and the proportion of white residents. All else being equal, the wealthier a tract in 1990, the more likely it was to decline by 2010. Similarly, tracts with higher rent levels were also more likely to decline. By contrast, tracts with higher initial home values were far less likely to decline by 2010. This combination of results suggests that solid property values provide a stronger bulwark against suburban neighborhood decline than do high incomes or rents. Suburban tracts with higher proportions of residents initially living in poverty were less likely to experience socioeconomic decline, as were tracts with higher percentages of white residents. Tracts with proportionately more pre–War housing were also more decline resistant. Other tract-level factors that mattered, albeit somewhat less so, were the proportion of multi family units, the proportion of homes built between 1950 and 1970, the proportion of African American residents, and the proportion of Hispanic residents; in all four cases, larger proportions increased the likelihood of decline. Among the tract-level factors that had no effect on the probability of decline were population size, the share of single-family housing, and the proportion of college-educated residents. Indeed, the initial proportion of college-educated residents had no effect on whether a suburban tract experienced any type of change. Higher-density suburban tracts were slightly more likely to experience socioeconomic decline between 1990 and 2010, as were tracts closer to the CBD. Higher price gap levels were also associated with an increased likelihood of decline, albeit quite modestly.

## 4. Neighborhood Change and Residential Turnover

Residential displacement is the great bugaboo of neighborhood change, and especially of gentrification. *Residential displacement* is defined as involuntary turnover, such as when a tenant is evicted from their apartment, or when a homeowner loses their home to fire or redevelopment. Some amount of residential turnover and displacement is inherent in all forms of neighborhood change, but when does some amount become too much? Or, under what conditions does neighborhood change promote displacement? These are topics of both research and public policy concern.

Part of the problem with addressing them is a lack reliable data. The U.S. Census Bureau, through its American Community Survey (ACS), asks about residential turnover—specifically, whether a household moved or changed house during the previous 12 months—but there is no comparable source of displacement information.[18]

A number of researchers have tried to fill the vacuum, but with differing results. An early study by Schill and Nathan (1983) of nine neighborhoods in five cities found that among renters, involuntary displacement typically accounted for between 10% and 40% of residential turnover. A later study by Vigdor et al. (2002) of metropolitan Boston in the late 1980s found that less-educated households living in gentrifying neighborhoods were no more likely to move than otherwise similar households living in nongentrifying neighborhoods. In a similar comparison of gentrifying and nongentrifying neighborhoods in New York City between 1991 and 1995, Freeman and Braconi (2004) found no evidence of higher outmigration rates among gentrifying neighborhoods. A later national study by Freeman (2005) using the Panel Study of Income Dynamics produced a similar result: Displacement rates were not found to be systematically higher in gentrifying neighborhoods. Using yet another national data source, McKinnish, Walsh, and White (2010) come to a similar conclusion.

Regardless of whether gentrification causes systematic displacement, it can create economic and social hardship, especially for low-income renters. Gentrification causes rents to delink from resident income levels, leading to rising rent burdens. Lease renewals become more difficult as landlords seek tenants able to pay higher rents. Long-time homeowners are faced with higher property taxes and insurance costs as assessments rise. And, as Freeman (2006) documents, new residents may have different expectations of appropriate behaviors than long-time residents do, creating potential social friction.

Starting from the perspective that higher displacement rates should be reflected in higher turnover, I begin by looking at residential turnover rates as reported in the 2010 Decennial Census and the one- and three-year American Community Survey series. Nationally, 1-year residential turnover rates (the share of household occupying a different dwelling unit than in the previous year) range between 14% and 16% per year depending on economic conditions.[19] Turnover rates vary widely across metropolitan areas. Among the 70 metropolitan areas considered in this study, the average 1-year turnover rate for the 10 highest turnover metros area in 2010 was 22%. Among the 10 lowest turnover rate metros area, it was 13%.

As Table 7 indicates, turnover rates can vary even more widely within metropolitan areas than between them. Among the factors that account for intra-metropolitan differences in turnover rates are age (older residents move less frequently than younger residents), tenure (renters generally move more frequently than homeowners), household income and poverty rates (wealthier residents have more residential mobility than poorer residents, but generally move less frequently), unemployment levels (the unemployed are more likely to move in search of a job), and household type (single-person households move more frequently than married-couple or family households).

With all this turnover activity in mind, the key question for this analysis is whether neighborhood change trajectories also play a role. Specifically, I ask whether residential turnover rates are consistently higher in census tracts that have recently experienced SNSEC, holding constant many of the household-level socioeconomic factors that also contribute to turnover. To the degree that higher turnover rates are found to be consistently associated with recent neighborhood upgrading, one could reasonably conclude that upgrading and/or gentrification accelerates turnover—and, by likely extension, displacement. To the degree that turnover rates are found to be independent of neighborhood upgrading, then the link between upgrading and displacement becomes more tenuous.

The likely relationship between neighborhood decline and turnover is not as apparent. On the one hand, households that have the economic wherewithal to do so are likely to leave a declining neighborhood, suggesting that turnover rates should be positively correlated with neighborhood decline. On the other hand, to the degree that it creates a

Table 7. Average and 75th-percentile census tract (1-year) turnover rates by metropolitan area, 2010 (sorted high to low).

| Metro area | Census tract average (%) | Census tract 75th percentile (%) | Number of tracts | Metro area | Census tract average (%) | Census tract 75th percentile (%) | Number of tracts |
|---|---|---|---|---|---|---|---|
| Colorado Springs, CO | 24 | 27 | 130 | Washington, DC | 17 | 22 | 1,161 |
| Austin, TX | 23 | 29 | 350 | Dayton, OH | 17 | 20 | 253 |
| Las Vegas, NV | 22 | 27 | 540 | Milwaukee, WI | 17 | 21 | 466 |
| New Orleans, LA | 22 | 28 | 402 | Knoxville, TN | 17 | 19 | 190 |
| Phoenix, AZ | 22 | 27 | 991 | San Francisco Bay Area, CA | 16 | 20 | 1,620 |
| Oklahoma City, OK | 21 | 26 | 362 | | | | |
| Sacramento, CA | 21 | 25 | 486 | Miami, FL | 16 | 20 | 1,280 |
| Columbia, SC | 21 | 24 | 164 | Fresno, CA | 16 | 20 | 223 |
| Little Rock, AR | 21 | 26 | 157 | Albuquerque, NM | 16 | 21 | 198 |
| Kansas City, MO | 21 | 24 | 522 | El Paso, TX | 16 | 20 | 160 |
| Tucson, AZ | 21 | 26 | 241 | Syracuse, NY | 16 | 20 | 204 |
| Bakersfield, CA | 21 | 25 | 151 | Louisville, KY | 16 | 20 | 280 |
| Denver, CO | 20 | 25 | 750 | Minneapolis, MN | 16 | 20 | 772 |
| Raleigh–Durham, NC | 20 | 26 | 325 | Greensboro, NC | 16 | 19 | 333 |
| San Antonio, TX | 20 | 24 | 430 | Boston, MA | 16 | 20 | 1,139 |
| Dallas–Ft. Worth, TX | 20 | 25 | 1,328 | Springfield, MA | 16 | 22 | 132 |
| Norfolk, VA | 19 | 24 | 398 | Grand Rapids, MI | 16 | 21 | 245 |
| Columbus, OH | 19 | 25 | 404 | McAllen, TX | 16 | 17 | 113 |
| Atlanta, GA | 19 | 24 | 918 | Rochester, NY | 15 | 20 | 279 |
| Stockton, CA | 19 | 24 | 139 | Baltimore, MD | 15 | 19 | 572 |
| Jacksonville, FL | 19 | 23 | 254 | Los Angeles, CA | 15 | 19 | 3,901 |
| Orlando, FL | 19 | 25 | 391 | Detroit, MI | 15 | 18 | 1,583 |
| Charlotte, NC | 19 | 24 | 470 | St Louis, MO | 15 | 19 | 596 |
| Houston, TX | 19 | 24 | 1,060 | Cleveland, OH | 15 | 19 | 824 |
| Omaha, NE | 19 | 24 | 240 | Albany, NY | 15 | 18 | 234 |
| Tulsa, OK | 19 | 24 | 257 | Providence, RI | 14 | 18 | 266 |
| Portland, OR | 19 | 22 | 556 | Hartford, CT | 14 | 18 | 296 |
| Indianapolis, IN | 18 | 23 | 386 | Chicago, IL | 14 | 18 | 2,022 |
| Nashville, TN | 18 | 23 | 343 | Pittsburgh, PA | 14 | 15 | 692 |
| San Diego, CA | 18 | 22 | 626 | Buffalo, NY | 14 | 17 | 297 |
| Tampa, FL | 18 | 22 | 723 | Philadelphia, PA | 13 | 15 | 998 |
| Baton Rouge, LA | 18 | 21 | 128 | New York City, NY | 12 | 14 | 2,697 |
| Richmond, VA | 18 | 21 | 277 | New Haven, CT | 12 | 15 | 417 |
| Birmingham, AL | 17 | 21 | 233 | Seattle, WA | 12 | 24 | 822 |
| Cincinnati, OH | 17 | 22 | 493 | Newark, NJ | 11 | 14 | 1,102 |

negative equity trap, neighborhood decline may serve to stifle turnover, especially for homeowners.

The available data create other complications as well. Turnover rates as reported in the ACS give no indication as to whether moving makes a household better off or worse off. It may be, for example, that some displaced households wind up living in better-quality or less-expensive housing than they did prior to being displaced, or in housing in better neighborhoods. By the same logic, some number of households that voluntarily leave a changing neighborhood may find themselves in a worse housing situation. There is also an issue of timing. As measured by the U.S. Census Bureau, tract-level turnover rates are reported for a single year, 2010, whereas displacement is a continuing process. In some cases, previously acute levels of turnover and displacement may have subsided by the 2010 ACS.

With these limitations in mind, I used regression analysis to compare 1-year turnover rates (among all the census tracts in the 70 largest U.S. metropolitan areas) from the 2010 Census with two nominal measures of neighborhood change: (a) a measure indicating whether a particular tract had experienced substantial upgrading between 1990 and 2010 and (b) a similar measure indicating whether a tract had experienced substantial decline. I did not consider gentrifying neighborhoods separately from those that had upgraded, nor did I differentiate between core and suburban census tracts. The regression results are presented in Table 8.

Three sets of regressions were tested. In the first, I regressed the percentage difference in 2010 turnover rates between each census tract and its corresponding metropolitan area, with just the upgrading and decline variables. A positive value of the dependent variable indicates a higher turnover rate in the census tract than in its metropolitan area, whereas a negative value indicates a lower relative turnover rate.

By themselves, the two neighborhood change variables do a poor job of accounting for tract-level turnover rate differentials, explaining just 5% of their variance. The coefficient for the neighborhood decline variable is large (relative to the constant), positive, and statistically significant (measured at the .05 level); indicating that turnover rates are indeed higher in declining neighborhoods. The coefficient for the neighborhood upgrading variable is small, negative, and marginally insignificant, indicating that there is only a very slight relationship between turnover rates and neighborhood upgrading when measured at the census tract level.

In the second regression model, I included six additional independent variables to control for some of the many household-level factors that might also contribute to residential turnover. The six additional variables, all measured at the census tract level in 2010, are median income, median age, poverty status, tenure, local unemployment rates, and the share of single-person households in each tract. Because these measures all vary among metropolitan areas as well as within them, I calculated relative measures for each tract by dividing the tract-level value by its corresponding metropolitan area value. To allow for the fact that household income might have an absolute effect as well as a relative effect, I also included the 2010 median household income level for each tract.

Altogether, the nine independent variables in this second regression explain 39% of the variation in 2010 turnover rates among census tracts in the 70 largest metropolitan areas. Not unexpectedly, household-level socioeconomic factors trump neighborhood change. Although all seven socioeconomic variables are statistically significant, the two neighborhood change measures are not. The two socioeconomic measures most strongly associated with neighborhood-level turnover rates are age and household type. For every 1-year increase in a census tract's median age (relative to its metropolitan area), its relative

Table 8. Regression results comparing 2010 residential turnover rates by census tract with socioeconomic characteristics and neighborhood change category.

| Dependent variable: Percentage difference in 2010 1-year turnover rates between each census tract and its corresponding metropolitan area | | | | |
|---|---|---|---|---|
| Independent variable | Coefficient | Significance level | Coefficient | Significance level |
| Declining tract, 1990–2010 (0/1) | 0.08 | 0.00 | −0.01 | 0.25 |
| Upgrading tract, 1990–2010 (0/1) | −0.02 | 0.06 | −0.01 | 0.60 |
| Median household income | | | 0.00 | 0.01 |
| Relative (median) household income | | | −0.18 | 0.00 |
| Relative median age | | | −1.91 | 0.00 |
| One-person households (relative %) | | | 0.53 | 0.00 |
| Renters (relative %) | | | 0.07 | 0.00 |
| Relative unemployment rate | | | −0.08 | 0.00 |
| In poverty (relative %) | | | −0.07 | 0.00 |
| Constant | −0.02 | 0.00 | 1.60 | 0.00 |
| $R^2$ | 0.046 | | 0.39 | |
| Number of observations | 41,991 | | 41,991 | |

turnover rate fell by nearly 2%. For every 1% increase in the share of single-person households in a census tract (again, relative to its metropolitan area), its relative turnover rate increased by just over 0.5%. Income had the next most important effect, followed by unemployment rates, poverty rates, and the share of renters.

Although the positive coefficient sign for the share of renters is clearly as expected—renters move more frequently than homeowners, on average—the negative signs associated with the relative income, poverty rate, and unemployment rate variables are more ambiguous. All else being equal, turnover rates are lower in tracts with higher poverty and unemployment rates. This is consistent with the view that poverty and unemployment tend to trap residents at their current locations rather than encouraging them to seek opportunities elsewhere. The negative coefficient associated with the median income variable suggests much the same dynamic. To the degree that turnover rates provide some indication of displacement activity, we may conclude that, on average, there does not seem to be any relationship between SNSEC, whether positive or negative, and displacement.

This on-average qualifier is important: It may be that turnover rates and neighborhood change are related in some metropolitan areas but not in others. To find out, I ran a third regression model incorporating the two neighborhood change variables and a unique 0/1 dummy variable, or fixed-effect variable, for each metropolitan area. The effect of including these fixed-effect variables is to pull out any unique variation in turnover rates associated with particular metropolitan areas, thereby leaving more (or perhaps less) variation to be accounted for by the two neighborhood change variables.

Because I expected many of the metropolitan dummy variables not to be statistically significant, I ran this model in stepwise form. None of the metropolitan dummy variables entered the model as statistically significant. Nor, as it turns out, did the neighborhood upgrading variable, leaving only the neighborhood decline variable as statistically significant. Because of the paucity of findings, the results of this third regression model are not reported in Table 8.

Taken together, these results suggest that neighborhood-level variations in residential turnover rates are not principally a result of prior neighborhood socioeconomic upgrading or decline. Significant neighborhood socioeconomic change may indeed promote turnover in some neighborhoods, but this effect is far from systematic.

## 5. Summary of Findings, Policy Implications, and an Agenda for Future Research

Using gentrification as a lens, this article has sought to answer four questions about the broader processes of neighborhood change in metropolitan America:

1. *Is it possible using census data to come up with a consistent and robust approach to measuring gentrification and other forms of SNSEC across all U.S. metropolitan areas?*

This article demonstrates the use of the 3-D method to consistently identify census tracts (as representative of neighborhoods) that experienced substantial socioeconomic change over an extend period of time in which both neighborhood geography and the distribution of socioeconomic characteristics are changing. The 3-D method has the advantage of being conceptually simple and easy to operationalize using readily available census data. Its disadvantage, at least as used here, is that it considers neighborhood change solely from a socioeconomic perspective, and not from a housing market, neighborhood quality, or resident experience perspective. To the degree that gentrification—and neighborhood change more generally—connects changes in neighborhood residential makeup to changes in housing prices, rents, and the local stock to changes residential composition, the the 3-D method may slightly understate the actual extent of neighborhood change.

Applying the 3-D method to the nation's 70 largest metropolitan areas indicates that neighborhood decline, not neighborhood upgrading, was the dominant form of neighborhood socioeconomic change between 1990 and 2010. Comparing metropolitan population shares reveals that roughly 20% (of the 1990 population of the 70 largest metro areas) lived in census tracts that would subsequently experience substantial socioeconomic decline, whereas only 6% lived in tracts that would experience socioeconomic upgrading, and only 3% lived in pregentrifying neighborhoods. Decline was more prevalent in the suburbs. Among suburban census tracts, the population of declining tracts exceeded that of upgrading tracts by a ratio of 4 to 1; among core areas, the ratio was just a little under 2 to 1.

2. *To what degree are gentrification and other forms of SNSEC the result of metropolitan-scale economic and demographic forces versus more bottom-up and neighborhood-specific forces and dynamics?*

Depending on the type of change and location, metropolitan-scale factors play a small-to-moderate role in determining how many residents are likely to be affected by neighborhood change. As a rule, metropolitan-scale effects play a greater role in suburban areas than in core areas, and correlate better with neighborhood decline than with neighborhood upgrading. Two metro-scale variables, the share of households with children, and lower core area densities, explain 44% of the extent of suburban gentrification activity between 1990 and 2000, as measured by population share. The same two variables explain 28% of suburban upgrading. Suburban decline, measured the same way, was proportionately greater in metros area with higher population growth rates and proportionately more immigrants.

Higher metropolitan growth rates were also strongly correlated with neighborhood decline in core areas, as were lower household incomes and higher core area densities. The effect of metropolitan-scale factors on core area upgrading was more limited, accounting for just 19% of upgrading and gentrification activity between 1990 and 2000. Except for the presence of an urban containment boundary, no metro-scale socioeconomic or growth factors were associated with neighborhood upgrading activity. The presence of a growth-limiting boundary was also correlated with greater gentrification activity, as was the initial presence of a higher proportion of nonwhites.

Taken together, these results suggest that too much population growth at the metropolitan scale tends to destabilize neighborhoods, whereas the presence of an urban containment boundary acts as a stabilizing force, especially in core areas. Density, however, is a two-edged sword: It seems to promote gentrification activity in core areas while discouraging it in suburban neighborhoods.

3. *To what degree are gentrification and other forms of SNSEC shaped by the characteristics of individuals and groups (including residents, property owners, and developers) operating at the neighborhood level?*

Neighborhood change is fundamentally a local process, so we might expect the characteristics of individual neighborhoods to be more important than metropolitan-scale factors in explaining patterns of neighborhood change. As is the case for metro-scale factors, neighborhood-scale factors do a better job of explaining neighborhood decline than neighborhood upgrading. Together with a single metro-scale effect variable and an estimate of the rent-gap—both of which are statistically significant—a combination of local factors correctly identifies 58% of suburban census tracts that experienced substantial socioeconomic decline between 1990 and 2000. The suburban tracts most likely to decline were those with initially higher incomes and rents, and lower home values. Suburban tracts with lower initial proportions of whites and higher proportions of African Americans and Hispanics were only slightly more likely to decline. Similar factors accounted for core area decline, except for rent levels and the proportion of African Americans, neither of which was statistically significant. Core area tracts near their CBDs were less likely to have declined.

Upgrading patterns are harder to explain. Among core areas, the principal local factors associated with whether a neighborhood experienced substantial socioeconomic upgrading between 1990 and 2010 were low initial incomes, high initial rents, and higher proportions of white and college-educated residents. (Even without the benefit of a logit model, it seems that Doonesbury got it exactly right.) The presence and availability of an older housing stock also contributed to the likelihood of neighborhood upgrading. The same factors also helped explain gentrification activity. Beyond a greater relative presence of white residents, the presence of less (or more) African American and Hispanic residents did not seem to affect the likelihood that a neighborhood would be upgraded or gentrify. Although each of these factors is individually important to understanding neighborhood upgrading, collectively, they could explain only 12% of core area upgrading activity, and just 3% of neighborhood gentrification. Neighborhood upgrading, it seems, remains a more ad hoc and idiosyncratic process than neighborhood decline.

Among suburban census tracts, upgrading and gentrification activity were most closely associated with a high initial proportion of white residents, higher home values, and low initial incomes. As in core areas, after accounting for the initial proportion of white residents, the proportions of African American and Hispanic residents did not seem to affect the probability that a suburban tract would be upgraded or gentrify. Except in the case of suburban gentrification, the presence of a potential price gap was not associated with either upgrading or gentrification activity.

4. *To what extent are gentrification and other forms of substantial neighborhood change always accompanied by the displacement of existing residents?*

To be sure, and although they track together, residential turnover and displacement are not the same thing. Residential turnover includes both voluntary and involuntary moves; displacement is inherently involuntary. This caveat notwithstanding, 2010 turnover rates were actually slightly lower in census tracts that experienced substantial upgrading between 1990 and 2010. Additional controlling for socioeconomic composition of the neighborhood causes the connection between recent turnover rates and neighborhood change to disappear altogether. This is not to say that neighborhood upgrading and decline cannot or does not generate displacement in particular neighborhoods; however, it does suggest that the relationship is not a systematic or widespread one. It is also consistent with the results of numerous studies that find that the decision to move is more a result of personal circumstances and aspirations than of neighborhood quality.

### *Policy Implications*

What is a nonacademic planner or policymaker to make of these results? The single most important takeaway is that despite the media's current fascination with gentrification, it is neighborhood decline—in both cities and suburbs—that remains the dominant form of neighborhood change, and the one that local urban development programs should continue to focus on. To the degree that *metropolitan* policymakers have any power to effectively promote neighborhood upgrading or combat neighborhood decline, they should focus their efforts on trying to limit suburban sprawl, on trying to attract immigrant households and households with children to suburban communities, and on trying to regularize the rate of metropolitan growth. These efforts will have small but noticeable effects on stabilizing both core area and suburban neighborhoods.

Center-city planners seeking to promote neighborhood upgrading should focus their efforts on older and walkable neighborhoods having a diverse and aspirational population. Center-city planners seeking to anticipate and stem decline should keep a close eye on more distant neighborhoods, those with proportionately more multifamily housing, and those with large populations already in poverty. They should also be aware that although decline is spatially contagious—that is, it tends to spill over from one neighborhood to another—upgrading is not. This research also indicates that in core areas, there are few structural differences between neighborhood upgrading and gentrification, other than the fact that gentrification tends to start from a lower income starting point. This suggests that rather than trying to regulate upgrading as a means of limiting gentrification, local planners are better off trying to more broadly redistribute the benefits of gentrification, such as through circuit-breaker mechanisms to limit the effects of rising property taxes on long-time low-income homeowners, through a local system of housing vouchers directed toward long-time low-income renters, and through high real estate transfer taxes on short-term property flippers and speculators. Should none of these less extreme mechanisms work, the possibility of a limited form of protection for low-income households from skyrocketing rents should not automatically be discarded.

Suburban planners seeking to promote neighborhood upgrading and reinvestment should focus their efforts on older, moderate-density neighborhoods with higher rates of owner occupancy, and a history of stable property values. These same characteristics also describe suburban neighborhoods poised for gentrification, so, as in central cities, the focus of local gentrification policy should not be to stop it, but to safeguard long-time residents from rapidly rising home prices and rents, and, where possible, to make sure that some of the increases in local tax revenues are directed back to the neighborhoods where those increases were generated. In terms of anticipating and heading off neighborhood decline, suburban planners should focus their efforts on racially diverse neighborhoods and neighborhoods with a higher proportion of multifamily homes (two characteristics that indicate greater vulnerability to disinvestment); on neighborhoods with comparatively high rents but low property values; and on older, *less-walkable* neighborhoods.

Beyond these analytical takeaways, local planners need to better understand processes of neighborhood change as they actually occur, not after the fact when it is too late to affect their trajectory.

### *Additional Considerations: An Agenda for Future Research*

Above all, this research reveals processes of neighborhood change, especially those involving neighborhood upgrading and gentrification, to be more complicated and idiosyncratic than can be captured through census-based measurement systems and statistical models. This argues for developing more qualitative measures of neighborhood change as well as for developing more robust measures and models of neighborhood change. Possible avenues of further work should include the following.

- *Expanding the use of the 3-D model to include other measures of neighborhood change*: The same 3-D model used here to explore changes in neighborhood status based on income can also be used to summarize changes based on housing prices, rent levels, poverty rates, and other socioeconomic measures of neighborhood change. It can also be used to summarize changes in neighborhood service levels, such as crime rates or school test scores. To what degree do these different 3-D measures of change coincide? Can they be used to present a more comprehensive picture of neighborhood change that combines demographic, social, economic, housing characteristics and prices, and resident turnover and displacement into a single and robust measure of neighborhood change?
- *Incorporating localized measures of community service quality and mortgage lending activity*: From the 1950s to the 1980s, millions of middle-class households departed core area neighborhoods in search of better schools and lower crime rates. A few returned as urban crime rates started falling in the early 1990s. This trend accelerated as more and more cities turned their attention to improving public-school quality. The increased availability of cheap and easy-to-get mortgage financing, especially to moderate-income households that had previously been locked out of homeownership, also benefitted urban neighborhoods. How localized were these effects? To find out, subsequent research might expand the logit model framework used in Section 3 to include localized information on reductions in crime rates, improvements in school test scores, and mortgage lending volumes.
- *Exploring the effects of spatial autocorrelation:* The term *spatial autocorrelation* refers to adjacent or nearby spatial features exhibiting similar behavior or characteristics. Most processes that are locationally based—and neighborhood change is certainly one such example—exhibit some degree of spatial autocorrelation. Subsequent research should examine the circumstances under which neighborhood change in one neighborhood, whether upgrading or decline, preconditions or spills over into similar types of neighborhood change in adjacent or nearby neighborhoods.
- *Developing better measures of displacement, and exploring the relationships between turnover and displacement*: Short of developing and administering an original survey instrument, this is easier said than done, especially because neither

the U.S. Census Bureau nor any other federal survey regularly asks about residential displacement. It might be possible to generate synthetic displacement rates by comparing residential turnover among renter households, controlling for employment status, income, household type, and source and destination area public service quality. This approach assumes that the only reason a renter household would voluntarily move to a nearby neighborhood with lower quality public services is because of rising housing costs in their previous neighborhood.

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## Notes

1. This includes the cities of Baltimore, Maryland; Detroit, Michigan; New Orleans, Louisiana; and St. Louis, Missouri—all of which lost significant population during the 2000 to 2010 period.
2. A quick Google search of news articles mentioning gentrification found over 6,600 articles during March 2014 alone.
3. Compared with population and household data, which are readily available through the Decennial Census and the ACS, information on the industrial, occupational, and economic performance characteristics of neighborhood businesses is generally less readily available.
4. The U.S. Census Bureau releases individual records as part of its Public Use Micro Sample (PUMS) series but only at the level of large-scale districts of 200,000 or more residents. PUMS data are not panel data, meaning that it is impossible to follow particular respondents across different surveys.
5. This is the method used by Thomas (2009, 2010) and Ramsey (2010), albeit at the city rather than the neighborhood level.
6. Different parties emphasize different aspects of neighborhood change when defining gentrification. The *Merriam–Webster dictionary* emphasizes both neighborhood upgrading and displacement when defining gentrification as "the process of renewal and rebuilding accompanying the influx of middle-class or affluent people into deteriorating areas that often displaces poorer residents p. 4" (http://www.merriam-webster.com/dictionary/gentrification). The U.S. Department of Housing and Urban Development (1979) defined *gentrification* in 1979 as the process "by which a neighborhood occupied by lower-income households undergoes revitalization or reinvestment through the arrival of upper-income households" (U.S. Department of Housing and Urban Development, 1979). In the *Encyclopedia of Housing,* Smith (1988) defined *gentrification* as "the process by which central urban neighborhoods that have undergone disinvestments and economic decline experience a reversal, reinvestment, and the in-migration of a relatively well-off, middle- and upper middle-class population" (pp. 198–199). More recently, Hammel and Wyly (1996) defined *gentrification* as "the replacement of low-income, inner-city working class residents by middle- or upper-class households, either through the market for existing housing or demolition to make way for new upscale housing construction" (p. 248).
7. Tracts in which the average cell difference (after rounding) increased by two or more deciles were identified as upgrading, whereas tracts in which the average difference decreased by two or more deciles were identified as declining. Tracts in which the average cell difference after rounding was between −1 and +1 were identified as stable, and those tracts with no data—that is, the census location did not exist in 1990 or 2010, or I could not calculate a reliable average difference—were discarded. To the extent that these few discarded tracts may have been more likely to have experienced substantial income change between 1990 and 2000, this last step may serve to slightly underestimate the extent of either upgrading or decline.
8. The core versus suburban area difference-of-means values and significance levels reported in Table 1 are for the sample as a whole and are not based on comparisons for each metropolitan area.

9. For an excellent review of this and other perspectives on gentrification and neighborhood change, see Ellen and O'Regan (2012).
10. Among the largest metro areas, Singer (2004) classifies Boston, Massachusetts; Chicago, Illinois; New York, New York; Newark, New Jersey; and San Francisco, California, as continuous gateways. Singer classifies Miami–Ft. Lauderdale, Florida; Houston, Texas; Los Angeles, California; and San Diego, California, as post–War gateways. Singer classifies Atlanta, Georgia; Dallas–Ft. Worth, Texas; Las Vegas, Nevada; Orlando, Florida; and Washington, DC, as *emerging gateways*.
11. Pendall, Puentes, and Martin (2006) identify the following large metro areas as falling into the "high" or "very high" urban containment category: Baltimore, MD Washington, DC; Boulder, CO, Las Vegas, NV, Memphis, TN; Nashville, TN; New Orleans, LA; Norfolk–Virginia Beach, VA; Portland, OR; the San Francisco Bay Area, CA; San Diego, CA; Seattle, WA; and Tampa, FL.
12. Pendall et al. (2006) identify the following large metro areas as falling into the "high" or "very high" infrastructure capacity limitations category: Austin, Texas; Baltimore, Maryland–Washington, DC; Boulder, Colorado; Dallas–Ft. Worth, Texas; Houston, Texas; Jacksonville, Florida; Los Angeles, California; Miami, Florida; Minneapolis, Minnesota; New Orleans, Louisiana; Orlando, Florida; Phoenix, Arizona; Norfolk–Virginia Beach, Virginia; Portland, Oregon; Sacramento, California; Salt Lake City, Utah; San Antonio, Texas; the San Francisco Bay Area, California; San Diego, California; Seattle, Washington; and Tampa, Florida.
13. These binary distinctions clearly overlap. For example, a non upgraded tract can also be a declining tract, a non declining tract can also be an upgraded tract or a gentrifying tract, and an upgraded tract can also be a gentrifying tract.
14. As a matter of convention, estimated probability values greater than .5 are generally rounded up to 1, whereas those less than .5 are rounded down to 0.
15. Because their resulting parameter estimates take the form of exponents rather than linear coefficients, logit models are harder to interpret. Fortunately, in the same way that dividing linear regression coefficients by their standard errors yields a *t*-statistic and a measure of statistical significance, dividing a logit coefficient estimate by its standard error yields a Wald statistic, which can be used the same way as *t*-statistics to assess statistical significance. Similarly, just as the beta coefficients in regression simplify the task of comparing variables having different units of measure, the odds ratio serves the same function in logit models. Odds ratios greater than 1.0 indicate that an increase in the variable value will be associated with an *increasing* outcome probability. Odds ratios less than 1.0 indicate that an increase in the variable value will be associated with a *decreasing* outcome probability.
16. Similar price gaps can also be estimated for owner-occupied homes, but because housing prices also track closely with macroeconomic measures such as mortgage rates, price gaps based on apartment rents provide a more localized picture of the pattern of property value premiums and discounts.
17. These percentages are calculated using a .25 probability cutoff instead of a .5 cutoff. What this means is that if the estimated probability of a particular tract gentrifying (or McMansionizing or degentrifying) exceeds .25, the tract is assigned to that discrete outcome.
18. As Freeman (2005) notes, the national Panel Study on Income Dynamics can be used to analyze the socioeconomic characteristics of households who move out of or into particular neighborhoods.
19. According to the 2008, 2010, and 2012 3-year samples of the American Community Survey (http://factfinder.census.gov/faces/nav/jsf/pages/programs.xhtml?program = acs), the proportion of U.S. households occupying the same dwelling unit as in the previous year was 16% in 2008, 15% in 2010, and 14% in 2012.

## Notes on Contributor

John D. Landis is Crossways Professor in the Department of City and Regional Planning at University of Pennsylvania where he teaches and conducts research in the areas of urban growth and change, housing, and urban real estate development.

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Appendix A. Distance and income thresholds used to distinguish core area from suburban tracts, and upgrading from gentrifying tracts.

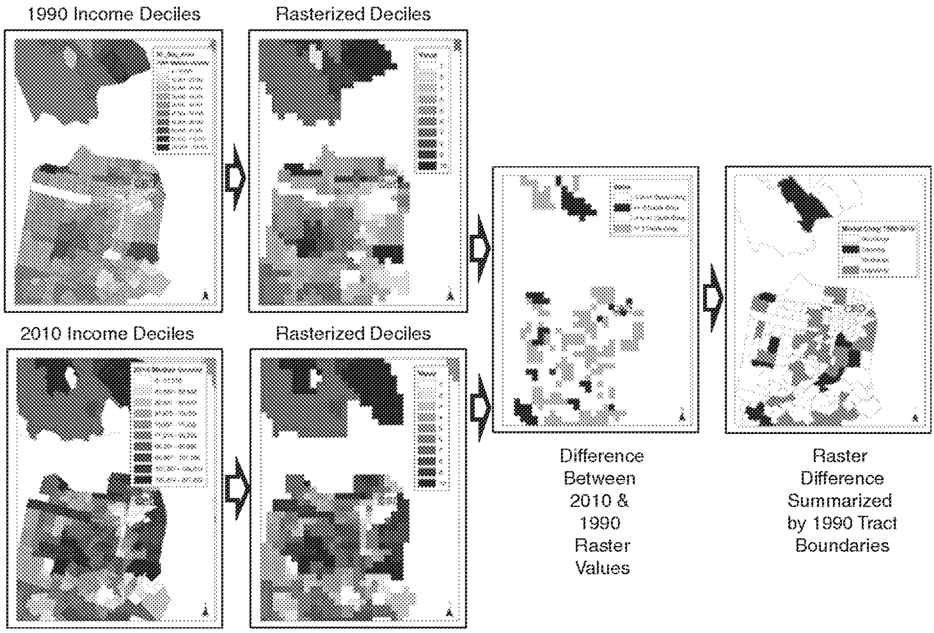
| Metro area | 1990 metropolitan population | Census tracts | Threshold distance (km) for distinguishing core area and suburban tracts | Share of 1990 metropolitan population in core area tracts (%) | 1990 household income level (40% of median) for distinguishing gentrifying from upgrading tracts ($) |
|---|---|---|---|---|---|
| Albany, NY | 861,424 | 216 | 5 | 27 | 28,452 |
| Albuquerque, NM | 589,131 | 137 | 5 | 35 | 24,589 |
| Atlanta, GA | 2,959,950 | 502 | 10 | 17 | 30,115 |
| Austin, TX | 858,987 | 222 | 6 | 25 | 24,338 |
| Bakersfield, CA | 545,865 | 110 | 5 | 33 | 25,544 |
| Baltimore, MD | 2,042,634 | 508 | 10 | 49 | 31,276 |
| Baton Rouge, LA | 528,236 | 110 | 6 | 31 | 22,361 |
| Birmingham, AL | 840,140 | 189 | 10 | 41 | 22,697 |
| Boston, MA | 4,724,047 | 1,032 | 10 | 25 | 34,794 |
| Buffalo, NY | 1,189,288 | 290 | 10 | 44 | 24,511 |
| Charleston, SC | 501,085 | 114 | 10 | 34 | 23,782 |
| Charlotte, NC | 1,156,742 | 262 | 10 | 27 | 26,157 |
| Chicago, IL | 7,526,933 | 1,800 | 10 | 19 | 29,777 |
| Cleveland, OH | 2,868,154 | 857 | 10 | 22 | 26,006 |
| Colorado Springs, CO | 397,014 | 84 | 5 | 31 | 25,530 |
| Columbia, SC | 456,855 | 106 | 6 | 29 | 26,096 |
| Columbus, OH | 1,345,450 | 343 | 10 | 42 | 26,336 |
| Dallas–Ft. Worth, TX | 4,037,282 | 875 | 10 | 23 | 31,413 |
| Dayton, OH | 965,008 | 246 | 10 | 34 | 26,425 |
| Denver, CO | 1,981,911 | 532 | 10 | 29 | 27,824 |
| Detroit, MI | 5,199,966 | 1,396 | 15 | 26 | 30,702 |
| El Paso, TX | 591,610 | 95 | 8 | 100 | 18,625 |
| Fresno, CA | 755,526 | 144 | 8 | 46 | 23,674 |
| Grand Rapids, MI | 937,879 | 209 | 8 | 17 | 29,915 |
| Greensboro, NC | 1,058,793 | 262 | 8 | 30 | 25,949 |
| Hartford, CT | 1,157,649 | 298 | 8 | 28 | 38,979 |
| Houston, TX | 3,733,606 | 804 | 15 | 31 | 24,701 |
| Indianapolis, IN | 1,380,491 | 331 | 10 | 36 | 27,283 |
| Jacksonville, FL | 904,434 | 170 | 10 | 39 | 25,793 |
| Kansas City, MO | 1,582,875 | 449 | 10 | 25 | 26,233 |
| Knoxville, TN | 588,956 | 139 | 10 | 32 | 22,099 |
| Las Vegas, NV | 860,693 | 162 | 8 | 51 | 26,250 |
| Los Angeles, CA | 14,521,077 | 2,549 | 15 | 39 | 33,262 |
| Louisville, KY | 948,829 | 250 | 8 | 38 | 24,349 |
| McAllen, TX | 383,545 | 63 | 6 | 36 | 14,103 |
| Miami, FL | 4,306,933 | 692 | 10 | 28 | 26,334 |
| Milwaukee, WI | 1,607,183 | 429 | 10 | 45 | 27,790 |
| Minneapolis, MN | 2,545,869 | 657 | 10 | 37 | 32,095 |
| Nashville, TN | 989,556 | 207 | 8 | 25 | 26,203 |
| New Haven, CT | 1,716,385 | 419 | 10 | 18 | 39,617 |
| New Orleans, LA | 1,282,817 | 382 | 8 | 41 | 20,145 |
| New York City, NY | 9,748,623 | 2,739 | 15 | 48 | 29,583 |
| Newark, NJ | 4,444,957 | 1,074 | 10 | 21 | 36,211 |
| Norfolk, VA | 1,282,817 | 382 | 8 | 24 | 26,061 |
| Oklahoma City, OK | 958,839 | 322 | 10 | 36 | 22,297 |
| Omaha, NE | 639,580 | 166 | 8 | 44 | 25,875 |
| Orlando, FL | 1,224,852 | 221 | 10 | 33 | 26,157 |
| Philadelphia, PA | 3,752,192 | 964 | 12 | 42 | 31,717 |
| Phoenix, AZ | 2,238,480 | 490 | 12 | 29 | 27,010 |
| Pittsburgh, PA | 2,420,231 | 760 | 10 | 30 | 24,554 |

Appendix A – *continued*

| Metro area | 1990 metropolitan population | Census tracts | Threshold distance (km) for distinguishing core area and suburban tracts | Share of 1990 metropolitan population in core area tracts (%) | 1990 household income level (40% of median) for distinguishing gentrifying from upgrading tracts ($) |
|---|---|---|---|---|---|
| Portland, OR | 1,793,371 | 404 | 10 | 26 | 27,383 |
| Providence, RI | 1,103,287 | 244 | 8 | 42 | 30,038 |
| Raleigh–Durham, NC | 855,545 | 196 | 6 | 25 | 27,004 |
| Richmond, VA | 865,640 | 246 | 8 | 29 | 28,438 |
| Rochester, NY | 1,062,470 | 264 | 8 | 35 | 29,583 |
| Sacramento, CA | 1,453,356 | 308 | 8 | 25 | 29,868 |
| San Antonio, TX | 1,329,723 | 256 | 8 | 38 | 21,470 |
| San Diego, CA | 2,473,370 | 437 | 10 | 26 | 31,921 |
| San Francisco Bay Area, CA | 6,194,367 | 1,325 | 8 | 36 | 37,388 |
| Seattle, WA | 2,827,096 | 582 | 10 | 13 | 31,815 |
| Springfield, MA | 577,630 | 116 | 5 | 30 | 28,257 |
| St Louis, MO | 2,492,497 | 464 | 10 | 24 | 26,113 |
| Stockton, CA | 480,613 | 112 | 6 | 40 | 27,296 |
| Syracuse, NY | 756,029 | 211 | 6 | 30 | 28,484 |
| Tampa, FL | 2,008,227 | 394 | 10 | 27 | 23,003 |
| Tucson, AZ | 666,880 | 115 | 6 | 38 | 21,000 |
| Tulsa, OK | 708,954 | 206 | 8 | 31 | 23,482 |
| Washington, DC | 3,674,011 | 872 | 10 | 32 | 41,678 |

**Appendix B**

San Francisco County: Conversion of 1990 and 2010 tract income to income deciles to neighborhood change categories.



Appendix C. Tabulation of 1990 census tracts and tract populations for core area and suburban upgrading, gentrifying, and declining census tracts.

| Metropolitan area | All metro area tracts: Census tracts | All metro area tracts: 1990 population | Core area upgrading: Census tracts | Core area upgrading: 1990 population | Core area upgrading: Metro population (%) | Core area gentrification: Census tracts | Core area gentrification: 1990 population | Core area gentrification: Metro population (%) | Core area declining: Census tracts | Core area declining: 1990 population | Core area declining: Metro population (%) | Suburban upgrading: Census tracts | Suburban upgrading: 1990 population | Suburban upgrading: Metro population (%) | Suburban gentrifying: Census tracts | Suburban gentrifying: 1990 population | Suburban gentrifying: Metro population (%) | Suburban declining: Census tracts | Suburban declining: 1990 population | Suburban declining: Metro population (%) |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Albany, NY | 216 | 861,424 | 1 | 4,232 | 0.5 | 1 | 4,232 | 0.5 | 9 | 43,887 | 5.1 | 9 | 29,326 | 3.4 | 5 | 14,796 | 1.7 | 18 | 72,340 | 8.4 |
| Albuquerque, NM | 137 | 589,131 | 0 | 0 | 0.0 | 0 | 0 | 0.0 | 18 | 75,195 | 12.8 | 11 | 31,841 | 5.4 | 9 | 25,838 | 4.4 | 12 | 61,712 | 10.5 |
| Atlanta, GA | 502 | 2,959,950 | 22 | 63,563 | 2.1 | 14 | 35,889 | 1.2 | 12 | 70,949 | 2.4 | 27 | 155,968 | 5.3 | 11 | 45,146 | 1.5 | 101 | 786,326 | 26.6 |
| Austin, TX | 222 | 858,987 | 5 | 13,827 | 1.6 | 4 | 11,075 | 1.3 | 7 | 20,271 | 2.4 | 8 | 34,327 | 4.0 | 5 | 23,288 | 2.7 | 53 | 203,715 | 23.7 |
| Bakersfield, CA | 110 | 545,865 | 1 | 4,197 | 0.8 | 0 | 0 | 0.0 | 6 | 47,041 | 8.6 | 12 | 69,060 | 12.7 | 9 | 50,735 | 9.3 | 15 | 62,903 | 11.5 |
| Baltimore, MD | 508 | 2,042,634 | 18 | 44,728 | 2.2 | 15 | 38,364 | 1.9 | 49 | 179,903 | 8.8 | 19 | 72,352 | 3.5 | 10 | 36,652 | 1.8 | 39 | 187,491 | 9.2 |
| Baton Rouge, LA | 110 | 528,236 | 4 | 9,598 | 1.8 | 4 | 9,598 | 1.8 | 9 | 43,235 | 8.2 | 7 | 53,178 | 10.1 | 2 | 15,635 | 3.0 | 17 | 83,013 | 15.7 |
| Birmingham, AL | 189 | 840,140 | 1 | 3,580 | 0.4 | 0 | 0 | 0.0 | 16 | 75,842 | 9.0 | 3 | 10,623 | 1.3 | 1 | 3,561 | 0.4 | 22 | 95,378 | 11.4 |
| Boston, MA | 1,032 | 4,724,047 | 28 | 89,915 | 1.9 | 17 | 47,269 | 1.0 | 12 | 51,446 | 1.1 | 33 | 166,868 | 3.5 | 7 | 24,278 | 0.5 | 26 | 146,361 | 3.1 |
| Buffalo, NY | 290 | 1,189,288 | 8 | 23,453 | 2.0 | 5 | 6,080 | 0.5 | 13 | 50,132 | 4.2 | 4 | 14,249 | 1.2 | 1 | 1,789 | 0.2 | 23 | 109,405 | 9.2 |
| Charleston, SC | 114 | 501,085 | 4 | 9,394 | 1.9 | 1 | 3,015 | 0.6 | 12 | 55,772 | 11.1 | 8 | 19,973 | 4.0 | 5 | 5,690 | 1.1 | 25 | 154,117 | 30.8 |
| Charlotte, NC | 262 | 1,156,742 | 6 | 14,898 | 1.3 | 5 | 11,428 | 1.0 | 23 | 125,129 | 10.8 | 9 | 38,508 | 3.3 | 6 | 24,268 | 2.1 | 57 | 280,349 | 24.2 |
| Chicago, IL | 1,800 | 7,526,933 | 74 | 220,016 | 2.9 | 51 | 174,002 | 2.3 | 31 | 78,324 | 1.0 | 30 | 110,335 | 1.5 | 12 | 33,129 | 0.4 | 389 | 1,900,461 | 25.2 |
| Cleveland, OH | 857 | 2,868,154 | 17 | 26,229 | 0.9 | 14 | 16,907 | 0.6 | 30 | 74,758 | 2.6 | 32 | 127,566 | 4.4 | 8 | 27,075 | 0.9 | 86 | 294,023 | 10.3 |
| Colorado Springs, CO | 84 | 397,014 | 2 | 3,623 | 0.9 | 2 | 3,623 | 0.9 | 9 | 34,536 | 8.7 | 0 | 0 | 0.0 | 0 | 0 | 0.0 | 17 | 103,951 | 26.2 |
| Columbia, SC | 106 | 456,855 | 30 | 136,566 | 29.9 | 7 | 27,534 | 6.0 | 0 | 0 | 0.0 | 0 | 0 | 0.0 | 0 | 0 | 0.0 | 3 | 12,696 | 2.8 |
| Columbus, OH | 343 | 1,345,450 | 14 | 33,381 | 2.5 | 9 | 20,641 | 1.5 | 38 | 123,469 | 9.2 | 12 | 50,924 | 3.8 | 5 | 14,043 | 1.0 | 45 | 234,857 | 17.5 |
| Dallas–Ft. Worth, TX | 875 | 4,037,282 | 29 | 69,238 | 1.7 | 23 | 54,652 | 1.4 | 44 | 172,720 | 4.3 | 30 | 138,513 | 3.4 | 21 | 80,383 | 2.0 | 197 | 1,038,480 | 25.7 |
| Dayton, OH | 246 | 965,008 | 5 | 12,134 | 1.3 | 2 | 3,702 | 0.4 | 16 | 52,894 | 5.5 | 21 | 78,846 | 8.2 | 8 | 29,194 | 3.0 | 19 | 85,909 | 8.9 |
| Denver, CO | 532 | 1,981,911 | 16 | 47,766 | 2.4 | 14 | 40,340 | 2.0 | 39 | 122,763 | 6.2 | 21 | 74,612 | 3.8 | 14 | 43,477 | 2.2 | 105 | 438,875 | 22.1 |
| Detroit, MI | 1,396 | 5,199,966 | 18 | 48,456 | 0.9 | 18 | 48,456 | 0.9 | 42 | 147,672 | 2.8 | 72 | 252,588 | 4.9 | 27 | 81,365 | 1.6 | 193 | 750,032 | 14.4 |
| El Paso, TX | 95 | 591,610 | 0 | 0 | 0.0 | 0 | 0 | 0.0 | 4 | 17,541 | 3.0 | 6 | 40,149 | 6.8 | 5 | 37,258 | 6.3 | 16 | 97,158 | 16.4 |
| Fresno, CA | 144 | 755,526 | 3 | 24,118 | 3.2 | 3 | 24,118 | 3.2 | 19 | 108,018 | 14.3 | 6 | 22,659 | 3.0 | 6 | 22,659 | 3.0 | 17 | 86,590 | 11.5 |
| Grand Rapids, MI | 209 | 937,879 | 0 | 0 | 0.0 | 0 | 0 | 0.0 | 13 | 68,145 | 7.3 | 20 | 91,203 | 9.7 | 9 | 33,562 | 3.6 | 30 | 142,823 | 15.2 |
| Greensboro, NC | 262 | 1,058,793 | 8 | 13,016 | 1.2 | 4 | 4,937 | 0.5 | 36 | 129,419 | 12.2 | 25 | 97,851 | 9.2 | 5 | 14,678 | 1.4 | 21 | 85,732 | 8.1 |
| Hartford, CT | 298 | 1,157,649 | 2 | 1,028 | 0.1 | 1 | 269 | 0.0 | 7 | 24,774 | 2.1 | 4 | 23,295 | 2.0 | 1 | 3,154 | 0.3 | 24 | 89,056 | 7.7 |
| Houston, TX | 804 | 3,733,606 | 30 | 87,871 | 2.4 | 16 | 38,474 | 1.0 | 47 | 166,266 | 4.5 | 41 | 114,787 | 3.1 | 21 | 55,869 | 1.5 | 167 | 1,069,257 | 28.6 |
| Indianapolis, IN | 331 | 1,380,491 | 13 | 26,668 | 1.9 | 12 | 24,312 | 1.8 | 32 | 124,993 | 9.1 | 11 | 41,844 | 3.0 | 3 | 9,174 | 0.7 | 38 | 160,977 | 11.7 |
| Jacksonville, FL | 170 | 904,434 | 1 | 6,222 | 0.7 | 0 | 0 | 0.0 | 30 | 138,508 | 15.3 | 13 | 45,264 | 5.0 | 8 | 29,618 | 3.3 | 22 | 159,214 | 17.6 |
| Kansas City, MO | 449 | 1,582,875 | 9 | 10,220 | 0.6 | 8 | 6,186 | 0.4 | 32 | 98,397 | 6.2 | 16 | 57,443 | 3.6 | 5 | 16,352 | 1.0 | 95 | 417,173 | 26.4 |
| Knoxville, TN | 139 | 588,956 | 0 | 0 | 0.0 | 0 | 0 | 0.0 | 10 | 40,925 | 6.9 | 7 | 30,858 | 5.2 | 2 | 11,598 | 2.0 | 17 | 87,119 | 14.8 |
| Las Vegas, NV | 162 | 860,693 | 0 | 0 | 0.0 | 0 | 0 | 0.0 | 45 | 265,229 | 30.8 | 3 | 17,828 | 2.1 | 2 | 5,917 | 0.7 | 42 | 252,546 | 29.3 |
| Los Angeles, CA | 2,549 | 14,521,077 | 118 | 644,279 | 4.4 | 80 | 445,646 | 3.1 | 66 | 401,373 | 2.8 | 149 | 841,545 | 5.8 | 73 | 410,437 | 2.8 | 156 | 849,548 | 5.9 |
| Louisville, KY | 250 | 948,829 | 11 | 30,587 | 3.2 | 6 | 18,256 | 1.9 | 17 | 51,055 | 5.4 | 9 | 40,766 | 4.3 | 3 | 11,227 | 1.2 | 33 | 161,021 | 17.0 |
| McAllen, TX | 63 | 383,545 | 2 | 10,355 | 2.7 | 1 | 5,518 | 1.4 | 6 | 37,267 | 9.7 | 8 | 41,558 | 10.8 | 7 | 32,334 | 8.4 | 3 | 24,126 | 6.3 |

*(Continued)*

Appendix C – *continued*

| Metropolitan area | All metro area tracts | | Core area upgrading | | | Core area gentrification | | | Core area declining | | | Suburban upgrading | | | Suburban gentrifying | | | Suburban declining | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Census tracts | 1990 population | Census tracts | 1990 population | Metro population (%) | Census tracts | 1990 population | Metro population (%) | Census tracts | 1990 population | Metro population (%) | Census tracts | 1990 population | Metro population (%) | Census tracts | 1990 population | Metro population (%) | Census tracts | 1990 population | Metro population (%) |
| Miami, FL | 692 | 4,306,933 | 18 | 90,183 | 2.1 | 11 | 52,586 | 1.2 | 31 | 188,881 | 4.4 | 24 | 102,944 | 2.4 | 13 | 56,521 | 1.3 | 106 | 715,584 | 16.6 |
| Milwaukee, WI | 429 | 1,607,183 | 8 | 13,973 | 0.9 | 5 | 7,209 | 0.4 | 30 | 119,284 | 7.4 | 8 | 41,896 | 2.6 | 1 | 3,471 | 0.2 | 44 | 211,885 | 13.2 |
| Minneapolis, MN | 657 | 2,545,869 | 21 | 61,247 | 2.4 | 14 | 37,048 | 1.5 | 37 | 126,508 | 5.0 | 41 | 170,553 | 6.7 | 21 | 69,904 | 2.7 | 100 | 429,924 | 16.9 |
| Nashville, TN | 207 | 989,556 | 7 | 20,845 | 2.1 | 6 | 16,045 | 1.6 | 11 | 53,247 | 5.4 | 7 | 29,363 | 3.0 | 2 | 7,970 | 0.8 | 40 | 247,044 | 25.0 |
| New Haven, CT | 419 | 1,716,385 | 2 | 9,371 | 0.5 | 2 | 9,371 | 0.5 | 1 | 8,355 | 0.5 | 23 | 84,854 | 4.9 | 9 | 29,250 | 1.7 | 19 | 73,806 | 4.3 |
| New Orleans, LA | 382 | 1,282,817 | 34 | 72,700 | 5.7 | 24 | 51,717 | 4.0 | 32 | 117,279 | 9.1 | 24 | 71,308 | 5.6 | 13 | 27,755 | 2.2 | 50 | 228,989 | 17.9 |
| New York City, NY | 2,739 | 9,748,623 | 31 | 95,350 | 1.0 | 15 | 52,103 | 0.5 | 120 | 367,195 | 3.8 | 12 | 33,494 | 0.3 | 6 | 9,299 | 0.1 | 172 | 585,356 | 6.0 |
| Newark, NJ | 1,074 | 4,444,957 | 22 | 70,002 | 1.6 | 15 | 44,450 | 1.0 | 23 | 79,240 | 1.8 | 27 | 94,253 | 2.1 | 12 | 36,766 | 0.8 | 85 | 362,053 | 8.1 |
| Norfolk, VA | 382 | 1,282,817 | 7 | 17,750 | 1.4 | 5 | 13,151 | 1.0 | 25 | 94,595 | 7.4 | 15 | 51,104 | 4.0 | 7 | 22,169 | 1.7 | 52 | 293,755 | 22.9 |
| Oklahoma City, OK | 322 | 958,839 | 6 | 11,005 | 1.1 | 5 | 9,053 | 0.9 | 42 | 117,562 | 12.3 | 12 | 22,660 | 2.4 | 8 | 10,902 | 1.1 | 35 | 146,515 | 15.3 |
| Omaha, NE | 166 | 639,580 | 1 | 1,592 | 0.2 | 1 | 1,592 | 0.2 | 17 | 66,338 | 10.4 | 5 | 16,700 | 2.6 | 3 | 9,368 | 1.5 | 25 | 136,597 | 21.4 |
| Orlando, FL | 221 | 1,224,852 | 12 | 37,740 | 3.1 | 8 | 23,071 | 1.9 | 26 | 167,337 | 13.7 | 16 | 80,894 | 6.6 | 8 | 37,021 | 3.0 | 22 | 169,684 | 13.9 |
| Philadelphia, PA | 964 | 3,752,192 | 10 | 41,675 | 1.1 | 8 | 27,785 | 0.7 | 30 | 120,580 | 3.2 | 13 | 23,797 | 0.6 | 4 | 7,272 | 0.2 | 56 | 222,161 | 5.9 |
| Phoenix, AZ | 490 | 2,238,480 | 10 | 31,165 | 1.4 | 7 | 18,743 | 0.8 | 36 | 195,597 | 8.7 | 23 | 106,357 | 4.8 | 17 | 70,217 | 3.1 | 116 | 536,205 | 24.0 |
| Pittsburgh, PA | 760 | 2,420,231 | 15 | 24,727 | 1.0 | 13 | 21,117 | 0.9 | 73 | 200,581 | 8.3 | 34 | 99,271 | 4.1 | 26 | 61,473 | 2.5 | 57 | 214,174 | 8.8 |
| Portland, OR | 404 | 1,793,371 | 21 | 69,832 | 3.9 | 12 | 40,441 | 2.3 | 23 | 85,114 | 4.7 | 21 | 99,207 | 5.5 | 6 | 18,994 | 1.1 | 63 | 332,316 | 18.5 |
| Providence, RI | 244 | 1,103,287 | 0 | 0 | 0.0 | 0 | 0 | 0.0 | 20 | 91,405 | 8.3 | 1 | 1,581 | 0.1 | 0 | 0 | 0.0 | 12 | 51,682 | 4.7 |
| Raleigh–Durham, NC | 196 | 855,545 | 2 | 3,045 | 0.4 | 2 | 3,054 | 0.4 | 19 | 76,541 | 8.9 | 7 | 32,794 | 3.8 | 3 | 13,888 | 1.6 | 44 | 217,052 | 25.4 |
| Richmond, VA | 246 | 865,640 | 9 | 18,244 | 2.1 | 7 | 12,760 | 1.5 | 13 | 47,070 | 5.4 | 7 | 22,270 | 2.6 | 3 | 5,523 | 0.6 | 51 | 209,528 | 24.2 |
| Rochester, NY | 264 | 1,062,470 | 2 | 6,818 | 0.6 | 1 | 2,089 | 0.2 | 16 | 59,764 | 5.6 | 18 | 87,712 | 8.3 | 3 | 13,181 | 1.2 | 10 | 53,295 | 5.0 |
| Sacramento, CA | 308 | 1,453,356 | 2 | 7,153 | 0.5 | 0 | 0 | 0.0 | 19 | 92,904 | 6.4 | 18 | 59,971 | 4.1 | 11 | 35,299 | 2.4 | 86 | 481,544 | 33.1 |
| San Antonio, TX | 256 | 1,329,723 | 3 | 6,720 | 0.5 | 3 | 6,720 | 0.5 | 9 | 53,583 | 4.0 | 13 | 36,018 | 2.7 | 5 | 12,308 | 0.9 | 64 | 89,504 | 6.7 |
| San Diego, CA | 437 | 2,473,370 | 16 | 54,670 | 2.2 | 11 | 34,025 | 1.4 | 6 | 26,070 | 1.1 | 20 | 114,713 | 4.6 | 9 | 62,424 | 2.5 | 45 | 249,149 | 10.1 |
| San Francisco Bay Area, CA | 1,325 | 6,194,367 | 71 | 310,376 | 5.0 | 38 | 159,526 | 2.6 | 52 | 263,529 | 4.3 | 74 | 291,346 | 4.7 | 34 | 114,816 | 1.9 | 143 | 705,116 | 11.4 |
| Seattle, WA | 582 | 2,827,096 | 24 | 96,538 | 3.4 | 12 | 50,075 | 1.8 | 3 | 9,821 | 0.3 | 33 | 176,872 | 6.3 | 19 | 99,174 | 3.5 | 123 | 644,214 | 22.8 |
| Springfield, MA | 116 | 577,630 | 0 | 0 | 0.0 | 0 | 0 | 0.0 | 3 | 1,866 | 0.3 | 1 | 6,300 | 1.1 | 1 | 6,300 | 1.1 | 8 | 58,431 | 10.1 |
| St. Louis, MO | 464 | 2,492,497 | 6 | 14,434 | 0.6 | 5 | 12,234 | 0.5 | 42 | 198,909 | 8.0 | 3 | 13,150 | 0.5 | 2 | 5,905 | 0.2 | 137 | 799,950 | 32.1 |
| Stockton, CA | 112 | 480,613 | 8 | 23,689 | 4.9 | 8 | 23,689 | 4.9 | 8 | 28,299 | 5.9 | 7 | 28,329 | 5.9 | 2 | 9,017 | 1.9 | 16 | 82,393 | 17.1 |
| Syracuse, NY | 211 | 756,029 | 3 | 1,874 | 0.2 | 3 | 1,874 | 0.2 | 10 | 31,879 | 4.2 | 15 | 57,795 | 7.6 | 5 | 21,754 | 2.9 | 17 | 71,892 | 9.5 |
| Tampa, FL | 394 | 2,008,227 | 24 | 90,449 | 4.5 | 18 | 72,645 | 3.6 | 25 | 127,822 | 6.4 | 27 | 141,535 | 7.0 | 12 | 61,565 | 3.1 | 55 | 344,302 | 17.1 |
| Tucson, AZ | 115 | 666,880 | 1 | 1,437 | 0.2 | 0 | 0 | 0.0 | 15 | 76,820 | 11.5 | 2 | 19,427 | 2.9 | 0 | 0 | 0.0 | 28 | 182,248 | 27.3 |
| Tulsa, OK | 206 | 708,954 | 4 | 8,675 | 1.2 | 3 | 6,308 | 0.9 | 21 | 68,030 | 9.6 | 18 | 76,010 | 10.7 | 11 | 37,819 | 5.3 | 34 | 126,467 | 17.8 |
| Washington, DC | 872 | 3,674,011 | 38 | 123,676 | 3.4 | 27 | 88,485 | 2.4 | 35 | 115,719 | 3.1 | 34 | 114,919 | 3.1 | 10 | 24,339 | 0.7 | 118 | 613,830 | 16.7 |

Appendix D. Density gradient estimates and policy variable inputs into the metropolitan driver model.

| | Estimates of density gradient parameters: average tract density = $D_0 e^{-b*\text{Distance}}$ to the central business district | | | | | |
|---|---|---|---|---|---|---|
| Metro | D0: Estimated intercept | b: Estimated slope coefficient | $R^2$ value | Urban expansion limits in place? | Infrastructure capacity limits in place? | Brookings immigration gateway city |
| Albany, NY | 3.26 | −0.035 | | No | No | No |
| Albuquerque, NM | 3.40 | −0.047 | | No | No | No |
| Atlanta, GA | 3.42 | −0.028 | | No | No | No |
| Austin, TX | 3.32 | −0.034 | | No | Yes | No |
| Bakersfield, CA | 3.00 | −0.014 | | No | No | No |
| Baltimore, MD | 3.83 | −0.05 | | Yes | Yes | No |
| Baton Rouge, LA | 3.22 | −0.045 | | No | No | No |
| Birmingham, AL | 3.26 | −0.04 | | No | No | No |
| Boston, MA | 3.60 | −0.015 | | No | No | Yes |
| Buffalo, NY | 3.70 | −0.042 | | No | No | No |
| Charleston, SC | 3.19 | −0.035 | | No | No | No |
| Charlotte, NC | 3.07 | −0.022 | | No | No | No |
| Chicago, IL | 3.94 | −0.022 | | No | No | Yes |
| Cleveland–Akron, OH | 3.54 | −0.019 | | No | No | No |
| Colorado Springs, CO | 3.53 | −0.075 | | No | No | No |
| Columbia, SC | 3.26 | −0.059 | | No | No | No |
| Columbus, OH | 3.43 | −0.03 | | No | No | No |
| Dallas–Ft. Worth, TX | 3.34 | −0.022 | | No | Yes | Yes |
| Dayton, OH | 3.33 | −0.029 | | No | No | No |
| Denver, CO | 3.44 | −0.02 | | No | No | No |
| Detroit, MI | 3.53 | −0.014 | | No | No | No |
| El Paso, TX | 3.67 | −0.053 | | No | No | No |
| Fresno, CA | 3.24 | −0.032 | | No | No | No |
| Grand Rapids, MI | 2.78 | −0.005 | | No | No | No |
| Greensboro, NC | 3.04 | −0.03 | | No | No | No |
| Hartford, CT | 3.48 | −0.039 | | No | No | No |
| Houston, TX | 3.41 | −0.021 | | No | Yes | Yes |
| Indianapolis, IN | 3.27 | −0.023 | | No | No | No |
| Jacksonville, FL | 3.14 | −0.025 | | No | Yes | No |
| Kansas City, MO | 3.51 | −0.038 | | No | No | No |
| Knoxville, TN | 3.11 | −0.037 | | No | No | No |
| Las Vegas, NV | 3.20 | −0.01 | | Yes | No | Yes |
| Los Angeles, CA | 3.66 | −0.013 | | No | Yes | Yes |
| Louisville, KY | 3.54 | −0.054 | | No | No | No |
| McAllen, TX | 3.04 | −0.046 | | No | No | No |
| Miami, FL | 3.41 | −0.012 | | No | Yes | Yes |
| Milwaukee, WI | 3.71 | −0.035 | | No | No | No |
| Minneapolis, MN | 3.53 | −0.035 | | No | Yes | No |
| Nashville, TN | 3.18 | −0.03 | | Yes | No | No |
| New Haven, CT | 3.18 | −0.006 | | No | No | No |
| New Orleans, LA | 3.65 | −0.034 | | Yes | Yes | No |
| New York City, NY | 4.39 | −0.023 | | No | No | Yes |
| Newark, NJ | 4.02 | −0.03 | | No | No | Yes |
| Norfolk, VA | 3.42 | −0.027 | | Yes | Yes | No |
| Oklahoma City, OK | 3.32 | −0.029 | | No | No | No |
| Omaha, NE | 3.53 | −0.061 | | No | No | No |
| Orlando, FL | 3.24 | −0.027 | | No | No | Yes |
| Philadelphia, PA | 3.92 | −0.03 | | No | No | No |
| Phoenix, AZ | 3.54 | −0.024 | | No | Yes | No |

Appendix D – *continued*

| Metro | Estimates of density gradient parameters: average tract density = $D_0e^{-b*Distance}$ to the central business district | | | Urban expansion limits in place? | Infrastructure capacity limits in place? | Brookings immigration gateway city |
|---|---|---|---|---|---|---|
| | D0: Estimated intercept | b: Estimated slope coefficient | $R^2$ value | | | |
| Pittsburgh, PA | 3.53 | −0.025 | | No | No | No |
| Portland, OR | 3.31 | −0.02 | | Yes | Yes | No |
| Providence, RI | 3.53 | −0.031 | | No | No | No |
| Raleigh–Durham, NC | 3.09 | −0.037 | | No | No | No |
| Richmond, VA | 3.40 | −0.039 | | No | No | No |
| Rochester, NY | 3.28 | −0.026 | | No | No | No |
| Sacramento, CA | 3.24 | −0.013 | | No | Yes | No |
| San Antonio, TX | 3.38 | −0.036 | | No | Yes | No |
| San Diego, CA | 3.61 | −0.019 | | Yes | No | Yes |
| San Francisco Bay Area, CA | 3.68 | −0.019 | | Yes | Yes | Yes |
| Seattle, WA | 3.46 | −0.018 | | Yes | No | No |
| Springfield, MA | 3.43 | −0.043 | | No | No | No |
| St. Louis, MO | 3.60 | −0.032 | | No | No | No |
| Stockton, CA | 3.35 | −0.043 | | No | No | No |
| Syracuse, NY | 3.25 | −0.032 | | No | No | No |
| Tampa, FL | 3.40 | −0.021 | | Yes | No | No |
| Tucson, AZ | 3.19 | −0.02 | | No | No | No |
| Tulsa, OK | 3.31 | −0.041 | | No | No | No |
| Washington, DC | 3.87 | −0.038 | | Yes | Yes | Yes |

Appendix E. Calculation of tract-level estimated 1990 rent level by metropolitan area, and predicted metropolitan neighborhood change effect.

| | Rent gap calculation: regression model of tract level gross rent in 1990 | | | | | | | | | | | Predicted metropolitan-level effect | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | B | | | | | | | | | Predicted Core area | | | Predicted Suburban | | |
| Metro area | Observations (tracts) | $R^2$ | distance to center | % DUs built prior to 1950 | % DUs built 1970 to 1990 | DU density | % White | % Hispanic | % African American | % one-family DUs | Mean prediction ($) | Upgrading (%) | Gentrifying (%) | area Decline (%) | Upgrading (%) | Gentrifying (%) | Decline (%) |
| Albany, NY | 216 | 0.49 | −2.97* | 0.70 | 2.93* | 0.008* | 1.40* | −1.28 | 0.516 | 1.75* | 457 | 1.3 | 3.9 | 30.8 | 4.7 | 2.4 | 11.5 |
| Albuquerque, NM | 137 | 0.84 | −2.26* | −0.85 | 1.38* | −0.005 | 2.70* | −0.84* | 3.583 | 3.02* | 441 | 0.6 | 6.0 | 16.0 | 8.3 | 6.7 | 16.0 |
| Atlanta, GA | 502 | 0.53 | −5.03* | −3.32* | 0.84* | 0.003 | 3.90* | 2.40 | 1.757 | 2.17* | 514 | 1.5 | 3.9 | 32.3 | 6.3 | 1.8 | 31.8 |
| Austin, TX | 222 | 0.66 | −3.68* | −0.48 | 1.41* | 0.001 | 2.09* | −0.66 | −0.738 | 3.32* | 438 | 2.3 | 2.7 | 37.7 | 5.3 | 3.6 | 31.6 |
| Bakersfield, CA | 110 | 0.50 | −0.76* | −2.24* | 0.58 | 0.000 | 1.23 | −0.98 | 1.909 | 3.10* | 468 | 1.4 | 8.5 | 25.8 | 18.9 | 13.9 | 17.2 |
| Baltimore, MD | 508 | 0.46 | 1.50 | −0.74* | 1.79* | 0.000 | 3.65* | 3.57 | 2.467* | 1.91* | 512 | 3.7 | 3.9 | 19.1 | 6.9 | 3.5 | 17.9 |
| Baton Rouge, LA | 110 | 0.69 | −3.71* | −0.91* | 0.87* | 0.002 | 3.45 | 14.57* | 2.267 | 2.16* | 366 | 1.7 | 6.2 | 28.7 | 14.6 | 4.3 | 22.8 |
| Birmingham, AL | 189 | 0.63 | −4.08* | −2.00* | 1.74* | 0.030* | −12.23* | 5.19 | −13.868* | 3.33* | 372 | 0.8 | 2.8 | 11.6 | 2.1 | 0.7 | 19.3 |
| Boston, MA | 1032 | 0.31 | −3.33* | 1.67* | 1.15* | 0.000 | 2.85* | 0.81 | 1.655* | 2.48* | 619 | 1.5 | 5.3 | 26.0 | 4.7 | 0.7 | 4.1 |
| Buffalo, NY | 290 | 0.39 | −1.13* | −0.25 | 1.11* | 0.008 | 2.61* | 0.96 | 2.066* | 1.89* | 386 | 0.9 | 2.4 | 13.2 | 2.1 | 0.3 | 16.4 |
| Charleston, SC | 114 | 0.78 | −3.30* | 1.68* | 2.79* | 0.001 | 2.22* | −3.93 | 0.459 | 2.14* | 396 | 1.9 | 5.6 | 28.0 | 6.0 | 1.7 | 46.5 |
| Charlotte, NC | 262 | 0.59 | −1.64* | 0.572 | 2.18* | 0.074* | 1.60* | −7.25 | 0.647 | 1.95* | 398 | 1.3 | 5.6 | 29.7 | 4.6 | 2.9 | 33.3 |
| Chicago, IL | 1800 | 0.42 | −2.28* | 0.30 | 2.32* | 0.003* | 2.61* | −0.11 | 1.097* | 2.17* | 511 | 1.7 | 1.6 | 13.2 | 1.8 | 0.5 | 31.0 |
| Cleveland–Akron, OH | 857 | 0.46 | −2.12* | −0.39 | 1.83* | 0.005 | 2.57* | −1.67* | 1.728* | 2.76* | 420 | 0.9 | 3.4 | 31.5 | 5.7 | 1.2 | 13.2 |
| Colorado Springs, CO | 84 | 0.66 | 0.60 | −0.19 | 1.46* | −0.007 | 3.30 | −2.54 | 4.326 | 2.94* | 440 | 1.0 | 3.7 | 24.6 | 0.0 | 0.0 | 37.9 |
| Columbia, SC | 106 | 0.56 | −8.47* | −0.342 | 2.23* | 0.000 | 2.63* | 18.67* | 1.387 | 2.21* | 415 | 1.2 | 3.3 | 16.5 | 0.0 | 0.0 | 3.9 |
| Columbus, OH | 343 | 0.43 | −2.47* | −0.90* | 0.91* | 0.009* | 2.87* | 18.90* | 1.182 | 1.73* | 412 | 1.7 | 4.9 | 30.2 | 6.5 | 1.8 | 30.0 |
| Dallas–Ft. Worth, TX | 875 | 0.50 | −2.36* | −0.13 | 1.55* | 0.014* | 2.23* | −0.76 | 0.306 | 3.10* | 488 | 2.4 | 4.9 | 28.7 | 4.5 | 2.6 | 33.6 |
| Dayton, OH | 246 | 0.38 | −1.23* | −1.45* | 0.51 | 0.000 | 2.96* | 18.21* | 1.823 | 0.81* | 401 | 1.0 | 4.9 | 19.9 | 12.4 | 4.6 | 13.5 |
| Denver, CO | 532 | 0.52 | −0.25 | 0.18 | 2.12* | 0.012* | 1.39* | −1.27* | 0.545 | 3.30* | 466 | 1.0 | 3.1 | 28.9 | 5.3 | 3.1 | 31.1 |
| Detroit, MI | 1396 | 0.35 | −1.49* | −0.93* | 1.47* | 0.000 | 1.32* | −2.22* | 0.319 | 2.32* | 482 | 1.3 | 4.7 | 17.4 | 6.6 | 2.1 | 19.5 |
| El Paso, TX | 95 | 0.83 | −1.64 | −0.35 | 0.87* | 0.005 | 1.57 | −2.80* | −2.653 | 2.06* | 354 | 1.2 | 6.0 | 19.2 | 9.1 | 8.5 | 22.1 |
| Fresno, CA | 144 | 0.73 | −0.99* | 0.38 | 2.77* | 0.033* | 0.33 | −1.20* | −0.282 | 3.65* | 436 | 1.7 | 7.2 | 21.6 | 5.6 | 5.6 | 21.3 |
| Grand Rapids, MI | 209 | 0.36 | −1.35* | 0.25 | 1.60* | 0.021* | −3.09 | −1.90 | −3.565 | 1.83* | 429 | 0.8 | 8.5 | 20.9 | 11.8 | 4.3 | 18.4 |

(*Continued*)

Appendix E – *continued*

| | | | Rent gap calculation: regression model of tract level gross rent in 1990 | | | | | | | | | Predicted metropolitan-level effect | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | B | | | | | | | | | Predicted Core area | | | Predicted Suburban | | |
| Metro area | Observations (tracts) | $R^2$ | distance to center | % DUs built prior to 1950 | % DUs built 1970 to 1990 | DU density | % White | % Hispanic | % African American | % one-family DUs | Mean prediction ($) | Upgrading (%) | Gentrifying (%) | area Decline (%) | Upgrading (%) | Gentrifying (%) | Decline (%) |
| Greensboro, NC | 262 | 0.49 | −4.15* | −1.99* | −0.56 | 0.001* | 3.80* | −1.62 | 2.291* | 1.35* | 394 | 1.2 | 5.7 | 26.7 | 13.3 | 2.0 | 11.6 |
| Hartford, CT | 298 | 0.41 | −5.29* | 1.22* | 1.80* | 0.010* | −1.81 | −4.21* | −3.305 | 3.04* | 617 | 1.0 | 3.8 | 17.2 | 2.8 | 0.4 | 10.7 |
| Houston, TX | 804 | 0.51 | −2.40* | −0.52 | 1.32* | 0.005* | 2.37* | −1.18* | 0.383 | 2.52* | 437 | 2.6 | 5.0 | 26.7 | 4.4 | 2.2 | 41.4 |
| Indianapolis, IN | 344 | 0.43 | −1.99* | −0.94* | 1.83* | 0.011* | 2.22* | 3.08 | 1.55 | 1.86* | 409 | 1.0 | 5.0 | 25.0 | 4.7 | 1.0 | 18.2 |
| Jacksonville, FL | 170 | 0.70 | −1.24* | 0.14 | 2.17* | 0.029* | 1.36* | 5.26 | −0.49 | 3.32* | 424 | 2.3 | 5.5 | 29.7 | 8.3 | 5.4 | 29.0 |
| Kansas City, MO | 449 | 0.44 | −2.17* | −0.73* | 1.30* | 0.015* | 3.57* | −1.56 | 2.19* | 2.25* | 420 | 1.2 | 3.7 | 23.9 | 4.8 | 1.4 | 35.1 |
| Knoxville, TN | 139 | 0.37 | −1.65* | −0.55 | 0.46 | 0.000 | −11.83* | 26.56* | −12.28* | 2.08* | 333 | 0.7 | 4.9 | 26.8 | 7.7 | 2.9 | 21.7 |
| Las Vegas, NV | 162 | 0.66 | −0.99* | −1.32 | 1.93* | 0.003 | 3.84* | 0.39 | 1.71 | 2.54* | 510 | 2.2 | 3.5 | 46.8 | 4.2 | 1.4 | 59.3 |
| Los Angeles, CA | 2549 | 0.58 | −1.66* | −1.75* | 0.51* | 0.011* | 1.42* | −2.38* | −1.16* | 3.30* | 699 | 2.6 | 4.0 | 12.2 | 9.5 | 4.6 | 9.6 |
| Louisville, KY | 250 | 0.49 | −3.51* | −0.51* | 2.11* | 0.013* | 1.31 | 9.57 | 0.54 | 2.53* | 540 | 1.0 | 3.3 | 23.3 | 6.9 | 1.9 | 27.3 |
| McAllen, TX | 63 | 0.69 | −1.52 | −1.99 | 0.93 | 0.030 | −1.45 | −4.72* | −16.19 | 1.54* | 267 | 1.3 | 9.3 | 30.0 | 17.0 | 13.2 | 9.9 |
| Miami, FL | 692 | 0.50 | −1.44* | 0.73 | 1.71* | 0.007* | 5.13* | −1.24* | 2.81* | 2.51* | 571 | 2.2 | 3.4 | 17.7 | 3.3 | 1.8 | 23.0 |
| Milwaukee, WI | 429 | 0.39 | −2.69* | −0.22 | 0.92* | −0.001 | 2.80* | −0.60 | 1.89* | 1.86* | 455 | 1.2 | 2.5 | 16.7 | 4.7 | 0.4 | 23.8 |
| Minneapolis, MN | 657 | 0.43 | −3.88* | 0.06 | 2.28* | 0.003 | 2.78* | −1.00 | 1.48 | 2.28* | 502 | 1.7 | 3.4 | 23.1 | 10.6 | 4.3 | 26.7 |
| Nashville, TN | 207 | 0.56 | −4.41* | −0.42 | 1.62* | 0.00 | 3.168* | −2.98 | 1.29* | 1.908* | 415 | 2.3 | 6.7 | 31.0 | 4.0 | 1.1 | 33.5 |
| New Haven, CT | 419 | 0.56 | 3.72* | 0.22 | −0.49 | 0.014* | −5.32* | −3.53* | −6.75* | 4.01* | 722 | 0.9 | 5.4 | 16.9 | 6.1 | 2.1 | 5.3 |
| New Orleans, LA | 382 | 0.49 | −1.75* | 0.65* | 0.96* | 0.002 | 1.70* | 1.62 | 0.06 | 2.09* | 403 | 4.1 | 6.0 | 17.6 | 9.4 | 3.7 | 30.2 |
| New York City, NY | 2739 | 0.46 | 1.00* | 0.87* | 1.38* | 0.002* | 2.63* | 0.17 | 1.141* | 3.33* | 569 | 1.9 | −1.2 | 2.7 | 0.7 | 0.2 | 11.6 |
| Newark, NJ | 1074 | 0.39 | 4.05* | 1.47* | 1.51* | 0.002 | 2.40* | −0.51 | 1.013* | 2.26* | 642 | 1.4 | 1.5 | 12.0 | 2.7 | 1.0 | 10.3 |
| Norfolk, VA | 320 | 0.61 | −2.15* | −0.27 | 1.83* | 0.010* | 2.89* | 7.39* | 0.85 | 2.26* | 466 | 3.1 | 7.2 | 24.0 | 5.3 | 2.3 | 30.2 |
| Oklahoma City, OK | 322 | 0.62 | −1.62* | −0.26 | 1.89* | 0.022* | 0.45 | −2.67* | −0.073 | 2.86* | 365 | 1.3 | 4.6 | 26.3 | 3.7 | 1.8 | 24.0 |
| Omaha, NE | 166 | 0.41 | −4.14* | −0.58 | 1.40* | 0.000 | 2.50* | −2.32 | 1.148 | 1.90* | 401 | 0.9 | 3.5 | 22.3 | 4.6 | 2.6 | 37.9 |
| Orlando, FL | 221 | 0.50 | −2.69* | −1.60* | 2.02* | 0.035* | −3.37 | −3.78 | −4.673 | 2.94* | 505 | 2.0 | 3.7 | 33.6 | 9.9 | 4.5 | 20.7 |
| Philadelphia, PA | 964 | 0.38 | −2.21* | −0.79* | 2.98* | 0.000 | 4.52* | 1.34 | 2.863* | 1.07* | 533 | 1.3 | 1.5 | 15.8 | 1.1 | 0.3 | 10.3 |

Appendix E – *continued*

| | Rent gap calculation: regression model of tract level gross rent in 1990 | | | | | | | | | | | Predicted metropolitan-level effect | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | B | | | | | | | | | Predicted Core area | | | Predicted Suburban | | |
| Metro area | Observations (tracts) | $R^2$ | distance to center | % DUs built prior to 1950 | % DUs built 1970 to 1990 | DU density | % White | % Hispanic | % African American | % one-family DUs | Mean prediction ($) | Upgrading (%) | Gentrifying (%) | area Decline (%) | Upgrading (%) | Gentrifying (%) | Decline (%) |
| Phoenix, AZ | 490 | 0.57 | −1.55* | 0.54 | 1.90* | 0.004 | 3.61* | −6.24 | 0.922 | 3.64* | 523 | 2.0 | 1.9 | 35.7 | 6.7 | 4.4 | 33.6 |
| Pittsburgh, PA | 760 | 0.33 | −2.87* | −0.14 | 3.05* | 0.006* | 2.02* | 7.07 | 0.722 | 1.48* | 366 | 0.8 | 2.9 | 14.3 | 5.9 | 3.6 | 12.7 |
| Portland, OR | 404 | 0.63 | −1.21* | 0.07 | 2.15* | 0.007* | 1.83* | −1.48 | 1.755* | 1.87* | 431 | 3.0 | 5.8 | 24.0 | 7.5 | 1.4 | 25.1 |
| Providence, RI | 244 | 0.36 | −0.05 | 1.23* | 0.61 | 0.001 | −1.58 | −0.74 | −1.782 | 2.80* | 490 | 0.7 | 3.6 | 12.9 | 0.2 | 0.0 | 8.1 |
| Raleigh–Durham, NC | 196 | 0.61 | −4.25* | −0.85 | 1.65* | 0.025* | 2.34* | 8.69 | 0.925 | 2.42* | 434 | 1.5 | 4.2 | 38.8 | 5.1 | 2.2 | 34.0 |
| Richmond, VA | 246 | 0.61 | −3.38* | −0.84 | 1.43* | 0.014* | 3.38* | 11.40 | 1.635* | 2.31* | 454 | 1.7 | 4.1 | 26.3 | 3.6 | 0.9 | 34.1 |
| Rochester, NY | 264 | 0.31 | −1.08* | −0.93* | −0.80 | 0.011* | 2.47* | 2.26* | 2.081* | 2.30* | 460 | 1.0 | 5.2 | 15.3 | 12.7 | 1.9 | 7.7 |
| Sacramento, CA | 308 | 0.76 | −0.45* | −1.05* | 2.01* | 0.020* | 1.80* | −0.91 | 1.004 | 3.48* | 541 | 2.2 | 4.9 | 26.3 | 5.5 | 3.2 | 44.0 |
| San Antonio, TX | 256 | 0.60 | −2.98* | −0.04 | 1.56* | 0.001 | 2.26* | −2.27* | −0.771 | 2.24* | 392 | 1.4 | 6.2 | 22.1 | 4.4 | 1.5 | 10.9 |
| San Diego, CA | 437 | 0.56 | −1.30* | −1.12* | 1.92* | 0.014* | 1.56* | −0.60# | 1.754 | 4.43* | 664 | 2.4 | 5.2 | 20.3 | 6.3 | 3.4 | 13.7 |
| San Francisco Bay Area, CA | 1325 | 0.63 | −4.45* | −0.76* | 2.06* | 0.006* | 3.70* | −1.72 | 0.019 | 4.02* | 717 | 3.7 | 4.4 | 11.9 | 7.3 | 2.9 | 17.8 |
| Seattle, WA | 582 | 0.55 | −3.08* | −1.40* | 0.90* | 0.002 | 2.60* | −2.80 | 2.257* | 2.95* | 522 | 3.1 | 5.1 | 22.8 | 7.2 | 4.1 | 26.3 |
| Springfield, MA | 116 | 0.38 | −0.08 | 1.71* | 0.08 | 0.018 | 2.38* | 0.56 | 1.601 | 2.88* | 493 | 1.0 | 4.0 | 15.6 | 1.6 | 1.6 | 14.4 |
| St. Louis, MO | 464 | 0.42 | −2.94* | −1.09* | 1.42* | 0.008* | 2.34* | 0.16 | 1.327* | 1.94* | 418 | 2.3 | 4.9 | 28.5 | 0.7 | 0.3 | 42.4 |
| Stockton, CA | 112 | 0.68 | −1.46 | −0.24 | 2.57* | 0.025* | 1.57* | −0.77 | 0.308 | 3.00* | 492 | 1.3 | 3.6 | 20.1 | 9.8 | 3.1 | 28.4 |
| Syracuse, NY | 211 | 0.34 | −1.75* | 0.77* | 1.47* | 0.008 | −1.11 | −3.42 | −1.443 | 2.12* | 430 | 0.7 | 5.5 | 15.6 | 10.9 | 4.1 | 13.5 |
| Tampa, FL | 394 | 0.47 | −3.06* | −2.03* | 1.01* | 0.001 | 3.40* | −1.34* | 1.605* | 1.58* | 448 | 3.1 | 4.2 | 27.6 | 9.6 | 4.2 | 23.4 |
| Tucson, AZ | 115 | 0.74 | −1.25* | −0.02 | 1.91* | −0.011 | 3.39* | 0.72 | 0.379 | 2.51* | 421 | 1.2 | 4.2 | 28.7 | 4.7 | 0.0 | 43.8 |
| Tulsa, OK | 206 | 0.51 | −2.15* | −1.44* | 1.31* | 0.016 | 1.95 | 0.06 | 0.529 | 3.67* | 397 | 1.0 | 4.9 | 26.1 | 15.6 | 7.7 | 25.9 |
| Washington, DC | 872 | 0.60 | −5.61* | −2.47* | 0.62* | 0.005* | 6.41* | −0.17 | 2.519* | 2.97* | 710 | 3.0 | 3.4 | 21.1 | 4.6 | 1.0 | 24.5 |

*Note*. B = estimated coefficient value. *Significant at the .05 level.