Gentrification and Eviction

Peter Hepburn, Renee Louis, and Matthew Desmond

Gentrification entails a mix of positive and negative effects for long-term neighborhood residents. These individuals are likely to experience declining crime rates (Kreager, Lyons, and Hays 2011; Papachristos et al. 2011), reductions in neighborhood poverty (McKinnish, Walsh, and White 2010), gains in income (Ellen and O'Regan 2011), and improvements in services (Freeman and Braconi 2004)—a set of changes that can be particularly beneficial to children (Brummet and Reed 2019; Dragan, Ellen, and Glied 2019). On the other hand, there is long-standing concern that these residents may be subject to displacement (Atkinson 2010; Brown-Saracino 2017; Zuk et al. 2015). If increasing rents or property taxes (Dragan et al. 2019; Martin and Beck 2018; Stabrowski 2014), disruptions to social networks (Marcuse 1985; Slater 2009), or alienation from place (Ahlfeldt 2011; Davidson 2008; Stabrowski 2014) force people out of gentrifying neighborhoods, then the plausible benefits accruing to those who are able to stay must be measured against the harm done to the displaced.

Whether long-term residents are displaced from gentrifying neighborhoods in large numbers—either in absolute terms or relative to equivalent non-gentrifying neighborhoods—has been the subject of considerable debate (Brown-Saracino 2017). Ethnographic and interview-based studies have provided compelling evidence that long-term residents are, either directly or indirectly, pushed out of gentrifying spaces (Mele 2000; Newman and Wyly 2006; Stabrowski 2014). Quantitative analyses, by contrast, have found little or no evidence of displacement (Ding, Hwang, and Divringi 2016; Freeman and Braconi 2004; McKinnish et al. 2010). Critics argue that these null findings are a function of overly restrictive definitions of displacement (Marcuse 1985; Slater 2006, 2009) and the fundamental difficulties in measuring the phenomenon (Carlson 2020; Easton et al. 2019; Wyly et al. 2010).

In this study we analyze the relationship between gentrification and one particular form of displacement: eviction. Evictions are a unique case of displacement for two reasons. First, evictions are clearly an instance of displacement, which is not true of all proxies used in the literature (Carlson 2020; Easton et al. 2019). Second, evictions leave a trace. While most forms of displacement are indeed "invisible" (Atkinson 2000), evictions are recorded by the courts in ways that allow researchers to track them to specific addresses and dates. Evictions constitute only a fraction of all displacement that may occur in a given neighborhood—an important limitation that we address below—but they nonetheless offer an important and heretofore under-utilized proxy for displacement (for exceptions, see Chum 2015 and Sims 2016).

We draw on 3,636,980 eviction court cases filed in 73 metropolitan areas between 2000 and 2016. Using these records, we are able to address our central question: does gentrification lead to higher eviction rates? In so doing we also turn this question on its head, asking if evictions are concentrated in areas undergoing gentrification. That is, how many evictions can we attribute to gentrification? Should we be thinking of eviction as a consequence of gentrification, or is it better treated as a characteristic of poverty in America? In answering these questions, we follow the lead suggested by Hwang (2016) and Brown-Saracino (2017), analyzing gentrification and persistent neighborhood poverty jointly rather than in isolation from one another.

Analyses employ a set of methodologies that allow us to describe the concentration of eviction in and out of gentrifying spaces and promote causal inference for if gentrification exacerbates eviction outcomes. Cognizant of disparities in the pace and form of gentrification, we pay particular attention to variations in relationships between gentrification and eviction across the metropolitan areas in our sample. Gentrification is subject to as many conceptual and measurement issues as displacement (Hwang 2016; Papachristos et al. 2011). To ensure that our findings are not simply a function of how we define our independent variable, we employ four recent and substantively distinct definitions of gentrification (Aron-Dine and Bunten 2019; Ding et al. 2016; Owens 2012; Timberlake and Johns-Wolfe 2017). In so doing, we make a significant contribution to the growing body of literature comparing gentrification definitions (Barton 2016; Kreager et al. 2011). In Methodological Appendix A we describe these definitions in detail and analyze differences in the allocation of neighborhoods; code to replicate these definitions is publicly available at ________.

We find that, on average, neighborhoods that gentrified between 2000 and 2016 had lower eviction rates at the end of this period than at the beginning. Many neighborhoods experienced declines over time in eviction rates, but they were on average smaller in poor neighborhoods that did not gentrify. We found very small differences in the scale of these changes between gentrifying and matched non-gentrifying neighborhoods. Employing multilevel Poisson regression, we found no evidence of significantly different temporal trends in eviction rates between gentrifying and gentrifiable tracts. On the other hand, we show that evictions were concentrated in poor neighborhoods not undergoing gentrification, and that such neighborhoods had the highest rates of both eviction filings and eviction judgments. Displacement—in the form of eviction—clearly occurs in gentrifying spaces, but it appears to be far more common in poor neighborhoods not experiencing gentrification.

Does Gentrification Entail Displacement?

From its earliest definition, displacement has been assumed to be a direct consequence of gentrification (Atkinson 2000). In Glass's seminal description, she notes that "once this process of 'gentrification' starts in a district it goes on rapidly until all or most of the working class occupiers are displaced and the whole social character of the district is changed" (1964:xvii). Likewise, Clay claims that new residents of gentrified neighborhoods "often displace lower-income households which have lived in the neighborhood for some time" (1980:20). Marcuse argues that "gentrification is linked inherently with the displacement of lower-income households" (1985:229).

Ample evidence—particularly from qualitative studies—supports a causal relationship between gentrification and displacement. As gentrifying neighborhoods attract a new wave of higher-income residents, landlords are able to demand higher rents (Mirabal 2009; Newman and Wyly 2006; Stabrowski 2014). Replacing tenants is particularly important in areas in which rent control regulations limit landlords' ability to raise rents on existing tenants (Mele 2000; Mirabal 2009). Landlords employ a range of tactics to force current residents out, including curtailing heat and water, verbal harassment, neglecting repairs, and buy-outs (Mele 2000; Stabrowski 2014). When these tactics fail, heightened monitoring and surveillance may provide the necessary pretext for eviction (Stabrowski 2014). In some cases, additional rent extraction may not be the goal of displacement. Some new homeowners, attracted to upgrading neighborhoods, inherit former tenants and must find ways to remove them in order to renovate and move into these properties (Taylor 2002:109). Under these conditions, tenants report fears of displacement, as well as frustration in keeping up with increasing rents (Newman and Wyly 2006).

Quantitative studies, on the other hand, have generally found little evidence of displacement from gentrifying neighborhoods, either in absolute terms or relative to equivalent poor neighborhoods not undergoing gentrification. This is true both at the national level (Brummet and Reed 2019; Ellen and O'Regan 2011; Freeman 2005; McKinnish et al. 2010) and in a number of large, East-coast cities—Boston (Vigdor 2002), New York City (Dragan et al. 2019; Freeman and Braconi 2004), and Philadelphia (Ding et al. 2016)—that have been the subjects of detailed case-studies. Null findings are by no means universal, however. Newman and Wyly (2006), argue that gentrification-led displacement is a significant phenomenon in New York City. Working at the national level, both Aron-Dine and Bunten (2019) and Martin and Beck (2018) present evidence of increased rates of displacement—particularly among renters—in gentrifying neighborhoods.

Mixed findings on the effects of gentrification in displacing long-term residents are rooted in a number of conceptual and methodological disagreements in the literature (Brown-Saracino 2017). The forms of displacement that are described in ethnographic or interview-based studies often align poorly with the measures used in quantitative analyses (Davidson 2008; Easton et al. 2019). The latter typically rely on mobility rates, in some cases disaggregated by cause (Carlson 2020). These rates are subject to measurement error (Zuk et al. 2015). To take one example, longitudinal surveys that sample housing units may yield systematically downward-biased mobility estimates (Wyly et al. 2010). Even if such rates were perfectly measured, however, available proxies for displacement would capture, at best, a fraction of the four forms of displacement defined by Marcuse (1985).

Eviction as a Form of Displacement

Court records of eviction cases provide a data source in which a certain type of displacement can be accurately tracked with a high degree of geographic and temporal specificity. These records offer a clear accounting of the number of households formally threatened with removal and forced from their homes (Sims 2016). While these records by no means represent all instances of displacement, they nonetheless have two notable advantages relative to other proxies used to measure the phenomenon.

First, eviction cases are clear instances of displacement, which is not true of most proxies used in the literature (Carlson 2020; Easton et al. 2019; Ellen and O'Regan 2011). The vast majority of evictions are for nonpayment of rent (Brescia 2009; Desmond 2012). In cases in which nonpayment is driven by landlord-initiated rent increases, eviction fits unmistakably into established definitions of displacement (Grier and Grier 1980; Marcuse 1985). Other cases may be harder to interpret (Grier and Grier 1980; Sims 2016). If tenants are not keeping up their end of an unchanged lease agreement, is eviction really displacement? In some such cases, tenants may be withholding rent so as to afford a move elsewhere (Desmond 2016), potentially due to growing exclusionary pressures in the community (Marcuse 1985; Stabrowski 2014). Other cases may stem from adverse life events—lay-offs, medical emergencies, unexpected bills—that limit tenants' ability to pay. Even in those instances, the enduring hardships caused by and stigma associated with eviction (Desmond and Kimbro 2015; Leung, Hepburn, and Desmond 2020) curtail evictees future housing options and thereby represent a form of "continued displacement" (Sims 2016:30)

Second, eviction records are a visible and statistically tractable form of displacement. Because they include addresses and action dates, court records allow the analyst to assess exactly where and when households are threatened with removal or forced from their homes. Administrative data, while requiring appropriate cleaning and validation, do not suffer from the sorts of measurement issues and response biases that have been observed in surveys and interviews related to eviction (Desmond 2016:330). This stands in stark contrast to other measures of direct displacement, which are often fuzzy at best (Carlson 2020; Easton et al. 2019). We are aware of no instances in which other, non-direct forms of displacement have been subject to sustained quantitative measurement.

Evictions should not be understood as synonymous with displacement. There are many ways that long-term residents can be directly or indirectly displaced from their neighborhoods other than via eviction (Davidson 2008; Grier and Grier 1980; Marcuse 1985). There are also many off-the-books, informal evictions that do not leave a trace in the court records. Still, formal evictions are a key form of displacement. The spatial and temporal concentration of these evictions in certain neighborhoods serves as a strong signal that displacement is ongoing (Sims 2016).

We are not the first to recognize the potential of eviction court records for analyzing the relationship between gentrification and displacement. Using 59,145 evictions filed in Toronto between 1999 and 2001, Chum (2015) shows that eviction rates are higher in neighborhoods in which gentrification occurred most recently or is actively ongoing. Sims (2016) employs spatial pattern analysis with a set of 70,460 eviction cases filed in Los Angeles between 1994 and 1999. He argues that there are four distinct "geographies of displacement" at play in the city during this period, and that gentrification accounts for only one of them. Employing survey data rather than court records, Desmond and Gershenson (2017) find no significant effect of neighborhood gentrification on eviction rates in Milwaukee.

Our study builds on previous work in this vein in several important ways. Each of the prior studies focused on a single city. By contrast, we analyze 80 of the 200 largest metropolitan areas in the U.S., which allows for both a stronger test of the gentrification-eviction relationship and an evaluation of heterogeneity across sites. Previous work has been essentially cross-sectional, analyzing eviction rate differentials at a given moment. We are able to provide both cross-sectional and, in a subset of metropolitan areas, longitudinal evidence. Where Chum (2015) and Sims (2016) provide a much-needed geographers' perspective, we ground analyses in a set of methods and comparisons that are now well-established within Sociology (Ding et al. 2016). In so doing, however, we also allow for multiple definitions of gentrification which serve to ensure that findings are robust to different specifications of the independent variable. We also make use of multiple descriptive and causal methods to draw out as clear and valid a set of comparisons as possible.

Research Questions

This study addresses two linked questions. First, are eviction rates *higher* and/or *increasing* in gentrifying areas relative to comparable neighborhoods not undergoing gentrification? If an influx of new, more-advantaged residents tends to push out previous tenants, we would expect that displacement to be reflected in higher eviction rates in neighborhoods that are in the process of gentrifying. If, on the other hand, long-term residents find ways to stay in gentrifying neighborhoods because they appreciate various changes and amenities—even at the cost of potentially increased rents—then rates may be stable or even decline relative to non-gentrifying low-income neighborhoods.

Second, to what extent is eviction concentrated in areas that are undergoing gentrification? Depending on the definition used, between 5.5 and 23.1 percent of neighborhoods are categorized as gentrifying. Do these areas account for a disproportionate share of evictions? Or is eviction more common in low-income areas that are not experiencing reinvestment? In focusing so closely on the effects of gentrification, are we missing the everyday displacement pressures faced by poor Americans?

Data & Methods

Measuring Eviction

This paper draws on a unique source of administrative data: the court records of 3,636,980 eviction cases filed between 2000 and 2016 across 73 of the 200 largest core based statistical areas (CBSAs, proxying metropolitan areas) in the United States. Evictions take place when tenants are forcibly removed from their homes as a result of legal proceedings initiated by landlords. As discussed above, *evictions*—measured as eviction judgments—provide a clear proxy for direct displacement. However, many tenants move out and "give up the battle" before the court process is completed (Hartman and Robinson 2003:463). Therefore, we also measure eviction *filings*—the initiation of the eviction process—to provide a broader measure of displacement pressure and mobility that takes place before formalized evictions are processed. Individual-level eviction records were collected by LexisNexis Risk Solutions and compiled by the Eviction Lab at Princeton University. Records were cleaned, stripped of duplicates and commercial eviction cases, geocoded, and validated against publicly-available data sources published by county- and state-court systems (Desmond et al. 2018).[1]

[1] County-year aggregate estimates were considered reliable if the total number of LexisNexis filings in a county fell between 87 and 114 percent of the county courts' publicly reported total. For years when county court level aggregates were not available, we extrapolated the most recently reported total a maximum of two years and applied the same validation range. We exclude county-years where the composition of LexisNexis cases has too many missing outcomes, setting a threshold of 60 percent for the full sample and 30 percent for the restricted sample. We present analyses including the extrapolated coverage and expanded composition criteria but replicate our methods on restricted criteria to confirm our results.

Measuring Gentrification

There is limited agreement in the literature about how best to measure gentrification, or at what scale. Typically, the procedure is to use Census, administrative, or geo-located survey data measured at two or more time points to assess net changes in the characteristics of neighborhood residents. Such neighborhoods are most often operationalized as Census tracts, though a number of studies rely on larger aggregates (Freeman and Braconi 2004; Hwang and Sampson 2014; Vigdor 2002). At baseline, low socio-economic status neighborhoods are classified as "gentrifiable," while more advantaged neighborhoods are listed as "not gentrifiable." Between time t and t+1, some share of gentrifiable neighborhoods meet an arbitrary cut-off and are classified as "gentrifying." Comparisons can then be made between those gentrifiable neighborhoods that did and did not gentrify.

Classification of neighborhoods may be done on the basis of a single variable such as occupational status (Atkinson 2000) or income (Ellen and O'Regan 2011; McKinnish et al. 2010), or a pair of such variables (Brummet and Reed 2019). More common is the use of principal components analysis (PCA) or a related technique to reduce multiple variables to a single factor proxying socioeconomic status (Desmond and Gershenson 2017; Papachristos et al. 2011). In either case, tracts are typically classified based on a threshold within the metro-specific distribution of this variable or factor at baseline. Gentrification is marked when a tract moves up the metro-specific distribution by a given amount between periods. Thresholds and cut-off measures vary from study to study.

To ensure that our findings were not a function of the specific definition of gentrification employed, we chose to replicate four measures that have been put forward in this literature over the last decade. Each of these represented a substantively distinct definition and resulted in different categorizations of neighborhoods. In applying these definitions, we set the year 2000 as our baseline and 2016 as our end-point. Unless otherwise specified, data were drawn from the 2000 Census—standardized to 2010 geographies in the Brown Longitudinal Tract Database (Logan, Xu, and Stults 2014)—and the 2012–2016 American Community Survey (ACS). Each definition operated at the level of the Census tract. We refer to these measures by the initials or names of the authors of the original studies.

1. *DHD measure*. Our first measure of gentrification was drawn from Ding, Hwang, and Divringi's (2016) study of gentrification and displacement in Philadelphia. They define tracts as gentrifiable at baseline if median household income was below the citywide median.[2] Gentrifiable tracts were considered gentrifying if median share of college-educated residents *and* either median gross rent or median home value increased by more than the citywide median percent between periods. Using data going back to 1980, the authors also allow for gradations within categories. Following their lead, we classified gentrifiable tracts that did not gentrify in the 2000–2016 period as either "stalled gentrification" (if those neighborhoods were classified as gentrifying during either the 1980–1990 or 1990–2000 periods) or "nongentrifying" (if there was no

[2] It bears highlighting that the authors' analyses were limited to the city of Philadelphia and did not include the broader metropolitan region. The classification of tracts will differ in our application of this definition as a function of both the broader geographic scope and the different temporal range.

evidence of prior gentrification). Among those neighborhoods that were gentrifying between 2000 and 2016, tracts were further subclassified as "continued gentrification" (if there was evidence of pre-2000 gentrification), "weak gentrification" (bottom quartile of rent or home values among gentrifying tracts), "moderate gentrification" (second and third quartiles of rent or home values among gentrifying tracts), and "intense gentrification" (top quartile of rent or home values among gentrifying tracts) (Ding et al. 2016:42–44).[3]

2. *TJW measure*. The second definition pulled from Timberlake and Johns-Wolfe's (2017) analysis of the correlates of gentrification in Chicago and New York City between 1980 and 2010. Following their model, we created a tract-level socioeconomic status (SES) scale in both 2000 and 2016 based on four variables: percentage of residents not in poverty; percentage over age 25 with more than a high school degree; percentage employed in technical or professional occupations; and average family income. We established CBSA-specific distributions of this scale in both 2000 and 2016 across the 200 largest metropolitan areas. Tracts were classified as gentrifiable if they fell in the lowest three quintiles of the distribution in 2000. Among that group, tracts whose position in their CBSA-specific distribution increased by 10 percentile points or more between 2000 and 2016, while also not losing more than 50% of their population, were marked as gentrifying.[4] Again, we followed the authors in carrying out a supplementary sub-classification, characterizing gentrifiable and gentrifying tracts by their racial majority in 2016 (white, black, Latinx, or other/none) (Timberlake and Johns-Wolfe 2017:245–47).

3. *Owens measure*. Owens's (2012) analysis of neighborhood ascent provides an important corrective to the study of gentrification. She demonstrates that very different types of neighborhoods experienced socioeconomic gains between 1970 and 2009, and that only some of this change fits traditional definitions of gentrification. While Owens's study deals with ascent more broadly, her two-stage classificatory scheme is particularly thoughtful and allows for important comparisons to be made. In the first stage we measured neighborhood ascent as a 10 percentile point (or greater) increase in a tract's position—regardless of starting percentile or population change—within the CBSA-specific distribution of an SES factor derived from PCA of five variables: average household income, average house values, average gross rent, share of population over age 25 with more than a high school degree, and share of population over age 16 working in a managerial, technical, or professional occupation (Owens 2012:350–52). In the second stage, we used PCA and cluster analysis over a larger set of socio-demographic variables

[3] In constructing this sub-classification, we relied on CBSA-specific distributions of rent or home values among gentrifying tracts.

[4] Timberlake and Johns-Wolfe's criteria to mark gentrification was a gain of at least two quintiles (as well as not losing 50% of population). We favor the 10 percentile point cut-off for two reasons. First, it allows for equal gains to be treated equivalently, rather than effectively changing the gentrification cut-off depending on starting percentile. Second, our study covers a shorter time period (2000–2016) than Timberlake and Johns-Wolfe's (1980–2010). As they and others have demonstrated, large SES gains are less common over short periods (Solari 2012; Timberlake and Johns-Wolfe 2017:266).

drawn from the 2000 Census to characterize all tracts into one of five broad categories: minority urban neighborhoods, diverse urban neighborhoods, affluent neighborhoods, upper-middle-class white suburbs, and booming suburbs (Owens 2012:353–58). Ascent between 2000 and 2016 experienced by neighborhoods falling in the first two categories comes closest to matching the typical definition of gentrification. This definition also allows us to explore the effects of ascent in other types of neighborhoods.

4. *ADB measure*. Our fourth measure of gentrification relied on a combination of income and home value data. Aron-Dine and Bunten (2019) argue that home values should respond more quickly than incomes to expectations of neighborhood upgrading, and that, therefore, spikes in price-to-income ratios serve as a signal of incipient gentrification. Following their model, we used annual median house price data from the Federal Housing Finance Association (FHFA) and Internal Revenue Service (IRS) income data to create CBSA-specific distributions of home values and income for every tract-year between 2000 and 2016.[5] All tracts that fell in the bottom 60% of their CBSA-specific distribution in 2000 were marked as gentrifiable.[6] In each year we assessed the gap between tracts' positions in the home value and income distributions. Among gentrifiable tracts, if the former led the latter by 25 percentile points in a given year, that tract was marked as gentrifying in that and all future years. One clear advantage of this measure was that, unlike the three previous definitions, it allowed us to pinpoint the onset of gentrification to a specific year rather than mark it as having gentrified at some point over the 2000–2016 window.

Sample

In total, 10,876,317 eviction filings in 247,989 valid tract-years were observed across the United States between 2000 and 2016. We focused our analysis on tracts in the 200 most populous CBSAs, regions which contain central cities and outlying areas (n = 185,904 tract-years). The decision to focus on full metropolitan areas bears note. Many authors choose to analyze gentrification as a strictly *urban* phenomenon (Ding et al. 2016; Hammel and Wyly 1996; Kreager et al. 2011). This distinction strikes us as theoretically under-motivated, however, and is hardly universal in the discipline (Brown-Saracino 2017; Clark 2005). As such, we included urban, suburban, and even some rural areas. The analyses described below relied on three distinct samples.

1. *Cross-sectional sample*. In the first sample, we included any of the top 200 CBSAs in which at least 50% of tracts had valid data for at least one year between 2012 and 2016 (n = 48,437 tract-years from 15,836 unique tracts in 73 CBSAs). For the average CBSA included in the sample, we have data covering 88.5% of all unique tracts (minimum 50.8%, maximum 100%). In total we observed 2,398,615 eviction filings and 1,164,888

[5] Both FHFA and IRS data contain a certain amount of missingness which we corrected following the same methods as Aron-Dine and Bunten (2019). Annual IRS data were only available at zip code level, which required cross-walks down to the tract level. Full details of data manipulation and processing decisions are detailed in Methodological Appendix A.

[6] Aron-Dine and Bunten (2019) do not clearly specify a threshold below which a tract is considered gentrifiable. Our choice of the 60% cut-off is arbitrary and may lead to incommensurability with their measure.

eviction judgments in this sample. To limit the effects of year-to-year noise in the data, we took the average number of filings and judgments per observed year within each tract.

2. *Matching sample*. In the second sample, we included any CBSA from the cross-sectional sample which met the same set of criteria for the period 2000–2004 (n = 38 CBSAs in the earlier period). We further restricted the sample to those CBSAs in which at least 50% of tracts observed in the later period were also observed in the earlier period (n = 37 CBSAs). Within the 37 CBSAs that made up the matching sample, this constituted 87% of tracts observed in the later period. In total, we observed 1,607,036 filings and 858,416 judgements in the matching sample. As with the cross-sectional sample, we averaged filings and judgments per observed year within each tract between 2000 and 2004. The resulting dataset included 6,995 unique tracts with two observations each (one in each period).

3. *Longitudinal sample*: In the third sample, we captured annual variations in eviction patterns. To do so, we started with 24,419 tracts in the 200 largest CBSAs that were classified as gentrifiable in the year 2000 according to the ADB measure. We included in the sample all of these tracts for which we observed at least four tract-years of valid data between 2000 and 2016. We then restricted our sample to remove any CBSAs in which we observed less than 50% of all unique tracts or in which none of the observed tracts ever gentrified. The final sample consisted of 20,698 tract-years from 2,039 unique tracts in 17 CBSAs. The median tract is observed for 12 years (minimum of four, maximum of 17).

Table 1 provides a description of the three samples and the prevalence of gentrification and eviction in each. To allow for comparison to the universe from which cases are drawn, we include a column summarizing the distribution of gentrification across the 200 most populous CBSAs. Because the longitudinal sample was built around the ADB definition, we omit summary statistics from the other measures for that sample

[TABLE 1 HERE]

The DHD measure offered the most capacious definition of gentrification. Nearly a quarter of all tracts—approximately half of all gentrifiable tracts—were listed as gentrifying between 2000 and 2016. This rate of gentrification was higher than that reported by Ding and colleagues (2016), a function of expanding the sample to include non-urban tracts. By contrast, the TJW measure classified 60% of tracts as gentrifiable and roughly 12% as gentrifying. Nearly one in every six neighborhoods experienced socio-economic ascent between 2000 and 2016 according to the Owens definition, which is in the expected range (Owens 2012). The majority of these ascending tracts were suburban. The ADB measure classified approximately five percent of all tracts as gentrifying, more than Aron-Dine and Bunten (2019) because we allowed for the gentrification of non-urban tracts. Differences across samples in the distribution of gentrifiable and gentrifying tracts within a given definition were generally quite small.

Methods

Preliminary tables and figures detailed the concentration of eviction by neighborhood type according to each of the definitions outlined above. We then turned to the question of whether gentrification promotes eviction. Analysis consisted of three steps. In the first, using the matching sample, we measured changes between periods in eviction filing and eviction rates according to each tract's gentrification classification. We examined whether these rates increased more over time in tracts that underwent gentrification than in tracts that were gentrifiable (but did not gentrify) or not gentrifiable.

In the second step we employed a set of matching methods—two propensity score-based algorithms and a form of coarsened exact matching—to promote causal inference of gentrification in evictions (Morgan and Winship 2015). The goal was to compare the experience of tracts that gentrified to the most similar possible tracts—within the same CBSA—that could have gentrified but did not.[7] In the first method, we fit a logistic regression to predict the probability of gentrifying conditional on a set of tract covariates.[8] Using the resulting propensity scores, we conducted a caliper match that matched every gentrifying tract to any non-gentrifying tract within the same CBSA that had a propensity score which fell within a standardized radius.[9] The advantage of a caliper match is that it retains as many (or as few) good matches as are available (Dehejia and Wahba 2002). The second method relies on a genetic search algorithm to determine weights that achieve optimal covariate balance before estimating a causal effect. If the logistic regression model is not properly specified, the resulting propensity score could be a poor tool for achieving covariate balance. While an iterative approach in specifying the propensity score model is recommended in the literature, it is rarely applied in practice (Diamond and Sekhon 2013). The genetic search algorithm has the advantage of automating this iterative approach to find weights that optimizes covariate balance. After the optimal weights are found, we again conducted a caliper match to drop dissimilar control tracts. In our final method, a form of coarsened exact matching, we temporarily coarsened a subset of the covariates used in the previous two algorithms such that an exact match between gentrifying and non-gentrifying tracts (within the same CBSA) could be made. For each algorithm and gentrification definition, the result was to estimate the mean difference in change in eviction filing rate and eviction rate between tracts that gentrified and paired tracts that could have gentrified but did not, which estimates the sample average treatment on the treated (SATT).

In the third step, we focused on the ADB measure of gentrification. As noted above, Aron-Dine and Bunten's definition allowed us to observe the first year in which potentially gentrifiable neighborhoods began gentrifying. Displacement pressure likely varies at different stages of the gentrification process (Aron-Dine and Bunten 2019; Ding et al. 2016). We expect that evictions—if they are occurring—will be concentrated relatively early following the onset of gentrification. Those at greatest risk of displacement will be forced out, leaving two groups who

[7] Tracts that were not gentrifiable were omitted from this analysis. We repeated this process for each of the gentrification definitions and for both eviction filing and eviction rates.
[8] For a full list of covariates and a summary table of the logistic regression, see Methodological Appendix B.
[9] We used calipers ranging from 0.05 to 0.2 standard deviations across the four measures, depending on the resulting covariate balance. Gentrifying tracts with no control tracts that fell within its radius were dropped from the sample.

are at low risk of being evicted: steadfast long-term residents and upwardly-mobile in-migrants. The ADB measure allows us to pinpoint when this process begins.

We developed a three-level Poisson model—appropriate due to the count nature of our dependent variable—with time (level 1) nested within tracts (level 2) nested within CBSAs (level 3). The level 1 model was:

$$Y_{tij} = \pi_{0ij} + \pi_{1ij} YEAR_{tij} + \pi_{2ij} GENT_{tij} + \pi_{3ij}(YEAR_{tij} * GENT_{tij}) + EXP_{tij} + e_{tij} \tag{1}$$

The dependent variable (Y_{tij}) was the count of evictions filed in year t in tract i of metropolitan area j.[10] We modeled the change in eviction filings over the years under analysis and depending on the onset of gentrification. The intercept (π_{0ij}) was the predicted count of eviction filings in 2000 among gentrifiable tracts. The π_{1ij} coefficient was the estimated rate of change in eviction filings between 2000 and 2016 for tracts that had not gentrified. The key time-varying variable was the indicator of gentrification ($GENT_{tij}$), which took value 0 for all gentrifiable tract-years up until the first year of gentrification, at which point it took on the value 1 for all remaining years.[11] The main effect of this term (π_{2ij}) represented the predicted change in the baseline number of eviction filings once gentrification began, while the interaction with time (π_{3ij}) allowed the predicted slope to change with the onset of gentrification. We included in the model an offset for the natural logarithm of the total number of renter households in the tract in year t (EXP_{tij}).[12] Given the offset, the resulting coefficients reflected effects upon the predicted log rate of eviction filings.

At level 2 we allowed the π_{0ij} and π_{2ij} terms to vary as a function of time-invariant tract characteristics. These models used an identical set of predictors, and can be written as:

$$\pi_{0ij} = \beta_{00j} + \beta_{01j} POV2K_{ij} + \beta_{02j} SUBURB_{ij} + \beta_{03j} RACE2K_{ij} + r_{0ij} \tag{2}$$

$$\pi_{2ij} = \beta_{20j} + \beta_{21j} POV2K_{ij} + \beta_{22j} SUBURB_{ij} + \beta_{23j} RACE2K_{ij} + r_{2ij} \tag{3}$$

In Equation 2, the tract's eviction filing rate in 2000 (the intercept π_{0ij}) was predicted as a function of the tract's poverty rate in 2000 ($POV2K_{ij}$), its status as a suburb ($SUBURB_{ij}$), and the tract's racial majority in 2000 ($RACE2K_{ij}$). In Equation 3 we allowed the direct effect of gentrification to vary by the same set of variables. These two models, jointly, allowed for the possibility that eviction filing rates are systematically higher or lower—and more or less affected by gentrification—in certain types of neighborhoods. The 2000 poverty rate and tract racial majority variables were based on Census data from 2000 that were standardized to 2010 Census

[10] We repeated all analyses with eviction judgments.
[11] Tracts that are not eligible for gentrification under this definition are omitted from analysis.
[12] Tract-level exposure counts are drawn from a mix of decennial Census and ACS data. The 2000 Census provides baseline counts of renter households; ACS five-year estimates are meant to be representative of the full period. This means that we have data for 2000 (decennial), 2007–2011 (ACS), and 2012–2016 (ACS). For 2001–2006, we interpolate between decennial and ACS figures making an assumption of exponential annualized growth.

tract boundaries (Logan et al. 2014); the suburb indicator is based on Kneebone and Berube's "census-convenient" definition (2013).[13]

We introduced no metro-level predictors at level 3. β terms were treated as fixed across metropolitan areas. Substituting across levels, the model could be rewritten as:

$$(4) \qquad Y_{tij} = \gamma_{000} + \gamma_{010}POV2K_{ij} + \gamma_{020}SUBURB_{ij} + \gamma_{030}RACE2K_{ij} + \gamma_{100}YEAR_{tij} + \gamma_{200}GEN$$

In this formulation, the intercept (γ_{000}) represented the predicted number of eviction filings in the year 2000 in a gentrifiable urban tract with no racial majority and—because the variable was mean-centered and standardized—an average poverty rate in 2000. The γ_{010}, γ_{020}, and γ_{030} terms adjusted this baseline prediction up or down depending on the tract's level of poverty in 2000, whether it was a suburb, and which racial majority existed in the tract (if any). The γ_{100} term gave the annual change in eviction filing rates prior to the onset of gentrification (or for those that never gentrify); this slope term was adjusted up or down by the γ_{300} term once gentrification begins. The onset of gentrification was also felt via the γ_{200}, γ_{210}, γ_{220}, and γ_{230} terms, which allowed the intercept to be shifted up or down given the onset of gentrification and the characteristics of the gentrifying neighborhood.

Results

For each tract in the cross-sectional sample, we measured the average number of eviction filings and eviction judgments between 2012 and 2016. In Table 2 we provide the percentage of total filings and evictions that fell in neighborhoods that were non-gentrifiable, that were gentrifiable but did not, and that gentrified according to each of the definitions.

[TABLE 2 HERE]

The plurality of eviction filings and evictions—by most definitions an outright majority—fell in neighborhoods that were gentrifiable but not undergoing gentrification. Evictions clearly took place in gentrifying neighborhoods, but most evictions happened elsewhere. A comparison of Tables 1 and 2 indicates that evictions were slightly over-represented relative to the share of gentrifying neighborhoods per the DHD and ADB measures. Using the former, for instance, we see that 22.95% of tracts in the cross-sectional sample gentrified between 2000 and 2016, but that 26.18% of evictions fell in such neighborhoods (114%). This pattern did not hold according to the Owens or TJW measures. More significant, however, was the over-representation of gentrifiable tracts. Turning again to the DHD measure, 27.53% of tracts were marked gentrifiable, but 44.42% of evictions occurred

[13] RACE2Kij is a categorical variable reflecting the tract's overall racial majority in 2000, coded as white, Black, Latinx, or other/none. For SUBURBij, we considered tracts to be urban if they were contained within either the first principal city in the OMB name of the metropolitan area or any subsequent named city with a population greater than 100,000. The remainder of tracts in the metropolitan area were marked as suburbs. We used GeoCorr 2014 to assign those tracts which straddled an urban/suburban boundary to a category by the majority of their population at the block level.

in these tracts (161%). With the exception of the Owens measure, higher-SES non-gentrifiable tracts saw proportionately lower shares of evictions.

Converting absolute figures into rates allowed for better comparison across neighborhoods with varying numbers of renting households. We calculated eviction filing and eviction rates across the denominator of renter-occupied housing units (as measured in the ACS). In Figure 1 we plot the distribution of these rates within each neighborhood type.

[FIGURE 1 HERE]

Both eviction filing and eviction rates were higher in gentrifiable than in the gentrifying neighborhoods. Using the DHD measure, for example, we found that residents of the median gentrifiable tract experienced an eviction filing rate of 4.8% and an eviction rate of 3.5%. In the median gentrifying neighborhood, by comparison, those figures were 4.0% and 2.7%. This pattern held using the DHD, TJW, and ADB measures, and in each case non-gentrifiable tracts experienced lowest reported rates. Per the Owens definition, ascending and non-ascending neighborhoods experienced nearly identical eviction filing rates, but the latter had higher eviction rates.

Table 2 and Figure 1 presented aggregate results across all 73 metro areas in the cross-sectional sample. In Figure 2 we plot, at the CBSA level, the percentage of eviction filings that fell in gentrifying tracts against the share of renters that lived in those gentrifying tracts. Because our sample does not necessarily cover complete CBSAs, the latter was calculated over the denominator of observed tracts within the CBSA. That denominator also determines the size of the point, such that CBSAs with larger observed renter populations are marked with larger circles. Each panel presents results from one of the definitions, and each has a 45-degree line drawn from the origin. If eviction filings were disproportionately occurring in gentrifying tracts, the CBSA will fall above the 45-degree line, and below it if gentrifying tracts were under-represented.

[FIGURE 2 HERE]

Taking the TJW measure (top-right panel) as an example, we see that most CBSAs (54 out of 73) fall below the 45-degree line: the share of renters living in gentrifying tracts was greater than the share of eviction filings in such tracts. This is true in particular of CBSAs with observed renter populations above 350,000, none of which fall above the 45-degree line. The same pattern holds when applying the Owens definition (bottom-left panel). Results using the DHD and ADB measures (top-left and bottom-right panels, respectively) are mixed, with a more equal distribution of tracts above and below the 45-degree line. In no definition, however, does the share of CBSAs above the line exceed 59%.

We then turn to the question of changes to eviction rates over time. In Table 3 we use the matching sample to present changes in eviction filing and eviction rates by gentrification status. Across neighborhoods classified as gentrifying per the DHD definition, the mean change in eviction filing rates was -1.16 percentage points and the median change in eviction rates was -0.63 percentage points. That is to say, eviction filing and eviction rates fell in neighborhoods that were, per this definition, gentrifiable as of 2000. Gentrifiable tracts that did not experience gentrification, by contrast, saw smaller declines in eviction filing and eviction rates (-0.18 percentage points and -0.09 percentage points, respectively). Turning to the sub-classification of neighborhoods, we see that areas classified as experiencing "continued gentrification"—indicating gentrification in a previous decade—experienced the largest median decreases in both rates. Among neighborhoods without a previous record of gentrification, however, differences according to the intensity of the process were minimal.

[TABLE 3 HERE]

The TJW measure produced similar results: larger decreases in eviction filing and eviction rates in gentrifying than in gentrifiable neighborhoods. Gentrifying neighborhoods with a majority-Latinx population in 2016 ("gentrifying Latinx") witnessed by far the largest declines in both measures, though all sub-categories of gentrifying neighborhoods saw at least some declines. By Owens's definition, neighborhoods experiencing socioeconomic ascent between 2000 and 2016 saw larger declines in eviction filing and eviction rates than neighborhoods not experiencing ascent. This effect was particularly strong in neighborhoods classified as "minority urban ascending" and "affluent ascending," though again was true of all sub-categories. Similarly, we found that both gentrifying and gentrifiable tracts identified by the ADB measure witnessed declines to their eviction filing and judgment rates. While the filing rates declined more sharply in gentrifying neighborhoods than gentrifiable neighborhoods, this was the reverse for eviction rates–gentrifying neighborhoods saw a more modest decline than those which did not gentrify. In none of these cases, however, do gentrifying neighborhoods break the mold of an overall decline in eviction outcomes over time. In fact, more often than not these neighborhoods saw the steepest declines.

Comparison of changes over time in eviction filing and eviction rates across all gentrifiable and gentrifying neighborhoods, as in Table 3, is complicated by heterogeneity within each category. It is easy enough to imagine two neighborhoods within the same metro area—one gentrifying and one gentrifiable—that would be fundamentally incommensurable for any number of economic, socio-demographic, or historical reasons. To clarify the contrast, we carried out a series of matching exercises in which we attempted to find the best possible comparison cases for each gentrifying tract. Table 4 presents results from these tests. The figures reported are average differences in the change over time in the eviction filing and eviction rates between gentrifying and matched gentrifiable tracts. Negative SATT values indicate that gentrifying tracts experienced smaller gains or greater declines in the given rate than their matched gentrifiable counterparts. The table also reports the sample size for each comparison.

[TABLE 4 HERE]

Two of the three matching algorithms indicate that tracts classified as gentrifying per the DHD definition experienced larger net decreases over time in eviction filing and eviction rates than matched gentrifiable tracts. The exception in both cases was the second propensity matching algorithm, which yielded SATT estimates very close to zero. Applying the TJW definition, all matches yield negative SATT estimates. When using the Owens definition of ascent, we found that the first propensity score matching algorithm and the CEM algorithm yielded negative

SATT estimates, while the second propensity score algorithm yielded positive estimates. For the ADB definition, we found positive SATT estimates with propensity score match 2 and CEM. The latter is notable for being especially large: 0.72 for the eviction filing rate and 0.44 for the eviction rate.

Lastly, we turn to the longitudinal sample and our analysis of changes over time using the ADB measure. In Table 5 we present results from the three-level Poisson model of eviction filing rates over time and as a function of gentrification.

[TABLE 5 HERE]

The key variables in Table 5 are the Year term, the Gentrifying term, and the interaction of the two. The significant negative Year term suggests that eviction filing rates declined each year in tracts characterized as gentrifiable in 2000 per the ADB definition. The non-significant interaction of Year with Gentrifying indicates that the pace of change in the filing rate did not change significantly with the onset of gentrification. The main effect of Gentrifying serves to adjust the intercept, in this case lowering (albeit non-significantly) the eviction filing rate in tract-years during which gentrification was ongoing. In other words, eviction filings decreased slightly over time, but they did so at the same rate in gentrifiable and gentifying tracts. There was no evidence that the eviction filing rate *increased* as neighborhoods began to gentrify.

Discussion

In this study, we conducted cross-sectional and longitudinal analyses of the prevalence of eviction in gentrifying and non-gentrifying neighborhoods. Going beyond the "superstar" cities that have been the focus of much previous research (Mirabal, 2009; Freeman and Braconi 2004; Hwang and Sampson, 2014), we provide the most comprehensive picture to date of the link between gentrification and eviction. Overall, the results show that while evictions happen in gentrifying neighborhoods, they do not appear to be disproportionately concentrated in such spaces. Evictions and eviction filings are only slightly overrepresented—relative to the rate of classification—in these neighborhoods. This trend holds when examining eviction outcomes both in absolute terms and as rates. In fact, the most consistent trend across the four measures we employ is that an outsized proportion of evictions and filings occur in tracts that were eligible to gentrify but did not. This is in line with the results of other empirical studies that fail to establish a strong link between displacement and gentrification in comparison to other poor neighborhoods that do not gentrify (Ellen and O'Regan, 2011; Freeman, 2005; McKinnish et al., 2010; Ding et al., 2016).

Neighborhood eviction patterns are generally stable over time, and this is no less true in gentrifying than non-gentrifying neighborhoods. Overall, filing and eviction rates have declined slightly across the U.S. between 2000 and 2016 in all neighborhood types. With regard to eviction filing rates, that decline appears to be slightly greater in gentrifying tracts than in gentrifiable ones. Results for eviction rates are mixed across the measures of gentrification. We document more heterogeneity once we account for the sub-classification of gentrifying neighborhoods; intensely gentrifying (DHD) or Black gentrifying (TJW) neighborhoods, for example, had smaller declines in eviction rates compared to gentrifiable neighborhoods overall.

A possible confounding factor is that neighborhoods classified as gentrifiable are not equally likely to gentrify and are thus expected to experience different eviction outcomes independently from the process of gentrification. For example, studies have shown that tracts that eventually gentrify are less likely to be majority Black (Timberlake and Johns-Wolfe, 2017), which also typically correlates with lower eviction outcomes (Desmond, 2012). Matching methods allowed us to draw more precise comparisons between gentrifying and comparable gentrifiable neighborhoods, and yielded mixed findings. The broader point should not be lost: the estimated differences we document are *very small*. Even after accounting for a range of demographic characteristics that are often highly predictive of eviction rates, the experience of gentrifying and gentrifiable tracts are quite similar. By no means does it appear that gentrifying tracts uniquely witnessed an absolute or relative spike in evictions.

Matching analyses allow us to compare eviction patterns in 2000-2004 to those in 2012-2016. It is possible that we miss a short-term jump in evictions as a neighborhood begins to gentrify, a pattern that reverses after neighborhood turnover stabilizes and the demographics of the residents shift. We address the potential shortfalls of the atemporality in the matching analysis through the multilevel regression model using the ADB gentrification definition, which accounts for the timing of incipient gentrification. While the TJW, DHD, and Owens measures had substantial overlap in their classification of neighborhoods, the ADB definition identifies a markedly different (and smaller) set of tracts as gentrifying than the other three definitions. Given its temporal component, this measure may be particularly effective at isolating the earliest stages of gentrification when we expect eviction pressure to be the strongest. Yet results from the MLM indicate no clear effect across 17 CBSAs for which we have best data.

Even though our sample is vastly more comprehensive than most recent studies on gentrification and displacement, it is still limited to where good data on evictions exist. As a result, many major sites of gentrification that are typically of scholarly interest are not included in our analyses. On the other hand, if we are to treat gentrification as a useful concept for understanding urban change and neighborhood poverty in America, it should be applicable beyond just Chicago, Los Angeles, and the Eastern seaboard.

It is important to emphasize that our analyses only measure formal, court-ordered eviction filings and judgments. These represent a fraction of the possible mechanisms of forced displacement that scholars of gentrification are typically interested in. We do not capture informal or illegal evictions that do not leave a trace in the court records nor do we account for the other ways gentrification could directly or indirectly displace incumbent residents. With that being said, we have no reason to believe that formal evictions are anything other than positively correlated with other forms of displacement and thus remain a reliable proxy for the spatial and temporal concentrations of displacement at large, particularly of low-income and minority residents.

One of our goals is to question whether long-standing, often-fraught academic and public debates over the meanings and consequences of gentrification are missing the bigger picture

(Brown-Saracino 2017; Brown-Saracino and Rumpf 2011; Hamnett 2009; Slater 2009). We have shown evictions do occur in gentrifying spaces. But they occur in even greater rates in poor places that are not undergoing gentrification. Displacement is a regular feature of life in poor neighborhoods in America. We should continue to analyze the novel displacement pressures faced by long-standing residents of gentrifying neighborhoods, but in doing so we should not lose sight of the fact that displacement pressures weigh heavily on the poor at all times.

Works Cited

Ahlfeldt, Gabriel M. 2011. "Blessing or Curse? Appreciation, Amenities and Resistance to Urban Renewal." *Regional Science and Urban Economics* 41:32–45.

Aron-Dine, Shifrah and Devin Michelle Bunten. 2019. *Yes , Gentrification Displaces People*.

Atkinson, Rowland. 2000. "The Hidden Costs of Gentrification : Displacement in Central London." *Journal of Housing and the Built Environment* 15(4):307–26.

Atkinson, Rowland. 2010. "The Evidence on the Impact of Gentrification: New Lessons for the Urban Renaissance?" *European Journal of Housing Policy* 4(1):107–31.

Barton, Michael. 2016. "An Exploration of the Importance of the Strategy Used to Identify Gentrification." *Urban Studies* 53(1):92–111.

Brescia, Raymond H. 2009. "Sheltering Counsel: Toward a Right to a Lawyer in Eviction Proceedings." *Touro Law Review* 25:187–271.

Brown-Saracino, Japonica. 2017. "Explicating Divided Approaches to Gentrification and Growing Income Inequality." *Annual Review of Sociology* 45:515–39.

Brown-Saracino, Japonica and Cesraea Rumpf. 2011. "Diverse Imageries of Gentrification : Evidence from Newspaper Coverage in Seven U.S. Cities, 1986 – 2006." *Journal of Urban Affairs* 33(3):289–315.

Brummet, Quentin and Davin Reed. 2019. *The Effects of Gentrification on the Well-Being and Opportunity of Original Resident Adults and Children*. WP 19-30. Philadelphia.

Carlson, H. Jacob. 2020. "Measuring Displacement: Assessing Proxies for Involuntary Residential Mobility." *City & Community* 1–20.

Chum, Antony. 2015. "The Impact of Gentrification on Residential Evictions." *Urban Geography* 36(7):1083–98.

Clark, Eric. 2005. "The Order and Simplicity of Gentrification — a Political Challenge." Pp. 261–69 in *Gentrification in a Global Context: The new urban colonialism*. New York: Routledge.

Clay, Phillip L. 1980. "The Rediscovery of City Neighborhoods: Reinvestment by Long-Time Residents and Newcomers." in *Back to the City: Issues in Neighborhood Renovation*, edited by S. Laska and D. Spain. Elmsford, NY: Pergamon Press.

Davidson, Mark. 2008. "Spoiled Mixture: Where Does State-Led 'Positive' Gentrification End?" *Urban Studies* 45(12):2385–2405.

Dehejia, Rajeev H. and Sadek Wahba. 2002. "Propensity Score-Matching Methods for Nonexperimental Causal Studies." *Review of Economics and Statistics* 84(1):151–61.

Desmond, Matthew. 2012. "Eviction and the Reproduction of Urban Poverty." *American Journal of Sociology* 118(1):88–133.

Desmond, Matthew. 2016. *Evicted: Poverty and Profit in the American City*. New York: Broadway Books.

Desmond, Matthew and Carl Gershenson. 2017. "Who Gets Evicted? Assessing Individual, Neighborhood, and Network Factors." *Social Science Research* 62:362–77.

Desmond, Matthew, Ashley Gromis, Lavar Edmonds, James Hendrickson, Katie Krywokulski, Lillian Leung, and Adam Porton. 2018. *Eviction Lab Methodology Report*.

Desmond, Matthew and Rachel Tolbert Kimbro. 2015. "Eviction's Fallout: Housing, Hardship, and Health." *Social Forces* 94(1):295–324.

Diamond, Alexis and Jasjeet S. Sekhon. 2013. "Genetic Matching for Estimating Causal Effects: A General Multivariate Matching Method for Achieving Balance in Observational Studies." *Review of Economics and Statistics* 95(3):932–45.

Ding, Lei, Jackelyn Hwang, and Eileen Divringi. 2016. "Gentrification and Residential Mobility in Philadelphia." *Regional Science and Urban Economics* 61:38–51.

Dragan, Kacie, Ingrid Gould Ellen, and Sherry Glied. 2019. "Does Gentrification Displace Poor Children and Their Families? New Evidence from Medicaid Data in New York City." *Regional Science and Urban Economics*.

Easton, Sue, Loretta Lees, Phil Hubbard, and Nicholas Tate. 2019. "Measuring and Mapping Displacement: The Problem of Quantification in the Battle against Gentrification." *Urban Studies*.

Ellen, Ingrid Gould and Katherine M. O'Regan. 2011. "How Low Income Neighborhoods Change: Entry, Exit, and Enhancement." *Regional Science and Urban Economics* 41:89–97.

Freeman, Lance. 2005. "Displacement or Succession? Residential Mobility in Gentrifying Neighborhoods." *Urban Affairs Review* 40(4):463–91.

Freeman, Lance and Frank Braconi. 2004. "Gentrification and Displacement: New York City in the 1990s." *Journal of the American Planning Association* 70(1):39–52.

Glass, Ruth. 1964. *London: Aspects of Change*. London: MacGibbon & Kee.

Grier, George and Eunice Grier. 1980. "Urban Displacement: A Reconnaissance." Pp. 252–68 in *Back to the City: Issues in Neighborhood Renovation*, edited by S. Laska and D. Spain. Elmsford, NY: Pergamon Press.

Hammel, Daniel J. and Elvin K. Wyly. 1996. "A Model for Identifying Gentrified Areas with Census Data." *Urban Geography* 17(3):248–68.

Hamnett, Chris. 2009. "The New Mikado? Tom Slater, Gentrification and Displacement." *City* 13(4):476–82.

Hartman, Chester and David Robinson. 2003. "Evictions: The Hidden Housing Problem." *Housing Policy Debate* 14(4):461–501.

Hwang, Jackelyn. 2016. "While Some Things Change, Some Things Stay The Same: Reflections on the Study of Gentrification." *City & Community* 15(3):226–30.

Hwang, Jackelyn and Robert J. Sampson. 2014. "Divergent Pathways of Gentrification: Racial Inequality and the Social Order of Renewal in Chicago Neighborhoods." *American Sociological Review* 79(4):726–51.

Kreager, Derek A., Christopher J. Lyons, and Zachary R. Hays. 2011. "Urban Revitalization and Seattle Crime, 1982−2000." *Social Problems* 58(4):615–39.

Leung, Lillian, Peter Hepburn, and Matthew Desmond. 2020. *Serial Evictions: Property Managers, Tenants, and Civil Court Sanctions*.

Logan, John R., Zengwang Xu, and Brian J. Stults. 2014. "Interpolating U.S. Decennial Census Tract Data from as Early as 1970 to 2010: A Longitudinal Tract Database." *The Professional Geographer* 66(3):412–20.

Marcuse, Peter. 1985. "Gentrification, Abandonment, and Displacement: Connections, Causes, and Policy Responses in New York City." *Washington University Journal of Urban & Contemporary Law* 28:195–240.

Martin, Isaac William and Kevin Beck. 2018. "Gentrification, Property Tax Limitation, and Displacement." *Urban Affairs Review* 54(1):33–73.

McKinnish, Terra, Randall Walsh, and T. Kirk White. 2010. "Who Gentrifies Low-Income Neighborhoods?" *Journal of Urban Economics* 67:180–93.

Mele, Christopher. 2000. *Selling the Lower East Side: Culture, Real Estate, and Resistance in New York City*. Minneapolis: University of Minnesota Press.

Mirabal, Nancy Raquel. 2009. "Geographies of Displacement: Latina/Os, Oral History, and the Politics of Gentrification in San Francisco's Mission District." *Public Historian* 31(2):7–31.

Morgan, Stephen L. and Christopher Winship. 2015. *Counterfactuals and Causal Inference: Methods and Principles for Social Research*. 2nd ed. New York: Cambridge University Press.

Newman, Kathe and Elvin K. Wyly. 2006. "The Right to Stay Put, Revisited: Gentrification and Resistance to Displacement in New York City." *Urban Studies* 43(1):23–57.

Owens, Ann. 2012. "Neighborhoods on the Rise: A Typology of Neighborhoods Experiencing Socioeconomic Ascent." *City & Community* 11(4):345–69.

Papachristos, Andrew V., Chris M. Smith, Mary L. Scherer, and Melissa A. Fugiero. 2011. "More Coffee, Less Crime? The Relationship between Gentrification and Neighborhood Crime Rates in Chicago, 1991 to 2005." *City & Community* 10(3):215–40.

Sims, J. Revel. 2016. "More than Gentrification: Geographies of Capitalist Displacement in Los Angeles 1994–1999." *Urban Geography* 37(1):26–56.

Slater, Tom. 2006. "The Eviction of Critical Perspectives from Gentrification Research." *International Journal of Urban and Regional Research* 30(4):737–57.

Slater, Tom. 2009. "Missing Marcuse: On Gentrification and Displacement." *City* 13(2–3):292–311.

Solari, Claudia D. 2012. "Affluent Neighborhood Persistence and Change in U.S. Cities." *City & Community* 11(4):370–88.

Stabrowski, Filip. 2014. "New-Build Gentrification and the Everyday Displacement of Polish Immigrant Tenants in Greenpoint, Brooklyn." *Antipode* 46(3):794–815.

Taylor, Monique M. 2002. *Harlem: Between Heaven and Hell*. Minneapolis: University of Minnesota Press.

Timberlake, Jeffrey M. and Elaina Johns-Wolfe. 2017. "Neighborhood Ethnoracial Composition and Gentrification in Chicago and New York, 1980 to 2010." *Urban Affairs Review* 53(2):236–72.

Vigdor, Jacob L. 2002. "Does Gentrification Harm the Poor?" *Brookings-Wharton Papers on Urban Affairs* 133–73.

Wyly, Elvin, Kathe Newman, Alex Schafran, and Elizabeth Lee. 2010. "Displacing New York." *Environment and Planning A* 42:2602–23.

Zuk, Miriam, Ariel H. Bierbaum, Karen Chapple, Karolina Gorska, Anastasia Loukaitou-Sideris, Paul Ong, and Trevor Thomas. 2015. *Gentrification, Displacement and the Role of Public Investment: A Literature Review*. 2015–05. San Francisco.

Table 1. Sample Description

	Top 200	**Cross-section**	**Matching**	**Longitudinal**
Total Number of Tracts	54,672	15,836	6,995	2,039
Total Number of CBSAs	200	73	37	17
Gentrification Measures				
DHD Definition				
Not Gentrifiable	27,388 (50.1%)	7,843 (49.5%)	3,467 (49.6%)	
Gentrifiable	14,661 (26.8%)	4,359 (27.5%)	1,989 (28.4%)	
Gentrifying	12,621 (23.1%)	3,634 (23%)	1,539(22%)	
Continued gentrification	6,068 (11.2%)	1,705 (10.8%)	718(10.3%)	
Weak gentrification	688(1.26%)	183 (1.16%)	80 (1.14%)	
Moderate gentrification	3,617 (6.62%)	1,068 (6.74%)	447 (6.39%)	
Intense gentrification	2,248 (4.11%)	678(4.28%)	294 (4.2%)	
Not Classified	2	0	0	
TJW Definition				
Not Gentrifiable	21,658 (40.2%)	6,367 (40.8%)	2,898 (41.8%)	
Gentrifiable	25,618 (47.5%)	7,317 (46.9%)	3,237 (46.7%)	
Gentrifying	6,669 (12.4%)	1,939 (12.4%)	800 (11.54%)	
Gentrifying white	4,219 (7.82%)	1,342 (8.59%)	578 (8.33%)	
Gentrifying black	602 (1.12%)	162 (1.04%)	69 (1%)	
Gentrifying Latinx	706 (1.31%)	153 (0.98%)	36 (0.52%)	
Gentrifying mixed	*1,142* (2.12%)	282 (1.81%)	117(1.69%)	
Not Classified	727	213	60	
Owens Definition				
Not Ascending	43,977 (84.2%)	12,828 (84.5%)	5,737 (85.1%)	

Ascending	8,242 (15.8%)	2,348 (15.5%)	1,003 (14.9%)	
Minority urban ascending	1,184 (2.27%)	343 (2.26%)	176 (2.61%)	
Affluent n'hoods	452 (0.87%)	83 (0.547%)	26 (0.39%)	
Diverse urban n'hoods	1,308 (2.5%)	251(1.65%)	73 (1.08%)	
UMC white suburbs	3,216 (6.16%)	1,086 (7.16%)	495 (7.34%)	
Booming suburbs	2,082 (3.99%)	585 (3.85%)	233 (3.46%)	
Not Classified	2,453	660	255	
ADB Definition				
Not Gentrifiable	27,757 (53.2%)	7,967 (52.1%)	3,364 (49.4%)	0
Gentrifiable	21,547 (41.3%)	6,547 (42.8%)	3,148(46.3%)	1,952 (95.7%)
Gentrifying	2,872 (5.5%)	780 (5.1%)	292 (4.29%)	87 (4.27%)
Not Classified	2,496	542	191	0
Eviction Measures				
Eviction Filings		2,398,615	1,607,036	1,049,996
Eviction Judgements		1,164,888	858,416	593,252
Total tract-years		48,437	38,678	20,698

Note: Tracts failed to be classified under a particular definition due to one of three reasons: (1) changing census geographies between 2000 and 2012-2016; (2) small population in 2012-2016; (3) tract-level data were missing in one or more of the variables used in constructing the measure

Table 2. Distribution of eviction filing and evictions by neighborhood gentrification status

	DHD	**TJW**	**Owens**	**ADB**
Eviction Filings				
Not Gentrifiable/Ascending	29.4%	25.1%	88.5%	35.2%
Gentrifiable	44.4%	64.2%		56.7%
Gentrifying/Ascending	26.2%	10.7%	11.5%	8.1%
Evictions				
Not Gentrifiable/Ascending	27.3%	22.3%	88.1%	32.7%
Gentrifiable	45.3	66.8%		59.3%
Gentrifying/Ascending	27.4%	10.8%	11.9%	8%

Note: Eviction filings and evictions are averages across all observed tract-years between 2012 and 2016.

Table 3. Average change over time to eviction filing and eviction rates by neighborhood gentrification status

	DHD	TJW	Owens	ADB
Eviction Filings				
Not Gentrifiable/Ascending	-1.03%	-0.88%	-0.75%	-1.01%
Gentrifiable	-0.87%	-0.56%		-0.66%
Gentrifying/Ascending	-1.16%	-1.51%	-1.41%	-1.06%
Continued gentrification	-1.59%			
Weak gentrification	-1.08%			
Moderate gentrification	-0.78%			
Intense gentrification	-0.72%			
Gentrifying white		-1.41%		
Gentrifying Black		-0.5%		
Gentrifying Latinx		-3.55%		
Gentrifying mixed		-1.96%		
Minority urban ascending			-2.51%	
Affluent n'hoods			-3.98%	
Diverse urban n'hoods			-0.98%	
UMC white suburbs			-0.95%	
Booming suburbs			-1.42%	
Evictions				
Not Gentrifiable/Ascending	-0.52%	-0.47%	-0.39%	-0.52%
Gentrifiable	-0.92%	-0.28%		-0.36%

Gentrifying/Ascending	-0.63%	-0.75%	-0.72%	-0.15%
Continued gentrification	-0.87%			
Weak gentrification	-0.51%			
Moderate gentrification	-0.31%			
Intense gentrification	-0.54%			
Gentrifying white		-0.72%		
Gentrifying black		-0.71%		
Gentrifying Latinx		-1.84%		
Gentrifying mixed		-0.6%		
Minority urban ascending			-1.59%	
Affluent n'hoods			-1.7%	
Diverse urban n'hoods			-0.74%	
UMC white suburbs			-0.47%	
Booming suburbs			-0.47%	

Note: Average change over time is the difference (in percentage points) between average eviction filing and judgment rates in 2000-2004 and 2012-2016.

Table 4. Estimated causal effect of gentrification on eviction filing and eviction rates, by definition and matching algorithm

	DHD		TJW		Owens		ADB	
	Est.	N	Est.	N	Est.	N	Est.	N
Eviction Filing Rate								
Prop. Match 1	-0.58	2,206	-0.56	1,305	-0.41	1,828	-0.12	309
Prop. Match 2	+0.074	887	-0.0047	625	+0.22	949	+0.26	69
CEM	-0.26	1,006	-0.69	937	-0.071	1,404	+0.72	153
Eviction Rate								
Prop. Match 1	-0.38	2,206	-0.49	1,305	-0.35	1,828	-0.11	309
Prop. Match 2	+0.012	887	-0.022	625	+0.1	949	+0.093	69
CEM	-0.13	1,006	-0.39	937	-0.05	1,404	+0.44	153

Table 5. Eviction Filing Rate Growth Model, Accounting for Gentrification

	Dependent variable:
	Log Filing Rate
Gentrifying	-0.271 (0.251)
Year	-0.002^{***} (0.0003)
Poverty	0.092^{***} (0.016)
Suburban	-0.452^{***} (0.032)
Maj. White	-0.354^{***} (0.064)
Maj. Black	0.160^{*} (0.066)
Maj. Latinx	0.086 (0.118)
Gentrifying: Year	-0.003 (0.002)
Gentrifying: Poverty	-0.061 (0.044)
Gentrifying: Suburban	0.253^{*} (0.121)
Gentrifying: Maj. White	0.108 (0.231)
Gentrifying: Maj. Black	0.280 (0.269)
Intercept	-2.337^{***} (0.115)
Observations	20,698
Log Likelihood	-96,075.400
Akaike Inf. Crit.	192,188.800
Bayesian Inf. Crit.	192,339.600
Note:	$^{*}p<0.05$; $^{**}p<0.01$; $^{***}p<0.001$

Figure 1. Average eviction judgment and filing rates for 2012-2016, by neighborhood classification and gentrification metric

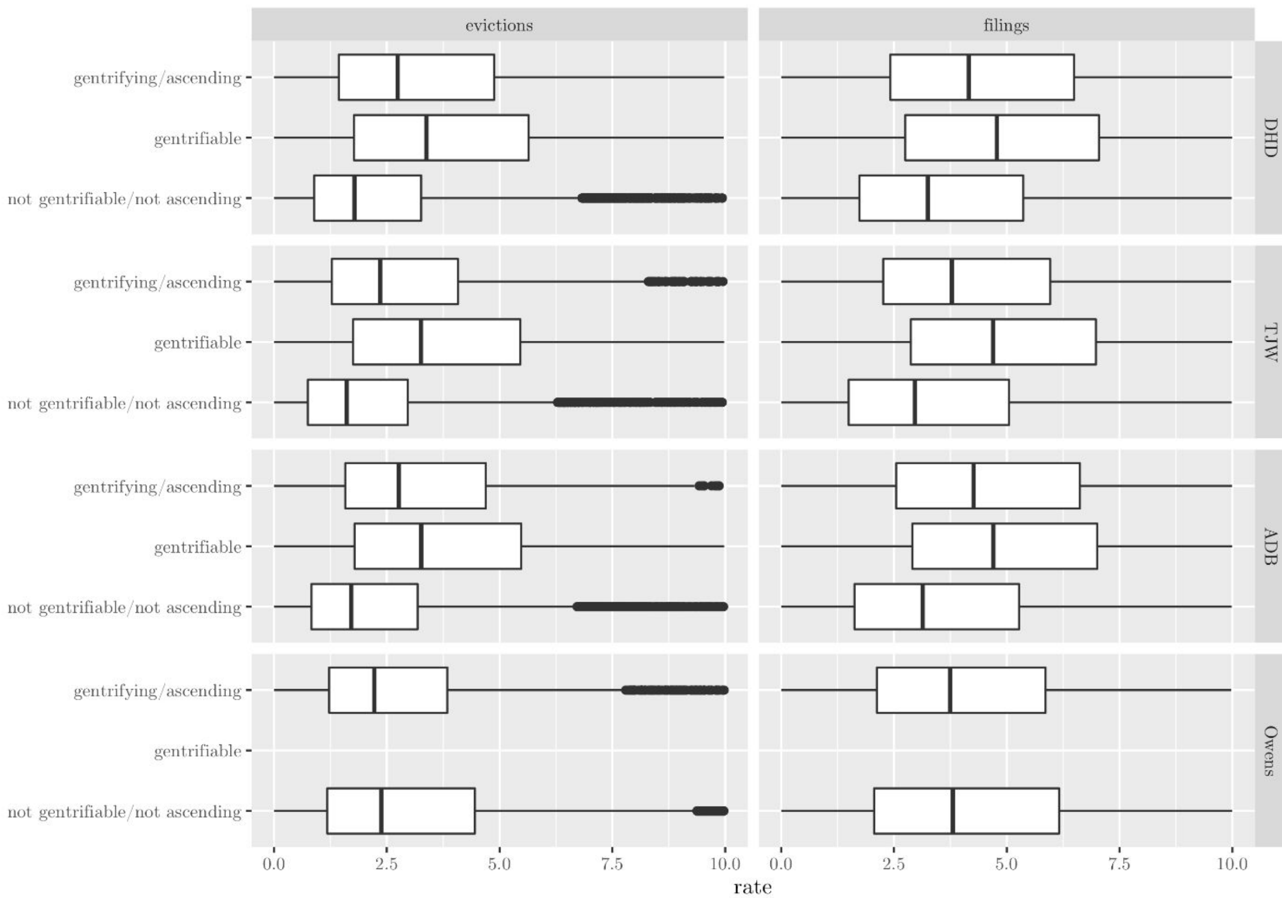

Figure 2. Share of CBSA Eviction Filings Against Share of CBSA Renter Households in Gentrifying tracts by Gentrification Metric