Fast and slow change in neighborhoods:

Characterization and consequences in Southern California

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Bio

John R. Hipp is a Professor in the departments of Criminology, Law and Society, and Sociology, at the University of California Irvine. His research interests focus on how neighborhoods change over time, how that change both affects and is affected by neighborhood crime, and the role networks and institutions play in that change. He approaches these questions using quantitative methods as well as social network analysis. He has published substantive work in such journals as *American Sociological Review, Criminology, Social Forces*, *Social Problems, Mobilization, City & Community, Urban Studies* and *Journal of Urban Affairs*. He has published methodological work in such journals as *Sociological Methodology*, *Psychological Methods*, and *Structural Equation Modeling*.

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Abstract

Due to data limitations, most studies of neighborhood change within regions assume that change over the years of a decade is relatively constant from year-to-year. We use data on home loan information to construct annual measures of key socio-demographic measures in neighborhoods (census tracts) in the Southern California region from 2000-10 to test this assumption. We use latent trajectory modeling to describe the extent to which neighborhood change exhibits temporal nonlinearity, rather than a constant rate of change from year to year. There were four key findings: 1) we detected nonlinear temporal change across all socio-demographic dimensions, as a quadratic function better fit the data than a linear one in the latent trajectories; 2) neighborhoods experiencing more nonlinear temporality also experienced larger overall changes in percent Asian, percent black, and residential stability during the decade; neighborhoods experiencing an increase in Latinos or a decrease in whites experienced more temporal nonlinearity in this change; 3) the strongest predictor of racial/ethnic temporal nonlinearity was a larger presence of the group at the beginning of the decade; however, the racial and SES composition of the surrounding area, as well as how this was changing in the prior decade, also affected the degree of temporal nonlinearity in the current decade; 4) this temporal nonlinearity has consequences for neighborhoods: greater temporal nonlinear change in percent black or Latino was associated with larger increases in violent and property crime during the decade, and the temporal pattern of residential turnover or changing average income impacted changes in crime. The usual assumption of constant year-to-year change when interpolating neighborhood measures over intervening years may not be appropriate.

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Neighborhoods are important contexts for the daily lives of individuals and have therefore been the focus of considerable scholarship. One area of interest in this scholarship is understanding the extent to which neighborhoods change, and the extent to which they are stable and unchanging. A body of research has focused on how the socio-economic and racial/ethnic composition of neighborhoods changes over time (Crowder, South, and Chavez 2006; Quillian 1999; South, Crowder, and Chavez 2005). Yet, a general challenge for this literature is exploring change at various temporal scales. On the one hand, certain neighborhoods can exhibit relatively little change over decades. On the other hand, when change does occur it can vary in pace and magnitude, sometimes happening over a slower scale of decades but on other occasions happening over a relatively short period of years. More research is needed to understand these processes, but data limitations are a challenge that often precludes studying change at shorter (e.g., year to year) temporal scales in neighborhoods. Furthermore, we do not know whether the form that change in neighborhoods takes has consequences for other processes, such as changes in levels of crime.

Given that much existing research is limited in its access to temporally fine-grained data that captures year-to-year change in neighborhoods, we employ a relatively under-utilized data source in the U.S., the Home Mortgage Disclosure Act (HMDA) data, to capture year-to-year change in neighborhoods based on socio-economic status and racial-ethnic composition. This allows us to explore whether there are differential patterns to how this change occurs. In particular, we ask whether the form of this change is relatively linear from year to year within neighborhoods, progressing at a constant rate, or whether there are in fact neighborhoods where change occurs within relatively short bursts of time. That is, the question is whether change occurs in a fast or slow fashion, which may in turn lead to differential consequences for neighborhoods.

We propose a series of objectives toward better understanding the process, character, and implications of neighborhood change. Our first goal is to describe the extent to which neighborhood change follows a constant, linear rate of change from year to year. We will then examine whether change instead takes on a non-linear form, suggesting short bursts in neighborhood change rather than a consistent rate. This analysis will be informative given that a common approach in existing literature is to obtain measures of a neighborhood at the beginning and end of the decade and then linearly interpolate values between those two time points to estimate change over time (Massey, Gross, and Shibuya 1994)(Quillian 1999). Our study will assess the extent to which this approach is indeed appropriate or whether a more nuanced design, drawing on annual-level data, better captures processes of neighborhood change. We also map out our change measures to observe whether these changes demonstrate spatial patterns.

Our second goal is to examine whether neighborhoods that experience greater temporal nonlinearity in their change are the neighborhoods that experience the greatest net levels of change over longer periods of time (i.e., decadal change). In other words, do neighborhoods that exhibit especially strong short-term “bursts” in change during the decade experience greater long-term shifts than neighborhoods with comparatively linear trajectories of change? Relatedly, we will explore which types of neighborhoods are more likely to experience this temporal nonlinear change along various socio-demographic measures.

Third, we wish to assess the potential consequences of these different change patterns for neighborhoods. Although there are various social consequences that we could focus on, we choose to focus on the consequences for the level of crime in neighborhoods, given that the criminology literature typically does not focus on possible threshold effects of nonlinear temporal change. We will assess whether neighborhoods that experience nonlinear temporal change in measures are more likely to experience increases in violent or property crime over the decade compared to neighborhoods with greater stability, or to neighborhoods with more constant rates of change. Whereas a large body of literature has explored the characteristics of neighborhoods that have higher levels of crime, there is a smaller literature discussing how *changes* in neighborhoods are related to changes in levels of crime. We will explore how our measures of fine-grained temporal change can inform some of these perspectives in viewing how socio-demographic change might translate into crime increases in certain neighborhoods.

Literature Review

Longer-term change in neighborhoods

Scholars have long been interested in how neighborhoods change, and a number of theories have arisen in response to this. Whereas two early theories of neighborhood change were the invasion-succession model and the life-cycle model, later scholars proposed the demographic/ecological model, the socio-cultural/organizational model, the stage model, the political economy model, and the social movements model (for a discussion of these theories, see Galster, Cutsinger, and Lim 2007). Although the temporal scale of these theories is often not explicitly specified, many of them are presumed to operate at a slower temporal scale. For example, the neighborhood life cycle model posits that neighborhoods with poorer initial construction quality will decline more quickly (Grigsby 1987) in what is a slow-moving process over decades. Research often studies decadal change in neighborhoods with the implicit presumption that focusing on annual change does not provide additional insights.

Research on the dynamics of neighborhoods highlights that much of this change occurs because of residential mobility (La Gory and Pipkin 1981). Indeed, one study of the effect of residential mobility on neighborhood composition found that neighborhood change was primarily due to differences between movers and newcomers rather than changes among stayers (Coulton, Theodos, and Turner 2012). As a consequence, scholars have focused on building residential mobility models to view economic and racial change in neighborhoods (Crowder, South, and Chavez 2006; Quillian 1999; South, Crowder, and Chavez 2005). One study used a unique panel survey from the Casey Foundation's Making Connections initiative targeting poor neighborhoods in 10 cities to study mobility decisions (Coulton, Theodos, and Turner 2012), classified households in the 10 cities as movers, newcomers, or stayers, and then evaluated the push and pull factors related to mobility decisions.

Although there are various dimensions of change that can be studied, a large body of research has focused on change in the racial composition of neighborhoods. This research has almost exclusively focused on decadal change, largely due to data limitations in which measures are only available when the U.S. Census is conducted every ten years. This research sometimes provides insights on even longer temporal patterns rather than within a decade. For example, a study looking at decadal change in neighborhoods found that in contrast to earlier decades, both the share of blacks and the poverty rate were positively related to subsequent economic gain in these neighborhoods during the 1990s (Ellen and O'Regan 2008). Another study examined how neighborhood minority composition is associated with change in neighborhoods' relative economic status from 1970 to 2010 in the largest 100 metropolitan areas of the USA (Jun 2016);

this study explored differences over this long time period, but was constrained to decadal change and the assumption that change within a decade is uniform over years.

More fine-grained temporal analysis: Yearly dynamics

Although the predominant focus of studies is upon decadal data and therefore decadal change, scholars have pointed out the possibility of more fine-grained temporal dynamics. Arguably the most active research in this area is being conducted by Galster and colleagues. For example, Galster (1987) proposed a theoretical model of housing upkeep behavior by homeowners that was based on homeowners' residential satisfaction, expectations of neighborhood changes, mobility plans, and housing upkeep behavior. This model specified the possibility that more rapid change might occur from year to year, rather than at a slower pace. Residents' perceptions can change relatively quickly, and this can then drive neighborhood change in some instances.

In later work, Galster and colleagues (Galster, Quercia, and Cortes 2000) used decadal data to explore possible neighborhood change threshold effects. This study discussed how threshold effects can be characterized in two manners: 1) as endodynamic, in which a measure that reaches a critical point can then subsequently cause a much greater change in itself (e.g., a neighborhood that reaches a certain threshold of percent Asian may subsequently experience a particularly large influx of Asians) , and 2) as exodynamic, in which an exogenous factor—when it reaches some critical point—can cause a much greater change in the measure of interest (Galster, Quercia, and Cortes 2000). Using data for the decadal points 1980 and 1990, these possible threshold effects in neighborhoods were explored in this study: the only endodynamic effect they found was for poverty, in that neighborhoods that exceeded 54% poverty experienced a subsequent large increase (though this occurred for few neighborhoods). They also found the exodynamic effect in which the lack of professional workers led to spikes in female-headed families with children, the nonemployment rate, and the poverty rate.

More recent research by Galster and colleagues (Galster, Cutsinger, and Lim 2007) again focused on endogenous neighborhood dynamics, but drew upon annual data. In this study the outcome measure of interest exhibited endogenous threshold points. This research utilized annual data for census tracts in five cities over the 1988-2003 period in which they had at least 7 years of data for each city. It focused on change in crime, health measures (low-weight birth rate and births to teenage mothers), home sales amounts and values, and property tax delinquency rates (Galster, Cutsinger, and Lim 2007). This evidence of thresholds and temporal nonlinearity suggests that this is a useful area of further research.

Consequences of neighborhood change: Changes in crime rates

Although nonlinear temporal change in neighborhood socio-demographic measures may have numerous consequences for neighborhoods—and there is some research focusing on the consequences of neighborhood change for certain outcome measures (Galster, Cutsinger, and Lim 2007)—to maintain scope we focus here on how this nonlinear temporal change may impact the level of crime in neighborhoods. We focus on crime given that: a) levels of crime in neighborhoods are of great importance to residents, and b) the criminology literature has generally not considered the possible importance of nonlinear temporal change for how crime levels change in neighborhoods. The most prominent theory in the neighborhoods and crime field is social disorganization theory, which posits that neighborhoods characterized by the key structural characteristics of high levels of poverty, racial/ethnic heterogeneity, and residential instability will have higher levels of social disorganization and hence more crime (Bursik 1988; Sampson and Groves 1989; Shaw and McKay 1942). Although this theory has an implicit temporal component to it, this temporality is not very clearly specified or tested. Furthermore, the theory tends to emphasize the relative stability of neighborhoods over time, and therefore pays limited attention to the possibility of rapid change (for a more complete discussion of neighborhood dynamics and crime, see Hipp and Chamberlain 2011; Kirk and Laub 2010).

Given the criminological literature's general reliance on social disorganization theory, studies tend to focus either on the relative lack of change over time, or on longer term changes in neighborhoods. For example, research in Los Angeles studied how the location of delinquents in the 1950s and 1960s evolved over time using data from decadal time points (Schuerman and Kobrin 1986). A more recent study of Los Angeles constructed change measures over the decade from 2000-10 to explore the relationship between spatial inequality and crime (Hipp and Kubrin 2017). In a broader context, a study of census tracts across 13 cities studied the reciprocal relationship between neighborhood structural characteristics and crime rates using decadal data (Hipp 2010). Despite the insights provided by these and other studies, however, they are all constrained to the assumption that the changes occurring within neighborhoods occur at a uniform pace over the years. Less attention has been paid to the possibility that this change may not occur in such a uniform manner, and, further, that there may be consequences when changes occur in nonlinear "bursts" rather than a gradual, constant pace.

There are studies that have explored more fine-grained temporal changes in crime rates, although they often are limited in the temporal granularity (i.e., how frequently they are measured) of their key independent variables of interest (Raleigh and Galster 2014). For example, studies that measure socio-demographic characteristics of neighborhoods often rely on census based measures that are only measured at decadal points. Thus, Raleigh and Galster (2014) developed a conceptual framework of neighborhood crime dynamics based on a synthesis of criminology and neighborhood change literatures that implied that neighborhood decline can produce a nonlinear response in crime rates. The authors were then able to explore this model using data from Detroit at the block-level with several annual measures and found some evidence of nonlinearity (although they were limited to measuring key socio-demographic measures at decadal points).

There have been studies that used annual data to explore the year-to-year relationship between neighborhood characteristics and crime. For example, studies of census tracts in Los Angeles City focused on the relationship between residential mobility and crime using annual data in the 1990s; these studies exploited home sales information as a way to capture yearly change in neighborhoods (Boggess and Hipp 2010; Hipp, Tita, and Greenbaum 2009). Another study used annual information on voluntary organizations to build a model exploring the relationship between the placement of new voluntary organizations and crime rates in blocks across a number of cities (Wo, Hipp, and Boessen 2016). Yes other research has found a negative relationship between "third places" such as coffee shops or cafes and crime in an annual longitudinal model (Wo 2016). Although these studies have examined how annual change in neighborhoods is related to crime the following year, they do not consider the possibility that relative temporal spikes of certain neighborhood characteristics may differentially impact changes in crime. That is, they presume a constant temporal linear relationship between the exogenous measure of interest and crime rates. Such an assumption also underlies decadal studies. However, to the extent that there are threshold effects, the assumption of linear change will be problematic. For example, consider a scenario where a neighborhood experiences equal yearly increases in a measure that have small effects on the corresponding change in crime, but then after a few years the neighborhood reaches a tipping point where the cumulative increase in the measure over several years results in a spike in crime (i.e., exodynamic change, in Galster's terminology). In such a scenario, linear change modeling strategies will not capture these effects. Instead, the annual relationship in such models will capture the average effect over multiple years, and will not capture the possibility that experiencing such changes several years in a row might manifest a tipping effect resulting in a much larger change in crime (but only when changes occur several years in a row). We explore this question in more depth in the present study.

Data and Methods

This study focuses on neighborhood change over a 10-year period, from 2000 to 2010, in the Southern California region. Southern California is a large and growing region that contains three metropolitan statistical areas: Los Angeles-Long Beach-Santa Ana, which is the second largest metro area in the U.S. (12.8 million population); Riverside-San Bernardino-Ontario, which is the 12th largest (4.2 million population); and San Diego-Carlsbad-San Marcos, which is the 17th largest (3.1 million population). This region includes six counties (Los Angeles, Orange, Riverside, San Bernardino, San Diego, and Ventura), and 341 cities and minor civil divisions (MCDs). With an expanding population of over 20 million persons, Southern California is the prototypical example of a booming Sunbelt area in which the population is increasing and in which the predominant spatial characteristic is one of sprawl. Moreover, it is a racially and ethnically heterogeneous area that has received, and continues to receive, a large inflow of immigrants.

We use data from the U.S. Census for 2000 and the American Community Survey 5-year estimates in 2008-12 to compute measures of the neighborhoods (defined as census tracts) at the beginning and end of the decade. Census tracts contain a mean of about 4,300 residents in 2000 (with 95% of the tracts containing between about 1,400 and 8,000 persons), and they were initially constructed by the Census Bureau to be relatively homogeneous neighborhoods (Green and Truesdell 1937; Lander 1954). Given that we have data from 2000 and 2010, we harmonized the data in 2010 boundaries into 2000 boundaries using a population-weighted apportioning technique. We constructed measures of the difference between 2000 and 2010 in the following measures: 1) *residential stability* (measured in two ways: a) average length of residence; and b) percent same owners in tract 10 years ago); 2) *racial composition* (percent white, percent black, percent Latino, percent Asian); 3) *average household income*; 4) *average home value*. These measures mirror the standard approach in the literature of capturing and describing change over a decade.

In addition, we use annual data from the Home Mortgage Disclosure Act (HMDA) that provide information on all home loans applied for and granted in these neighborhoods over this period. These data allow us to compute measures of change annually. To account for possibly low numbers of housing units changing residents in a year in a tract, we smooth data over years by constructing 2-year moving averages of each measure (thus, 2000 and 2001 for 2001; 2001 and 2002 for 2002; etc). We construct measures in each 2-year period for each tract along four dimensions: 1) *housing turnover* (the number of housing transactions divided by the number of housing units)[1]; 2) *racial composition of the new residents* (percent white, percent black, percent Latino, percent Asian)[2]; 3) *average income of new residents (logged)*; 4) *average loan value (logged)*. For each measure, we then created a standardized version for each year; this

[1] This measure of the number of housing units in a tract is provided each year in the HMDA data.
[2] This is computed by taking the number of households of a particular race/ethnicity moving in during the year and dividing by the total number of households moving in during the year.

standardization by year allows us to capture change in a measure over the decade after parsing out the macro changes that occurred during the decade in the region.

Using these annual variables based on the HMDA data, we construct measures describing change over the decade based on the results of latent trajectory models (LTM) (Bollen and Curran 2006). In these trajectory models, we used the annual measures of change from the HMDA data from 2000 to 2010 as the indicators of this latent change. For each of our measures in the four dimensions just described we estimated two trajectory models: 1) a linear trajectory model; 2) a quadratic trajectory model. The LTM approach allows us to obtain a unique trajectory for each tract, and we obtained these trajectories using the techniques described in Bollen and Curran (2006). The intercept for each trajectory provides the average value for a measure when time is set to '0'; the choice of when to set time to '0' does not impact the model estimation, and simply changes the interpretation of the intercept (Biesanz, Deeb-Sossa, Papadakis, Bollen, and Curran 2004). Rather than coding time to values from 0 to 10 to represent the years 2000-10, we coded it from -5 to 5 such that 0 captures the value of the measure at the midpoint of the decade (2005).

The slope terms of the trajectory models indicate different conclusions about neighborhood change patterns depending on which coefficients demonstrate statistical significance. For the models capturing change in housing unit turnover, average income, or average loan amount: 1) an insignificant slope indicates that there was no change over the decade; 2) a significant linear trajectory indicates that change occurred at a constant rate across years; and 3) a significant quadratic trajectory indicates nonlinear annual change. For the models capturing change in the racial/ethnic variables: 1) an insignificant slope indicates that there was no pattern to annual change across years; 2) a significant linear trajectory indicates that change increased/decreased at a constant rate; and 3) a quadratic trajectory indicates nonlinear annual change.

Methods

First, we explored whether the degree of nonlinearity in the annual change of a measure helps explain the overall change observed during the decade for a tract. We estimated a series of linear regression models in which the outcome variables were the net decadal change in the various Census-based socio-demographic measures. For each outcome variable, we specified models with two different sets of HMDA-based independent variables that included the linear term and: 1) the quadratic term; 2) the *absolute value* of the quadratic term. This latter set of models assessed whether it is simply the degree to which the neighborhood deviates from yearly linear change (either positively or negatively) that matters for explaining the degree of change over the decade, whereas the first set of models assessed whether it matters whether the change mostly occurs specifically in the first part of the decade or in the second part of the decade. We evaluated these models and present the results of the approach that showed the best fit to the data based on R-square. In addition, for each outcome measure we also estimated and present models for three different samples: 1) the complete sample, 2) the subsample of tracts that experienced an increase over the decade in the measure of interest; 3) the subsample of tracts that experienced a decrease over the decade in the measure of interest.

A second set of linear regression models were estimated in which the outcome variables were the quadratic parameters for the tract-based trajectories of change, estimated earlier, for each of the four dimensions of change we study. Thus, we describe which tracts experienced the most nonlinear temporal change, or the greatest “blooms” of change, for each measure over the decade. We estimated a model in which the outcome variable was the raw value of the quadratic term, and another in which it was the absolute value, and chose the optimal fitting model based on R-square. For each model, the independent variables were based on Census variables that corresponded to the same construct as the dependent variable; for example, we used various measures (as described next) of average income based on the U.S. Census to predict the degree of nonlinearity of income change. The independent variables are: 1) the net change in the measure over the same decade (2000-10) and its quadratic term; 2) the level of the measure at the beginning of the decade (2000); 3) the change in the measure in the surrounding area (based on an inverse distance decay capped at 5 miles) during 2000-10; 4) the level of the measure in the surrounding area in 2000; 5) the change in the measure in the tract itself in the prior decade (1990-2000) and its quadratic term. The measures capturing change from 2000-10 assess whether tracts experiencing more change are more likely to experience temporal nonlinearity in the change. The measures capturing the level at the beginning of the decade (2000) assess whether tracts are more likely to experience temporal nonlinear change if they already are at higher values on the construct. The two spatial lag measures ask whether these focal effects have a spatial spillover effect on nearby neighborhoods. And the measure capturing change from 1990-2000 assesses whether earlier patterns of neighborhood change have consequences for the degree of temporal nonlinearity in the following decade.

In our final set of analyses, we examined how these forms of fast and slow neighborhood change are related to changes in violent and property crime from 2000-10. The outcome variables in these models are: 1) violent crime counts (a sum of aggravated assaults, robberies, and homicides); 2) property crime counts (a sum of burglaries, motor vehicle thefts, and larcenies). Given that the outcome variable is a count variable, we estimated these models as negative binomial regression models (a Poisson model that accounts for overdispersion). We included the count of violent or property crimes at the beginning of the decade in the models, and thus the outcome variables are effectively change measures over the decade. We follow the common approach in the ecology of crime literature and control for key socio-demographic measures. We measure these variables as the change in the measure from 2000 to 2010. These are the same measures as we have explored in the rest of the study: the change in each of the racial/ethnic categories (percent black, percent Asian, and percent Latino; the reference category is percent white and other); change in average household income; change in residential stability (average length of residence). In subsequent models we included the nonlinear temporal variables (or their absolute values) of each of these measures to assess whether they help understand which neighborhoods experience the largest increases in violent or property crime.

Results

We begin by describing the trajectory results using the annual change data from HMDA. Table 1 provides the summary statistics. The first panel of results in this table presents the average linear component of these trajectories over the period. The mean column presents the average change for a measure over this decade across tracts. Given that we have standardized our measures per year, the expected value for this change is 0, and in fact we observe values very close to this. If we had chosen not to standardize these measures per year our approach could detect regional changes that were occurring and thus obfuscate our findings. However, our goal was instead to detect changes across neighborhoods once partitioning out the region-wide changes. Indeed, we observe considerable variability across tracts in the trajectory of this change in annual turnover, as the standard deviation across tracts is .0883, with a minimum change for a tract of -.442 and a maximum slope increase of .962. Given that the measures are standardized, these results indicate that a tract one standard deviation above the mean experiences an increase per year in housing turnover that is .0883 standard deviations greater than a tract at the mean. We likewise see variation across tracts in the linear slope of change for the other measures. The standard deviation is typically about .05 for the four measures of racial/ethnic change, as well as the measures of income and home value change.

<<<Table 1 about here>>>

Turning to the quadratic terms, recall that these variables are capturing the extent to which the standardized change in tracts for a measure is nonlinear over years. Again, because of our annual standardizing approach, these have mean values across tracts that are effectively zero. Nonetheless, there is variability in the amount of nonlinearity experienced across tracts, as seen in the standard deviations across these measures. To get a sense of the magnitude of this nonlinearity, in Figure 1 we plot the projected change for three hypothetical tracts experiencing a large increase in housing turnover over the decade (a linear term that is one standard deviation above the mean), but in which they differ in the quadratic term (low, which is one standard deviation below the mean; average, which is at the mean; and high, which is one standard deviation above the mean). The middle line shows the change in housing turnover for a tract experiencing a linear trajectory, as the tract goes from a standardized value of -.446 at the beginning of the decade (2000) to a standardized value of .437 at the end of the decade (2010). The other two lines in this figure show the trajectory for tracts with high or low values of quadratic change, and they are bowed out, or in, from the linear line. The top line shows a tract with a high positive value (one standard deviation above the mean) on the quadratic term, and it shows that the change in standardized housing turnover is essentially flat in the first part of the decade. However, starting around 2004, this exemplary tract shows a sharp increase in the rate of housing turnover. In contrast, the bottom line shows a tract with a low value (one standard deviation below the mean) on the quadratic term, and this tract experiences a sharp increase in the standardized housing turnover measure in the first part of the decade, but is essentially flat over the latter part of the decade from about 2007 on. This finding demonstrates that there is a considerable amount of nonlinearity present for some tracts that is not apparent if one simply uses a linear interpolation over the years of the decade.

<<<Figure 1 about here>>>

In Figure 2 we display the change in standardized housing turnover for a tract that experiences decreasing turnover during the decade. This plot makes clear that the quadratic term has a reversed temporal meaning when the tract is experiencing a decrease in the measure over the decade. Here, a tract with a positive quadratic term (the top line in Figure 2) experiences the sharpest decrease in housing turnover in the first part of the decade, but then flattens out in the latter part of the decade after about 2007. In contrast, a tract with a negative quadratic term in the context of a general decline over the decade experiences relatively flat change during the initial part of the decade but then almost all of the decade decline occurs during the last six years beginning in about 2004.

<<<Figure 2 about here>>>

We also demonstrate the degree of nonlinearity present in the measures of racial/ethnic change in Figure 3 for change in percent Asians in the tract. Whereas a tract experiencing a linear trend of high increasing percent Asian goes from -.25 to .265 over the years of the decade, there is considerable nonlinearity for the high and low quadratic tracts. Again, the top line in Figure 3 shows a tract with a high value (one standard deviation above the mean) on the quadratic term, and demonstrates that the increase in standardized percent Asian is essentially flat in the first part of the decade. Again, starting around 2004, this tract shows a sharp increase in the relative proportion of Asian residents. In contrast, the bottom line shows a tract with a low value (one standard deviation below the mean) on the quadratic term, and this tract experiences a sharp increase in the relative presence of Asians in the first part of the decade, but this change is essentially flat over the latter part of the decade. The level of nonlinearity in change observed is similar for the other racial/ethnic groups, as well as for the change in average housing income or home value.

<<<Figure 3 about here>>>

The third and fourth panels in Table 1 show the summary statistics for the tract-level R-squares for the linear and quadratic models. These values capture the extent to which the annual change over the decade for a particular tract is best measured using a linear or quadratic function. One feature to observe is that the average R-squares across tracts is higher in the quadratic models compared to the linear models for virtually all of the measures of change we study. For example, whereas the average R-square for the linear models of housing turnover change is .205, it is .274 for the quadratic models. This provides evidence that the nonlinear model more accurately captures neighborhood change over the decade for many of the tracts. There is much variability over tracts, as some tracts exhibit an almost exactly quadratic trajectory of standardized housing turnover (the maximum R-square value is .958, indicating an almost perfect fit to the data), whereas others show a completely random trajectory (R-square of 0). The standard deviation of the quadratic r-squares of .21 is further evidence of this variability across tracts. We observe this same pattern across all measures of neighborhood change.

The fifth panel of Table 1 shows the summary statistics for how the R-square of the quadratic model improves over the linear model across tracts. This improvement in R-square capture the extent to which a tract exhibits a nonlinear trend in the measure over the decade rather than a linear trend based on the increased explanatory power. The average increase in R-square is .069 for the housing turnover model across tracts, indicating that a considerable number of tracts exhibit a nonlinear change over the decade. This finding, along with the standard deviation of .07 for this measure, indicates that for some tracts the degree of nonlinearity is quite substantial. For example, a .10 improvement in r-square is quite notable, as between 21.5% and 30.6% of tracts achieved this level of improvement across the four racial/ethnic measures, 28% achieved this in the housing turnover measure, and between 9.6% and 11.6% achieved it for the SES measures. The improvement in model fit when considering nonlinearity is slightly less for the measures of socio-economic change (household income and home values), but are nonetheless notable.

Correlations among standardized change measures

We next display the correlations among our measures of interest. In the top panel of Table 2 we display the correlations among the quadratic terms for the various outcome measures. These correlations show the extent to which tracts that exhibit nonlinear change based on one socio-demographic measure also exhibit nonlinear change on another socio-demographic measure. For example, the first column shows the correlation between tracts exhibiting high values of nonlinear change in standardized percent Asians over the years of the decade with the other measures. The strongest value of -.29 shows that tracts exhibiting a positive quadratic value in change in percent Asian (thus greater growth at the end of the decade) are more likely to exhibit a negative value in quadratic change in percent Latino (thus greater decline at the end of the decade, if this group is being replaced by Asians in the tract). Refer back to Figures 1 and 2 to understand the implication of this negative correlation in the context of racial/ethnic change in which an increasing proportion of one group in the population usually indicates the decline of at least one other group. Likewise, the correlation of the Asian quadratic term with the white quadratic term is negative (-.16). The correlations with the nonlinearity of home value change and turnover change are positive, which indicate that these changes occur in a relatively similar nonlinear fashion. Thus, general turnover, increasing average home values, and increasing percent Asians tend to move together in the years within the 2000-2010 decade.

<<<Table 2 about here>>>

Although there appears to be little correlation among the nonlinear change in percent black (column 2) with the nonlinear change in the other measures, there are stronger patterns for the nonlinear change in percent Latino (column 3). There is a very strong negative correlation (-.46) between the nonlinear change in Latinos and whites, indicating a likely turnover scenario between these two groups in which Latinos replace whites in the tract during the decade. There is also a relatively strong correlation between the nonlinear change in Latinos and home values during the years of the decade. It is perhaps unsurprising that there is a very strong positive correlation (.7) in the nonlinear change of household income and home values as higher income households tend to move into areas with increasing home values; however, a particularly interesting result is the positive correlation between the nonlinear change in turnover and these two SES measures (.37 and .29). This is consistent with the idea of relatively rapid change in gentrifying neighborhoods (Wyly and Dammel 1999).

In panel 2 of Table 2, the correlations among the change in decadal Census measures is shown. As expected, there are typically negative correlations among the racial/ethnic change measures, indicating that a tract increasing in composition of one group is more likely to decrease in the composition of another group. The negative correlation between percent Latino and white (-.68) is likely an important regional characteristic capturing the large influx of

Latinos over the last several decades. There is also a negative correlation (-.22) between the change in percent Latinos and the change in average home values.

Models predicting change over decade

We next present in Table 3 models that ask to what extent the level of net change over the decade across Census measures is explained by the annual trajectory measures, particularly the quadratic term capturing the temporal nonlinearity of the change. For the outcome of the change in percent Asian, we find that the absolute value of the quadratic term better explains the degree of change over the decade than does the actual value of the quadratic term based on comparisons of the model R-squares, and therefore we present the results using the absolute value of the quadratic term. For the complete sample (the first column), the linear and quadratic terms are both positively associated with the change in percent Asians over the decade. To compare the magnitude of these effects, we created fully standardized coefficients. We find that whereas a one standard deviation increase in the linear term is associated with a .096 standard deviation increase in percent Asians over the decade, a one standard deviation increase in the quadratic term is associated with a .163 standard deviation increase in percent Asian over the decade. Thus, tracts experiencing greater temporal nonlinearity in the change of percent Asians (higher values on the quadratic term) experience a greater influx of Asians during the decade. In the subsample of tracts experiencing an increase in percent Asians over the decade we find that the quadratic term is particularly strongly related to this increase (β=.225) compared to the linear term (β=.028). Among tracts experiencing a decrease in percent Asians, the quadratic term has a substantial relationship with tracts experiencing the largest decrease (β=-.13).

<<<Table 3 about here>>>

In the second set of models, we see strong evidence that tracts experiencing a larger change in percent black also have a considerable amount of nonlinearity in this yearly change (again, the absolute value of the quadratic term performed better in these models based on R-square than did the actual values of the quadratic term). For the complete sample, there is a substantial negative relationship between the quadratic term and change in percent black over the decade. When we split the sample by whether the tract was experiencing an increase or decrease in percent black, we see that tracts undergoing a decrease in black population (the last column), on average, experienced particularly sharp drops if the change occurred over a relatively short period of the decade (as indicated by the negative term for the absolute value of the quadratic term). In other words, tracts in which the quadratic term was very different from zero, either positive or negative, and therefore indicating that much of the change occurred either at the beginning or end of the decade, experienced the sharpest decrease in percent black over the decade (β=-.281). This model also has a relatively large R-square compared to the other models, implying that this is a relatively robust effect. In addition, tracts experiencing an increase in percent black were typically also those with a larger absolute value of the quadratic term.

The change in percent Latinos over the decade was best explained by the actual quadratic trajectory term rather than its absolute value (and therefore we present the models including this measure). Both the linear (β=.309) and the quadratic (β=-.179) terms explain a considerable amount of this change for the complete sample. Most of the tracts in the region experienced an increase in Latinos in the region during this decade, and the model has a relatively high R-square for this subsample. However, there does not appear to be much evidence that nonlinearity matters for the relatively small number of tracts that experienced a decrease in percent Latinos over the decade, suggesting instead that a linear approach is appropriate.

In contrast to the change in Latino population, we observed that our model best explains the *decrease* in percent white over the decade. For the total sample there are particularly strong relationships between the linear term (β=.363) or the quadratic term (β=-.199) and the change in percent white over the decade. The coefficients were similar between the total sample and the large number of tracts experiencing a decrease in percent white over the decade, whereas the model demonstrated a poor fit for the small number of tracts experiencing an increase in percent white.

Turning to the models predicting change in SES over the decade, the model predicting change in average household income over the decade explains very little of this change. There is some evidence of nonlinearity, but it is quite weak. For the models explaining the change in home values over the decade, there is evidence that the absolute value of the quadratic term better explains (relative to the linear term) change for tracts experiencing a relative decrease in home values (when splitting the sample based on the average change in home values over the decade), whereas the linear term better explains change for tracts experiencing a relative increase in home values over the decade.

The bottom panel of Table 3 looks at the change in residential stability (measured in two manners: change in average length of residence and change in percent new homeowners). Among tracts undergoing increasing average length of residence, the positive quadratic term indicates that greater residential turnover later in the decade results in greater increases in average length of residence (β=.093). However, for the subsample of tracts experiencing a decrease in average length of residence during the decade, the positive quadratic coefficient indicates that the largest change occurs earlier in the decade (see Figure 2 for an example of this pattern). We see that the quadratic term measured in absolute value largely explains the change in the percent new owners in a tract during the decade, where tracts with a higher absolute value of the quadratic coefficient, on average, experienced larger increases among increasing tracts and larger decreases among decreasing tracts. This finding may be a function of the particular decade in which the housing bubble in the earlier part of the decade likely drove these results, and may not generalize to other time periods and other locations.

Models predicting quadratic parameter (nonlinear change over decade)

For our next set of models, the outcome variables are the quadratic parameters estimated for each tract in the earlier trajectory analyses; these models attempt to explain which tracts will experience the greatest nonlinear temporal change during the decade. To motivate these models, we first present two maps of the spatial distribution of where nonlinear temporal change occurs for percent Asian (Figure 4) and average home loan values (Figure 5). Figure 4 demonstrates that there is a fair amount of spatial clustering to where nonlinear temporal change occurs for percent Asian. The nonlinear temporal change in Asians tends to occur in the suburban areas of the San Gabriel Valley to the north or Orange County to the south. In contrast, Figure 5 demonstrates that whereas there is some spatial clustering to the locations of nonlinear temporal home loan value change, it occurs across a broader range of the region including a considerable amount in the downtown area. These nonrandom spatial patterns suggest the importance of accounting for what is occurring in nearby tracts when exploring nonlinear temporal change.

<<<Figures 4 and 5 about here>>>

We tested models with both the actual parameter as the outcome, and the absolute value of the parameter as the outcome, and present the results for the models with the best fit based on R-square. We present the standardized coefficients from these models in Table 4. In model 1, there is no evidence that nonlinear temporal change in the percent Asian is explained by the amount of change in percent Asian during the decade (2000-10). Instead, the strongest predictor is the percent Asian at the beginning of the decade (β=.384), as tracts with a higher percentage Asian in 2000 experience the most pronounced nonlinear change in Asians during the decade. There is also evidence that tracts in which there is a larger increase in Asians in the surrounding area from 2000-10 (β=.077) or in which there are more Asians in the surrounding area in 2000 (β=.123) experienced more nonlinear change in Asians during the decade. Finally, there is evidence that a greater increase in percent Asians in the prior decade (1990-2000) is negatively related to the degree of nonlinearity in the change of Asians in the current decade (plotting the linear and quadratic parameters showed that this is simply a slowing negative relationship).

<<<Table 4 about here>>>

Regarding nonlinear change in percent black, there is modest evidence that tracts experiencing a larger increase in black population from 2000-10 experience more nonlinearity in that change (β=.059). Nonetheless, we see that a much stronger predictor of this nonlinearity is the percentage blacks in the tract in 2000 (β=.258), as well as the percentage blacks in the surrounding tracts in 2000 (β=.272). Whereas tracts in which there is a greater increase in percent blacks in the surrounding tracts from 2000-10 experience more nonlinearity in change during the decade (β=.073), tracts in which there was a greater increase in percent black from 1990-2000 actually experienced less nonlinearity (plotting the linear and quadratic parameters showed this as a negative relationship that flattened and turned slightly upwards at high increases in black population from 1990-2000).

Whereas our models do a relatively good job explaining the tracts in which nonlinearity in change of Asians or blacks will occur, with R-squares above .21, our model explaining which tracts will experience nonlinearity in change of Latinos is not as strong (with an R-square of .12).

The strongest predictor of which tracts will experience a nonlinear change in Latinos during the decade are those with a higher percentage Latino in 2000 (β=.318). The only other significant predictor of nonlinear change is the net change in percent Latino from 2000 to 2010.

For the models explaining nonlinear change in percent white or average household income, we found that the models with the outcome of the actual quadratic term showed stronger results than models using the absolute value of the measure. Further, it is interesting to note that the parameters in these two models behave very differently. Tracts experiencing a larger decrease in percent white from 2000-10 experienced greater nonlinearity in change (plotting the quadratic showed it to be a slowing negative relationship), whereas tracts undergoing a larger increase in average income from 2000-10 experienced greater nonlinearity in change (plotting the quadratic showed a slowing positive relationship). And whereas tracts with fewer whites in 2000 experienced greater nonlinear change, tracts with higher average income were particularly likely to experience nonlinear change (β=.365). Tracts in which the surrounding area experienced a larger increase in percent white were less likely to experience nonlinear change (β=-.126), whereas no such pattern was noted for household income. And while tracts surrounded by a high percentage of whites in 2000 were particularly likely to experience nonlinear change during the decade (β=.194), it was tracts surrounded by *lower* average income that experienced more nonlinear change. The only measure that shows a similar pattern across these two outcome measures is the amount of change in the prior decade: tracts experiencing a greater increase in percent white or average household income from 1990 to 2000 experienced less nonlinear change in the 2000-10 decade for these measures.

In the model predicting nonlinearity in the change in the loan value parameter, tracts with the largest increase in average home values from 2000 to 2010 experienced the least nonlinearity in their decadal change (plotting this quadratic function showed it to be a slowing negative relationship that flattens at the higher changes in average home values). We also observed that tracts with a lower average home value in 2000 demonstrated the greatest nonlinearity in their change from 2000 to 2010 (β=-.137), whereas greater increase in home values from 1990-2000 was associated with greater nonlinearity. Nonetheless, our model explained the least variance for this outcome measure.

Finally, we used two different measures of residential stability to explain the nonlinearity in the change in housing turnover (average length of residence in model 7 and percent homeowners living in the same home in model 8 of Table 4). We find that tracts experiencing either a large decrease or large increase in average length of residence from 2000 to 2010 experienced the greatest nonlinearity in housing turnover during the decade (plotting this quadratic function showed it to be u-shaped). This same pattern is observed when viewing the change in average length of residence in the prior decade. On the other hand, tracts experiencing the largest decrease in the percent same owners demonstrated the greatest nonlinearity between 2000 and 2010 (plotting this function showed it to be a slowing negative relationship that flattens at high increases in percent same owners); yet, the pattern was the opposite for change in the prior decade as tracts with the largest increase in percent same owners from 1990-2000 experienced more nonlinearity in the current decade. Tracts with less residential stability in 2000 (by either measure) exhibited greater nonlinearity in housing turnover during the decade. Finally, tracts in which there is more residential instability in the surrounding area in 2000 or as change from 2000-10 experienced the greatest nonlinearity in housing turnover.

Models predicting change in crime over decade

In our final set of analyses, we asked whether these measures of temporal nonlinearity help explain the change in crime during the decade. The results are shown in Table 5. Turning first to property crime, model 1 shows that the standard decennial change measures are related to changes in property crime: tracts experiencing an increase in average household income or percent Latino were both associated with lower property crime rates at the end of the decade. In model 2, we included our measures of temporal nonlinearity and found that tracts with a positive temporal quadratic trajectory for housing turnover corresponded with larger increases in property crime during the decade. In model 3, we instead included the absolute value of the temporal quadratic measures and we detected stronger effects than in model 2. Tracts experiencing greater nonlinear change of Latinos or blacks during the decade corresponded with larger increases in property crime.

<<<Table 5 about here>>>

Turning to the violent crime results, we again see strong evidence that it is important to account for nonlinearity in the temporal change of these measures. In Model 4 we see that all of the standard measures of neighborhood change significantly explain change in violent crime. Thus, tracts with greater increases in percent black, Latino, or Asian corresponded with larger decreases in violence. Likewise, tracts with increasing residential stability or average household income corresponded with lower violent crime levels at the end of the decade. In Model 5, we observe that when the increase in average household income occurs later in the decade (based on the positive quadratic term), there is a greater reduction in violence. In Model 6, we see that a burst of racial/ethnic change that occurs during the decade, regardless of whether the change is earlier or later (thus the positive absolute value of temporal nonlinearity), is associated with increases in violence. On the other hand, housing turnover that occurred with temporal nonlinearity actually reduced the expected level of violence at the end of the decade. Using the absolute value of these measures in Model 6 exhibits the best model fit based on r-square.

Discussion

This study has focused on neighborhood change based on socio-demographic characteristics and advanced the idea that accounting for nonlinearity in the temporal change in neighborhoods is important. Given the possibility of various threshold effects (Galster, Cutsinger, and Lim 2007; Galster, Quercia, and Cortes 2000), the assumption that change during a decade in a neighborhood happens in a linear, uniform manner year by year may not always be reasonable. We employed an under-utilized dataset on home loan activity in census tracts in the U.S. that allowed us to create better approximations of yearly socio-demographic change in these neighborhoods. Our results demonstrated considerable temporal nonlinearity in the change that occurs from year to year in neighborhoods. Furthermore, our final set of analyses demonstrated that this temporal nonlinearity in neighborhood socio-demographic change has consequences for changing crime rates over the decade. We highlight four key findings.

An important first point is that we detected nonlinear temporal change across all socio-demographic dimensions that we measured. There was consistent evidence in the latent trajectories that a quadratic function better fit the data than a linear one for many neighborhoods. This calls into question the common assumption that change occurs in a linear fashion during a decade, along with the typical strategy of linearly interpolating data. Consistent with the theorizing of Galster and colleagues (Galster, Cutsinger, and Lim 2007; Galster, Quercia, and Cortes 2000) there is a considerable amount of temporal nonlinearity in the change in the socio-demographic characteristics of neighborhoods that is worthy of additional consideration and empirical assessment.

A key second point is that this nonlinear temporality appears to have consequences for the overall amount of socio-demographic change experienced in neighborhoods. We found that neighborhoods in which this temporal nonlinearity was more pronounced were likely to experience larger net increases in percent Asian, percent black, or residential stability (percent same homeowners). This finding is notable given that scholars are typically interested in neighborhoods experiencing the greatest amount of change; the fact that these neighborhoods experienced more temporal nonlinearity in their change than other neighborhoods highlights the importance of understanding these temporal processes better. We likewise found that neighborhoods experiencing an increase in Latinos or those experiencing a decrease in whites (the general demographic shift in the region) were more likely to be characterized by temporal nonlinearity in this change. It was only change in SES (measured as average income or loan values) that exhibited less temporal nonlinearity, suggesting that standard linear change models may be appropriate for examining socioeconomic change. Whether the minimal temporal nonlinearity in SES will generalize to other regions, or is simply a peculiarity of this particular region and decade, is something that needs to be explored in future work.

A third key point is that we detected some regularities regarding which neighborhoods are most likely to exhibit temporal nonlinearity. The strongest predictor of temporal nonlinearity for the racial/ethnic measures was the larger presence of the group at the beginning of the decade (i.e., 2000) in the tract. There was an additional effect based on the racial/ethnic composition of the surrounding tracts, suggesting spatial patterning with regards to which neighborhoods members of certain racial/ethnic groups elect to move into. This information is important, as it highlights that researchers using a linear interpolation for such neighborhoods are most at peril of inaccurately characterizing the change in neighborhoods with a high composition of the racial/ethnic group at the beginning of the decade. Moreover, researchers modeling neighborhood change should account for the composition of nearby neighborhoods as an important factor in understanding patterns of change rather than relying solely on focal neighborhood measures. We also found that neighborhoods experiencing larger increases in SES (average income or home loans) were the most likely to experience temporal nonlinearity. These are the neighborhoods that are often of most interest to scholars, so the fact that they are the most likely to exhibit temporal nonlinearity highlights the importance of understanding these processes better. And the fact that neighborhoods experiencing larger increases in percent Asians, percent whites, or average income in the 1990-00 decade were less likely to experience temporal nonlinearity in the 2000-10 decade highlights that there are potentially longer-term processes that inform this year to year change. In other words, the past history of change in a neighborhood can have important implications for understanding future changes. Clearly, much more work is needed to empirically explore the determinants of this temporal nonlinearity, and this study was simply an initial step in this direction.

A final key point is that our analyses demonstrated that the nonlinear change observed in neighborhoods had consequences for the change in violent and property crime over the decade. Criminologists have given very little attention to the possible role of temporal nonlinearity for changes in neighborhood crime, and our results provide an important corrective highlighting that this is an important avenue for future research. We found robust evidence that neighborhoods experiencing temporal nonlinear change in percent black or Latino experienced larger increases in violent and property crime. We also found that the temporal pattern of residential turnover or the change in average income had consequences for the change in crime. These results highlight that a fruitful direction for future research is to understand *why* this temporal nonlinearity results in greater increases in crime; for example, whether nonlinear change leads to neighborhood disruption and subsequent decreases in informal control.

Before concluding, we note a few limitations. We measured household turnover based on home purchases, which does not account for turnover in rental units. We thus have an under-estimate of the amount of turnover occurring within neighborhoods. Additionally, our measure of income change is based on the reported income of those receiving home loans. This is clearly a subset of the total population in a tract, as such households typically have higher income. This reduces our variability in average income. Likewise, we did not have measures of average home values, but rather average loan amounts. Although households typically put down a somewhat consistent percentage down payment for a home loan, this can vary across households introducing error into this as a measure across neighborhoods. We also note that we only focused on one specific form of nonlinearity: quadratic change. Although our primary goal was to test for temporal nonlinearity—and our models demonstrated that this exists—given our results, future work should carefully test other possible functional forms that may characterize this change.

In conclusion, we have highlighted that researchers should not simply ignore the year to year temporal pattern of change in neighborhoods. Instead, it appears that change in neighborhoods can sometimes occur in short bursts rather than a gradual, linear pace as often assumed by prior research. This fast and slow pattern of change not only differs across neighborhoods, but we showed that it is also associated with the overall level of change observed in a neighborhood during the decade. Furthermore, the temporal nonlinearity of this change can help explain which neighborhoods experience larger increases of violent or property crime during the decade. Although measuring this temporal nonlinearity is challenging due to data limitations, we believe that our results highlight that it is nonetheless a fruitful area of future research and will spur additional theoretical development about neighborhood change.

References

Biesanz, Jeremy C., Natalia Deeb-Sossa, Alison A. Papadakis, Kenneth A. Bollen, and Patrick J. Curran. 2004. "The Role of Coding Time in Estimating and Interpreting Growth Curve Models." *Psychological Methods* 9:30-52.

Boggess, Lyndsay N. and John R. Hipp. 2010. "Violent crime, residential instability and mobility: Does the relationship differ in minority neighborhoods?" *Journal of Quantitative Criminology* 26:351-370.

Bollen, Kenneth A. and Patrick J. Curran. 2006. *Latent Curve Models: A Structural Equation Perspective*. New York: John Wiley & Sons.

Bursik, Robert J. 1988. "Social Disorganization and Theories of Crime and Delinquency: Problems and Prospects." *Criminology* 26:519-551.

Coulton, Claudia J., Brett Theodos, and Margery A. Turner. 2012. "Residential Mobility and Neighborhood Change: Real Neighborhoods Under the Microscope." *Cityscape* 14:55-89.

Crowder, Kyle, Scott J. South, and Erick Chavez. 2006. "Wealth, race, and inter-neighborhood migration." *American Sociological Review* 71:72-94.

Ellen, Ingrid Gould and Katherine O'Regan. 2008. "Reversal of Fortunes? Lower-income Urban Neighbourhoods in the US in the 1990s." *Urban Studies* 45:845-869.

Galster, George C. 1987. *Homeowners and Neighborhood Reinvestment*. Durham, NC: Duke.

Galster, George C., Jackie Cutsinger, and Up Lim. 2007. "Are Neighbourhoods Self-stabilising? Exploring Endogenous Dynamics." *Urban Studies* 44:167-185.

Galster, George C., Roberto G. Quercia, and Alvaro Cortes. 2000. "Identifying Neighborhood Thresholds: An Empirical Exploration." *Housing Policy Debate* 11:701-732.

Grigsby, William G. 1987. *The Dynamics of Neighborhood Change and Decline*. Oxford: Pergamon.

Hipp, John R. 2010. "A dynamic view of neighborhoods: The reciprocal relationship between crime and neighborhood structural characteristics." *Social Problems* 57:205-230.

Hipp, John R. and Alyssa Chamberlain. 2011. "Community Change and Crime." *Oxford Bibliographies*.

Hipp, John R. and Charis E. Kubrin. 2017. "From Bad to Worse: How Changing Inequality in Nearby Areas Impacts Local Crime." *Russell Sage Foundation Journal* 3:129-151.

Hipp, John R., George E. Tita, and Robert T. Greenbaum. 2009. "Drive-bys and Trade-ups: The Impact of Crime on Residential Mobility Patterns in Los Angeles." *Social Forces* 87:1777-1812.

Jun, Hee-Jung. 2016. "The Effect of Racial and Ethnic Composition on Neighborhood Economic Change: A Multilevel and Longitudinal Look." *Housing Studies* 31:102-125.

Kirk, David S. and John H. Laub. 2010. "Neighborhood Change and Crime in the Modern Metropolis." *Crime and Justice* 39.

La Gory, Mark and John Pipkin. 1981. *Urban Social Space*. Belmont, CA: Wadsworth.

Massey, Douglas S., Andrew B. Gross, and Kumiko Shibuya. 1994. "Migration, Segregation, and the Geographic Concentration of Poverty." *American Sociological Review* 59:425-445.

Quillian, Lincoln. 1999. "Migration Patterns and the Growth of High-Poverty Neighborhoods, 1970-1990." *American Journal of Sociology* 105:1-37.
Raleigh, Erica and George Galster. 2014. "Neighborhood Disinvestment, Abandonment, and Crime Dynamics." *Journal of Urban Affairs*:online.
Sampson, Robert J. and W. Byron Groves. 1989. "Community Structure and Crime: Testing Social-Disorganization Theory." *American Journal of Sociology* 94:774-802.
Schuerman, Leo and Solomon Kobrin. 1986. "Community Careers in Crime." *Crime and Justice* 8:67-100.
Shaw, Clifford and Henry D. McKay. 1942. *Juvenile Delinquency and Urban Areas*. Chicago: University of Chicago Press.
South, Scott J., Kyle D. Crowder, and Erick Chavez. 2005. "Exiting and Entering High-Poverty Neighborhoods: Latinos, Blacks and Anglos Compared." *Social Forces* 84:873-900.
Wo, James C. 2016. "Community context of crime: A longitudinal examination of the effects of local institutions on neighborhood crime." *Crime & Delinquency* 62:1286-1312.
Wo, James C., John R. Hipp, and Adam Boessen. 2016. "Voluntary Organizations and Neighborhood Crime: A Dynamic Perspective." *Criminology* 54:212-241.
Wyly, Elvin K. and Daniel J. Dammel. 1999. "Islands of Decay in Seas of Renewal: Housing Policty and the Resurgence of Gentrification." *Housing Policy Debate* 10:711-771.

Tables and Figures

Table 1. Summary statistics for HMDA annual change trajectories

	Mean	Std Dev	Min	Max
Linear term				
Housing turnover	-0.003	0.088	-0.442	0.962
Asian	0.000	0.051	-0.411	0.369
Black	0.000	0.057	-0.517	0.557
Latino	0.001	0.051	-0.384	0.267
White	-0.002	0.046	-0.230	0.325
Average household income	-0.001	0.047	-0.245	0.288
Average loan amount	-0.001	0.049	-0.379	0.297
Quadratic term				
Housing turnover	0.000	0.013	-0.081	0.139
Asian	0.000	0.009	-0.055	0.059
Black	0.000	0.009	-0.074	0.081
Latino	0.000	0.008	-0.039	0.042
White	0.000	0.008	-0.035	0.035
Average household income	0.000	0.009	-0.048	0.054
Average loan amount	0.000	0.008	-0.050	0.036
R-square linear model				
Housing turnover	0.205	0.208	0.000	0.939
Asian	0.210	0.207	0.000	0.942
Black	0.188	0.190	0.000	0.916
Latino	0.165	0.189	0.000	0.903
White	0.170	0.191	0.000	0.918
Average household income	0.103	0.131	0.000	0.856
Average loan amount	0.114	0.141	0.000	0.903
R-square quadratic model				
Housing turnover	0.274	0.206	0.000	0.958
Asian	0.276	0.199	0.000	0.942
Black	0.262	0.189	0.000	0.927
Latino	0.240	0.180	0.000	0.903
White	0.228	0.190	0.000	0.923
Average household income	0.142	0.136	0.000	0.861

Average loan amount	0.149	0.144	0.000	0.903
Increase in r-square for quadratic model				
Housing turnover	0.069	0.070	0.000	0.321
Asian	0.065	0.069	0.000	0.351
Black	0.074	0.079	0.000	0.362
Latino	0.075	0.078	0.000	0.360
White	0.058	0.064	0.000	0.328
Average household income	0.040	0.049	0.000	0.330
Average loan amount	0.036	0.045	0.000	0.317
Change in Census measures 2000-10				
Asian	1.87	4.71	-39.32	30.76
Black	-0.61	3.91	-33.91	25.00
Latino	4.74	8.18	-90.03	56.44
White	-5.39	8.29	-75.00	98.56
Average household income	18,846	16,021	-75,436	187,790
Average home value	265,080	125,770	-40,977	985,454
Average length of residence	0.01	1.73	-27.30	13.53
Percent same owners	-8.46	14.75	-100.00	100.00

Table 2. Correlations among annual HMDA quadratic term measures, and among Census-based decadal change measures

		Correlations in quadratic annual change terms							
		(1)	(2)	(3)	(4)	(5)	(6)	(7)	
(1)	Asian	1							
(2)	Black	0.01	1						
(3)	Latino	-0.29	-0.08	1					
(4)	White	-0.16	-0.03	-0.46	1				
(5)	Household income	0.11	0.02	0.16	0.22	1			
(6)	Home value	0.19	0.08	0.28	0.18	0.70	1		
(7)	Turnover	0.17	0.07	0.00	0.13	0.37	0.29	1	
		Correlations of changes in Census-based measures							
		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
(1)	Asian	1							
(2)	Black	0.00	1						
(3)	Latino	-0.29	-0.24	1					
(4)	White	-0.27	-0.22	-0.68	1				
(5)	Household income	0.10	0.11	-0.14	0.00	1			
(6)	Home value	0.12	0.06	-0.22	0.12	0.39	1		
(7)	Avg length of residence	-0.08	-0.02	-0.04	0.10	-0.01	0.08	1	
(8)	Percent same owners	-0.08	-0.04	-0.04	0.10	-0.02	0.06	0.54	1

Table 3. Predicting change in socio-demographic measures from 2000 to 2010 based on U.S. Census data

	Change in percent Asian from 2000-10			Change in percent Black from 2000-10		
	Total	Increasing	Decreasing	Total	Increasing	Decreasing
Linear	0.096 **	0.028 †	0.122 **	0.253 **	0.004	0.262 **
Quadratic (absolute value)	0.163 **	0.225 **	-0.130 **	-0.150 **	0.126 **	-0.281 **
Number of tracts	3798	2433	1414	3798	1746	2126
R square	0.041	0.075	0.112	0.099	0.042	0.237
	Change in percent Latino from 2000-10			Change in percent white from 2000-10		
	Total	Increasing	Decreasing	Total	Increasing	Decreasing
Linear	0.309 **	0.251 **	0.049 **	0.363 **	0.025	0.303 **
Quadratic	-0.179 **	-0.153 **	-0.001	-0.199 **	-0.002	-0.171 **
Number of tracts	3798	2940	858	3798	783	3015
R square	0.154	0.158	0.009	0.219	0.002	0.216
	Change in average household income ($1000s)			Change in average home value ($1000s)		
	Total	Increasing	Decreasing	Total	Increasing	Decreasing
Linear	-0.016	-0.001	0.015 †	0.006	-0.102 **	0.048 **
Quadratic	0.101 **	-0.013	0.033 **			
Quadratic (absolute value)				-0.161 **	0.020	-0.088 **
Number of tracts	3807	1551	2256	3834	1814	2020
R square	0.012	0.000	0.007	0.028	0.018	0.045
	Change in average length of residence			Change in percent same owners		
	Total	Increasing	Decreasing	Total	Increasing	Decreasing
Linear	-0.106 **	0.052 **	-0.123 **	-0.172 **	0.001	-0.155 **
Quadratic	0.140 **	0.093 **	0.060 **			
Quadratic (absolute value)				-0.043 **	0.131 **	-0.141 **
Number of tracts	3885	1906	1979	3882	866	3024
R square	0.047	0.018	0.069	0.036	0.053	0.086

Note: fully standardized coefficients shown.

Note: a - indicates tracts experiencing relative increase or decrease (using the mean value of the change as the cut-point.

*Note: ** p < .01; * p < .05; † p < .10.*

Table 4. Models predicting quadratic parameter (capturing nonlinearity over decade) for various measures

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Asian quadratic parameter	Black quadratic parameter	Latino quadratic parameter	White quadratic parameter (a)	Average household income quadratic parameter (a)	Loan amount quadratic parameter	Turnover quadratic parameter (predicted by length of residence)	Turnover quadratic parameter (Predicted by percent same owners)
Change from 2000-10	0.023	0.059 **	0.089 **	-0.083 **	0.139 **	-0.412 **	-0.005	-0.011
Change from 2000-10 squared	0.036 †	-0.004	0.025	0.067 **	-0.161 **	0.324 **	0.206 **	0.193 **
Level in 2000	0.384 **	0.258 **	0.318 **	-0.150 **	0.365 **	-0.137 **	-0.174 **	-0.154 **
Change in surrounding 5-mile area from 2000-10	0.077 **	0.073 **	-0.023	-0.126 **	-0.022	-0.014	-0.065 **	0.063 **
Surrounding 5-mile area in 2000	0.123 **	0.272 **	0.000	0.194 **	-0.048 *	-0.042	-0.122 **	
Change during 1990-2000	-0.231 **	-0.009	0.007	-0.286 **	-0.272 **	0.007	-0.058 **	0.023
Change during 1990-2000 squared	0.047 *	0.090 **	0.027	-0.084 *	-0.012	0.116 **	0.137 **	0.095 **
Number of tracts	3739	3739	3739	3739	3746	3773	3821	3818
R square	0.209	0.237	0.116	0.154	0.066	0.054	0.120	0.094

Note: fully standardized coefficients shown.

Note: (a) outcome is quadratic term from trajectory models. For all other models, outcome is absolute value of quadratic term from trajectory models.

*Note: ** p < .01; * p < .05; † p < .10. T-values in parentheses.*

Table 5. Predicting change in property and violent crime in tracts from 2000-10

	Property crimes in 2010			Violent crimes in 2010		
	(1)	(2)	(3)	(4)	(5)	(6)
Crime count at beginning of decade	0.005 **	0.005 **	0.005 **	0.019 **	0.018 **	0.018 **
	(19.38)	(19.55)	(19.51)	(23.60)	(22.49)	(23.21)
Change in percent Asian	-0.002	-0.002	0.000	-0.026 **	-0.025 **	-0.025 **
	-(0.39)	-(0.29)	-(0.08)	-(4.67)	-(4.35)	-(4.56)
Change in percent Black	-0.007	-0.006	-0.003	-0.013 *	-0.012 *	-0.009
	-(1.23)	-(1.01)	-(0.62)	-(2.19)	-(2.07)	-(1.61)
Change in percent Latino	-0.006 *	-0.004	-0.005 †	-0.013 **	-0.013 **	-0.011 **
	-(2.18)	-(1.48)	-(1.95)	-(4.41)	-(4.26)	-(3.90)
Change in average household income	-0.003 *	-0.003 **	-0.002	-0.011 **	-0.010 **	-0.009 **
	-(2.19)	-(2.62)	-(1.26)	-(7.93)	-(7.20)	-(6.63)
Change in residential stability	0.000	-0.006	0.005	-0.030 *	-0.025 †	-0.028 *
	(0.00)	-(0.43)	(0.43)	-(2.24)	-(1.83)	-(2.08)
Temporal nonlinearity in Asians		2.357			3.276	
		(0.84)			(1.20)	
Temporal nonlinearity in Blacks		1.494			1.943	
		(0.68)			(0.94)	
Temporal nonlinearity in Latinos		2.082			2.517	
		(0.74)			(0.91)	
Temporal nonlinearity in housing turnover		4.573 **			-3.463 †	
		(2.63)			-(1.89)	
Temporal nonlinearity in household income		-2.321			-5.136 *	
		-(0.94)			-(2.07)	
Temporal nonlinearity in Asians (absolute value)			4.620			7.341 *
			(1.22)			(2.01)
Temporal nonlinearity in Blacks (absolute value)			9.013 **			11.913 **
			(2.82)			(3.97)
Temporal nonlinearity in Latinos (absolute value)			11.555 **			19.108 **
			(2.81)			(4.72)
Temporal nonlinearity in housing turnover			-4.032 †			-8.412 **
(absolute value)			-(1.86)			-(3.60)
Temporal nonlinearity in household income			2.554			4.662
(absolute value)			(0.71)			(1.31)
Intercept	-4.489 **	-4.491 **	-4.647 **	-6.336 **	-6.343 **	-6.538 **
	-(92.02)	-(90.83)	-(68.53)	-(118.48)	-(118.66)	-(95.00)
Number of tracts	1497	1497	1497	1497	1497	1497
Pseudo R-square	0.033	0.033	0.034	0.096	0.097	0.101

*Note: ** p < .01; * p < .05; † p < .10. T-values in parentheses.*

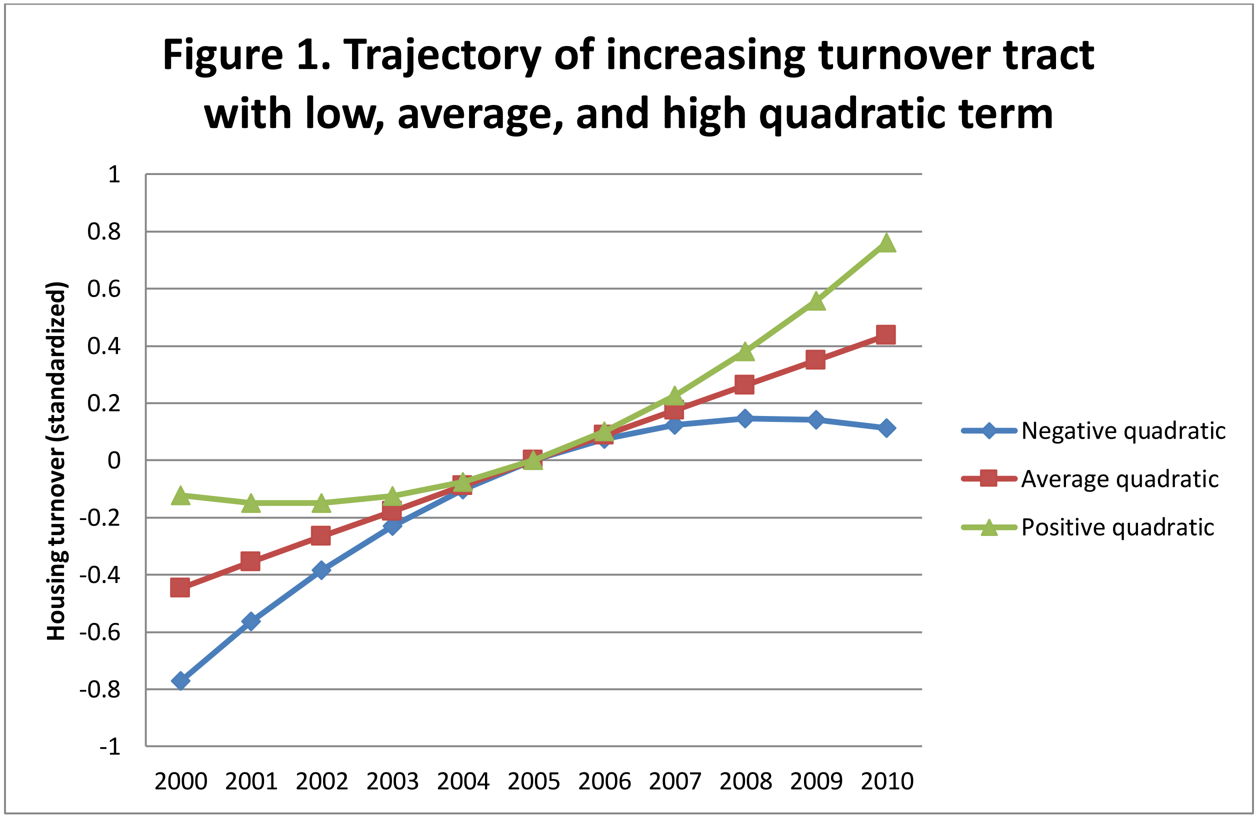


Figure 1. Trajectory of increasing turnover tract with low, average, and high quadratic term
Housing turnover (standardized)
1
0.8
0.6
0.4
0.2
0
-0.2
-0.4
-0.6
-0.8
-1
2000
2001
2002
2003
2004
2005
2006
2007
2008
2009
2010
Negative quadratic
Average quadratic
Positive quadratic

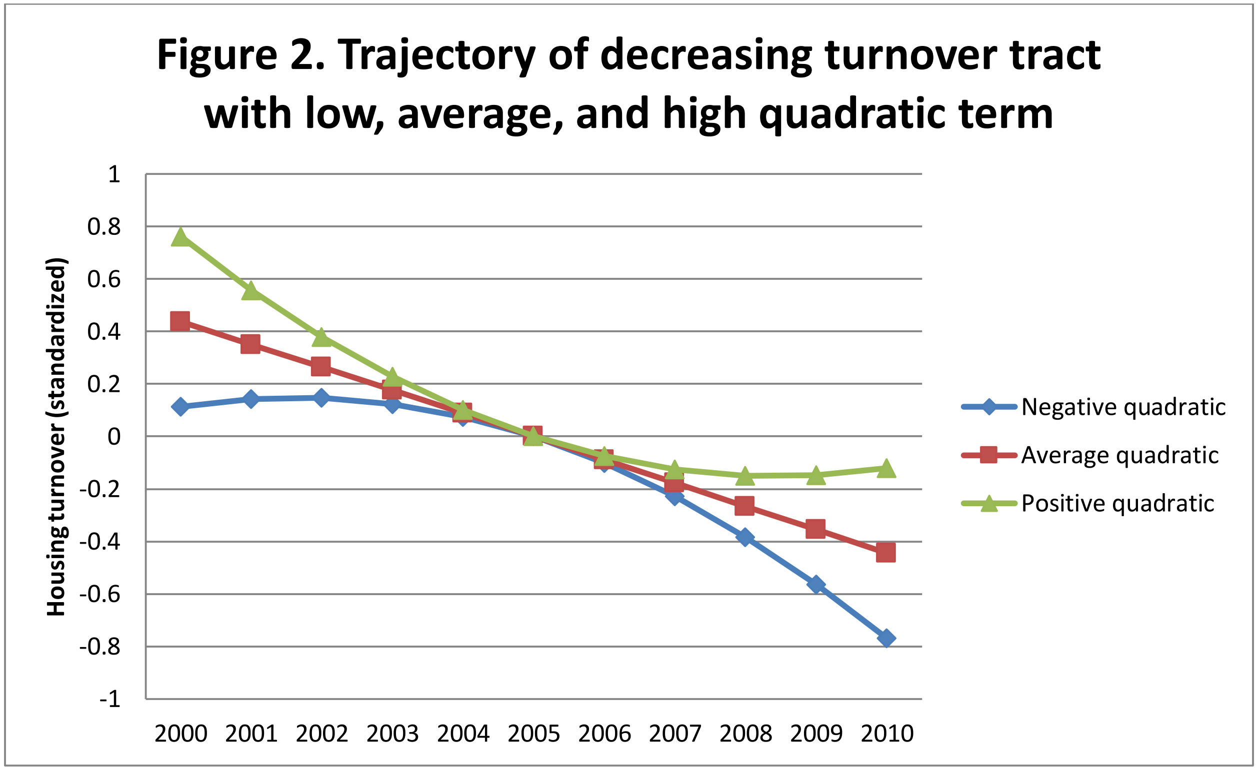


Figure 2. Trajectory of decreasing turnover tract
with low, average, and high quadratic term
Housing turnover (standardized)
1
0.8
0.6
0.4
0.2
0
-0.2
-0.4
-0.6
-0.8
-1
2000
2001
2002
2003
2004
2005
2006
2007
2008
2009
2010
Negative quadratic
Average quadratic
Positive quadratic

Figure 3. Trajectory of increasing percent Asian tract with low, average, and high quadratic term

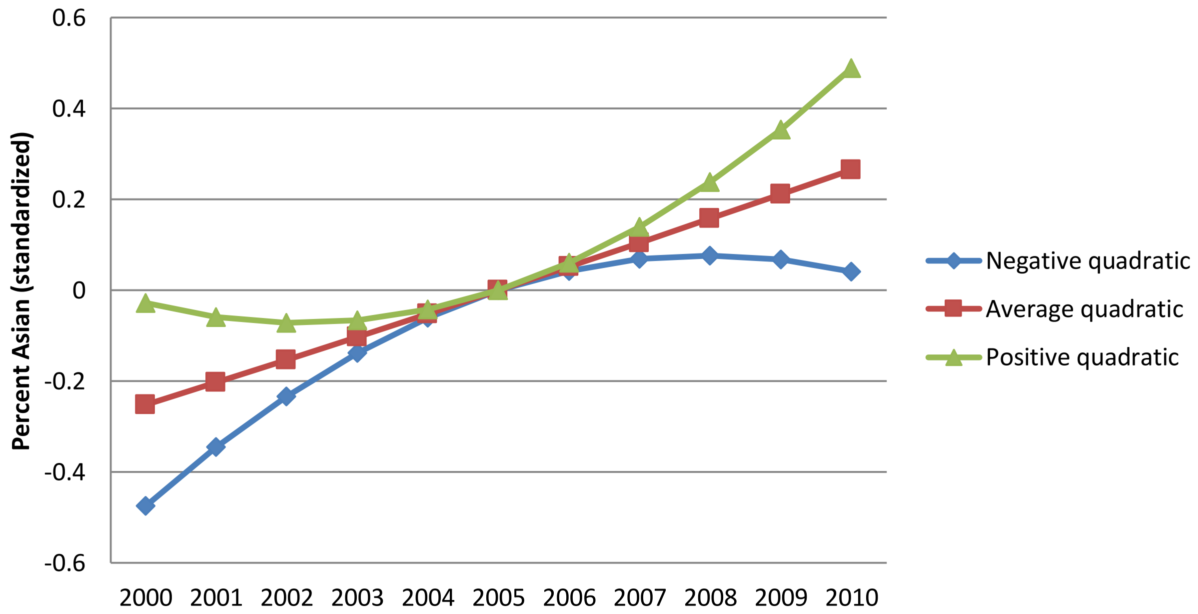


Figure 4.

Quadratic Change in Percent Asian in Los Angeles, Orange Counties (2000 to 2010)

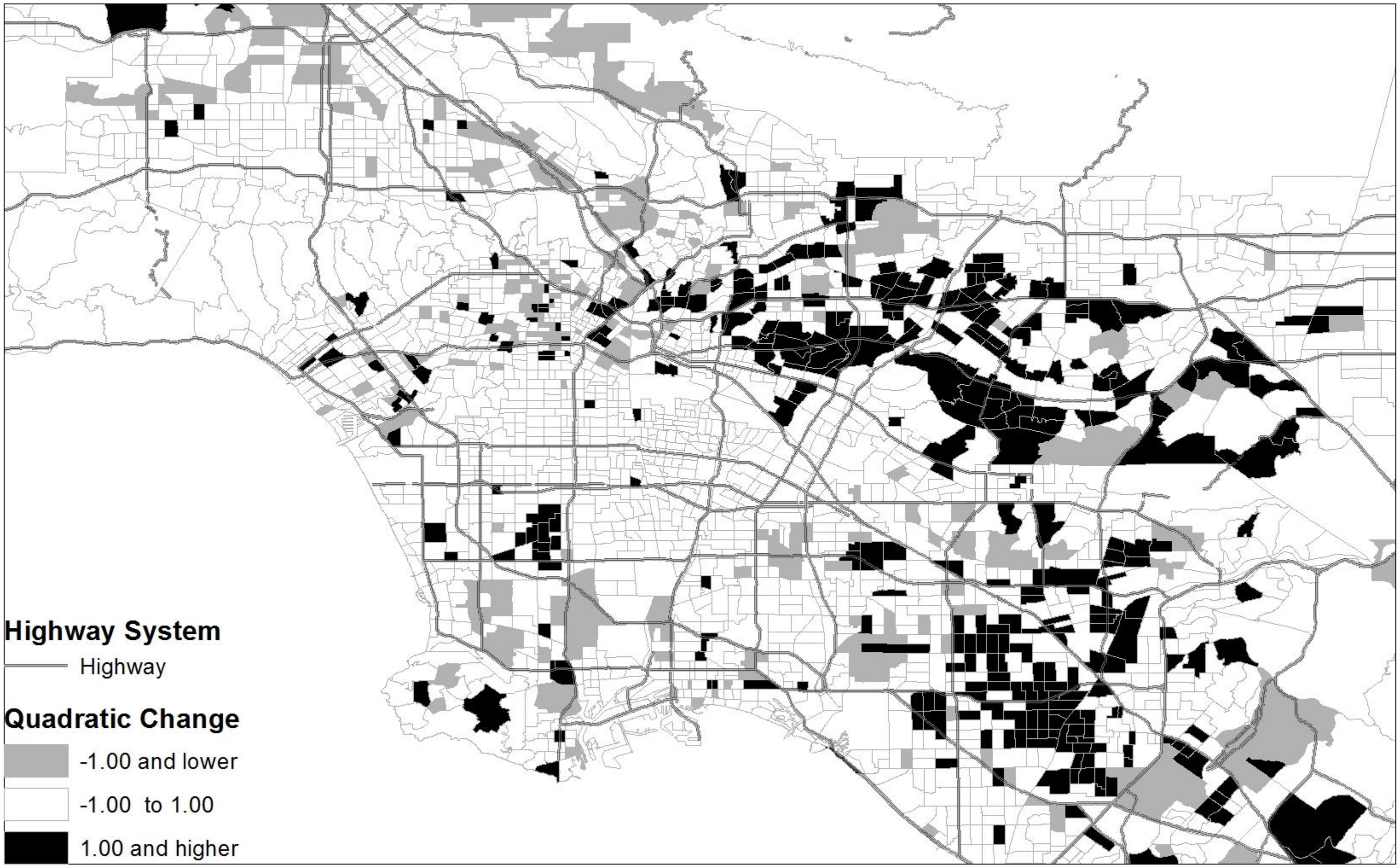
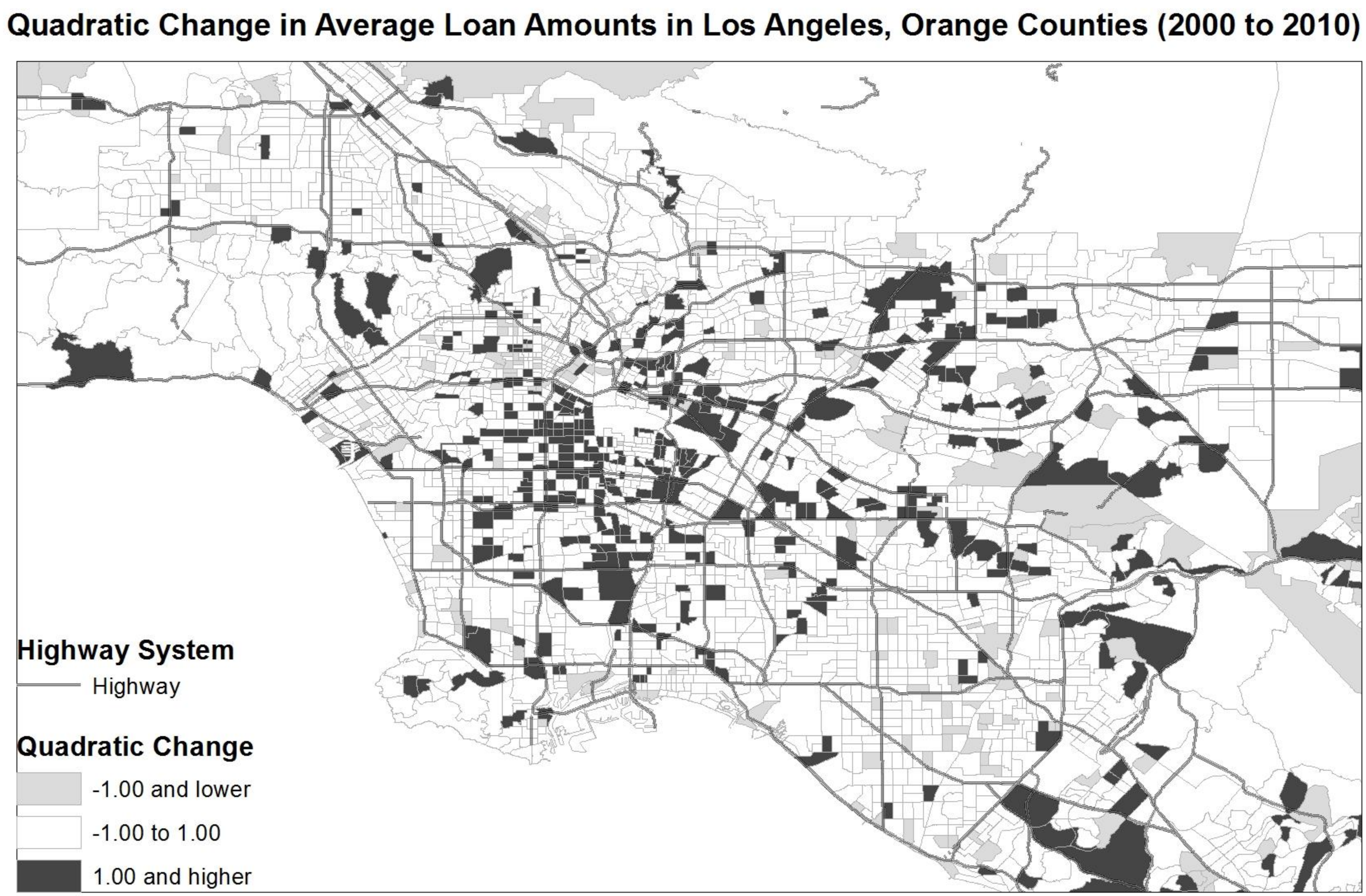


Figure 5


Quadratic Change in Average Loan Amounts in Los Angeles, Orange Counties (2000 to 2010)
Highway System
Highway
Quadratic Change
-1.00 and lower
-1.00 to 1.00
1.00 and higher