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# Growing Pains or Appreciable Gains? Latent Classes of Neighborhood Change, and Consequences for Crime in Southern California Neighborhoods

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# Growing Pains or Appreciable Gains? Latent Classes of Neighborhood Change, and Consequences for Crime in Southern California Neighborhoods

## Abstract

This study explored the dynamic nature of neighborhoods using a relatively novel approach and data source. By using a nonparametric holistic approach of neighborhood change based on latent class analysis (LCA), we have explored how changes in the socio-demographic characteristics of residents, as well as home improvement and refinance activity by residents, are related to changes in neighborhood crime over a decade. Utilizing annual home mortgage loan data in the city of Los Angeles from the years 2000 to 2010, we 1) conducted principle components factor analyses using measures of residential in-migration and home investment activities; 2) estimated LCA models to identify classes of neighborhoods that shared common patterns of change over the decade; 3) described these 11 classes; 4) estimated change-score regression models to assess the relationship of these classes with changing crime rates. The analyses detected six broad types of neighborhood change: 1) stability; 2) urban investors; 3) higher-income home buyers; 4) in-mover oscillating; 5) oscillating refinance; 6) mixed-trait. The study describes the characteristics of each of these classes, and how they are related to changes in crime rates over the decade.

***Keywords***: neighborhoods; crime; change; temporal; spatial.

***Bio***

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# Growing Pains or Appreciable Gains? Latent Classes of Neighborhood Change, and Consequences for Crime in Southern California Neighborhoods

Although most neighborhoods remain stable over time and do not experience much change, a smaller subset of neighborhoods does undergo transitions that can have long-term and varied consequences for their respective neighborhood characteristics. This poses a challenge for scholars studying neighborhood change, including those in the social disorganization tradition studying the relationship between neighborhood demographic change and crime, who posit that change in neighborhood residential instability, economic disadvantage, and racial/ethnic heterogeneity impact levels of crime (Krivo, Peterson, and Kuhl 2009; Sampson and Groves 1989). The fact that relatively few neighborhoods exhibit change over time implies that standard approaches focusing on average levels of change across all neighborhoods in a region may not be appropriate. In other words, if most neighborhoods exhibit very little change but a small number exhibit comparatively large, and varied, changes, then it may be better to examine change using an approach that does not assume a smooth linear transformation, but rather accounts for sharper, discontinuous changes (Hipp and Branic 2017). We suggest that a better way to capture such discrete changes in neighborhoods is through a latent clustering approach, as we adopt here, rather than a standard linear change model. Furthermore, given theories about how neighborhood trajectories impact levels of crime over longer temporal periods (Skogan 1990)—rather than just year-to-year—we argue that an approach accounting for change over multiple years (rather than a single year) is more appropriate.

Whereas social disorganization theory focuses on the consequences of socio-demographic change for changes in neighborhood crime (Hipp, Tita, and Greenbaum 2009;

Kubrin and Herting 2003; Markowitz, Bellair, Liska, and Liu 2001; Wickes and Hipp 2018), a second, relatively understudied mechanism includes the activities and financial investments undertaken by current residents to improve the neighborhood (Ellen and O'Regan 2011; Raleigh and Galster 2015). Furthermore, these financial investments can co-occur along with residential mobility, thus operating simultaneously to shape the trajectory of a neighborhood (Baum and Hassan 1999). We therefore argue that it is important to study these patterns of neighborhood change in a holistic fashion—rather than measuring each variable while "controlling" for the others—to better understand their consequences for subsequent levels of crime in neighborhoods. In this paper, we address how residential mobility and investment activities contribute to patterns of neighborhood socioeconomic change and how this change subsequently affects levels of crime. While some existing studies have used housing data to explore neighborhood change (Galster, Hayes, and Johnson 2005; Immergluck and Smith 2005; Schwartz 1998), or the role of home loans (Velez, Lyons, and Boursaw 2017), relatively fewer studies that have looked at how the actions of existing residents to improve their housing might impact the neighborhood and therefore have consequences for levels of crime.

An additional, novel feature of our study is to use residents' home refinancing activities as a proxy for *economic fragility* in neighborhoods that may impact levels of crime. We emphasize that this measure should have different consequences during different historic periods. During "normal" periods, increasing home values provide greater wealth to homeowners, and they can remove some of this equity by refinancing their homes to use for their own expenditures. However, the fact that this equity removal reduces residents' economic buffer for potential bad times implies that in historic contexts where a sharp rise in home values is followed by a sharp decline, this removal of home equity can result in refinancers facing a financial

shortfall during the sudden drop in home values, which, in aggregation, leads to neighborhood economic fragility. This was the case during the 2007 housing market crash, as a large number of refinancings during the 2000-2010 decade were simultaneously removing some of the home equity.[1] We posit here that this economic fragility will impact neighborhood crime through similar mechanisms as those posited for the relationship between foreclosures and crime (Arnio, Baumer, and Wolff 2012; Immergluck and Smith 2006), as we elaborate below. We are not aware of any studies viewing how such refinancing activity might increase neighborhood economic fragility and therefore result in crime increases.

In this paper, we propose a new strategy to holistically measure neighborhood socioeconomic change, using longitudinal home loan data to empirically identify a set of neighborhood types. Using data for the city of Los Angeles over the decade of 2000-10, this classification scheme incorporates the amount of change in both the income level of persons moving into neighborhoods and residents' home-related investments and refinancings occurring within neighborhoods. This paper provides three key contributions: 1) creating a classification scheme for socioeconomic change in neighborhoods based on change in home loan activity; 2) describing the patterns of these neighborhood changes over the spatial landscape; 3) assessing how these identified classes of neighborhood change correspond with changing crime rates. We will next describe the literature on residential mobility and the consequences for neighborhoods. Following that, we will discuss the impact that residents can have on neighborhood change through reinvestment or refinance activity. We will then describe our notion of economic fragility based on refinance activity, and the possible mechanisms through which it would be

[1] Between 2000 and 2007, 64% of home loan refinancing events were for amounts at least 5% greater than the original loan amount, which Freddie Mac notes is evidence of extracting equity (http://www.freddiemac.com/research/datasets/refinance-stats/archive.html).

expected to impact levels of crime. We will then describe our data and analytic strategy, and present our analytic results. We will conclude by discussing the implications of using this classification strategy for understanding how neighborhoods change over time and their consequences for changes in crime.

## Literature Review

### *Residential mobility*

The relationship between residential mobility and neighborhood change depends largely on who moves into the neighborhood. The process of residential mobility, or residential migration, involves two conceptually distinct but related elements: new residents moving into a neighborhood (in-migration) and existing residents moving out of their current neighborhood (out-migration). In cases where new residents are not much different from former residents, residential mobility would amount to a substitution of the residents within a neighborhood, which can lead to a growing sense of instability and reduce social ties (Sampson and Groves 1989; Sampson and Raudenbush 1999) but otherwise may not stimulate much change (Sampson and Sharkey 2008; Theodos, Coulton, and Pitingolo 2015). The introduction of new residents who *are* substantially different from former and current residents, however, can have broader impacts. In their review of neighborhood change literature, Kirk and Laub (2010: 443) conclude, "One of the most fundamental ways in which neighborhoods change is through shifts in the number and composition of its inhabitants." Such incoming residents can contribute to changes in a neighborhood's characteristics, such as when gentrification occurs.

Consistent with Kirk and Laub's (2010) assertion, longitudinal research on neighborhoods finds that residential migration is a key mechanism influencing neighborhood socioeconomic change (Bruch and Mare 2006; Coulton, Theodos, and Turner 2012; Crowder and

South 2005; Ellen and O'Regan 2011; Quercia and Galster 2000; Sampson and Sharkey 2008; Schwirian 1983; Theodos, Coulton, and Pitingolo 2015). In particular, the introduction of comparatively affluent, middle- and higher-income residents into lower-income neighborhoods can shift neighborhood characteristics such as average income and home values. The growing literature on gentrification discusses how the in-migration of middle- and upper-class residents back into urban neighborhoods in recent decades can lead to socioeconomic appreciation and revitalization (Hwang and Sampson 2014; Wyly and Hammel 1998; Zukin 1987). A key point to emphasize, however, is that neighborhood socioeconomic change is a *process* that occurs over time (Tunstall 2016); thus, the implications of new residents moving into a neighborhood will take time to manifest. It is also important to note that many individuals face barriers to neighborhood in-migration in the forms of constrained choices and limited opportunities. Income plays a large role in determining whether and where individuals can move due to the high home values and costs associated with many desirable neighborhoods (Clark and Ledwith 2007; South and Crowder 1998).[2] Similarly, some residents lack the economic ability to make improvements to their homes, an issue to which we turn shortly.

*Residential mobility and crime*

Residential migration and changing neighborhood socioeconomic characteristics can have important consequences for the amounts of crime experienced within neighborhoods, particularly where residential mobility leads to changing income levels among neighborhood residents. In the short-term, there is increased income inequality due to the different economic

[2] Relatedly, a potential consequence of the in-migration of affluent residents into lower-income neighborhoods is displacement of current residents. As neighborhood socioeconomic conditions improve, those who rent homes within the neighborhood may be priced out as rents increase. In effect, such residents are pushed out of the neighborhood and forced to locate affordable housing elsewhere, endure the economic costs of moving, and potentially suffer the loss of established social ties.

level of in-migrants, and this inequality can reduce informal social control capability (Hipp 2007), and provide more crime opportunities given the close proximity of those with high and low income levels (Boggess and Hipp 2016; Chamberlain and Hipp 2015). Prior literature on gentrification similarly finds that gentrifying low-income neighborhoods can sometimes experience increasing crime in the early part of the process followed by long-term decreases in crime as a neighborhood progressively gentrifies (Kreager, Lyons, and Hays 2011). Other research has focused on the number of home purchase loans—and the dollar amount—as evidence of the willingness of outside lenders to invest in neighborhoods, finding a negative relationship with changes in crime (Velez, Lyons, and Boursaw 2017).

*Resident activity: home improvement*

The financial capital and investment activities of neighborhood residents can also serve as important drivers of neighborhood socioeconomic change by improving the quality of housing units, raising neighborhood home values, and contributing to broader development within neighborhoods. These investment practices create a conceptually distinct method by which the individual and collective actions of residents can improve neighborhood socioeconomic characteristics.

One of the primary ways that residents invest financial capital into their neighborhoods is by improving their homes. Some housing units undergo renovation during occupants' tenures, especially when occupants are homeowners (Molina 2016; Rohe and Stewart 1996; Smith 1979). Moreover, research suggests that new residents entering neighborhoods can influence future financial investment and mortgage capital flows (Hwang and Sampson 2014; Immergluck 1999), implying that residential migration and neighborhood investment can exhibit a reciprocal relationship with one another (Baum and Hassan 1999). The growing trend of urban in-migration

by middle- and higher-income residents in recent decades provides a salient example of how broader patterns of residential mobility have contributed to financial investments and socioeconomic changes across neighborhoods. Tracing flows of home mortgage lending in U.S. cities from 1993 to 2000, Wyly and colleagues (Wyly, Atia, and Hammel 2004) find that annual rates of home purchase and improvement loans concentrated simultaneously within urban areas at levels that far surpassed the rates observed in suburban areas. Other researchers have made similar observations, noting the trends of wealthy middle- and upper-class residents purchasing homes in urban neighborhoods and investing capital to improve their homes and neighborhoods (Hwang and Sampson 2014; Zukin 1987).

Current residents (i.e., "stayers") also engage in home improvement and renovation activities that may complement the investment behaviors of in-moving residents. In their examination of residential mobility and home renovations, Baum and Hassan (1999) compare "mover" and "non-mover" renovators and find that both groups engage in substantial home improvement activities, although their reasons for doing so may differ. Some households move into a neighborhood and subsequently renovate their homes, although others renovate as an alternative to moving from the neighborhood. For both current and new residents, these home improvement behaviors can fundamentally change the trajectory of a neighborhood (Owens 2012). Moreover, these socioeconomic shifts can occur in suburban and urban neighborhoods with vastly different population characteristics such as income levels, racial and ethnic composition, and foreign-born population, meaning that socioeconomic change is not inherently restricted to certain places or groups of people.

Although residents' capital investments often focus on individual housing units, these improvement activities can lead to rising home values throughout the neighborhood and

increased satisfaction among residents as the neighborhood progressively changes (Ellen and O'Regan 2011). Moreover, neighborhood appreciation can produce an atmosphere that motivates additional financial capital into the area as the neighborhood transforms (Boehm and Ihlanfeldt 1986; Hwang 2015; Hwang and Sampson 2014; Velez, Lyons, and Boursaw 2017). Current residents may choose to improve their homes later as the perceived value and quality of the neighborhood develops and improving neighborhood conditions may attract additional middle- and upper-class individuals to the neighborhood (Baum and Hassan 1999; Wyly and Hammel 1999).

*Home improvement and crime*

The improvement activities of neighborhood residents can have consequences for local crime rates. First, as residents work to improve their housing units, local signs of physical disorder are likely to decrease. To the extent that disorder serves as a cue affecting the perceptions of potential offenders and residents, lower levels of disorder may lead to lower levels of crime (Skogan 2015). Second, as new and current residents continue to improve their homes, the broader neighborhood may attract additional in-movers, leading to higher home values, better socioeconomic conditions, and additional investment activities from residents (Ellen and O'Regan 2011; Owens 2012) that subsequently reduce local crime rates. It is important to note, however, that socioeconomic appreciation within neighborhoods may lead to short-term increases in crime before long-term decreases manifest (Kreager, Lyons, and Hays 2011).

As with residential mobility, the investment activities of residents can also depend on relative access to home improvement loans and financial capital. If such loans are disproportionately unavailable in some types of neighborhoods, then those neighborhoods may

face barriers to socioeconomic growth or even experience worsening disadvantage over time that may exacerbate local crime levels.

*Resident activity: refinancing as a form of economic fragility*

Home refinancing is another form of resident activity that might impact neighborhood socioeconomic change and yet has received relatively little scholarly consideration. On the one hand, some refinance activity by residents is simply an effort to take advantage of lower home loan interest rates, where residents update their existing home loan for a new one with better financial terms, and there is little reason to expect an impact on neighborhoods. If anything, residents in these instances might end up in a somewhat better economic situation, as they will have lower home loan payments and thus more financial capital available. On the other hand, some refinance activity by residents also removes equity from the home. In some cases, this activity occurs in homes in which residents have a considerable amount of realized equity (e.g., when they have been paying down on the loan for many years). In many other cases, however, equity extraction occurs as a way to capitalize on real or projected appreciation of home values in an area. In these instances, the homes have a considerable amount of "paper value" and some residents choose to extract some of this value. By refinancing the home for a higher amount of money, the resident takes advantage of the fact that the home is now worth considerably more than its purchase value, effectively receiving a cash payout.[3]

An important implication of this refinancing activity is that if the home value subsequently drops sharply, the resident will potentially owe more than the home is worth. Such

[3] There is evidence that this sort of refinancing behavior was particularly common during the housing boom of the 2000s. Freddie Mac defines any refinancing loan for an amount at least 5% greater than the original loan amount as evidence that the resident is extracting equity (http://www.freddiemac.com/research/datasets/refinance-stats/archive.html). Based on this definition, between 2000 and 2007 fully 64% of home loan refinancing events extracted equity. Given the sharp rise in home values during this decade, this behavior is not surprising.

a situation can place the resident into economic insecurity. Indeed, this large drop in home values is precisely what occurred across the U.S. after the housing bubble burst in 2007-2008. Thus, what is not typically considered in the neighborhood effects literature is that refinance behavior that extracts equity increases risk of economic fragility in a neighborhood. For an individual household, the negative consequences are certainly unfortunate, although there would not necessarily be large consequences for the neighborhood. In neighborhoods where numerous residents engage in such behavior, however, this can have a devastating impact.

*Resident refinancing and crime*

This economic fragility can have a number of potentially negative implications for neighborhood crime. These negative consequences are analogous to those discussed in the literature on foreclosures and crime in neighborhoods, as we posit the same mechanisms will be at work (Hipp and Chamberlain 2015; Immergluck 2010; Immergluck and Smith 2006). A sharp drop in home values can place a household into an economically tenuous situation in which residents owe more than the house is worth, which may tempt some to walk away from the house and the loan. As the economic situation worsens, the household may defer maintenance if they consider abandoning the unit (Mast and Wilson 2013), which can add to neighborhood physical disorder and impact crime levels (Skogan 2015). Furthermore, the household may withdraw from neighborhood activities if they expect to abandon the neighborhood. Residents in other households may perceive the economic struggles and withdrawal of their neighbors and similarly withdraw from neighborhood engagement. This can all reduce neighborhood cohesion and informal social control, which can result in increasing crime (Sampson and Groves 1989). Ultimately, the household may be foreclosed upon, which can lead to further disorder and unoccupied units in the neighborhood.

We use refinance activity as a measure of potential economic risk in neighborhoods. This measure is historically dependent; whereas in some decades such activity is likely quite limited, and in other time periods it might be more prevalent and yet not have much consequence if there is not a subsequent large drop in home values, during the decade of 2000-10 it is a particularly important measure. The large amount of refinancing early in the decade, combined with the large drop in home values later in the decade, had harmful consequences for neighborhoods. The housing bubble was particularly prominent in the Southern California region. Median housing values in the region's counties increased between 157% in San Bernardino County to 196% in Los Angeles County from 2000 to 2007, yet median housing values were much higher in 2007 compared to 2010 (after the large drop in housing values): from 30% higher in Orange County to 115% higher in San Bernardino County.[4] These large fluctuations make this a particularly interesting decade and region to study.

*Holistic assessment of neighborhoods*

Finally, an important theoretical and methodological strategy we adopt is to measure neighborhood characteristics holistically. Our discussion up to this point has considered three distinct characteristics of neighborhoods: 1) the income level of incoming residents; 2) the re-investment activity of residents to improve their units; and 3) the refinance behavior of residents as a measure of economic risk and instability. However, rather than assessing the individual impacts of each dimension on changing neighborhood crime levels, we are instead interested in how these three dimensions might occur simultaneously and the consequences if more than one occurs within a neighborhood. For example, the process of gentrification features both the in-migration of higher income residents and their subsequent investment activity to improve the

[4] Data obtained from the California Association of Realtors (https://www.car.org/marketdata/data/housingdata/).

housing units (Hwang and Sampson 2014). As another example, whereas refinance activity by residents can increase economic fragility in the neighborhood, deleterious consequences may be offset by the home improvement activities of other residents or the in-migration of new residents. We therefore adopt a holistic strategy in which we use latent class analysis to describe how neighborhoods simultaneously change along all three of these dimensions from year to year, and then assess how the latent classes we detect are related to changes in the level of crime during the decade.

Another methodological choice we make is to focus on the long-term change in both neighborhood characteristics and crime rates over the decade, rather than focusing on year to year change. We make this choice because we posit longer-term processes in these neighborhoods. Thus, we do not posit that some of these changes necessarily have immediate effects on changes in crime levels, but rather that it is the gradual unrolling of these processes that changes the level of crime in the neighborhood. In this way, we borrow insights from a recent study that focused on the relative speed of yearly demographic change in neighborhoods and consequences for changes in crime levels (Hipp and Branic 2017). That is, Hipp and Branic found that it was not simply demographic change in neighborhoods that was related to changes in crime levels; rather, it was also the *relative quickness* of such change that impacted the level of change in crime that occurred over the decade. In that study, it was not simply year to year change that mattered, but rather a cumulative effect in which rapid changes occurring over a few years had a larger impact on crime shifts in neighborhoods than gradually-paced changes. We assess here whether the changes that we observe in neighborhood mobility and investment/refinancing activity give rise to a longer-term change in crime rates over the decade, rather than testing whether there are year to year impacts.

## Data and Methods

The current study sought to identify patterns of neighborhood socioeconomic change across 838 census tracts in the city of Los Angeles and examine how these forms of neighborhood change related to changes in neighborhood crime from 2000 to 2010.[5] We employed three successive stages of analysis. First, we identified how socioeconomic changes manifest within neighborhoods by creating a series of two-year change variables using home mortgage loan data and conducting principle components analysis (PCA) on them to see how they clustered together. This process yielded five composite measures that describe how neighborhoods changed incrementally each year from 2000 to 2010. Second, we included these five composite measures in a latent class analysis (LCA) to identify unique classes, or decennial "trajectories[6]," of neighborhood change within our sample. Finally, we included these latent classes in a change-score regression analysis to examine how distinct modes of neighborhood change related to shifting violent and property crime rates in neighborhoods over the decade.

The first two stages of analysis utilized Home Mortgage Disclosure Act (HMDA) data, which annually report home mortgage loans (applied for and granted) across the U.S. and certain demographic characteristics of loan applicants. Measured at the census tract level, HMDA data record the quantities and dollar values for different types of home mortgage loans[7] (i.e., purchase, improvement, refinance). Additionally, HMDA provides data on borrowers' income levels, which offers insight into who receives home loans within a neighborhood and provides some indication of neighborhood population characteristics. Although a substantial body of

[5] The tracts were harmonized to 2000 boundaries using population-weighted interpolation based on files obtained from the Missouri Census Data Center (http://mcdc2.missouri.edu/websas/geocorr2k.html).
[6] We use the word "trajectories" conceptually to suggest longitudinal trends of neighborhood change, not to be confused with specific techniques such as semi-parametric group-based trajectory modeling that assumes a particular parametric form of change (Nagin 1999); in contrast, ours is a non-parametric approach.
[7] Prior literature suggests the utility of home loan data for capturing neighborhood socioeconomic change (Kreager, Lyons, and Hays 2011; Wyly, Atia, and Hammel 2004; Wyly and Hammel 1999).

literature employs census data to measure neighborhood change over time, some argue that decennial census variables are not adequately detailed to capture ongoing processes of neighborhood change (Kreager, Lyons, and Hays 2011). In other words, a ten-year measure of change neglects many of the short-term fluctuations in neighborhood characteristics (Hipp and Branic 2017). In the following sections, we first describe the variables included in the third stage of analyses, and then describe the approach, and results, of the three analytic stages.

*Dependent variables*

We computed six dependent variables using UCR Part I crime data collected from the Los Angeles Police Department. After geocoding incident addresses using ArcGIS v10.2 and aggregating the data to census tracts, we averaged the counts of individual property (burglary, larceny, motor vehicle theft) and violent (aggravated assault, murder, robbery) crimes[8], respectively, for the years 2000 to 2001 and 2009 to 2010, divided by population to create rates, log transformed the variables, and computed change scores over the decade for each crime type. Thus, our dependent variables measured the decennial change in annual crime rates within each neighborhood in the sample. Because of the possibility of negative values on the dependent variables (i.e., crime reduction over the decade), we analyzed the crime data using OLS regression models rather than Poisson models.

*Independent variables*

To account for change in socio-demographic neighborhood characteristics not measured by HMDA, we used 2000 census and 2008-2012 (5 year average) American Community Survey (ACS) data to compute difference-score measures over the decade. We computed decennial change in the percentage of Asian, black, and Latino residents, respectively, as well as the

[8] Due to high under-reporting issues, we exclude the crime of rape from our analyses.

percentage of occupied housing units. We measured changes in neighborhood disadvantage and residential stability by first estimating principle components factors for each of the two constructs at the beginning and end of the decade, respectively, and then computing each factor's difference score to capture change over time. The neighborhood disadvantage factor included measures of 1) median household income, 2) percent residents with a bachelor's degree, 3) percent poverty, 4) percent unemployed, and 5) percent overcrowded homes. These five measures indicated strong internal reliability in both 2000 ($\alpha = 0.902$) and 2008-2012 ($\alpha = 0.858$). The residential stability factor included measures of 1) percent homeowners, and 2) percent living in the same home, which demonstrated good internal reliability in 2000 ($\alpha = 0.813$) but somewhat lower reliability from the 2008-2012 ACS measures ($\alpha = 0.648$).[9] We accounted for changing population size by measuring the difference in total population over the decade.

To account for spatial effects, we constructed spatially lagged versions of all of our exogenous change variables in the models. These were constructed by defining the nearby area with an inverse distance decay, capped at 2.5 miles. This approach more heavily weights nearby neighborhoods and down-weights ones further away. This weights matrix was row standardized, and then multiplied by the variables of interest to create our spatially lagged measures, which were then included in the models. We adopt this approach rather than spatially lagging the outcome variables as we believe that this specification appropriately captures spatial effects (Morenoff 2003; Peterson and Krivo 2010).

**Analyses**

[9] While the 2000 census measured the percentage of residents who lived in the same house five years ago, the American Community Survey measured instead the percentage of residents who lived in the same house one year ago. Thus, there is some discontinuity in these particular census measures.

*Stage 1: principle components analysis*

In this first stage of the analysis, our goal is to describe the change in loan activity and residential mobility across the years of the decade from 2000-10. The annual structure of HMDA data allowed us to examine this neighborhood change in finer detail than decennial census measures. We used HMDA data from 1998 to 2010 to capture progressive intervals of socioeconomic change in Los Angeles by constructing a series of change-score measures. To do so, we initially generated a series of base variables that would later be used to calculate change scores. This process yielded thirteen variables in each year based on types of loans granted and the income levels of loan recipients. First, we created nine variables capturing different characteristics of home mortgage loans granted within neighborhoods. For home purchase, refinance, and improvement loans, respectively, we computed the 1) average loan amounts in dollars (natural logged)[10], 2) total number of loans granted, and 3) percentage of all granted loans. Next, we computed the number of in-movers per year within each tract based on four categories of borrower income -- very low, low, middle, and high[11]. For each of these 13 measures, we then computed two-year difference scores for each year (e.g., 1998 to 2000, 1999 to 2001) up to the year 2010. We computed two-year changes because one-year changes can be subject to random noise from idiosyncratic year to year changes, and three-year changes yielded very similar results to the two-year changes. This process yielded thirteen variables measuring successive two-year changes at eleven time points – one for each year from 2000 to 2010.

[10] To measure percentage change in loan values rather than raw total change in dollars, we took the natural log of average loan values for each home loan type prior to computing change-scores.

[11] We adopted the standards of the Federal Financial Institutions Examination Council (FFIEC), which collects and prepares HMDA data each year, for classifying income brackets. Relative to MSA median income, we coded borrowers' incomes as very low (< 50%), low (>= 50% and < 80%), middle (>= 80% and < 120%), and high (>= 120%).

We next wished to assess which of these features move together, and if similar features are present at each time point (e.g., 2000, 2001, 2002) for these two-year difference measures. Conducting principle components analyses on the change-score variables at each time point consistently revealed five principle components factors in each year across the decade. First, the *higher-income homebuyers* factor loaded strongly on the change in total number of home purchase loans and the number of high-income borrowers. Higher values on this factor corresponded with increases in both the number of purchase loans in general and upper-income residents entering a neighborhood, while lower values indicated the opposite trend. Second, the *lower-income homebuyers* factor loaded on counts of very low, low, and middle-income borrowers, where higher values on the factor indicated greater increases of home purchase loans received by these income groups (and thus, greater levels of in-migration). Third, the *appreciating value* factor captured changes in the average values of purchase, improvement, and refinance loans, respectively. Higher values on this factor corresponded with appreciating average loan values. Home purchase values demonstrated the strongest and most consistent factor loadings. Fourth, the *home improvement* factor loaded strongly with both the number and percentage composition of home improvement loans. Higher values on this factor indicated more home improvement and a greater amount of financial capital investment in homes. Finally, the *home refinance* factor loaded strongly and positively with the percentage composition of loans granted for home refinancing and strongly and *negatively* for percentage composition of home purchase loans[12]. Higher values on this factor indicated an increasing percentage of households

[12] This factor was consistent across the decade with the exception of the year 2003, where percent composition of purchase and refinance loans was captured within the *higher-income homebuyers* factor. In this instance, purchase loan composition loaded positively and refinancing loaded negatively.

refinancing debt and a decreasing percentage of loans going to residents moving into the neighborhood.

Given the general consistency across years in the factor structure, we converted each of the two-year change score variables into z-scores and averaged the appropriate ones for each of the five PCA factors for each year across the decade.[13] For example, we replicated the *higher-income homebuyers* factor by averaging the z-scores for the change in total home purchase loans and the change in total high-income borrowers in each year. This approach yielded five standardized composite measures based on the five factors just described in terms of constituent variables and interpretations.

*Stage 2: latent class analysis*

In the stage two analysis, our goal was to assess whether there are classes of neighborhoods that exhibit similar patterns of change across the five standardized composite measures just identified. We accomplished this by estimating latent class analyses using MPlus v5.21. These latent classes captured patterns of decennial change in the composite variables across LA City tracts and produced nonparametric patterns of neighborhood change from 2000 to 2010. We estimated a series of LCA models with increasing numbers of specified classes to identify the model that best fit our data. Following the suggestions of Hipp and Bauer (2006), for each estimated model we used 100 random start values for the parameters for 10 iterations each in the first phase, and then in the second phase took the 10 models with the highest maximum likelihood and estimated them completely. We compared model BIC values to identify the optimal number of latent classes, and the eleven-class model provided the optimal solution (Entropy = .984).

[13] In a few years certain factors failed to materialize on their own and instead were conflated with another factor, so our strategy created standardized composite measures in each year.

While the LCA model yielded eleven unique classes of loan activity change in neighborhoods, we observed certain pairs of classes that demonstrated similar types of change at stronger and weaker magnitudes. For example, one class demonstrated a strong influx of higher-income homebuyers over time while another class indicated a similar but weaker trend of higher-income in-movers. We next describe these eleven patterns of neighborhood change and pair class discussions together where appropriate (the patterns are shown in the Online Appendix). A general caution for interpretation is that our annual measures are capturing *change*, and not *levels*, and this should be kept in mind for interpretations. Thus, when we detect that the number of high income residents moving into a neighborhood is increasing, this is not simply capturing that there are a number of high income households moving in (which could be a consistent pattern year to year), but rather that the number is *increasing*. The general descriptions of these classes are listed in Table 1.

<<<Table 1 about here>>>

*Results of latent class analyses*

We begin by discussing the two neighborhood classes that showed relative stability. Scholars often view neighborhoods as generally stable entities and, indeed, over 30% of the tracts in the sample demonstrated stable trends. The *High Stability Neighborhoods* (N = 120) and *Moderate Stability Neighborhoods* (N = 142) classes included many Los Angeles neighborhoods that underwent minimal change in home loan activity over the study period and were the two classes containing the largest numbers of neighborhoods. The former class demonstrated virtually no change at all and showed little reaction to the housing market crash. The moderately stable neighborhoods generally did not exhibit sharp changes over the decade, although home refinancing consistently declined from 2000 to 2002 (one standard deviation), showed increases

through 2005 (one standard deviation), and began a slow decline until a sharp drop in 2009.[14] Moreover, average loan values gradually increased somewhat over the decade but then dropped following 2008. Moderately stable neighborhoods showed some spatial clustering in the downtown areas of Los Angeles, although many of these neighborhoods were scattered across the city (see Figure A1 in the Appendix). The high stability neighborhoods generally resided in the suburban north and northeast of the city (including the suburban tracts of the San Fernando Valley) with almost no presence in the city's urban core (which includes the downtown area near the center of the map), nor in the southern part of the city (what was traditionally known as "South LA," and is relatively impoverished). Taken together, the spatial distribution of these classes reinforces the finding from past literature that many neighborhoods remain stable over time and that this stability occurred in neighborhoods spanning across the city.

The *Strong Urban Investors* (N = 71) and *Moderate Urban Investors* (N = 109) classes of neighborhoods exhibited slight declines in higher-income home buying early in the decade but then saw increasing numbers of higher-income in-movers between 2003 and the 2008 housing market crash, at which time higher-income home purchases fell into decline. Neighborhoods in both classes revealed a time-lagged change in home improvement activity that followed the trends in higher-income home purchasing. As higher-income residents moved into neighborhoods in greater numbers, home improvement loans subsequently increased in these neighborhoods at a similar pace and magnitude. After higher-income home buying declined toward the end of the decade, home improvement activity declined shortly afterward. These trends suggest a process where prospective in-movers selected into neighborhoods with relatively inexpensive housing and then invested financial capital into their homes soon

[14] In this section, we focus on changes of measures that were at least one standard deviation. This helps to assure that we are discussing substantively meaningful shifts in these neighborhoods.

afterward. As their names suggest, both classes spatially concentrated in the urban downtown area of Los Angeles (see Figure 1), which includes neighborhoods populated largely by Latino and foreign-born residents (see Table 2). Over the decade, Asian and white populations rose by about 2% each in these neighborhoods, on average, and average incomes increased as well, reflecting the in-migration of new and comparatively wealthier residents.

<<<Figure 1 about here>>>

<<<Table 2 about here>>>

The *Strong In-Mover Oscillating* (N = 46) and *Moderate In-Mover Oscillating* (N = 80) classes each captured two distinct phases of neighborhood in-migration over the decade, beginning with a period of higher-income residents entering the neighborhood followed by a later surge of lower- and middle-income residents. From approximately 2001 to 2005, the number of higher-income homebuyers increased in these neighborhoods and, as with the urban investment classes, was accompanied by time-lagged increases in home improvement activities. At the same time, the number of lower-income home purchasers declined while higher-income borrowers were on the rise. After 2005, however, these trends reversed. Higher-income homebuyers and home improvement declined while the number of lower-income residents entering the neighborhood increased rapidly, especially for the *Strong In-Mover Oscillating* neighborhoods. While higher- and lower-income home buying initially demonstrated opposite trajectories earlier in the decade, both groups of in-movers increased together toward the end of the decade. After the years 2007 and 2008, during the onset of the housing market crash, higher-income home purchasing again began to rise until 2010.

Both the *Strong* and *Moderate In-Mover Oscillating* classes demonstrated similar patterns of change from 2000 to 2010, although there were several notable differences between the two

types of neighborhoods. The former almost exclusively clustered in the south downtown area with a slight presence in the suburban area of northern Los Angeles, whereas the latter exhibited strong spatial clustering in the suburban north and a minor downtown presence. Neighborhoods in both classes were characterized by a largely Latino population that increased over the decade. They also had considerably larger black populations in 2000 than other Los Angeles neighborhoods (17% in *Moderate In-Mover Oscillating* neighborhoods and 39% in *Strong In-Mover Oscillating* neighborhoods). Moreover, appreciable changes in home loan values occurred only within the *Strong In-Mover Oscillating* class. In the period following the rise of higher-income home purchasers and home investment, changes in average home loan values began increasing until the beginning of the housing market crash (i.e., 2004 to 2007), at which time average values quickly declined.[15]

The *Strong Higher-Income Buyers* (N = 12) and *Moderate Higher-Income Buyers* (N = 40) are the two smallest classes, and included neighborhoods that experienced large increases in higher-income home buyers but later saw dramatic reductions in numbers of affluent in-movers. Beginning in 2002, the *Strong Higher-Income Buyers* neighborhoods witnessed a tremendous increase in higher-income home purchasing until 2005, at which time the number of higher-income in-movers fell rapidly until 2008 and then rebounded with increasing numbers through 2010. The *Moderate Higher-Income Buyers* class of neighborhoods showed a similar, although less extreme, pattern. For neighborhoods in both classes, a strong influx of new higher-income residents preceded stronger declines in higher-income movers in the years leading up to and through the housing market crash, although surprisingly both neighborhood classes demonstrated

[15] An interesting feature is that these neighborhoods tended to experience large increases in average income along with relative decreases in median income. This combination might indicate increasing inequality in these neighborhoods.

a quick turn-around after the initial market decline. Both of the *Higher-Income Buyers* classes were scattered across the city and lacked any notable spatial clustering.

As their names imply, the predominate trends identified in the *Strong Oscillating Refinance* (N = 78) and *Moderate Oscillating Refinance* (N = 83) classes were periods of increasing and decreasing home refinancing activities, which largely corresponded inversely with trends in home improvement. Thus, these appear to be neighborhoods experiencing increases in economic fragility given the periods of rising refinance activity. Between 2000 and 2002, changes in home refinancing sharply increased, especially in the Strong class, which was accompanied by a simultaneous and almost equally sharp decline in home improvement loans. From 2002 to 2004, however, these trends switched, with the change in home refinancing declining rapidly in both classes and home improvement beginning to increase sharply in the Strong class. During this period, the Strong class also experienced a decline in higher-income home buying. After 2005, home refinancing increased considerably in both classes. Higher-income home buying rose during this period, albeit at a lesser magnitude than refinancing, until wavering after 2008.

Both the *Strong* and *Moderate Oscillating Refinance* classes tended to cluster spatially around the central and western areas of Los Angeles. In terms of population, these neighborhoods were comprised of over two-thirds white residents and approximately 10% Asian and Latino, respectively. Average household incomes in these two classes were also considerably higher than most of the other neighborhood classes, over $100,000 each in the year 2000 and increasing approximately 40-50% over the decade (not adjusted for inflation). Additionally, average home values remained the highest in these two classes, even with some value depreciation over the decade, and the majority of the housing stock was 15 years or older.

The final class to emerge from our analysis, *Mixed-Trait Change* (N = 58), featured a combination of change patterns observed in the other neighborhood classes but remained empirically distinct in the model. Like the *In-Mover Oscillating* classes, higher-income home buying trends fell into decline through the middle of the decade while lower-income home purchasing increased between 2003 and 2009. After 2007, higher-income home buying began to rise again somewhat. Moreover, the *Mixed-Trait Change* class resembled the *Oscillating Refinance* classes in several ways. These neighborhoods observed an increase in home refinancing early in the decade that fell into decline over several years and later rose again. Average loan values increased somewhat in the second half of the decade. These neighborhoods demonstrated some spatial clustering in the suburban north of LA, although they were also found in the east and south sections of the city.

We have different hypotheses regarding how these classes will be related to changes in crime levels over the decade. On the one hand, we hypothesize that the *Urban Investors* and *Higher-Income Buyers* neighborhoods are generally improving socioeconomically and therefore will tend to experience lower crime rates over the decade. On the other hand, we hypothesize that the residential instability generated by the *In-Mover Oscillating* neighborhoods will be associated with higher crime rates, and the economic fragility generated by the *Oscillating Refinance* neighborhoods will also be associated with crime increases. We next turn to the models testing these hypotheses.

*Stage 3: change-score regression for crime outcomes*

The final stage of analysis examined how our estimated classes of neighborhood change were differentially associated with changes in crime rates across Los Angeles neighborhoods. We analyzed each crime type by first estimating OLS models for the outcome variables (change

in logged crime rates) with only the dummy indicators of the neighborhood change classes and then re-estimating each model after including control variables. The results were generally similar, so we present and discuss only the results from the full models with all control variables in Table 3. For all regression models, we used the *High Stability Neighborhoods* class as the reference category—neighborhoods that demonstrated very little change over the decade. There was no evidence of multicollinearity in these models, as variance inflation factors were below 4.

<<< Table 3 about here>>>

Beginning with the *Moderate Stability Neighborhoods* class, we find that neighborhoods in this class differ from the *High Stability Neighborhoods* class in terms of crime change over the decade. The neighborhoods in the *Moderate Stability Neighborhoods* class experienced an increase in aggravated assaults, robberies, and motor vehicle thefts, compared to the *High Stability Neighborhoods* class (they underwent a .25, .33, and .44 standard deviation increase for each of these crime types, respectively). However, the *Moderate Stability Neighborhoods* class neighborhoods experienced a .59 standard deviation decrease in larcenies over the decade compared to the *High Stability Neighborhoods* class.

The *Strong* and *Moderate Urban Investors* neighborhoods tended to experience declines in crime compared to the high stability neighborhoods. Compared to high stability neighborhoods, *Strong Urban Investors* neighborhoods experienced declines of .63 standard deviations in burglaries and .72 standard deviations in larcenies during the decade, controlling for the other measures in the model. And *Moderate Urban Investors* neighborhoods experienced a decline of .33 standard deviations in homicides and .42 standard deviations in larcenies, on average, over the decade.

We see evidence that the bursts of in-movers characteristic of the *In-Mover Oscillating* neighborhoods correspond with certain crime types increasing during the decade. The *Strong In-Mover Oscillating* neighborhoods experienced increases in aggravated assaults, robberies, and motor vehicle thefts during the decade relative to stable neighborhoods (.52, .52, and .37 standard deviations, respectively). However, they did experience a drop in homicides during the decade. The *Moderate In-Mover Oscillating* neighborhoods experienced increasing aggravated assaults and motor vehicle thefts during the decade (.35 and .32 standard deviations).

The *Strong* and *Moderate Higher-Income Buyers* classes differed in their experiences. On the one hand, the *Strong Higher-Income Buyers* class neighborhoods surprisingly experienced increases in aggravated assaults, burglaries, and larcenies relative to the *High Stability Neighborhoods* class. On the other hand, *Moderate Higher-Income Buyers* class neighborhoods experienced decreases in burglaries and larcenies compared to the highly stable neighborhoods (of about .5 standard deviations each). It appears that this extreme change in income has deleterious consequences.

The final three neighborhood classes exhibited modest effects. Whereas the *Moderate Oscillating Refinance* class did not exhibit any significant relationships with crime change, relative to the highly stable neighborhoods, the *Strong Oscillating Refinance* class neighborhoods experienced increasing burglaries but decreasing robberies (each about .28 standard deviations). Lastly, the *Mixed-Trait Change* class neighborhoods experienced increasing burglaries during the decade, compared to the high stability neighborhoods.

As a point of comparison for interpreting the magnitudes of the neighborhood class coefficients, we point out that each standard deviation increase in concentrated disadvantage corresponded with a .09 standard deviation increase in aggravated assaults and a .08 standard

deviation increase in larcenies, net of controls (but was non-significant for the other crime types). A standard deviation increase in the percentage of Latino residents corresponded with a .14 standard deviation increase in aggravated assaults, but was not significant for the other crime types. Thus, the effects detected for the latent classes appear to be roughly of a similar magnitude—or even stronger—as those for structural measures that are commonly used in studies of neighborhoods and crime.

**Discussion and Conclusion**

This study explored the dynamic nature of neighborhoods using a relatively novel approach and data source. Focusing on the city of Los Angeles from the years 2000 to 2010 and drawing on annual home mortgage loan data, we first used principle components factor analyses to examine how patterns of residential in-migration and residents' home investment activities clustered across neighborhoods at successive time points. This first stage of analysis consistently revealed five distinct modes of neighborhood socioeconomic change. Next, we included this set of indices into a latent class analysis to identify specific classes (groups of neighborhoods) that shared common patterns of change over time. The LCA model produced eleven unique classes of neighborhood socioeconomic change over the decade and, based on the observed neighborhood class pairings, provided evidence of six broad categories of neighborhoods. Lastly, we utilized change-score regression analyses to investigate how the estimated neighborhood change classes corresponded with changing amounts of neighborhood crime. Model results indicated that the neighborhood classes experienced distinct relationships with crime change over the decade. Our analysis of neighborhood socioeconomic change suggested several key patterns corresponding with changing crime rates.

First, although nearly one-third of the neighborhoods in Los Angeles were classified in the two latent classes that experienced very little change over the decade (consistent with prior research), we nonetheless detected some notable changes in other neighborhoods. Two particularly interesting classes to emerge from our analyses were the *Moderate* and *Strong Urban Investor* neighborhoods, which included 21.5% of the neighborhoods in Los Angeles. These neighborhoods concentrated in the city's urban core, experienced increasing higher-income individuals purchasing homes in the area, and subsequently realized increasing home improvement activity, all of which is consistent with the literature on urban reinvestment and gentrification processes (Hwang and Sampson 2014; Zukin 1987). These *Urban Investor* classes typically experienced decreases in crime, which is also consistent with past literature on gentrification and crime (e.g., Barton 2016; Kreager, Lyons, and Hays 2011) (but see Taylor and Covington 1988). Neighborhoods in these classes were particularly likely to experience decreases in property crime, and less likely to experience a change in violent crime, which differs from the evidence of some prior research detecting property crime increases for neighborhoods experiencing an increase in home values (Boggess and Hipp 2016).

Second, the *Higher Income Buyers* classes also experienced higher-income residents moving into neighborhoods, although these patterns were notably different than those found in the city's urban core. One of the key differences is the rate at which higher-income residents moved into their respective neighborhoods. Whereas the *Urban Investor* classes demonstrated gradual, smoother influxes of higher-income home-buyers entering their neighborhoods, the *Higher-Income Buyers* classes featured sharp, dramatic shifts in higher-income in-migration. In the case of the *Strong Higher-Income Buyers* neighborhoods, this resulted in increasing levels of crime, which may indicate that these sharp changes are particularly disruptive to the social fabric

of these neighborhoods. These pronounced shifts in the in-migration of residents with differing income levels might result in greater residential instability, or more crime opportunities given the close proximity of those with high and low income levels (Boggess and Hipp 2016; Chamberlain and Hipp 2015). The subsequent rise in refinancing activity following the dramatic decrease in higher-income in-migration might also have contributed to crime increases if refinancing contributed to greater neighborhood economic insecurity among residents. Interestingly, the *Moderate Higher-Income Buyers* neighborhoods did not experience such crime increases, which may imply that their more modest income changes did not impact the fabric of the neighborhood as strongly. That is, they may have experienced less residential instability overall, and less inequality based on the income levels of new residents. Another possibility is that these neighborhoods did not experience the increases in refinance activity that the *Strong Higher-Income Buyers* neighborhoods did in a couple years earlier in the decade, and this economic fragility may be the explanation. We cannot distinguish between these competing explanations.

Third, our analyses revealed two pairs of neighborhood classes that have not been highly theorized within the neighborhood change literature. We discovered two *In-Mover Oscillating* classes, in which rates of residential in-migration based on the income level of new residents fluctuated over the course of the decade. A key characteristic of the *In-Mover Oscillating* classes is their relative increases in crime, particularly aggravated assault, over the decade. This additional population churning may provide one explanation for why the *In-Mover Oscillating* classes exhibited increases in crime while the *Urban Investors* classes generally experienced decreases over the decade, despite the fact that both pairs of classes experienced in-migrations of affluent residents who may have increased the number of attractive targets in the neighborhood. Consistent with social disorganization theory, the varied waves of in-migration in the *In-Mover*

*Oscillating* classes may have disrupted social networks and ties within the neighborhood that otherwise could have fostered informal social control and dissuaded crime. Furthermore, the heterogeneity of residents entering the neighborhood – recall that a mixture of lower-middle and higher-income residents moved in over the decade – may have affected social ties and consensus within the neighborhood.

It is unclear why a period of higher-income in-migration and investment was followed by a rapid influx of lower- and middle-income (and then a second round of higher-income) homebuyers into the neighborhood. One possible explanation is that earlier in-migration of higher-income homeowners and their renovation activities increased the appeal of and satisfaction with the neighborhood (Ellen and O'Regan 2011; Owens 2012), triggering in-migration from a range of prospective residents. In other words, periods of higher-income homebuyers entering a neighborhood and improving housing conditions may then prompt periods of residential influx. The fact that these neighborhoods had more modest average home values at the beginning of the decade compared to neighborhoods in some of the other classes may have made them more accessible to households with more moderate income levels (Clark and Ledwith 2007; South and Crowder 1998). We cannot extrapolate beyond our data, which focuses only on the years between 2000 and 2010, but we do observe conceptual overlap between the *Urban Investors* classes, where in-migration and investment occurred in the latter half of the decade, and the *In-Mover Oscillating* classes where this same pattern occurred earlier in the decade and was followed by subsequent in-movers. Another possibility is that this pattern was driven by the housing boom in the early part of the decade, followed by the bust in the latter part of the decade. The lower home values may have induced an inflow of lower income

residents. Whereas some neighborhoods were less impacted by the housing bubble, it might be that these neighborhoods were particularly strongly impacted.

The second set of neighborhood classes that has not received much theorizing is the pair of *Oscillating Refinance* neighborhood classes. These neighborhoods experienced spikes in refinancing behavior, which we have suggested may be a sign of potential economic fragility for these neighborhoods. The *Strong Oscillating Refinance* neighborhoods tended to experience increases in burglaries compared to stable neighborhoods (but decreasing robberies), even when controlling for the standard ecological measures of neighborhoods. This is a surprising result, given that other characteristics of these neighborhoods would typically *not* be considered crime enhancing: i.e., the residents in these neighborhoods tended to be older with a higher proportion white, and featured some of the highest average incomes and home values and lowest rates of poverty and unemployment. We believe these results may therefore be consistent with the idea that this refinance behavior induced economic fragility, which then placed these neighborhoods at greater risk. Although this refinance behavior will likely only increase neighborhood economic fragility in the event of a relatively sharp drop in home values, the fact that the U.S. observed such a sharp drop in the early 1990s as well as the late 2000s suggests that such events—although rare—will likely occur sporadically. In such instances, we suggest that scholars would be well-served to explore such neighborhoods more deeply in future studies to assess this potential for destabilization.

While this study has provided some useful insights, we acknowledge some limitations. First, we examined and identified patterns of neighborhood socioeconomic change at the level of census tracts, which are the smallest reported units for HMDA data. It is possible that a smaller spatial scale would be better suited to examining processes of neighborhood change, as using

smaller units may capture greater nuance in the distinct ways that neighborhoods change over time. A second limitation lies with our decennial analysis of change in neighborhood crime. Our analysis examined how processes of neighborhood socioeconomic change corresponded with net changes in crime counts over the decade; yet, prior research suggests that this approach may have failed to capture shorter-scale changes in crime in the years between 2000 and 2010 (e.g., Kreager, Lyons, and Hays 2011). For example, while our analysis was able to account for the effects of the 2007-2008 housing market crash on our neighborhood change classes, which we identified using annual home mortgage data, this major macro-economic shock may have led to fluctuations in neighborhood crime rates that were not measured by decennial change variables. Nonetheless, our primary goal was to understand these longer-term processes, regardless of the short-term fluctuations that occurred in the intervening period. Third, we did not have a measure of home values, but rather loan values. Although this is a proxy for home values, it is imperfect given that applicants can make differing sized down payments on their homes. Finally, we acknowledge that our study site of Los Angeles may differ in particular ways from other locations, and therefore studies in other geographic locations are needed to assess the generalizability of the results.

Despite these limitations, we highlight that this study has introduced a new approach for theorizing and measuring neighborhood change. We have argued that neighborhood loan information can be used as a dynamic measure of neighborhood change. By focusing on year-to-year changes in types of loan activity and the types of people moving into neighborhoods, we propose that this approach provides novel insights into how neighborhoods evolve over time. Thus, this methodology moves beyond measures of net change in neighborhoods based on specific demographic measures to instead create a more holistic picture of how neighborhoods

are changing by year. Furthermore, we did not wish to study how this year-to-year activity impacts annual changes in crime, but rather our interest was in cumulative long-term effects that can result in changes in neighborhood crime over the longer time-period of a decade. We have demonstrated that understanding this change is important as it helps explain shifts in crime rates over the decade above and beyond what is explained by the standard measures used in the neighborhoods and crime literature.

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## Tables and Figures

*Table 1. Descriptions of Neighborhoods in Latent Classes.*

| Class | Tracts | Description |
|---|---|---|
| High Stability Neighborhoods | 120 (14.3%) | • Little to no loan activity<br>• Spatially diffuse |
| Moderate Stability Neighborhoods | 142 (16.9%) | |
| Strong Urban Investors | 71 (8.5%) | • Mid-decade influx of higher-income in-movers<br>• Lagged home improvement activity<br>• Indicative of revitalization, gentrification<br>• Concentration in downtown Los Angeles |
| Moderate Urban Investors | 109 (13.0%) | |
| Strong In-Mover Oscillating | 46 (5.5%) | • Early-decade wave of higher-income in-movers<br>• Lagged home improvement activity<br>• Later-decade middle-, lower-income in-movers<br>• Large black, Latino populations |
| Moderate In-Mover Oscillating | 80 (9.5%) | |
| Strong Higher-Income Buyers | 12 (1.4%) | • Early sharp influx of higher-income in-movers<br>• Later dramatic decline in affluent in-movers<br>• Episodic shifts in middle, lower-income movers<br>• Spatially diffuse |
| Moderate Higher-Income Buyers | 40 (4.8%) | |
| Strong Oscillating Refinance | 78 (9.3%) | • Sharp increases, decreases in refinancing activity<br>• Home improvement as refinancing declined<br>• Highly affluent neighborhoods<br>• Concentration in middle, west Los Angeles |
| Moderate Oscillating Refinance | 83 (9.9%) | |
| Mixed-Trait Change | 58 (6.9%) | • Declining higher-income buyers over decade<br>• Rising middle-, lower-income buyers<br>• Periods of rising, falling refinancing<br>• Periods of home loan value appreciation |

*Table 2. Neighborhood Mean Descriptive Statistics from 2000 to 2010, by Neighborhood Class.*

| | High Stability Neighborhoods | Moderate Stability Neighborhoods | Strong Urban Investors | Moderate Urban Investors | Strong In-Mover Oscillating | Moderate In-Mover Oscillating | Strong Higher-Income Buyers | Moderate Higher-Income Buyers | Strong Oscillating Refinance | Moderate Oscillating Refinance | Mixed-Trait Change |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | N = 120 (14.3%) | N = 142 (16.9%) | N = 71 (8.5%) | N = 109 (13.0%) | N = 46 (5.5%) | N = 80 (9.5%) | N = 12 (1.4%) | N = 40 (4.8%) | N = 78 (9.3%) | N = 83 (9.9%) | N = 58 (6.9%) |
| Pct. Age 25-44 | 31.51 | 30.21 | 33.03 | 35.12 | 27.62 | 29.51 | 34.32 | 38.88 | 27.83 | 34.24 | 29.60 |
| | (-2.59) | (-1.42) | (-2.01) | (-0.80) | (-1.38) | (-2.33) | (0.66) | (-0.68) | (-5.09) | (-3.34) | (-4.14) |
| Pct. Age 45-64 | 25.38 | 20.16 | 19.67 | 21.70 | 20.46 | 23.03 | 26.98 | 20.39 | 29.84 | 26.51 | 26.98 |
| | (4.78) | (5.67) | (5.52) | (5.29) | (5.72) | (5.61) | (1.74) | (3.84) | (2.60) | (2.59) | (4.73) |
| Pct. Age 65 + | 11.85 | 7.38 | 8.20 | 9.15 | 7.78 | 9.57 | 13.58 | 10.54 | 16.91 | 14.83 | 12.71 |
| | (0.95) | (0.77) | (1.39) | (1.35) | (0.22) | (1.13) | (-0.54) | (0.68) | (0.94) | (0.43) | (1.15) |
| Pct. Asian | 13.33 | 5.48 | 14.26 | 16.28 | 1.50 | 7.79 | 19.10 | 19.88 | 9.69 | 12.27 | 13.57 |
| | (1.08) | (0.00) | (1.53) | (2.19) | (-0.11) | (1.11) | (1.95) | (4.74) | (1.32) | (1.50) | (1.92) |
| Pct. Black | 5.71 | 11.43 | 8.61 | 8.15 | 30.41 | 14.47 | 7.14 | 8.29 | 2.93 | 3.78 | 3.84 |
| | (-0.44) | (-2.94) | (-0.49) | (-1.54) | (-8.68) | (-2.71) | (1.05) | (-1.32) | (0.49) | (0.21) | (-0.04) |
| Pct. Latino | 41.00 | 77.27 | 59.76 | 58.52 | 65.05 | 64.50 | 22.57 | 38.09 | 11.21 | 13.36 | 39.65 |
| | (1.92) | (3.08) | (-0.85) | (-2.56) | (8.97) | (5.18) | (-0.91) | (-3.91) | (2.59) | (0.51) | (7.43) |
| Pct. White | 37.11 | 4.84 | 15.79 | 14.88 | 1.82 | 11.64 | 48.13 | 30.87 | 71.87 | 66.77 | 40.17 |
| | (-1.29) | (0.22) | (0.90) | (2.40) | (-0.12) | (-2.61) | (-0.69) | (0.65) | (-4.90) | (-1.62) | (-8.12) |
| Pct. Owner-Occ. | 48.31 | 30.49 | 4.80 | 16.44 | 41.71 | 51.88 | 52.24 | 20.71 | 67.84 | 50.85 | 63.73 |
| | (-0.87) | (-1.25) | (-0.97) | (0.25) | (-2.04) | (-2.34) | (3.64) | (3.56) | (-1.66) | (-0.61) | (-0.30) |
| Pct. Same House | 82.33 | 82.46 | 74.42 | 80.76 | 81.13 | 83.79 | 77.76 | 75.12 | 83.38 | 80.63 | 84.05 |
| | (30.64) | (30.22) | (35.18) | (35.14) | (25.91) | (30.98) | (30.58) | (35.64) | (26.56) | (28.69) | (30.80) |
| Avg. Income | 92,926 | 48,135 | 46,278 | 59,695 | 59,190 | 74,739 | 164,014 | 81,821 | 176,951 | 145,556 | 107,981 |

| | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | (36,864) | (11,087) | (17,171) | (22,397) | (23,297) | (26,605) | (92,984) | (37,885) | (59,724) | (37,536) | (46,303) |
| Med. Income | 34,801 | 18,452 | 19,062 | 24,211 | 23,147 | 27,200 | 62,277 | 35,899 | 57,407 | 49,563 | 41,651 |
| | (-9,319) | (-8,692) | (-1,218) | (-1,854) | (-2,616) | (-12,017) | (8,707) | (5,242) | (-24,423) | (-22,584) | (-9,818) |
| Avg. Home Value | 197,711 | 78,764 | 39,888 | 121,350 | 85,796 | 108,566 | 355,756 | 200,407 | 462,613 | 452,183 | 174,869 |
| | (-989) | (-54,820) | (-70,436) | (-25,509) | (-38,310) | (-35,979) | (133,703) | (90,513) | (27,125) | (28,950) | (-9,878) |

*Note: Values presented as 2008-2012 mean values and (change from 2000 to 2008-2012)*

*Table 3. Change-Score Regression Results for Estimated Neighborhood Classes and Neighborhood Crime Rates.*

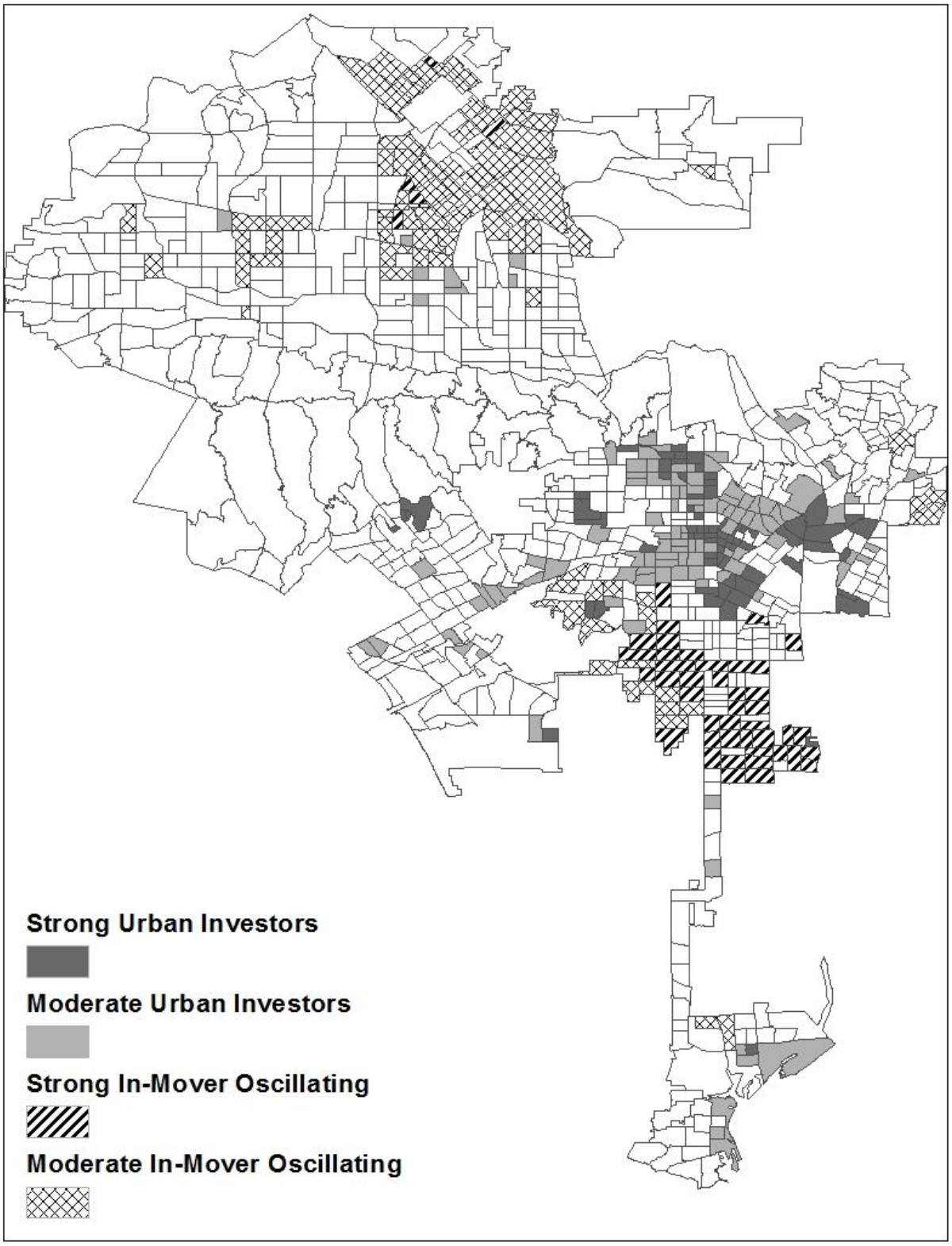
| | Assault | | Robbery | | Homicide | | Burglary | | MV Theft | | Larceny | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Moderate Stability | 0.154 | * | 0.175 | * | -0.111 | | -0.106 | | 0.216 | ** | -0.244 | ** |
| | (0.076) | | (0.069) | | (0.087) | | (0.061) | | (0.059) | | (0.048) | |
| Strong Urban Investors | 0.013 | | 0.080 | | -0.204 | | -0.314 | ** | 0.020 | | -0.297 | ** |
| | (0.094) | | (0.085) | | (0.107) | | (0.074) | | (0.072) | | (0.060) | |
| Moderate Urban Investors | 0.068 | | 0.040 | | -0.216 | * | -0.092 | | 0.114 | | -0.175 | ** |
| | (0.081) | | (0.073) | | (0.092) | | (0.064) | | (0.062) | | (0.051) | |
| Strong In-Mover Oscillating | 0.317 | ** | 0.274 | * | -0.324 | * | 0.022 | | 0.183 | * | -0.143 | |
| | (0.121) | | (0.109) | | (0.137) | | (0.096) | | (0.093) | | (0.076) | |
| Moderate In-Mover Oscillating | 0.210 | * | 0.134 | | -0.016 | | 0.089 | | 0.159 | * | -0.078 | |
| | (0.085) | | (0.077) | | (0.096) | | (0.067) | | (0.065) | | (0.054) | |
| Strong Higher-Income Buyers | 0.870 | ** | 0.306 | | -0.338 | | 0.466 | ** | 0.241 | | 0.322 | ** |
| | (0.181) | | (0.164) | | (0.206) | | (0.143) | | (0.140) | | (0.115) | |
| Moderate Higher-Income Buyers | 0.173 | | -0.027 | | -0.056 | | -0.252 | ** | -0.136 | | -0.194 | ** |
| | (0.107) | | (0.097) | | (0.122) | | (0.085) | | (0.082) | | (0.068) | |
| Strong Oscillating Refinance | 0.074 | | -0.152 | * | 0.007 | | 0.141 | * | -0.117 | | 0.056 | |
| | (0.084) | | (0.076) | | (0.096) | | (0.066) | | (0.065) | | (0.053) | |
| Moderate Oscillating Refinance | 0.053 | | -0.026 | | 0.024 | | 0.048 | | -0.079 | | 0.004 | |
| | (0.082) | | (0.074) | | (0.094) | | (0.065) | | (0.063) | | (0.052) | |
| Mixed Trait Change | 0.000 | | 0.008 | | 0.058 | | 0.165 | * | -0.130 | | 0.013 | |
| | (0.094) | | (0.085) | | (0.107) | | (0.075) | | (0.073) | | (0.060) | |
| Pct. Asian | 0.004 | | 0.003 | | 0.006 | | 0.002 | | 0.004 | | 0.007 | |

| | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | (0.006) | | (0.005) | | (0.006) | | (0.004) | | (0.004) | | (0.004) | |
| Pct. Asian Spatial Lag | -0.065 | ** | -0.004 | | -0.006 | | 0.036 | ** | -0.031 | * | -0.003 | |
| | (0.017) | | (0.016) | | (0.020) | | (0.014) | | (0.013) | | (0.011) | |
| Pct. Black | 0.010 | | -0.001 | | 0.003 | | -0.004 | | 0.003 | | 0.002 | |
| | (0.006) | | (0.005) | | (0.007) | | (0.005) | | (0.005) | | (0.004) | |
| Pct. Black Spatial Lag | -0.005 | | -0.001 | | 0.042 | ** | -0.026 | * | -0.001 | | -0.008 | |
| | (0.014) | | (0.012) | | (0.015) | | (0.011) | | (0.010) | | (0.009) | |
| Pct. Latino | 0.011 | ** | 0.001 | | 0.006 | | 0.000 | | -0.001 | | -0.001 | |
| | (0.004) | | (0.004) | | (0.005) | | (0.003) | | (0.003) | | (0.003) | |
| Pct. Latino Spatial Lag | 0.008 | | 0.001 | | 0.012 | | 0.009 | | -0.006 | | -0.003 | |
| | (0.008) | | (0.007) | | (0.009) | | (0.006) | | (0.006) | | (0.005) | |
| Conc. Disadvantage | 0.132 | * | 0.019 | | 0.016 | | 0.019 | | 0.002 | | 0.082 | * |
| | (0.059) | | (0.053) | | (0.067) | | (0.047) | | (0.045) | | (0.037) | |
| Conc. Disadvantage Spatial Lag | -0.329 | ** | 0.041 | | 0.007 | | 0.100 | | -0.431 | ** | 0.038 | |
| | (0.121) | | (0.109) | | (0.137) | | (0.096) | | (0.093) | | (0.077) | |
| Res. Stability | -0.014 | | 0.018 | | -0.017 | | 0.008 | | 0.065 | * | 0.010 | |
| | (0.039) | | (0.035) | | (0.044) | | (0.031) | | (0.030) | | (0.025) | |
| Res. Stability Spatial Lag | -0.016 | | -0.012 | | 0.028 | | -0.036 | ** | -0.094 | ** | -0.049 | ** |
| | (0.016) | | (0.014) | | (0.018) | | (0.013) | | (0.012) | | (0.010) | |
| Pct. Occupied | -0.019 | ** | 0.002 | | -0.001 | | -0.001 | | 0.001 | | -0.003 | |
| | (0.004) | | (0.003) | | (0.004) | | (0.003) | | (0.003) | | (0.002) | |
| Pct. Occupied Spatial Lag | 0.020 | | 0.001 | | -0.005 | | -0.009 | | 0.032 | * | -0.016 | |
| | (0.018) | | (0.016) | | (0.021) | | (0.014) | | (0.014) | | (0.011) | |
| Total Population | -0.181 | ** | -0.202 | ** | -0.029 | | -0.239 | ** | -0.173 | ** | -0.212 | ** |
| | (0.032) | | (0.029) | | (0.036) | | (0.025) | | (0.024) | | (0.020) | |
| Total Population Spatial Lag | -0.002 | | -0.007 | | -0.021 | | -0.033 | | 0.003 | | 0.009 | |
| | (0.026) | | (0.023) | | (0.029) | | (0.020) | | (0.020) | | (0.016) | |
| _cons | -1.682 | ** | -0.367 | ** | -0.157 | | -0.354 | ** | -0.404 | ** | -0.113 | * |
| | (0.072) | | (0.065) | | (0.082) | | (0.057) | | (0.056) | | (0.046) | |
| r2 | 0.174 | | 0.105 | | 0.078 | | 0.231 | | 0.262 | | 0.280 | |

| | | | | | | |
|---|---|---|---|---|---|---|
| N | 838 | 838 | 838 | 838 | 838 | 838 |

*Note: Results presented as unstandardized coefficients and (standard errors).*
** p < .05, ** p < .01*

Figure 1. Map of Urban Investors classes (Strong and Moderate) and In-Mover Oscillating classes (Strong and Moderate) in Los Angeles City.



## Appendix

Figure A1. Map of Oscillating Refinance classes (Strong and Moderate) and Stability classes (High and Moderate) in Los Angeles City.

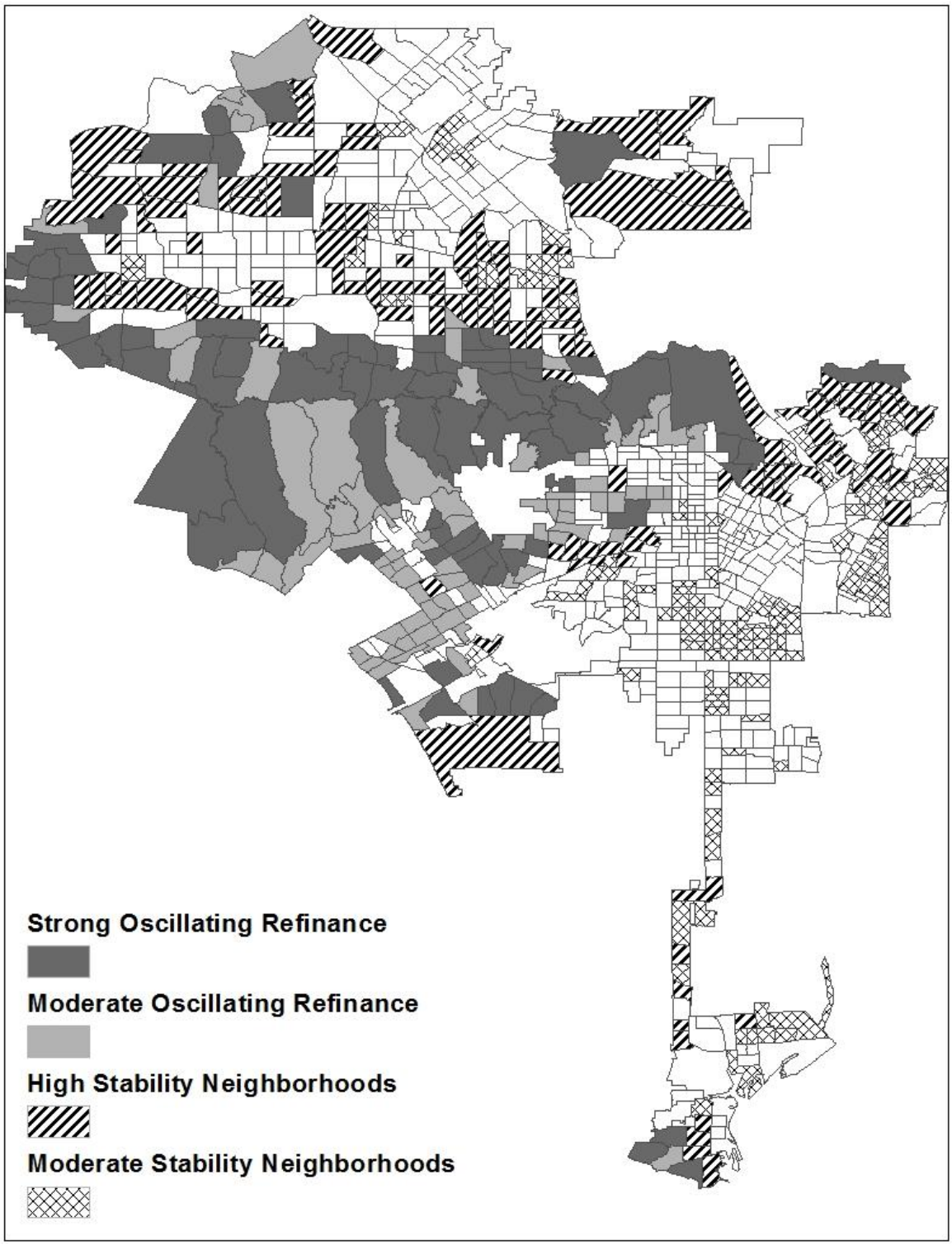


Figure A2. Map of Higher-Income Buyers classes (Strong and Moderate) and Mixed-Trait Change class in Los Angeles City.