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Race and uneven recovery: neighborhood home value trajectories in Atlanta before and after the housing crisis

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ABSTRACT

We use zip-code-level home value data and cluster analysis to define three types of neighborhood housing markets in the Atlanta region based on their levels of volatility and stability before, during, and after the housing crisis. We identify the demographic and housing market characteristics of each of these clusters and use multivariate analysis to measure their predictive association with the neighborhood types. We also examine factors that predict long-term price appreciation over the 2001–2014 period. One key finding is that many black neighborhoods exhibited steep rates of price decline with only little recovery following the crisis. Meanwhile, many predominantly white, middle- and upper-income neighborhoods generally more than recovered from any housing price declines. The findings suggest that the legacies of the mortgage crisis may have long-lasting implications for housing wealth inequality and housing markets. Implications include a call for a renewed commitment to fair housing, community reinvestment, and equitable housing finance policies to support more evenness in recovery.

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During the U.S. housing boom and bust, U.S. home prices rose to unprecedented heights, lifted by poorly underwritten mortgages. When the U.S. housing crisis began in late 2006 and 2007, home values crashed and foreclosures and vacancies skyrocketed. In 2011, a modest recovery began. However, this national story obscures a great deal of variation underlying the averages. We examine the phenomenon of uneven recovery within the Atlanta region, a metropolitan area hit hard by the foreclosure and broader housing crisis.

Some research has investigated metropolitan-level variation in outcomes during the bubble and foreclosure crisis, focusing on institutional factors leading to the density of subprime lending (Williams *et al.*, 2001), variation in state foreclosure law (Immergluck, 2010; Mian *et al.*, 2011), or patterns in new home construction (Saiz, 2010) as a key factor differentiating home price bubbles and recovery from others. However, there has been little work to date on intrametropolitan – or neighborhood-level – variation in home prices up through the recovery period. There is no clear evidence which types of neighborhoods have fared better than others within a metropolitan area.

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In this analysis of intrametropolitan variation in housing values, we use zip-code-level home value data and cluster analysis to define three different types of neighborhood housing markets in one large, hard-hit metropolitan area – Atlanta – based on the neighborhoods' levels of volatility and stability before, during, and after the crisis. We then analyze housing stock and demographic factors as to their predictive association with the three neighborhood types.

This article aims at understanding the initial conditions – as of 2000 – that predict whether a neighborhood experiences extreme volatility in housing prices during the boom and bust of the 2000s and the extent to which housing price recovery occurs after the bust. It develops a method of categorizing and understanding the types of uneven housing market recovery and identifies fundamental demographic and housing market factors associated with different housing market trajectories within a region hit hard by the subprime and foreclosure crises. We begin with a review of the literature on the housing crisis and intrametropolitan home value trends. Using the Zillow home value index at the zip code level, we then analyze home value trends across three periods the Boom (2001–2006), Bust (2006–2012), and Recovery (2012–2014) to identify whether different zip codes experienced different trajectories in home values throughout the larger metropolitan housing boom, bust, and recovery. We find that the 137 zip codes in the Atlanta region tend to fall into three housing trajectory types or submarkets: Full Recovery, in which prices rose in the boom, fell in the bust, but have easily recovered since 2012; Bust-Partial Recovery, in which prices rose somewhat during the boom, fell sharply during the bust and have only partially recovered during the broader recovery (and are still generally well below their 2001 levels); and Bust-No Recovery, where prices rose during the boom, fell dramatically during the bust, and have not appreciably recovered during the broader metropolitan recovery.

In order to understand the initial conditions that predict a zip code's housing value trajectory, we first use a multinomial logistic model. While our model is not one that identifies or isolates causal factors, we find that, even after controlling for poverty rate, age of housing, and housing stock variables, zip codes with larger black, and Hispanic populations are more likely to have ended up in the Bust-No Recovery or Bust-Partial Recovery categories. Not surprisingly perhaps, zip codes with higher initial home values were more likely to end up in the Full Recovery category. We also run OLS and spatial lag models on the change in home value index from 2001 to 2014. The findings are generally consistent with the multinomial results. Zip codes with higher median home values and lower percentages of blacks and Hispanics saw values increase more over this period. These communities were not hit as hard by the mortgage crisis, benefitted from low interest rates and broader economic stimulus measures, and have more than recovered from any earlier losses in home values. The unevenness of the recovery is striking.

The housing crisis and home value trajectories

Several studies investigating home price volatility at the city or state level identify financial institution characteristics and practices as a prime factor. Dell'Arricia *et al.* (2012) investigated deterioration of lending standards in a panel of metropolitan areas during the lead up to the bubble. They revealed that metropolitan areas with multiple subprime lenders were more likely to see declining underwriting standards in the presence of a rise of applications. They confirmed the importance of the structure of the secondary market in maintaining lending standards. Other analyses found that poor underwriting – and home price bubbles

– were strongest in places that lacked formal connections to mortgage lending prior to the emergence of risk-based pricing in the 1990s (Williams *et al.*, 2005). The lack of formal relationships with traditional mortgage lenders has been documented as one reason why minority borrowers were receptive to subprime lenders in the 1990s, while some authors emphasized a lack of familiarity or existing networks and experience to integrate borrowers with trustworthy lenders.

Other metropolitan-level studies have examined housing supply factors and constraints, such as geography and land use law. According to this line of research, the potential for price declines is in part determined by the characteristics of local housing markets. Houses are supplied more elastically in some cities than others, and there is a strain of research on how national credit cycles – independent of underwriting standards – interact with different cities based on supply elasticities. Krugman (2005) described this phenomenon by comparing "flatland" and "zoned zone", describing how credit-driven booms result in increased starts in places with forgiving geography and zoning and home price spikes in geographically constrained, heavily regulated cities. Saiz (2010) confirmed this phenomenon between cities, though with notable exceptions: Places like Phoenix experienced both home price bubbles and an explosion in starts, in contradiction to theory. Ray (2012) attempted to identify the characteristics of housing recovery area – as measured by foreclosure rate – at the county level from 2000 to 2009. He found that the common characteristics of recovery are a more diversified workforce, more small business activities, less dependence on housing construction, and a higher number of housing submarkets.

A good deal of research has examined intrametropolitan patterns of housing market differences before and during the mortgage crisis. A particularly large amount of literature has looked at neighborhood-level factors that drove concentrations of subprime lending and foreclosures. Kingsley & Pettit (2009) found that the density of subprime loans was highest in black and Hispanic neighborhoods during the 2004–2006 subprime boom period. They also found that the highest subprime densities were in relatively low-poverty, but high-minority neighborhoods. Mayer & Pence (2008) also focused on the spatial distribution of subprime lending in 2005 and, using loan data from the firm Loan Performance (now known as CoreLogic), found that predominantly black and Hispanic zip codes received much higher levels of subprime lending than other areas. Even after controlling for credit scores and other economic characteristics of zip codes, they showed that subprime lending at the peak of the boom was especially prevalent in predominantly minority zip codes. Calem *et al.* (2010) analyzed home loans in seven major cities in 1997 and 2002 and found that blacks were more likely than whites to receive subprime versus prime loans, even after controlling for borrower income and a variety of neighborhood characteristics including educational levels and average credit score. Gruenstein-Bocian *et al.* (2008) were among the first to combine publicly available home mortgage disclosure act (HMDA) data (including data on the race and income of borrowers) with private data from a major loan data vendor (including information on loan terms and credit quality) and calculated that black homebuyers were 31 per cent more likely to receive a high-rate (versus a low-rate), fixed-rate mortgage with a prepayment penalty than white borrowers with similar characteristics.

Researchers at the Federal Reserve Bank of Philadelphia combined data from HMDA with data from a national proprietary dataset on loan and borrower characteristics from 1999 through 2007 for three states – Pennsylvania, New Jersey, and Delaware (Smith & Hevener, 2011). Smith & Hevener (2014) found that blacks had a high probability of

receiving a subprime versus a prime loan for all years of the study. They also estimated the difference in the propensity of whites and blacks to receive subprime loans due to factors other than race, including income, credit score, and neighborhood and loan characteristics, but found that these characteristics explained at most only two-thirds of the higher propensity of blacks to receive subprime loans in 2005. This left one-third of the difference explained solely by race, providing substantial evidence for the existence of discriminatory forces in the mortgage market. Similar results have been obtained by researchers in other locations (Courchane, 2007).

Due especially to the racial concentration of subprime lending, minority homeowners were disproportionately impacted by foreclosures, especially in the early years of the crisis when subprime loans accounted for the bulk of the foreclosure problems. After merging HMDA data with industry data from Lender Processing Services, a major provider of loan-level data, Gruenstein-Bocian *et al.* (2010) analyzed foreclosures between 2007 and 2009 at the height of the subprime phase of the foreclosure crisis, and found that blacks and Hispanics were disproportionately impacted. Almost 8 per cent of first mortgages to black homeowners originated between 2005 and 2008 went into foreclosure between 2007 and 2009. This compared to only 4.5 per cent for white homeowners; the black foreclosure rate was 76 per cent greater than the white rate.

Immergluck (2010) examined between-city variation in the accumulation and duration of bank-owned properties. He developed a typology of metropolitan areas using the density of real-estate-owned (REO) properties at an initial period (August 2006) and home value appreciation from August 2006 to August 2008. Metropolitan housing markets were classified into "modest," "weak," and "boom-bust" markets. Using this topology, he employed three different geographical scales (state, metropolitan area, and neighborhood) to identify factors that resulted in greater growth in REO properties. He found that the degree of subprime lending in a zip code during the boom was a strong predictor of REO growth during the study period, even after controlling for a wide variety of other neighborhood characteristics.

Much less recent research has looked at neighborhood-level housing price trajectories, especially during and after the depths of the crisis. Research on changes in neighborhood quality of life or economic distress – especially in response to broader economic shocks – is somewhat relevant here, especially when they use home values as indictors of neighborhood well-being. Ong *et al.* (2003) examined the effects of the economic changes on neighborhood dynamics. They measured the quality of life of six neighborhoods in the Los Angeles Metro region during the recession in the 1990s. They found that households in low-income neighborhoods were more vulnerable to economic recession in terms of relative incomes, jobs, and home values. Williams *et al.* (2013) had similar results in examining the disparate impacts of the 2000–2009 economic cycles on neighborhoods in the city of Chicago. They found that lower income and minority neighborhoods were susceptible to the Great Recession in terms of jobs, home values, and home foreclosures.

Subprime lending drove up prices in neighborhoods and cities during the early 2000s and then led to rapid price declines during the bust. Regions with higher levels of subprime and aggressive forms of mortgage lending experienced greater price increases during the subprime boom and greater declines in prices during the subsequent crisis (Pavlov & Wachter, 2011). Mian & Sufi (2008) have shown that home prices increased more rapidly in zip codes where denial rates declined more than what would have been expected due to

borrower characteristics alone. Housing prices rose in the places where credit standards declined the most (Barakova *et al.*, 2012).

Although policy-related factors such as the density of subprime lending, the state foreclosure process, the penetration of loan modifications, code enforcement and blight remediation efforts, and types of private investment are all likely to be important mechanisms of neighborhood housing market recovery, the goal here is not to identify the causal factors that determine whether a neighborhood is likely to recover from housing market distress. The goal, more simply, is to identify and describe clusters of housing market trajectories, and to describe initial housing and demographic characteristics that predict whether a neighborhood is likely to fall into one cluster versus another. Of course, these basic demographic and housing characteristics, in turn, were likely associated with whether a neighborhood was subject to high levels of subprime lending (and resulting foreclosure), speculative real estate investment, spikes in unemployment, and other proximate drivers of booms or busts in home values.

Atlanta as context for uneven recovery

The Atlanta metropolitan area is a particularly relevant region in which to study the problem of uneven housing market recovery. It is very diverse, with one of the largest black populations in the country. In 2010, the 20-county Atlanta region (slightly larger than the 16 county area used in the analyses below) was just over 50 per cent white, 31.7 per cent black, and 11.3 per cent Hispanic (Atlanta Regional Commission, 2011).

The region's black population is extensively suburbanized, with a substantial number of zip codes having sizeable black populations. Of the 137 zip codes in this study, 27 were majority black in 2000, with another 30 being more than 20 per cent black. While there are certainly zip codes in the region where the population is both predominantly black and tends to have quite low incomes, many other black neighborhoods are predominantly moderate or middle income, with the median majority-black zip code having a median family income in 2000 of over $37,000 ($53,000 in 2015 dollars) and the top quartile having a median income of over $48,000 in 2000 ($69,000 in 2015 dollars). While Atlanta is more diverse than many smaller metropolitan areas, it still had 9 zip codes with less than 10 per cent of the population being either black or Hispanic as of 2000, with another 35 where blacks and Hispanics constituted less than 25 per cent of the population. The segregation of the area by race, and to some extent by poverty and income, makes it an ideal region within which to study the evenness of housing market recovery over space. The region was also hit hard by subprime lending and the resulting foreclosure and housing market crisis, especially in heavily minority neighborhoods (Ding *et al.*, 2008; Duda & Apgar, 2005).

Data and methods

The objectives of this research are to identify different neighborhood housing price trajectories during the 2001–2014 period and to identify predictors of recovery. We assembled a dataset composed of housing market and demographic variables for 137 zip codes in metropolitan Atlanta. We draw on Zillow (2014a) zip-code-level home value index data for 3-bedroom homes for 16 counties in the Atlanta metropolitan area from January 2001 through August of 2014. The Zillow index utilizes real estate data acquired from local county

records to develop home value indices for various sizes of homes. The three-bedroom home index was chosen to control for differences in housing type across zip codes because 3-bedroom homes constitute the largest segment of the single-family housing stock. The Zillow index is a constant-quality measure of home values in the zip code. It relies on the estimated values of all homes in the zip code and not just on those that happen to sell in a particular period of time. (However, those sales influence the values of homes in the zip code so they do have an effect on the Zillow index.) The index has advantages over other small-area house price indices because it does not rely only on homes selling repeatedly within a zip code, which can cause a bias toward more-frequently selling segments of an area. Repeat-sales indices suffer from the problem that only a very small fraction of homes may sell over a period, and these may be very unrepresentative of the larger stock. The index provides a more representative and robust indicator of small-area home values than repeat-sales indicators, median home sale prices, or other available measures of home values. The Zillow index is also a monthly one, which provides for more precisely pinpointing peaks and troughs. (See Zillow [2014b] for a detailed discussion of the generation of the index.)

The remainder of housing and demographic data comes from the 2000 decennial census. To control for aspects relating to the quality of the housing stock, we obtained measures of vacant units, owner-occupancy rates, as well as median age of housing stock. We control for the initial value of homes in 2001 using the Zillow data. Finally, we measure the per cent of the population in poverty, and the per cent of residents who are black or Hispanic.

We use cluster analysis to identify three distinct submarkets with different growth and decline trajectories over the 2001–2014 period. We wanted to understand how different neighborhood housing markets behaved during the regional housing market boom, bust, and recovery. Therefore, we used the average of the Zillow home value indices for the zip codes in the 16-county region to identify the peak and trough of the market over this period. The peak turns out to have been November 2006, and the trough of the decline was in March 2012. For each of the 137 zip codes in the region, we then measured the per cent change in the price index from January 2001 to November 2006 (the growth period), the change from November 2006 to March 2012 (the decline period), and the change from March 2012 until August 2014, the latest data available (the recovery period). These three per cent change variables were then selected as the clustering variables. Because we did not have in mind a certain number of clusters that we envisioned or desired (other than expecting the number of clusters would be small given the modest-sized dataset and the desire for each cluster to be "not too small"), we chose a simple two-step cluster analysis without specifying the number of clusters and set the maximum number of clusters set initially to 15. We then analyzed demographic differences among the clusters using ANOVA.

To understand the basic demographic and housing market characteristics predicting housing market recovery, we then perform two predictive regressions. First, we perform a multinomial logistic regression predicting the likelihood of being in different clusters. Then, we use a spatial regression approach to predict home price change over the entire period, from 2001 to 2014.

Cluster analysis results

The cluster analysis resulted in the three clusters of zip codes described in Table 1. The clustering, which was driven by minimizing the bayes information criterion (BIC), resulted

Table 1. Results of cluster analysis of Atlanta metropolitan zip codes by changes in housing price index for 3-bedroom homes (2001–2006; 2006–2012; 2012–2014).

		Per cent change 2001–2006		Per cent change 2006–2012		Per cent change 2012–2014		Per cent change 2001–2014	
Cluster	Number of zip codes	Mean (%)	Std. deviation (%)	Mean (%)	Std. deviation (%)	Mean (%)	Std. deviation (%)	Mean (%)	Std. deviation (%)
Full Recovery	74	24.46	4.68	−21.33	8.37	22.59	7.59	20.25	17.07
Bust-Partial Recovery	50	22.22	5.46	−46.72	11.22	34.53	6.57	−12.70	18.07
Bust-No Recovery	13	44.49	18.27	−44.63	13.16	−1.87	13.04	−23.86	11.80
All clusters	137	25.54	9.54	−32.81	15.95	24.63	12.92	4.04	24.64

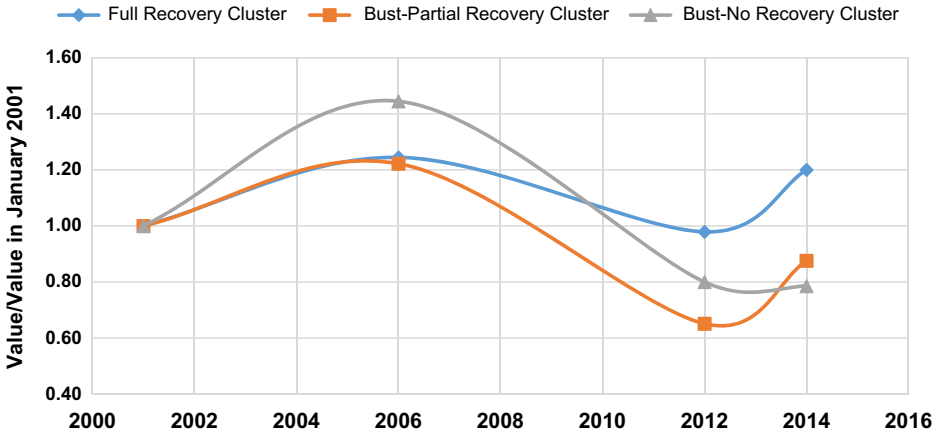

Figure 1. Three clusters of home value trajectory.

in 3 distinct clusters as indicated by a silhouette measure of cohesion and separation above 0.5 (Norusis, 2012). (Minimizing the Akaike information criterion (AIC) resulted in the same three clusters.) The names of the clusters correspond to their value trajectories over the 2001–2014 period: Full Recovery; Bust-Partial Recovery; and Bust-No Recovery. Figure 1 illustrates the general price trajectories across these three different zip code clusters from 2001 to 2014.

In the Full Recovery cluster, values grew steadily, but not rapidly – at about 4 per cent per year – during the national price boom, reflecting the general moderate growth rates reflected in Atlanta metropolitan home prices in indices such as those provided by S&P/Case-Shiller or the Federal Housing Finance Agency. Values did fall in this cluster during the national housing crisis, but only by an average of 21 per cent over the five-and-one-half years of the housing bust. Then, in the national housing recovery period of early 2012 to late 2014, values in this cluster returned essentially to their 2006 peak values, and 20 per cent over their 2001 values (not adjusting for inflation).

In the Bust-Partial Recovery cluster, values generally grew steadily as well over the 2001–2006 period, at a just slightly slower average rate than in the Full Recovery cluster. However,

values fell much further in this cluster during the housing bust, declining an average of 47 per cent, so that values were down to 65 per cent of their 2001 values by 2012. These zip codes generally experienced some recovery, but not nearly a complete one, by 2014, with values reaching 88 per cent of their 2001 values by 2014 (again, none of these number adjust for inflation or use constant dollars), but still at only about 72 per cent of their 2006 peak levels. Because values fell so far during the national housing bust, the gains starting in 2012 have not been enough to call these areas fully recovered.

Zip codes in the Bust-No Recovery cluster tended to experience much greater appreciation rates than the typical Atlanta zip code. These thirteen zip codes saw values rise by an average of 45 per cent from 2001 to late 2006, for an annual appreciation rate of about 8 per cent. Four of these zip codes saw significantly greater rates of appreciation, with values rising over 60 per cent over the boom period. Similar to the metro areas that saw the fastest appreciation rates during the subprime boom, this cluster experienced rapid depreciation during the housing bust, with values declining 45 per cent on average over the 2006–2012 period, dropping to 56 per cent of their peak values and to 80 per cent of their 2001 values. The recent trajectories among these zip codes have generally been flat, calling into question the possibility of a very long time before values reach even their 2001 levels.

Demographic and housing market differences among the three clusters

The three clusters, which exhibited distinct home price trajectories through the bubble, crisis and recovery, differ along an array of key demographic and housing market factors. The ANOVA results in Table 2 describe the differences between cluster means on these variables. For each of these variables, there is a statistically significant difference among the three clusters (with a maximum p-value of 0.038 and with five of seven p-values falling below 0.01). The magnitudes of the mean differences also suggest that the clusters are meaningfully distinct from one another along housing stock and demographic factors. Full Recovery neighborhoods had significantly higher initial home values (mean of 186,715) than Bust-Partial Recovery neighborhoods (mean of 119,106), with Bust-No Recovery neighborhoods having the smallest initial value (mean of 91,323). Full Recovery and Bust-Partial Recovery neighborhoods both had high owner-occupancy rates (approximately 70 per cent), especially compared to the Bust-No Recovery areas (mean of 51.6 per cent). Bust-No Recovery neighborhoods have high initial black percentages (mean of 64.5 per cent) compared to Bust-Partial Recovery (mean of 36.2 per cent) and Full Recovery (mean of 13.7 per cent) areas. Bust-Partial Recovery neighborhoods tend to have the largest Hispanic populations (mean of 21.6 per cent), with Full Recovery and Bust-No Recovery neighborhoods having mean per cent Hispanic rates of between 13 and 14 per cent. Poverty rates were similar among Full Recovery and Bust-Partial Recovery neighborhoods (means of 7.92 and 8.76 per cent, respectively) but were substantially higher in Bust-No Recovery neighborhoods (mean of 22.34 per cent). Figure 2 illustrates the confidence intervals for these key housing and demographic variables for the three clusters.

One characteristic whose pattern across the clusters is perhaps not entirely anticipated is per cent vacant in 2000. Bust-Partial Recovery neighborhoods actually had the lowest initial vacancy rates (mean of 4.3 per cent) with Bust-No Recovery zip codes having the highest initial rates (mean of 7.79 per cent). Some of this difference may be due to there

Table 2. Descriptive statistics and ANOVA analysis of the submarket clusters.

Zip code characteristic	Cluster	*N*	Mean	Std. deviation	95% confidence interval for mean		ANOVA results	
					Lower bound	Upper bound	*F*	Sig.
Value index, January 2001	Full Recovery	74	186,715	87,397	166,467	206,963	22.29	0.000
	Bust-Partial Recovery	50	119,106	17,075	114,253	123,959		
	Bust-No Recovery	13	91,323	14,117	82,792	99,854		
	Total	137	152,988	75,014	140,314	165,662		
Per cent vacant, 2000	Full Recovery	74	6.01	5.26	4.79	7.23	4.78	0.010
	Bust-Partial Recovery	50	4.30	1.28	3.93	4.66		
	Bust-No Recovery	13	7.79	3.33	5.78	9.81		
	Total	137	5.55	4.19	4.84	6.26		
Per cent owner occupancy, 2000	Full Recovery	74	70.01	20.28	65.32	74.71	5.33	0.006
	Bust-Partial Recovery	50	69.33	18.49	64.07	74.59		
	Bust-No Recovery	13	51.62	12.94	43.80	59.44		
	Total	137	68.02	19.68	64.69	71.34		
Per cent black, 2000	Full Recovery	74	13.65	15.54	10.05	17.25	37.02	0.000
	Bust-Partial Recovery	50	36.20	26.76	28.60	43.81		
	Bust-No Recovery	13	64.52	31.51	45.48	83.57		
	Total	137	26.71	27.16	22.12	31.30		
Per cent Hispanic, 2000	Full Recovery	74	13.65	13.48	10.53	16.77	3.35	0.038
	Bust-Partial Recovery	50	21.60	22.95	15.08	28.12		
	Bust-No Recovery	13	13.20	12.37	5.72	20.67		
	Total	137	16.51	17.77	13.51	19.51		
Median age of housing, 2000	Full Recovery	74	18.50	11.67	15.80	21.20	11.43	0.000
	Bust-Partial Recovery	50	17.48	7.71	15.29	19.67		
	Bust-No Recovery	13	32.08	8.32	27.05	37.11		
	Total	137	19.42	10.85	17.58	21.25		
Per cent below poverty, 1999	Full Recovery	74	7.92	7.10	6.28	9.57	25.90	0.000
	Bust-Partial Recovery	50	8.76	4.72	7.41	10.10		
	Bust-No Recovery	13	22.34	10.46	16.02	28.66		
	Total	137	9.60	7.88	8.26	10.93		

being less rental housing (which tends to have higher vacancy rates) in the Bust-Partial Recovery neighborhoods which tend to be moderate-and middle-income bedroom suburbs.

Figure 3 shows spatial distribution of three neighborhood clusters across metropolitan Atlanta. Full Recovery neighborhoods tend to lie in the mostly affluent northern suburbs of the region, in what is often referred to as the "favored quarter" of the region, but also in the north and northeastern neighborhoods in the city of Atlanta and in some southwestern suburbs and other scattered areas. (It should be noted that some of the southwest and southeastern suburbs in the cluster are not very densely populated.) The Bust-Partial Recovery zip codes tend to lie in southern, eastern, and western suburbs, many of which are middle-income, bedroom communities with populations that are quite racially and ethnically diverse. The southern suburbs, especially, tend to have large African-American populations. This cluster forms somewhat of a u-shape around the southern half of in town Atlanta. The Bust-No Recovery cluster is concentrated in the historically black neighborhoods in southwest Atlanta, and in three zip codes in the southern and eastern suburbs.

Multivariate models predicting housing market trajectories

We use multinomial logistic regression to predict the likelihood of being in the Bust-Partial Recovery cluster, or in the Bust-No Recovery cluster, rather than the Full Recovery cluster. Then, we use ordinary least squares (OLS) and spatial regression to predict home price

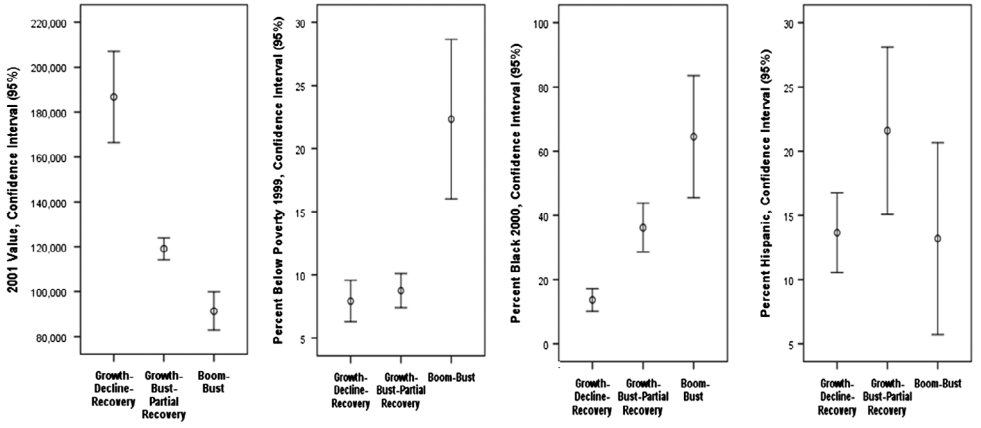

Figure 2. Confidence intervals by cluster for four key housing market and demographic characteristics.

change over the entire period, from 2001 to 2014. Table 3 provides the descriptive statistics for the variables used in the two regressions, and Table 4 provides the results of the multinomial logistic regression. Table 5 then provides the results of the OLS and spatial models.

The results in Table 4 show that the model correctly predicts the cluster for the 137 zip codes 88 per cent of the time. The exponentiated coefficients provide the effect of a one-unit change in the independent variable on the relative risk of being in the cluster rather than in the reference cluster, which is the Full Recovery cluster. These exponentiated coefficients are sometimes referred to as "relative risk ratios (RRRs)." In comparing Bust-Partial Recovery cluster to the reference cluster (the top half of Table 4), the RRRs are statistically significant at $p < 0.10$ for the 2001 value of homes, per cent vacant, median age of housing, per cent black, and per cent Hispanic, with all but the median age of housing significant at $p < 0.05$. (No other variables are close to being statistically significant.) When these ratios are above 1.0, higher levels of these variables lead to higher odds of being in the Bust-Partial Recovery cluster relative to the reference cluster (the Full Recovery cluster). This is the case for per cent black and per cent Hispanic. Higher levels in the other variables lead to lower risk of being in this cluster relative to the reference cluster. Due to the limited number of observations, the results were checked for problems of severe multicollinearity. Variance inflation factors (VIFs) were all below 5, suggesting that multicollinearity should not be a severe problem. Of course, the limited sample size and some modest levels of multicollinearity among the independent variables suggest that caution should be taken in findings of statistical insignificance, especially when *p*-values are just marginally above 0.10. If the number of observations were substantially larger, some of these variables could very well come in as statistically significant.

Higher initial housing values are important predictors of the housing market trajectory of a zip code. For every one dollar increase in median 3-bedroom home value in 2001, the relative risk of being in the Bust-Partial Recovery cluster (versus the Full Recovery cluster) declines by what appears to be a very small 0.000123 (1–0.999877). However, this means that, other things equal, an increase of $10,000 in initial median home value results in a relative risk ratio for the Bust-Partial Recovery category that is 71 per cent lower than an otherwise similar zip code. In other words, the risk of falling into the Bust-Partial Recovery category versus the Full Recovery category is reduced by more than two-thirds for every

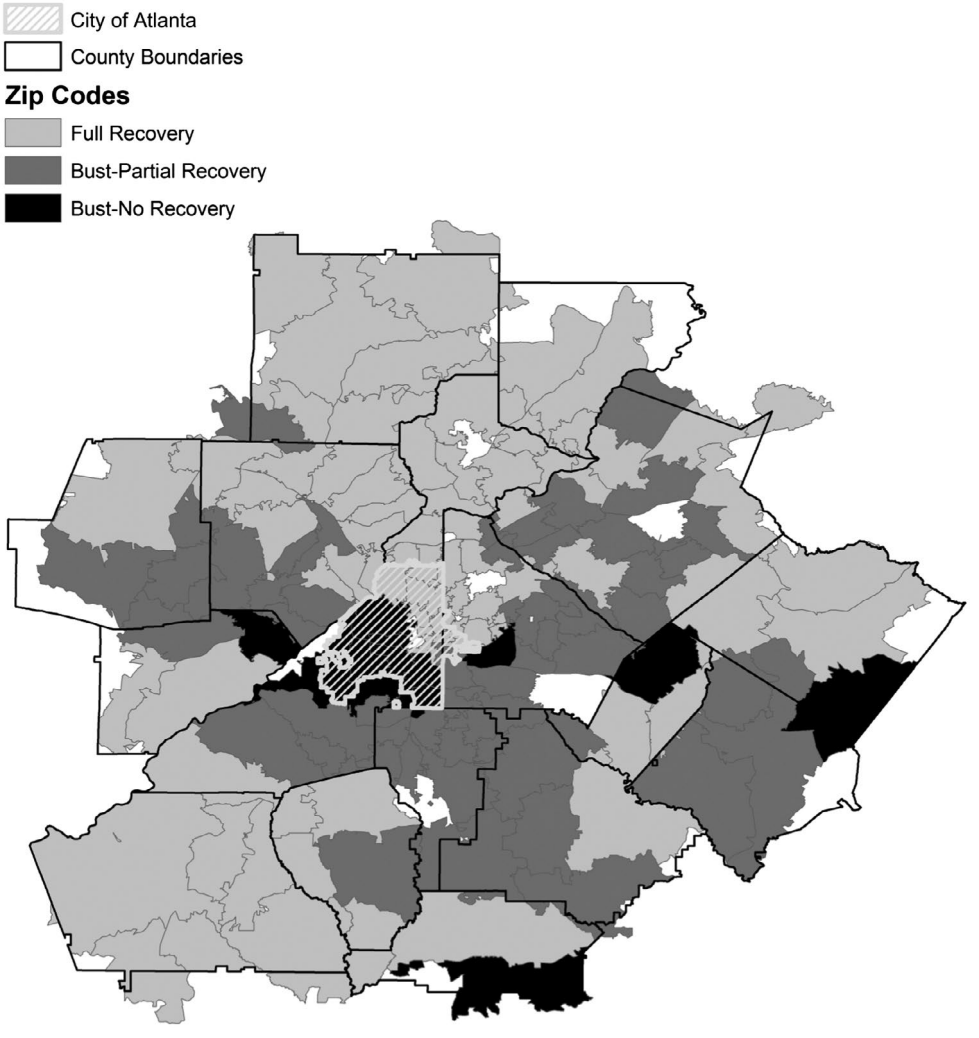

Figure 3. Map of clusters.

Table 3. Descriptive statistics for regression models.

Variable	Obs	Mean	Std. deviation	Min	Max	Source
Cluster	137	1.55	0.66	1	3	Calculated
2001 value	137	$152,988	$75,014	$66,500	$481,900	Zillow
2000% vacant	137	5.55	4.19	1.82	44.56	2000 census
2000% owner-occupied	137	68.02	19.68	17.59	95.13	2000 census
2000 median age of housing	137	19.42	10.85	4.00	55.00	2000 census
2000% black	137	26.71	27.16	0.00	98.10	2000 census
2000% Hispanic	137	16.51	17.77	1.90	100.00	2000 census
1999% below poverty	137	9.60	7.88	0.80	41.20	2000 census
2000% age 65 or over	137	7.40	2.96	2.58	18.31	2000 census
Within 5 core counties	137	0.72	.453	0	1	Calculated

$10,000 in median home value. The risk of falling into the Bust-No Recovery category is reduced even more as the initial home value gets larger. The relative risk declines by more than 88 per cent for each $10,000 in value.

Table 4. Multinomial logistic regression results (Full Recovery cluster is reference category).

	B	Std. error	Wald	Exp(B)	Sig.
Bust-Partial Recovery					
2001 median home value	−1.23E-04	3.08E-05	16.045	0.999877	0.000***
2000 per cent vacant	−0.766	0.333	5.297	0.465	0.021**
2000 median age of housing	−0.201	0.106	3.582	0.818	0.058*
2000 per cent owner-occupied units	0.030	0.048	0.395	1.031	0.530
2000 per cent black	0.180	0.059	9.308	1.198	0.002***
2000 per cent hispanic	0.153	0.052	8.594	1.166	0.003***
1999 per cent below poverty	−0.134	0.160	0.696	0.875	0.404
2000 per cent 65 and over	−0.221	0.229	0.928	0.802	0.335
Within 5 core counties	0.295	0.916	0.104	1.343	0.748
Bust-No Recovery					
2001 median home value	−2.14E-04	5.75E-05	13.785	0.999786	0.000***
2000 per cent vacant	−1.060	0.509	4.331	0.346	0.037**
2000 median age of housing	1.15E-03	0.160	0.000	1.001	0.994
2000 per cent owner-occupied units	0.049	0.084	0.340	1.050	0.560
2000 per cent black	0.175	0.073	5.825	1.192	0.016**
2000 per cent Hispanic	0.072	0.072	1.009	1.075	0.315
1999 per cent below poverty	−0.048	0.171	0.077	0.954	0.781
2000 per cent 65 and over	0.501	0.405	1.528	1.650	0.216
Within 5 core counties	0.693	2.375	0.085	2.000	0.770

Notes: $N = 137$.
Pseudo $R^2 = 0.679$.
Per cent correctly predicted = 88.3%.
***Significant at less than 0.01.
**Significant at less than 0.05.
*Significant at less than 0.10.

One potentially surprising finding, at least at first blush, is the fact that the RRRs for the per cent vacant variable are well under 1.0. Thus, higher vacancy rates in 2000 are associated with a lower chance of falling into the Bust-Partial Recovery or Bust-No Recovery cluster. It is important to keep in mind, however, that these findings control for poverty, race and other factors and that many vacant units included in the census vacancy numbers are units that are actively being marketed for rent or sale (which can accompany higher housing demand and gentrification). Also included in this figure are units that have recently been constructed, suggesting potential increases in local housing demand. Therefore, total vacancy should not be viewed as a measure of long-term vacancy and abandonment, which, in most census tracts, constitute a very small share of overall vacant units.

The results in Table 4 indicate that zip codes with larger black or Hispanic populations are more likely to fall into the Bust-Partial Recovery cluster than the Full Recovery cluster. The results for the Bust-No Recovery cluster (the lower half of Table 4) are generally consistent with the results for the Bust-Partial Recovery cluster for the per cent black variable, with a RRRs of 1.192 and 1.198. The per cent Hispanic variable is not a significant predictor of falling into the Bust-No Recovery cluster; these 13 zip codes are predominantly black zip codes in or near the central city, and Hispanics tend to be located more in the suburbs in Atlanta.

After controlling for race and other demographic and housing characteristics, the poverty rate of a zip code had no significant impact on the cluster that the zip code ended up in. Overall, the dominant drivers were initial home values, race, and ethnicity.

The results suggest that race and ethnicity are strong predictors of the housing market trajectory of a neighborhood, even after controlling for the other independent variables. A one percentage-point increase in per cent black, after controlling for these other

Table 5. Results of OLS and spatial lag models predicting per cent change in median home value, 2001–2014.

	b	Standard error[ψ]	Beta	Sig.	b	Standard error	Beta	Sig
2001 median home value	1.64E-04	3.63E-05	0.500	0.000***	8.91E-05	2.46E-05	0.271	0.000***
2000 per cent vacant	−0.542	0.358	−0.092	0.130	−0.448	0.300	−0.076	0.136
2000 median age of housing	0.455	0.250	0.201	0.068*	0.452	0.177	0.199	0.011**
2000 per cent owner occupied	0.089	0.141	0.071	0.525	0.125	0.091	0.100	0.170
2000 per cent black	−0.659	0.079	−0.727	0.000***	−0.332	0.073	−0.366	0.000***
2000 per cent Hispanic	−0.187	0.084	−0.135	0.025**	−0.139	0.067	−0.100	0.038**
1999 per cent below poverty	1.033	0.356	0.330	0.004***	0.361	0.263	0.115	0.170
2000 per cent age 65 +	−0.656	0.426	−0.079	0.124	−0.171	0.399	−0.021	0.668
Within 5 core counties	2.172	2.686	0.040	0.419	1.021	2.735	0.019	0.709
Constant	−18.559	17.928		0.301	−18.421	10.565		0.081
Spatial lag variable					0.618	0.070		0.000
R^2	0.69				0.81			

Note: $N = 137$.
[ψ]Heteroskedastic-robust standard error.
***Significant at less than 0.01.
**Significant at less than 0.05.
*Significant at less than 0.10.

variables, increases the odds of a neighborhood falling into the Bust-Partial Recovery cluster versus the Full Recovery cluster by 19.8 per cent. A similar increase in per cent Hispanic increases such odds by 16.6 per cent. Similarly, a one percentage-point increase in per cent black is associated with a 19.2 per cent increase in the odds of a neighborhood falling into the Bust-No Recovery cluster versus the Full Recovery cluster. These are very large effects. Importantly, race, even after controlling for poverty, is a major predictor of housing market trajectories.

Table 5 provides the results of an OLS regression and a spatial lag regression of the 2001–2014 percentage-point change in home value in a zip code using the same independent variables that were used in the multinomial logistic regression in Table 4. The spatial lag was formed through the use of a queen contiguity matrix. For each zip code, a spatial lag variable was created that involved summing the dependent variable for all the contiguous (borders or vertices) zip codes. In this way, 2001–2014 home values in adjacent zip codes were explicitly incorporated on the right-hand side of the model.

Because spatial autocorrelation was detected in the OLS residuals, both spatial error and spatial lag models were considered for estimating the model. The spatial lag specification produced slightly better goodness-of-fit measures, so it was selected and is presented in the right-hand columns of Table 5. The results are quite consistent with the multinomial regression results of Table 4 with some exceptions. First, the per cent vacant variable is not significant. Second, once spatial autocorrelation is addressed via the spatial lag model, the per cent below poverty variable becomes insignificant.

The effects of race and ethnicity remain robust to controls for spatial autocorrelation. Each one percentage-point increase in the initial black population in a zip code is associated with 0.33 percentage-points less increase in the home value index from 2001 to 2014. A one standard deviation increase in per cent black (27.2 percentage points) is associated with a 9.0 percentage-point decline in 2001–2014 home value appreciation, certainly a nontrivial amount compared to an average across zip codes of 4.0 per cent over this period. Each one percentage-point change in the initial Hispanic population in a zip code is associated with 0.14 percentage-points less increase in the home value index. A one standard deviation increase in per cent Hispanic (17.8) is associated with a 2.5 percentage-point decline in 2001–2014 home value appreciation.

We need to provide a critical caution here. These results are not aimed at identifying proximate causation. Just because higher black populations in these models are associated with subsequent weaker home value trajectories, it does not imply that an influx of black residents directly led to lower property values. Given what we know about the subprime crisis and the Great Recession, it is likely that these patterns are the result of mediating factors not identified here, including the fact that black neighborhoods bore a disproportionate share of high-risk, reckless subprime lending and resulting foreclosures – as well as other hardships of the Great Recession, such as higher unemployment rates and greater declines in household wealth. Moreover, tighter credit markets and possible stigma associated with areas hit hard by the crisis may have disproportionately impacted minority neighborhoods.

Regardless of mediating or intervening factors, it is important to understand the extent to which disparate home value trajectories played out by neighborhood racial and ethnic composition – after controlling for poverty and fundamental differences in housing stock – during the greatest housing crisis since the Great Depression.

Conclusion

This research identifies three housing submarket trajectories in the Atlanta metropolitan area before, during and after the U.S. housing crisis. It shows that the neighborhoods falling into these different trajectories exhibit substantially distinct racial, ethnic, and housing market characteristics. When we investigate the direction and magnitude of the relationships between race, ethnicity, poverty, housing stock, and recovery, we find consistently strong relationships that suggest that many black neighborhoods – even those with lower degrees of poverty – exhibited steep rates of price decline with only modest or essentially no recovery following the crisis. Meanwhile, many predominantly white, middle- , and upper-income neighborhoods experience less volatility during the boom and bust and have generally more than recovered from the modest housing price declines that they did face. The reasons behind these patterns are complex and certainly not directly addressed here. However, it is important to understand that such variations occurred and that they were associated with racial differences.

The literature on racialized subprime lending and resulting foreclosures and the issues of the timing of policy remedies such as loan modifications suggests that predominantly black neighborhoods were disproportionately targeted and may have been less likely to receive effective remedies, especially during the earlier stages of the crisis when minority communities were hit especially hard (Immergluck, in press). This research contributes to the literature in two key ways. First, it investigates the nature of uneven housing market decline

within a large, diverse region hit hard by the U.S. housing crisis. Second, it demonstrates the racial and ethnic nature of the unevenness of housing market trajectories and recoveries. From the literature, we know that minority neighborhoods were targeted with poorly underwritten loans and that the federal policy response to the crisis did not reach effective scale until much of the damage had already been done in many minority neighborhoods.

There is also evidence that tighter mortgage markets have disproportionately affected minorities and possibly curbed housing demand in minority neighborhoods. Goodman *et al.* (2015) estimate that tight credit meant the number of home purchase loans to black borrowers in 2013 was 50 per cent less than what it was in 2001, before the subprime boom. Tight credit also reduced lending to white borrowers, but only by 31 per cent. Some have argued that the pendulum of credit access has swung too far in the direction of restrictive markets. Renewed attention is needed to policy tools such as the Community Reinvestment Act and the Fair Housing Act to ensure that prospective homeowners are able to access credit in all neighborhoods. Higher loan guarantee fees by the Federal Housing Administration – a key lender to minority homebuyers – may be having adverse effects in some communities who have relied on the FHA a good deal since the crisis (Joint Center for Housing Studies, 2014). In the long run, the prospects of much greater levels of risk-based pricing, in which borrowers with marginally lower credit scores and lower down payments may face much higher borrowing costs, could dampen recovery in minority neighborhoods even further (Immergluck, in press).

Efforts to restore housing markets must take into account the uneven nature of crisis and recovery, and be particularly cognizant of the tendency of housing volatility and recovery to benefit certain neighborhoods and not others. Without understanding any tendencies of housing market recovery to bypass certain types of neighborhoods, it will be difficult to formulate policy responses in the future that can assist those communities most in need of intervention.

Disclosure statement

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