Debt Relief and Slow Recovery: A Decade after Lehman

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Abstract

We follow a representative panel of millions of consumers in the U.S. from 2007 to 2017 and document several facts on the long-term effects of the Great Recession. There were about six million foreclosures in the ten-year period after Lehman's collapse. Owners of multiple homes accounted for 25% of these foreclosures, while comprising only 13% of the market. Foreclosures displaced homeowners, with most of them moving at least once. Only a quarter of foreclosed households regained homeownership, taking an average four years to do so. Despite massive stimulus and debt relief policies, recovery was slow and varied dramatically across regions. House prices, consumption and unemployment remain below pre-crisis levels in about half of the zip codes in the U.S. Regions that recovered to pre-crisis levels took on average four to five years from the depths of the Great Recession. Regional variation in the extent and speed of recovery is strongly related to frictions affecting the pass-through of lower interest rates and debt relief to households including mortgage contract rigidity, refinancing constraints, and the organizational capacity of intermediaries to conduct loan renegotiations. A simple counterfactual based on our estimates suggest that, regardless of the narratives of the causes of housing boom and bust, alleviating these frictions could have reduced the relative foreclosure rate by more than half and resulted in up to twice as fast recovery of house prices, consumption, and employment. Our findings have implications for mortgage market design, monetary policy pass-through, and macro-prudential and housing policy interventions.

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I. Introduction

The Great Recession, widely assumed to have started with the collapse of Lehman Brothers, was unprecedented in terms of the devastation it caused to the financial sector, as well as the real economy. By the time its full impact was ascertained, it resulted in several million households with foreclosed homes, the loss of 8.7 million jobs, and the contraction of real GDP by about 3% between the start of the recession in 2007:Q2 and 2009:Q4 (Bureau of Labor Statistics, Bureau of Economic Analysis). Since the epicenter of these problems was the mortgage sector, there were several large stimulus and debt relief interventions passed by the government (Piskorski and Seru 2018). A decade after Lehman, there are signs of recovery with national unemployment rates and house prices recovering to pre-crisis levels. At the same time, there seems to be a wide disparity in the extent and speed of recovery across regions.[2] The main goal of this paper is to document facts on the long-term consequences of the Great Recession and the subsequent recovery. Moreover, by using spatial variation, we assess why recovery was more sluggish in some regions than in others, focusing on the factors affecting the pass-through of lower interest rates and debt relief to households. We conclude by discussing the implications of our findings for mortgage market design, monetary policy pass-through, and macro-prudential and housing policy interventions.

We exploit a representative panel of millions of consumers in the U.S. from 2007 to 2017 in our analysis. This novel dataset allows us to identify individual, regional and aggregate mortgage defaults and foreclosures during the last decade and assess their association with a broader set of outcomes, including household mobility and their homeownership rate. We estimate that there were about six million completed foreclosures over the 2007-2017 period. Owners of multiple homes accounted for 25% of foreclosures, despite accounting for only 13% of the market. Foreclosures displaced homeowners, with most of these borrowers moving at least once. Only a quarter of foreclosed households regained homeownership, taking an average of four years to do so.

The response to crisis resulted in massive stimulus and debt relief policies. The Federal Reserve altered its monetary policy by lowering short-term interest rates to historic lows and engaged in

[2] See for instance, https://www.pewtrusts.org/en/research-and-analysis/articles/2014/09/state-fiscal-recovery-from-great-recession-is-slow-and-uneven.

the Quantitative Easing (QE) polices. Also, the administration passed two unprecedented, large-scale debt relief programs: the Home Affordable Refinance Program (HARP), which aimed to stimulate mortgage refinancing activity for up to eight million heavily indebted borrowers; and the Home Affordable Modification Program (HAMP), which aimed to stimulate a mortgage restructuring effort for up to four million borrowers at risk of foreclosure (see Figure 1).[3] Despite these unprecedented measures, there was slow recovery from the crisis, with significant regional heterogeneity in both the extent and time of recovery. House prices, consumption and unemployment have still not reached pre-crisis levels in about half the zip codes in the U.S. Those that did recover took on average four to five years from the depths of the Great Recession to do so.[4]

We next assess the role played by a number of factors related to the nature of the financial intermediation sector in accounting for the extent and speed of recovery across regions. Our analysis is motivated by a series of papers that argue that a number of factors related to the rigidity of contract terms, along with a variety of frictions in the design of the mortgage market and the intermediation sector, hindered the pass-through of lower rates and efforts to restructure or refinance household debt (Piskorski, Seru, and Vig 2010; Mayer et al. 2014; Di Maggio et al. 2017; Agarwal et al. 2015 and 2017; Fuster and Willen 2017). We find that regional mobility patterns and neighborhood characteristics explain significant spatial variation in recovery. However, even after accounting for these factors, a large variation remains that can be explained to some degree by mortgage contract rigidity and refinancing constraints affecting the pass-through of lower rates to households and the organizational capacity of financial intermediaries to conduct renegotiations. A simple counterfactual based on our estimates suggests that alleviating these frictions would result in a relative sense, more than a fifty percent reduction in foreclosures and a up to twice as fast recovery in house prices, consumption, and employment.

Besides providing facts that are interesting in their own right, our work generates several important lessons. First, our analysis suggests that *regardless* of the inherent causes of the housing boom and

[3] These programs were motivated among others by perceived negative externalities of debt overhang and foreclosures (see Campbell et al. 2011, Melzer 2017, Gupta 2018 for a recent evidence).
[4] These programs were coupled with other simulative measures such as first-time homebuyer tax credits aimed at stimulating house purchases (Berger et al. 2016) and programs aimed at stimulating consumer spending, such as economic stimulus payments (Parker et al. 2013) and subsidies for new car purchases (Mian and Sufi 2012).

its subsequent bust[5], the crisis would have been *much less severe* if frictions in the financial intermediation sector that impact the pass-through of stimulus and debt relief to households had been alleviated.

Second, our findings underscore the central importance of household balance sheets and mortgage market rigidities in the transmission of monetary policy and debt relief measures to the real economy. These findings also suggest that macro-prudential polices should not only focus on ex-ante monitoring and reacting to the buildup of risk in the economy. It is also important to recognize and address various factors and frictions in the household sector that can affect the transmission of debt relief and monetary policy to households and real economy ex-post after the crisis.

Third, our evidence, along with prior work, suggests a number of approaches that could alleviate the impact of such frictions in the future. These approaches center on both ex-ante and ex-post changes in the mortgage market design that would result in a more effective pass-through of debt relief and more efficient sharing of aggregate risk between borrowers and lenders during the time of the crisis. We discuss these in more detail in Section VII.

II. Data Sources

The main dataset used in this paper is the Analytic Dataset provided by Equifax. Equifax is a credit-reporting agency that provides monthly borrower-level data on credit risk scores, consumer age, geography, debt balances, and delinquency status at the loan level for all consumer loan obligations and asset classes. The Analytic Dataset is created from a 10% random sample of the U.S. credit population from 2005 to 2017 across all U.S. geographical boundaries. Randomization in the sample is based on social security numbers. Our sample consists of around 18.5 million consumers (18,496,567) and is representative of the U.S. credit population. Our analysis will assess the patterns in the data in the aftermath of the Great Recession. Accordingly, we focus on the time period from the end of 2007:Q2 to the end of 2017:Q4. We start in 2007:Q2 as private-label subprime securitization virtually collapsed after this quarter, which is commonly viewed as the beginning of the crisis (see Keys et al. 2013).[6] Since some consumers exit the sample during

[5] See, among others, Mian and Sufi (2009 and 2011), Mayer et al. (2009), Keys et al. (2010) and (2013), Purnanandam (2011), Piskorski et al. (2015), Landvoigt et al. (2015), Adelino et al. (2016), Guerrieri and Uhlig (2016), Griffin and Maturana (2017), Kaplan et al. (2017), Favilukis et al. (2017), Gennaioli and Shleifer (2018) for a discussion of possible causes of housing boom and its subsequent bust.

[6] We obtain a very similar inference if we start our time period around this data (e.g., in Q4:2006).

this time period, we restrict out sample to the around 13.5 million *active* consumers (13,558,277) that remain during this entire period for cleaner analysis. This represents around 7.33% of the U.S. credit population. In unreported tables, available upon request, we verify that our results are robust to the inclusion of consumers who we exclude from the analysis reported in this paper.

We use this data to investigate consumer age, delinquency and foreclosure status, mobility, homeownership status, income, vantage score, and debt balances from end of 2007:Q2 to end of 2017:Q4. Additionally, we use the Equifax data to compute mortgage delinquency rate, foreclosure rate, and combined loan-to-value (CLTV) ratios at the zip code level.[7]

In order to investigate how the Great Recession impacted different regions, we supplement the borrower-level data with regional information provided by the United States Census Bureau's American Community Survey 5-year estimates. The 5-year estimates are created from 60 months of collected data and are available at the Zip Code Tabulation Areas (ZCTA) level from 2011 to 2016. As an example, the 5-year estimates for 2016 are the result of data collected between start of 2012:Q1 and the end of 2016:Q4. We use the following variables at the ZCTA level: unemployment rate, median income, percent college educated, percent high school educated, percent white, percent black, percent Hispanic or Latino, median age, and percent married with children. In most instances, ZCTAs are the same as zip codes. However, we note that because the Census Bureau creates ZCTAs by taking the most frequently occurring zip code in an area, some addresses have ZCTAs that are different from their zip codes.

We are also interested in how the crisis affected house prices and consumption levels, information which is not available in the Census Bureau data. As a result, we use the Zillow Home Value Index (ZHVI), which tracks the monthly median home value in a particular zip code, from 2006 to 2017 in order to understand patterns in house price levels and growth. In addition, we use Polk monthly auto sales data from 2006 to 2016 to analyze consumption at the zip code level.

Finally, to explore how frictions to debt relief impacted the speed of recovery and the severity of the crisis, we use data on the share of loans that are of ARM type (ARM share), the share of loans

[7] We compute CLTV by dividing the average combined mortgage debt level of borrowers with first mortgages on their credit files by the median house price in a region (obtained from Zillow). We verified that our measure of average CLTV in a region is closely related to the CLTV measure from widely used Credit Risk Insight Servicing McDash (CRISM) data that cover approximately 70 percent of mortgage borrowers (see also Piskorski and Seru 2018).

that are HARP eligible (HARP Eligible share), and the share of loans serviced by high organizational capacity intermediaries (High Capacity share). These variables are available at the zip code level. ARM share comes from Di Maggio et al. (2017), HARP Eligible share comes from Agarwal et al. (2015), and High Capacity share comes from Agarwal et al. (2017).

III. Individual and Aggregate Descriptive Statistics

III.A Individual Level Statistics

We begin by describing our sample of consumers in the Equifax dataset. In Table 1A, we begin by describing the static variables – i.e., at a particular point of time; in our case end of 2007: Q2 -- for the 13.5 million active consumers in our data, regardless of whether they have a mortgage. Around a third of active consumers (30%) have a mortgage as of June 2007 and about 13% of mortgage borrowers have multiple first mortgages, implying they have more than one home (e.g., a second home or an investment property). For those with mortgages, the average first mortgage balance is around $185,440. Not surprisingly, income and vantage credit score is higher for borrowers with mortgages relative to all the consumers. Moreover, within consumers with mortgages, those whose homes are foreclosed are younger, have higher mortgage debt balance, lower income and lower vantage credit scores. These consumers are also likely to have higher debt balance of other types (revolving debt, student debt or auto debt) relative to other consumers.

Table 1B describes the dynamic variables – i.e., over the time period from the end of 2007: Q2 to end of 2017: Q4 – for active consumers in our data. Around a quarter of all consumers who had mortgages (24.3%) become seriously delinquent over this period.[8] This amounts to about 9.8% of all consumers. Looking more finely, mortgage borrowers with single homes have a delinquency rate of 22.6% while mortgage borrowers with multiple homes (e.g., mortgage investors) have a higher rate of 35.9%. Borrowers in the bottom 10% of the credit score distribution, which include the so-called subprime borrowers, have a very high serious delinquency rate of 71%. These rates can be calculated from a weighted average of the fraction seriously delinquent provided in Table 1B.

[8] We define serious delinquency status as being 60 days or more past due on mortgage payments.

Not all delinquent borrowers face foreclosure (see Keys et al. 2013). About 10% of borrowers with mortgages (as of Q2 2007) face completed foreclosure during 2007-2017 period.[9] This fraction suggests that about 40% of borrowers who became seriously delinquent on their mortgages face foreclosure during our sample period.[10] Looking more finely, mortgage borrowers with single homes have a lower rate of foreclosure (8.6%), while those with multiple homes have a much higher rate of 19.8%. Borrowers in the bottom 10% of the credit score distribution experience a 25% foreclosure rate, accounting for about one quarter of all foreclosures.

We also note that foreclosures take significant time to complete: it takes on average about 18 months to foreclose a property counting from the first month of serious delinquency. While part of this delay may reflect borrowers' attempts to cure their delinquency status, this statistic indicates that the foreclosure process was relatively sluggish during the Great Recession. Remarkably, among borrowers in the bottom 10 percent of credit distribution the time-to-foreclosure is much slower, taking on average 26.4 months. This longer delay may reflect among other factors, the limited capacity of subprime servicers to handle a large amount of distressed loans and various disruptions related to bankruptcy and transfer of ownership of mortgage servicers handling risky loans.

Table 1B also reveals that 40.7% of all active consumers move during this decade, determined by observing changes in a consumer's zip code of primary residence. This mobility rate is similar to those found in other studies. For instance, a Gallup study conducted in 2013 found that 24% of U.S. adults reported moving at least once in the past five years. This statistic is broadly consistent with our moving rate of 40.7% within ten years.[11] Consumers with mortgages have a lower mobility rate if they do not experience foreclosure. For instance, those with a single home have a mobility rate of 30%, while those with multiple homes have a mobility rate of around 35%. In contrast, those whose homes are foreclosed have a significantly higher mobility rate, with the majority of these borrowers moving during our sample period (around 60%).[12]

[9] We do not count events where the foreclosure process was initiated but was not completed by the end of 2017 as foreclosures.

[10] Alternatively, of the consumers who do not suffer foreclosure, 15.3% become seriously delinquent at some point during our sample period.

[11] Notably, if we estimate mobility rate only between 2008 to 2013, the years on which the Gallup study was based, we find the mobility rate to be 26%. This squares very well with the Gallup study's numbers.

[12] There are several reasons why some foreclosed borrowers may remain in their initial zip code of residence. First, some of these borrowers may decide to stay near their initial residence due to job related reasons and to avoid moving

Finally, Table 1B also reveals that foreclosures resulted in permanent loss of homeownership. Of the borrowers with a single home, only one quarter (22.8%) of those who lost their homes through foreclosure regain homeownership by the end of 2017: Q4. It takes on average about four years for them to do so (47 months).[13]

It is worth discussing some of the statistics related to borrowers with multiple homes, especially since recent work has suggested the important role of such consumers in perpetuating the crisis (see, Chinco and Mayer 2015, DeFusco et al. 2017, Mian and Sufi 2018). In our sample, such borrowers have an average of 2.3 homes. These borrowers are older, wealthier, and more credit worthy than their counterparts with single homes. As expected, they have much higher levels of mortgage debt. They also have higher student, credit card, and auto debt. As previous work (e.g., Piskorski et al. 2015) has suggested, these borrowers have higher delinquency and foreclosure rates. In particular, they default at a rate around 1.6 times higher than borrowers with single homes (about 36% versus 22.6%). Moreover, these borrowers face foreclosures at a rate that is 2.3 times higher relative to those with single homes (19.9% versus 8.6%).

III.B Aggregate Statistics

We now use descriptive statistics provided in Table 1A and 1B to estimate aggregate delinquency and foreclosures in the U.S. economy over the last decade. As discussed earlier, our sample represents 7.33% of the total credit population. To calculate aggregate statistics for the entire population, we therefore need to scale the raw numbers by a factor of 13.6 (1/0.0733). We report these in Table 1C.

Our descriptive statistics suggest that, as of the end of 2007:Q2, around a third of active borrowers (around 4.13 million) have mortgages. In scaled terms, this implies that around 56 million

their children to different schools. Second, staying in the local area (e.g., by renting an apartment) may be simpler due to potentially lower moving/informational costs. Third, due to local social and family networks, some foreclosed borrowers may prefer to stay near their initial residence. Fourth, we note that our mobility measure relies on the borrowers' mailing addresses. In this regard, we may not be able to identify some movers who do not promptly update their mailing zip code addresses. Finally, we classify movers based on their location at the end of our sample period (2017:Q4). If borrowers move back to their original zip codes after foreclosure, they will not be counted as "moved".

[13] Note that we classify consumers in the "regain homeownership rate" if we observe a new mortgage debt on their credit file following a completed foreclosure of their previous home. This measure is likely an underestimate, since it does not capture borrowers who might have regained homeownership by purchasing their homes without debt financing. Despite this limitation, our homeownership numbers in the aggregate match well with those reported elsewhere (e.g., American Community Survey).

consumers (56,293,952) have mortgages. Moreover, around 48 million of these borrowers have single homes, while the remaining 7 million have multiple homes.[14]

Next, we estimate the number of borrowers who experienced foreclosures and delinquencies over the last decade. For this calculation, we start with columns 2 and 4 of Table 1B, where we report the delinquency and foreclosure rates of different groups of borrowers. As discussed earlier, around a quarter (24.3%) of borrowers with mortgages experience delinquency, with the rate around 22.6% for borrowers with single homes and about 36% for borrowers with multiple homes. Similarly, around 10% of all mortgage borrowers experience a foreclosure, with a much higher rate for those with multiple homes (19.8%) when compared to those with single homes (8.6%). As a second step, we multiply the delinquency and foreclosure rates of various groups with the estimated number of borrowers in each category. Doing so reveals that during the last decade around 13 million borrowers experienced serious delinquency. Borrowers with single homes accounted for 11 million of these delinquencies, with about 4.2 million going through a completed foreclosure.

Our estimates suggest that 5.7 million borrowers suffered a foreclosure in the U.S. economy during the last decade.[15] Of these borrowers, around 4.2 million had single homes and the remaining 1.5 million were borrowers with multiple homes. These findings highlight the important role that borrowers with multiple homes, including so called "investors", played in the foreclosure crisis. While borrowers with multiple homes made up only 13% of total mortgage borrowers, they account for about 19% of delinquencies and nearly 26% of total foreclosures. Finally, we note that some borrowers with multiple homes experience multiple foreclosures. Adding such cases, we end up with about 6 million completed foreclosures during the 2007:Q2 to 2017:Q4 period among borrowers who owned homes as of the beginning of the crisis (2007:Q2).[16]

[14] These numbers are consistent with aggregate number of mortgage borrowers reported by the Corelogic.

[15] Accounting for the fact that borrowers with multiple homes can experience multiple foreclosures adds about additional 200,000 foreclosures, resulting in a total of about 6 million foreclosures. Note that this number does not include borrowers who bought homes after 2007 and experienced foreclosure by 2017.

[16] We note that our estimate of completed foreclosures is broadly in line with aggregate numbers reported by the data providers during similar sample periods. For example, according to a 2016 report by the real estate data company RealtyTrac, there were 6.3 million completed foreclosures from January 2006 to April 2016. Corelogic reports more than 7 million foreclosures during our sample period. We note that unlike these estimates, our calculation quantifies the number of completed foreclosures among borrowers who were homeowners as of the beginning of the crisis (2007:Q2) and thus does not include foreclosures among those borrowers who became homeowners later on. This

Next, we investigate the relation between foreclosure and borrower creditworthiness. Figure 2 plots mean vantage score of borrowers with single homes who suffered foreclosure for twelve quarters (three years) prior to foreclosure and twenty quarters (five years) after foreclosure, where Quarter 0 is the quarter in which the borrower experiences foreclosure. To investigate the recovery of vantage scores following foreclosure more formally, we calculate the percentage of borrowers with vantage scores at or above their original Period -12 level in each period (the level 12 quarters before foreclosure). In Period 0 (when the borrower suffers foreclosure), the percentage of borrowers with vantage scores at least as high as their Period -12 level is 15.7%. This percentage increases steady throughout the remaining periods, though even five years after foreclosure only 51% of borrowers had recovered. Moreover, the average time to recover after foreclosure was 11.99 quarters (3 years), with a standard deviation of 9.03 quarters (2.25 years). These findings illustrate that many borrowers had not recovered their creditworthiness as measured by their vantage scores five years after foreclosure, recovery was slow for those who did recover, and there was significant variation in recovery time.

Finally, we also estimate the aggregate number of households who suffered loss of homeownership due to the crisis. Table 1B shows that only 22.75% of borrowers with single homes who suffered foreclosure regained homeownership by the end of 2017. Alternatively put, 77.75% of the borrowers with single homes who suffered foreclosure in our sample lost homeownership permanently. This corresponds to an aggregate number of 3.3 million borrowers in the U.S economy. Similarly, around 65.8% of borrowers with multiple homes lost homeownership over the sample period. This corresponds to an aggregate number of around 0.96 million borrowers. Thus, around 4.3 million borrowers have lost homeownership during the decade after the crisis.

We note that this estimate suggests that permanent loss of homeownership due to foreclosures can account for the majority of the decline in the US homeownership rate from about 68% in 2007 to about 64% in 2017 (see Figure 6). In particular, according to the American Community Survey there were about 119 million occupied housing units in the US in 2017 of which about 76 million were owner-occupied. If the estimated 4.3 million foreclosed borrowers who lost homeownership

may explain why our aggregate estimate of completed foreclosures (5.9 million) is somewhat lower than some estimates from real estate data providers.

during the Great Recession would have retained their homes, the US homeownership rate in 2017 would be about 67% (as opposed to the actual rate of 64%).

IV. Delinquency, Foreclosures and Regaining Homeownership: Consumer Level Analysis

We have provided descriptive statistics to understand the characteristics of various types of borrowers in our dataset and how our consumer level statistics relate to the aggregate number of delinquencies and foreclosures. In this section we estimate simple regressions to assess how the probability of delinquency, foreclosure, and regaining homeownership relate to various consumer level and regional characteristics. In these analyses, we focus only on borrowers with single homes.

Table 2A regresses whether a borrower with a single home becomes delinquent over the sample period (end of 2007:Q2 to end of 2017:Q4) on consumer and zip code level variables as of end of 2007:Q2. The independent variables are scaled by their standard deviations. Therefore, we can interpret the coefficients as the change in the dependent variable when an explanatory variable changes by one standard deviation. In the table, we progressively add more controls. Column (1) contains all consumer level variables, except for vantage score. Column (2) adds vantage score, and we see that its addition more than doubles the adjusted R-squared. Column (3) adds zip code fixed effects to the variables in Column (2), while Column (4) adds zip code level variables to Column (2). The coefficients, significance levels, and R-squares are similar in Columns (3) and (4), suggesting that our zip code controls account well for zip-code level fixed effects.

In general, we find that consumers who have lower income, are younger, have more debt, and have lower credit worthiness are more likely to become delinquent. In Column (4), we see that consumers living in zip codes with higher unemployment rates, higher mean CLTVs, lower house prices, younger ages, and lower percentages of the population with at least a college education are more likely to become delinquent. In terms of magnitudes, the credit score of the consumer appears the most important for explaining delinquency. These relationships seem quite sensible and are consistent with previous work (e.g., Mian and Sufi 2009, Rajan et al. 2015).

Table 2B provides results from an analogous specification using the probability of foreclosure over the sample period (end of 2007:Q2 to end of 2017:Q4) as a dependent variable, rather than probability of delinquency. Similar to results in Table 2A, borrowers who are younger, have lower incomes, higher debt balance, and lower vantage scores are more likely to suffer foreclosure.

Borrowers who live in zip codes with higher unemployment, lower house prices, younger populations, and smaller percentages of the population with a college education are more likely to become foreclosed. These patterns are also consistent with what is known from previous literature (e.g., Piskorski et al. 2015)

Next, we explore how borrower and regional characteristics relate to the propensity of regaining homeownership after foreclosure, as well as the time it takes to regain a home. In Table 3A we restrict our analysis to borrowers with single homes who experienced a foreclosure to estimate this group's probability of regaining homeownership. Our specifications mirror those in Table 2, with an indicator for whether a borrower who suffered foreclosure regained a home at some point during the sample period (end of 2007:Q2 to end of 2017:Q4) as the dependent variable. Borrowers who have higher incomes, are younger, and have higher vantage scores are more likely to regain a home. Additionally, borrowers who live in zip codes with higher incomes, lower house prices, younger populations, and lower percentages black and Hispanic or Latino are more likely to regain homeownership.

Finally, in Table 3B we investigate the time (in months) it takes to regain a home for borrowers with single homes who both suffered foreclosure and regained homeownership during the sample period (end of 2007:Q2 to end of 2017:Q4). Borrowers who are younger and have higher vantage scores regain homeownership relatively quickly after foreclosure. Looking at debt balances, borrowers with higher mortgage and student debt regain homeownership relatively quickly, while those with higher credit card and auto debt take longer to regain homes. At the zip code level, consumers who live in areas with higher CLTVs, lower unemployment rates, and higher house prices take longer to regain homes while those who live in zip codes with smaller changes in house prices and higher percentages of the population black and Hispanic or Latino regain homeownership more quickly.

Overall, our findings suggest that borrowers who suffered foreclosure and delinquency during the last decade were younger, poorer, less creditworthy, and had more debt than those who did not. In addition, such borrowers were more likely to live in zip codes with lower house prices and lower percentages of the population with a college degree. Finally, we find that borrowers who faced foreclosure and regained homeownership over the last decade were younger and had higher incomes and vantage scores.

V. Slow Recovery Following Great Recession

V.A Regional Patterns of Housing Variables

We now explore spatial variation in the data to investigate the patterns of key economic variables during the financial crisis and the subsequent recovery. We begin by plotting housing variables measured at the regional (zip code) level. Figure 3 shows mean and standard deviation of delinquency and foreclosure rates from 2006 to 2017. Panels (a) and (b) reveal that delinquencies and foreclosures began climbing in 2007 and, on average, reached their highest levels in 2011. These patterns are broadly consistent with what has been reported in academic research and reports by data providers (e.g., by Corelogic).

These figures also illustrate that the recovery of zip codes to pre-crisis foreclosure and delinquency rates was relatively slow, taking several years. This slow recovery is despite the series of massive debt relief and housing stimulus programs that were implemented from the 2008-2009 period onwards and included, among others, a record and persistent low-level interest rates (see Figure 1 for timeline), Quantitative Easing, and HARP (Home Affordability Refinancing Program) and HAMP (Home Affordability Modification Program).

Just as importantly, panels (c) and (d) of Figure 3 show that there was considerable regional heterogeneity in both the severity of the crisis and recovery. In particular, the standard deviation of delinquencies and foreclosures across regions are considerable during the entire time period, reaching their peaks during the height of the crisis in 2011. The regional variation in both delinquency and foreclosure rates decrease after 2011, indicating that as the regions recover from the crisis, heterogeneity across regions also begins to revert to previous levels.

Next, we plot the means and standard deviations of additional regional housing variables -- house prices and CLTV – over the period 2006 to 2017. Panel (a) of Figure 4 plots the mean of the house price index, where the index in each zip code is normalized to 100 in 2006. We see that house prices reached their lowest levels in 2012. Similarly, panel (b) of Figure 4 shows that CLTV reached its highest point in 2011. Consistent with Figure 3, we find that the recovery of house prices and CLTV was slow. Average house prices took approximately four years to recover and

CLTV, while declining since 2012, had not completely reverted to its mean pre-crisis level as of 2017. [17]

Panels (c) and (d) of Figure 4 plot the standard deviation of house prices and CLTV across regions over time. Standard deviation of house prices across regions increases throughout most of the time period, indicating that house price variation across zip codes was increasing, even as regions began to recover from the crisis.[18] On the other hand, the variation of CLTV across regions increased sharply from 2008 until 2011, before decreasing throughout the following years. Despite this decline, the standard deviation of CLTV in 2017 was still higher than its pre-crisis level. Taken together, Figures 3 and 4 suggest that housing variables worsened substantially during the Great Recession and the recovery to pre-crisis levels was sluggish. There was also substantial regional variation in both the severity of the crisis and the following recovery.

V.B Regional Patterns of Durable Consumption and Unemployment

Next, in Figure 5 we explore additional economic variables that we can measure accurately at regional level -- specifically consumption and unemployment levels. Following the literature, we use auto sales at the zip code level from 2006 to 2016 as a measure of durable consumption (see Mian and Sufi 2012) and unemployment rates at the county level from 2006 to 2016. Panels (a) and (b) show that both durable consumption and unemployment rates reach their worst levels in the middle of the financial crisis, with average auto sales at their lowest point in 2009 and mean unemployment rates reaching their peak in 2010. This is consistent with what has been documented in the literature (see Benmelech et al. 2017). Similar to earlier patterns, the recovery to pre-crisis levels was slow with unemployment rates and auto sales taking roughly five and three years to recover, respectively.

In panels (c) and (d) of Figure 5, we see that standard deviations across regions remain considerable throughout the entire time period. Standard deviation of auto sales increased sharply in 2009 and remained high throughout the following years, indicating that regional heterogeneity in auto sales remained substantial even as consumption began to recover. In addition, standard

[17] We note that areas with high CLTV levels during the crisis often correspond to the areas that experienced high house price growth before the crisis. This reflects, in part, a significant amount of home equity extraction in areas that experience rapid house price growth before the bust (Mian and Sufi 2011; Bhutta and Keys 2016).
[18] This evidence is also consistent with empirical literature, which documents significant heterogeneity in local house price movements (Glaeser et al. 2008; Sinai 2013).

deviation in unemployment also jumped during the height of the recession. While these unemployment standard deviations begin to decrease as counties recover to their pre-crisis employment rates, variation remains substantial even in 2016. Overall, these patterns reaffirm the conclusions drawn earlier. There was considerable worsening of economic outcomes during the Great Recession, with significant regional heterogeneity in the severity of the crisis's effects. On average, the reversion of economic variables to their pre- crisis levels took considerable time, with several regions still below their crisis levels.

We end this section by examining the regional evolution of homeownership rates. Figure 6 plots the mean and standard deviation of homeownership rates across states from 2006 to 2017. Homeownership rates across regions declined continuously from 2006 to 2015, after which they appear to increase slightly. Moreover, standard deviation of homeownership rates across regions also increased throughout most of the time period and remained well above pre-crisis levels in 2017. These patterns suggest that recovery on the dimension of homeownership rates was not only slow, but had not completely occurred even a decade after the crisis. Additionally, the heterogeneity of homeownership rates across regions not only increased during the crisis, but also remained high in its aftermath. These findings are broadly in line with the homeownership statistics in Table 1, which show that only 22% of mortgage borrowers with single homes who experienced foreclosure regained a home from 2007 to 2017 and that for those borrowers who regained a home, regaining homeownership took considerable time (around four years).

V.C Evolution of Sluggish Recovery across Regions

While we have visually illustrated the sluggish recovery of different real economic variables during the Great Recession, we now assess the spatial heterogeneity in both the severity of the crisis and the extent of the recovery. We begin by illustrating the intensity of the crisis across regions through a series of heat maps in Figure 7. This figure shows the changes or growths in delinquencies, foreclosures, house prices, auto sales, and unemployment rates across regions from 2007 to 2010. Delinquency rates, foreclosure rates, house prices, and auto sales are measured at the zip code level, while unemployment rate is measured at the county level. These maps allow us to visually examine which areas of the country were impacted the most severely by the crisis.

Panels (a) and (b) of Figure 7 show changes in delinquency rates and foreclosure rates from 2007 to 2010. The majority of zip codes experienced increases in delinquencies and foreclosures, but some zip codes experienced no change and some zip codes actually saw improvements during this time period. Similarly, panel (c) shows that growth in house prices decreased in most areas, with the greatest declines occurring in the coastal areas, particularly Florida and California. Again, we see that the decline in house prices was not universal, with some zip codes experiencing positive growth. Auto sales and unemployment rates follow similar patterns. The vast majority of zip codes saw negative auto sales growth from 2007 to 2010, but some zip codes, mostly located in the Great Plains, saw increasing auto sales. Additionally, unemployment rates increased almost universally, though a few counties experienced decreases. Overall, Figure 7 shows that there was significant spatial heterogeneity in the severity of the crisis, with some regions experiencing dramatic declines in economic conditions and others experiencing little to no effect.

Next, we formally assess the patterns of the crisis and recovery in Table 4. In panel (a) of Table 4, we document the percent of regions at or above their pre-crisis levels in each year from 2007 to 2017, where the pre-crisis period is defined as the mean of a given variable in a region in 2007.[19] Columns (1) and (2) document the recovery of zip code delinquency and foreclosure rates. By definition, 100% of zip codes in 2007 "recovered", since 2007 serves as the base year. Consistent with Figure 3, foreclosure and delinquency rates worsen until 2011. Subsequently, the percent of zip codes that recover to their 2007 level begin to increase. By 2017, 75% and 87% of zip codes had recovered in terms of having 2007 level (low) delinquency and foreclosure rates, respectively.

Column (3) documents the recovery of zip code house prices. The results in this column are consistent with Figure 4. House prices decrease until 2012, after which zip codes begin to recover at an increasing rate. As of 2017, 48% of zip codes had recovered to their pre-crisis house price levels. Column (4) shows a similar pattern for durable consumption, measured by auto sales, with sales reaching their lowest point in 2009. The results are again in agreement with Figure 5 and show that 53% of zip codes had recovered as of 2017. Finally, Column (5) shows the recovery of county level unemployment rates. Here, we see that unemployment worsens quickly and does not begin to significantly improve until 2014, when the percent of recovered counties increases from 4.4% to 15.7%. As of 2016 (the latest available data), only about 41% of counties reverted to their pre-crisis unemployment levels.

[19] The results are very similar when we use means as of 2006 instead of 2007.

Figure 8 presents the findings from panel (a) of Table 4 visually, clearly demonstrating the deterioration in economic conditions due to the crisis and the slow, uneven recovery. Again, we see that both delinquency rates and foreclosure rates increased quickly from 2007 to 2010 in most regions relative to their pre-crisis level. After 2010, delinquency rates and foreclosure rates began to slowly recover. The recovery for house prices, auto sales, and unemployment rates was even more sluggish than the recovery for delinquencies and foreclosures. House prices dropped quickly across zip codes, with a steady but slow recovery from 2012 onwards. Auto sales follow a similar pattern. Finally, we see that unemployment rate had the most dramatic decline and the slowest recovery. In 2009, nearly all counties had higher unemployment rates than their 2007 rates. The recovery in unemployment has been quite slow, with no significant improvement until 2013. Overall, Figure 8 demonstrates, that about half of the zip codes have yet to recover to their pre-crisis levels on a number of key economic dimensions, even ten years after the beginning of the crisis.

Panel (b) of Table 4 formally investigates the time it takes recovered regions to return to their pre-crisis levels among those regions that have already recovered. In measuring this time, we start from 2010 since various stimulus programs were already implemented by this year, as Figure 1 shows. As can be observed from Columns (1) and (2), delinquency rates and foreclosure rates take an average of 3.65 and 3.15 years to recover from the end of 2010. Column (3) shows that auto sales take an average of 3.19 years to return to their pre-crisis levels after 2010. Similarly zip codes took an average of 5.3 years from 2010 to return to their 2007 house price levels and counties took an average of 4.9 years to recover to pre-crisis unemployment rates.[20]

To show the spatial heterogeneity in the recovery, we next present another set of heat maps in Figure 9. Specifically, we consider whether a region has recovered to its pre-crisis level ten years after the start of the crisis. The dark color indicates that the region has not recovered to its pre-crisis (2007) level and the light color indicates that it has recovered. Panels (a) and (b) show that most zip codes had recovered in foreclosure rates and delinquency rates by 2017. Still, we see that the recovery was not universal, with some zip codes remaining worse off than they were in 2007. Panel (c) shows that recovery in house prices has been slower, with many zip codes below their

[20] Notably, standard deviations for recovery times are nontrivial, ranging from 1.02 to 1.88. These standard deviations indicate significant heterogeneity in recovery time across regions, with some regions recovering relatively quickly and others taking longer to revert to pre-crisis levels. These patterns are consistent with our earlier discussion.

2007 house price levels. While these zip codes are scattered across the country, they are concentrated in areas that experienced the largest decreases in house price growth according to Figure 7, such as Florida, California, and the northeast region. Similarly, Panel (d) shows that the recovery of consumption has been mixed, with many regions remaining below their pre-crisis auto sales. Panel (e) demonstrates that the recovery of unemployment rate has been the slowest, with large sections of the country remaining dark. Appendix A1 provides more detailed heat maps of the extent of the recovery across regions.

We conclude this section by investigating how the extent of the recovery relates to the extent of pre-crisis housing boom. To shed light on this question, we estimate a series of simple regressions where the dependent variables are dummy variables that take on the value of 1 if a zip code recovered on a given dimension and 0 otherwise and the explanatory variable is the regional house price growth in the pre-crisis period (2003 to 2007). Table 5 presents these results. As we observe from Table 5, zip codes that experienced higher pre-crisis house price growth are less likely to subsequently recover from the crisis in terms of foreclosures, delinquencies, house prices, and durable spending (though the last estimate is statistically insignificant). Finally, we also find that counties experiencing a higher pre-crisis house price growth are less likely to recover in terms of their employment level.

Taken together, this section illustrates that the recovery, like the crisis itself, was heterogeneous across regions. Some regions were almost completely unaffected by the crisis, and of those that were affected, some regions recovered nearly immediately while others have still have not recovered. Many regions that recovered experienced a sluggish recovery that spanned several years.

VI. What Explains Slow Recovery?

VI.A Frictions to Stimulus and Debt Relief

We have documented that the recovery from the financial crisis was slow and heterogeneous. The sluggish recovery was despite the fact that large and unprecedented stimulus and debt relief measures, such as the Home Affordability Refinancing Program (HARP), the Home Affordable Modification Program (HAMP) and Quantitative Easing (QE) were enacted beginning in early 2008 to mid of 2009 (Figure 1). To better understand the forces that may have prevented or delayed stimulus and debt relief from reaching millions of distressed households, we focus on three potential frictions identified in the prior literature (Agarwal et al. 2015 and 2017; Di Maggio et al. 2017): the share of loans in a region that are of ARM type, the share of loans in a region that are eligible for HARP, and the share of loans in a region serviced by intermediaries who have high organizational capacity to renegotiate loans.

The first friction we consider is contract rigidity, i.e., the percentage of loans in a zip code that are adjustable rate mortgages (ARM). Previous work has highlighted that rigidity of fixed rate mortgages (FRMs), in contrast to more flexible ARMs, hampers the pass-through of debt relief during periods of low interest rates. In particular, Di Maggio et al. (2017) show that the reduction of interest rates during the Great Recession provided borrowers with certain types of ARMs an automatic debt relief, which was not available to households with FRMs. Moreover, there was spatial variation in the response to the debt relief and regions with a larger share of ARM borrowers experiencing declines in foreclosure rates, faster recoveries in house prices, increased durable (auto) consumption, and increased employment growth.[21] As such, we expect that regions with high shares of ARM loans recover at higher rates and more quickly than those with higher percentages of the more rigid FRMs.

Next, we consider the friction that involves refinancing of insufficiently collateralized mortgages with government credit guarantees (agency loans). This friction is particularly relevant for households with FRMs, the predominant financial obligation of U.S. households, since they do not receive the automatic debt relief experienced by ARM borrowers. Instead, such households rely primarily on refinancing to receive debt relief from the low interest rate environment induced by monetary policy. Many of these households were left with little equity as house prices dropped during the Great Recession, making them ineligible for loan refinancing that requires a certain amount of borrower equity (see Beraja et al. 2017).[22] Agarwal et al. (2015) find that by relaxing the equity constraint for refinancing, HARP led more than three million borrowers to refinance their loans and savings from debt relief resulted in purchase of durable goods, such as autos. Moreover, regions more exposed to HARP experienced relative increases in consumer spending,

[21] These findings also consistent with Auclert (2017), who presents a model evaluating the role of redistribution in the transmission of monetary policy to consumption, which implies that the effect of monetary policy shocks on consumer spending would be significantly higher if all U.S. mortgages were ARMs.
[22] See also Di Maggio et al. (2016) who document refinancing patterns during the QE period.

declines in foreclosure rates, and faster recoveries in house prices.[23] Thus, we expect regions with higher shares of HARP eligible borrowers to be more likely to recover from the crisis and do so relatively quickly.[24]

In addition to refinancing, renegotiation of their loans is another channel through which borrowers can obtain debt relief. The U.S. economy experienced limited loan restructuring during the crisis, despite the surge in distressed borrowers, due to various frictions.[25] Motivated by such frictions and perceived negative externalities of debt overhang and foreclosures, the federal government implemented HAMP which provided financial intermediaries ("servicers") with substantial financial incentives for renegotiating loans. Agarwal et al. (2017) study the effects of this program and find that intermediary specific factors impacted the extent of debt relief that was passed to households (and regions), with certain intermediaries having the organizational ability to renegotiate loans significantly more than other. Exploiting regional variation in the intensity of program implementation by intermediaries suggests that the program was associated with relatively lower rate of foreclosures, consumer debt delinquencies, house price declines, and an increase in durable spending in areas where the program was implemented more intensively.[26] These findings suggest that the share of loans serviced by intermediaries with high organizational capacity to renegotiate ('High Capacity share') might impact recovery and the speed at which regions recover from the crisis.

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[23] For recent quantitative models emphasizing the importance of housing and refinancing for household consumption, see, among others, Chen et al. (2014), Beraja et al. (2017), Guren et al. (2017, 2018), Berger et al. (2017, 2018), Wong (2018), Greenwald (2018), Eichenbaum et al. (2018),

[24] Agarwal et al. (2015) also documents a spatial variation in these effects, depending on the degree of competitiveness in the refinancing market. These findings resonate well with those of Scharfstein and Sunderam (2016)—and also with those of Drechsler et al. (2017)—who show that the extent of the pass-through of low interest rates in the refinancing and bank deposit market is affected by the degree of competition. They are also broadly connected with the findings of Agarwal et al. (2018) and of Benmelech et al. (2017) who demonstrate the importance of financial intermediaries for the pass-through of interest rate shocks in the credit card and auto loan markets. Finally, we note that the demand-driven factors, such as borrower inertia and inattention, can also limit the extent of interest rate pass-through through mortgage refinancing. For recent evidence on these factors, see Agarwal et al. (2016), Keys et al. (2016); and Andersen et al. (2017).

[25] Research attributes the lack of restructuring activity to lender concerns about future moral hazard by borrowers and the inability of lenders to evaluate the repayment ability of borrowers (Mayer, Morrison, Piskorski and Gupta 2014; Adelino, Gerardi, Willen 2014) and institutional frictions due to securitization that prevented renegotiation (Piskorski, Seru and Vig 2010, Agarwal et al. 2011, Kruger 2017, Maturana 2017).

[26] Ganong and Noel (2017) further show that temporary mortgage interest rate reductions induced by HAMP played an important role in accounting for these effects.

Figure 10 plots the regional heat maps of the ARM share, HARP eligible share, and high capacity share in each zip code. Panel (a) shows that there is a large spatial variation in the ARM share of mortgages in a zip code. This implies that the "automatic" pass through of low interest rates is differentially passed through across regions. Similarly, Panel (b) illustrates the significant regional heterogeneity in the fraction of loans eligible for HARP, suggesting that debt relief through refinancing was less likely in some regions than others.[27] Finally, Panel (c) shows significant regional variation in the share of intermediaries with organizational design that is conducive for renegotiation, suggesting that the debt relief through a program like HAMP was differentially passed through across zip codes. Next, we formally investigate the role that these frictions played in the slow recovery from the crisis by estimating a series of regressions.

VI.B Regression Analysis

We implement a series of regressions that analyze the change in zip code outcomes after the major interventions in the housing market. As noted earlier, by 2010 various debt relief programs, including HARP, HAMP, and QE had been implemented and a firm commitment to the prolonged low interest rate policy had been confirmed. Consequently, we assess how various economic variables changed in period 2010-2016 relative to the period 2007-2009.

There are number of notable differences between our analysis in this section and prior work in this area. First, our study is the first to considers the role of these three potential frictions to debt relief together.[28] Second, due to the longer time-series data we can investigate the association of these factors with the extent of economic recovery and the presence of such effects at a much longer horizon than the prior literature. This also allows us to conduct simple counterfactual exercises on the impact of such frictions on the extent and the speed of recovery. Finally, in all of our regressions we account not only for a richer array of zip code characteristics, but also for the net changes in population across regions due to mobility, including the mobility associated with foreclosures. Without accounting for mobility, our inferences on economic variables such as

[27] We note that there are two main sources of variation in HARP eligible share. First, areas where house prices declined more will have more loans eligible for HARP since to be eligible for HARP borrowers need to have updated loan-to-value ratio in excess of 80%. Second, areas with a larger share of loans guaranteed by the GSEs will have more loans eligible for HARP since non-GSE loans were not eligible for the program. Note that in our regional regression we control for regional house price patterns.

[28] The only exception is Piskorski and Seru (2018) who perform partial analysis of such form but only applied to delinquency and foreclosure rate.

consumption could be easily confounded by net inflows or outflows during the sample period, especially since mobility is quite high and heterogeneous across different consumers (Table 1).

Table 6 presents several key zip code summary statistics. Panel (a) shows means and standard deviations of socio-economic variables at the zip code level. The first three columns provide information for all available zip codes, while the last three columns are limited to the subset of zip codes used in our regressions, which are constrained by information on variables where we have information on frictions. Panel (b) of Table 6 shows the means and standard deviations of these friction variables. The first three columns are based on all the zip codes we have data for while the last three columns report information for zip codes used in the regressions. Both panels (a) and (b) suggest that means and standard deviations are comparable between all zip codes and the restricted subset used in regressions.

In Tables 7 to 11, we present the results from specifications of the form:

$$Y_{i,after} - Y_{i,before} = \alpha + \beta F_i + \mu X_i + \epsilon_i \qquad (1)$$

where $Y_{i,after}$ is the mean zip code outcome after the implementation of various stimulus and debt relief policies (2010 to 2016) in zip code i and $Y_{i,before}$ is the mean outcome in the same zip code in the period before these interventions (2007-2009). The vector F_i includes our empirical measures of debt relief frictions at a region i level. The vector X_i accounts for several zip code i level controls that include the mean vantage, CLTV, education level, racial composition, percent married with children, net gain in total population, and net gain in population experiencing foreclosure. The net gain in total population for zip code i is defined as the difference between the percentage of people who moved into zip code i from June 2007 to December 2017 and the percentage of people who moved out of i during the same time period. Similarly, the net gain in population experiencing foreclosure is defined as the difference between the percentage of people who moved into zip code i and experienced foreclosure and the percentage of people who moved out of i and faced foreclosure. This measure is useful, as it allows us to investigate the mobility patterns of borrowers who suffer foreclosures.

Table 7 reports the results for zip code delinquency rate change. To be precise, the independent variable is the difference between the mean zip code quarterly delinquency rate change in 2010 to 2016 period and the mean zip code quarterly delinquency rate change from 2007 to 2009. Column

(1) includes ARM share and all zip code controls. Column (2) includes HARP eligible share and all zip code controls. Column (3) includes High Capacity share and all other zip code controls. Finally, in Column (4) we include all controls and add ARM share, HARP eligible share, and high capacity share simultaneously.

In Columns (1) through (3), we see that when regressed independently, ARM share, HARP Eligible share, and high capacity share are negative, indicating that zip codes with higher shares of ARM, high capacity servicers, and HARP eligible loans experience faster declines in delinquency during the stimulus period relative to less exposed areas. We note the coefficients on these variables are both statistically and economically significant, even after controlling for a variety of neighborhood characteristics and mobility patterns. In Column (4), putting all these measures together, we continue to observe highly significant and negative coefficient estimates for these variables.

Next, Table 8 reports similar results for the change in zip code foreclosure rate. Here, the dependent variable is the difference between mean zip code quarterly foreclosure rate change during the 2010-2016 period and the 2007-2009 period. Again, we see that when regressed independently, the coefficients on HARP eligible share, ARM share, and high capacity share are negative and highly significant. Even more notably, the coefficients remain highly significant and negative in Column (4), when all three frictions are included in the regressions. These results are striking, as even when controlling for observables and population changes, regions with higher HARP eligible shares, ARM shares, and high capacity shares experience faster recoveries in foreclosure growth. These findings resonate well with what has been established in prior work (e.g., Agarwal et al. 2015, 2017; Di Maggio et al. 2017)

Table 9 provides the results from regressions of the change in zip code house price growth rates, where the dependent variable is the difference between mean zip code house price growth in each period. When regressed separately, the coefficients on ARM share, HARP eligible share, and high capacity share are positive and highly significant, indicating that zip codes with higher shares experienced faster increases in house price growths. Again, Column (6) includes all three variables, and we see that even when included together, the variables remain positive and significant.

The results for changes in zip code consumption growth rates in Table 10 (measured by auto sales) are similar. When regressed independently, the coefficients on ARM share, HARP eligible share, and high capacity share are positive and significant, indicating a relative increase in auto sales growth for zip codes with higher shares of these variables during 2010-2016 period relative to less exposed areas. Finally, when all three variables are included in Column (4), the signs on ARM share and HARP eligible share remain positive and significant. The coefficient on high capacity share becomes negative, but we note that it is insignificant.

Finally, Table 11 reports the results for changes in zip code unemployment rate. Zip code unemployment rate comes from the U.S. Census Bureau 5-year estimates, so the dependent variable in these regressions is the difference between mean unemployment rate from 2012 to 2016 and the mean unemployment rate from 2007 to 2011. In Columns (1) through (3), the coefficients are highly significant and negative. These results indicate that zip codes with higher ARM shares, HARP eligible shares, and high capacity shares experience relatively faster improvements in unemployment rates during the stimulus period. In Column (4), we see that the coefficients on ARM share and HARP eligible share remain both negative and highly significant. The coefficient on high capacity share is no longer significant, but it remains negative.

VI.C Simple Counterfactuals

We now conduct several simple counterfactual exercises to estimate the effects of reducing the frictions to debt relief on the speed of regional recovery. First, we consider the impact of increasing ARM share, HARP eligible share, and High capacity share by one standard deviation on the decline in foreclosure growth rates. From Table 6, the mean ARM share in zip codes is 23.06%, with a standard deviation of 8.93. From Column (4) of Table 7, we see that increasing mean ARM share from 23.06% to 31.99% (a one standard deviation increase) would result in a reduction of the post-intervention mean delinquency change from -0.78 to -1.73, implying that the reduction in delinquency rates would be about twice as fast. Similar calculations show that if the share of borrowers eligible for HARP increased by one standard deviation from 24.59% to 36.43%, the 2010-2016 period delinquency rate changes would be 0.25 lower, implying about one third faster recovery. If high capacity share increased by one standard deviation from 22.5% to 28.0%, the mean delinquency rate changes in the post period would decrease from -0.77 to -0.97, resulting in about a quarter faster recovery. We replicate this counterfactual analysis for foreclosure rate changes and find comparable results. A one standard deviation decrease increase in ARM share and one standard deviation increase in high capacity share leads to a recovery that is about 2.6 times and 50% faster, respectively. Similarly, increasing HARP share by one standard deviation results in a 23% faster recovery.

Next, we replicate this counterfactual analysis for house price growth rates, consumption growth rate, and unemployment change. The speed of house price growth increases by 2.8 times, about 2.2 times, and about 27% for one standard deviation increases in ARM share, HARP eligible share, and high capacity share, respectively. For changes in consumption growth rates, we only consider the impact of increasing ARM share and HARP eligible share, since the coefficient on high capacity share is insignificant. We find that increasing ARM share by one standard deviation would result in about 23% relative increase in the auto sales growth and increasing the share of borrowers eligible for HARP would lead to about 6.5% relative increase in the auto sales growth. Finally, we look at the effects of increasing these shares on the change in unemployment rate. We find that the decrease in the unemployment rate would be 16%, 38%, and 6% larger in relative terms if ARM share, HARP eligible share, and high capacity share were increased by one standard deviation, respectively.

Taken together, Tables 7 through 11 show that zip codes with higher ARM share, HARP eligible share, and high capacity share experience faster recoveries in delinquency growth, foreclosure growth, house price growth, auto sales growth, and unemployment rates. By conducting counterfactual analysis on the results from these regressions, we estimate how the speed of recovery would change if we increased ARM share, HARP eligible share, and high capacity share by one standard deviation. In general, we find that increasing ARM share leads to the largest differential reduction in recovery times, which is not surprising since the pass-through of the low interest rate stimulus is automatic in the case of ARMs. HARP eligible share and high capacity share also have a sizeable impact. Increasing these shares has a large impact on the relative recovery times of foreclosures, delinquencies, house price growth, and unemployment rate. The impact is smaller, though nontrivial, on the recovery of auto sales (depending on the specification).

We note that due to the nature of our empirical setting, we are not able to quantity an economy-wide effects of relaxing the debt relief frictions and just compare the evolution of economic outcomes in areas more exposed to debt relief *relative* to less exposed areas. To the extent that debt relief has positive economy-wide effects on the speed and extent of economic recovery the above exercise may underestimate the overall impact of relaxing debt relief frictions.

VII. Summary and Discussion

VII.A Summary

We follow a representative panel of millions of consumers in the U.S. from 2007 to 2017 to document several facts on the long-term effects of the Great Recession. The crisis induced an unprecedented six million forecloses over a decade after the collapse of Lehman. Owners of multiple homes accounted for 25% of foreclosures, despite accounting for only 13% of the market. Foreclosures displaced homeowners, with most of these borrowers moving at least once. Only one quarter of foreclosed households regained homeownership, taking an average of four years to do so.

Despite massive stimulus and debt relief policies, recovery is slow and varies dramatically across regions. House prices, consumption and unemployment have still not reached pre-crisis levels in about half the zip codes in the U.S. Those that recovered took on average of four to five years from the depths of the Great Recession to return to their pre-crisis levels. Regional variation in the speed of recovery can be explained to a significant degree by contract rigidity, refinancing constraints, and the organizational capacity of financial intermediaries to conduct renegotiations. A simple counterfactual based on our estimates suggests that regardless of the narratives of the causes of the housing boom and bust, alleviating these frictions could have reduced a large number of foreclosures and resulted in a significantly faster recovery of house prices and employment. This evidence suggests that a variety of frictions in the design of the market and the intermediation sector significantly hindered the pass-through of lower rates and various debt relief measures to households and the real economy.[29]

[29] It is useful to compare the severity of the Great Recession with that of the Great Depression. Between the peak and the trough of the Great Depression, real GDP fell 30%, which is about 10 times more severe than the drop during the Great Recession. Wheelock (2008) reports that the fraction of loans in foreclosure peaked at about 13% in 1933, which is more than four times larger than the foreclosure rate peak of 2010 (see panel (b) of Figure 3). It is possible that a more aggressive policy response during the Great Recession, along with other institutional differences, alleviated the severity of the Great Recession compared to the experience of Great Depression. In this regard, our evidence suggests that the Great Recession would have been even less severe if a number of frictions affecting the pass-through of low interest rates and debt relief measures to households were alleviated.

Overall, our findings underscore the central role of the housing sector in explaining the dynamics of the crisis and the subsequent long-drawn recovery. They also highlight the central role of household balance sheets and mortgage market rigidities in the transmission of monetary policy and debt relief measures onto real economy.

VII.B Macro-Prudential Polices, and Mortgage Market Design

There are number of lessons that emerge from our analysis. First, a significant body of work has debated various narratives for the buildup in household debt and increase in house prices *prior* to the crisis. This includes the role played by credit supply, optimistic beliefs, and the overall decline in interest rates (e.g., Mian and Sufi 2009 and 2018; Keys et al. 2010 and 2013; Adelino et al. 2016; Guerrieri and Uhlig 2016; Kaplan et al. 2017; Favilukis et al. 2017; Gennaioli and Shleifer 2018). In this regard, our analysis suggests that *regardless* of the causes of the housing boom and its subsequent bust, the crisis would have been much less severe if some specific frictions in the financial intermediation sector affecting the pass-through of lower rates and debt relief measures had been alleviated.

Our evidence, combined with prior work, suggests a number of approaches that could alleviate the impact of such frictions. These involve both ex-ante and ex-post solutions that are aimed at a more efficient sharing of aggregate risk between borrowers and lenders when crisis occurs.[30] We note that such solutions could also have a positive impact on financial stability by lowering the extent of foreclosures with their associated deadweight losses (see Cochrane 2014 for a discussion of solutions aimed at making financial system more "run-free").

One solution is to rely on the mortgage market design literature that demonstrates that ex-ante solutions, such as automatically indexed mortgages and policies, can facilitate a quick implementation of debt relief during a crisis (e.g., Piskorski and Tchistyi 2010, 2011, 2017; Eberly and Krishnamurthy 2014; Guren et al. 2017; Greenwald et al. 2018; Campbell et al. 2018, Piskorski

[30] A number of proposals argue for more efficient risk-sharing between borrowers and lenders to lower the incidence of costly foreclosures and the severity of future housing market downturns (Shiller 2008; Caplin et al. 2008; Piskorski and Tchistyi 2011; Campbell 2013; Keys et al. 2013; Mian and Sufi 2014a; Eberly and Krishnamurthy 2014, Piskorski and Seru 2018). These proposals start from the premise that the current risk-sharing arrangement between borrowers and lenders in the mortgage market particularly relies on an option to default that can induce a large number of foreclosures during a crisis, with significant associated deadweight losses.

and Seru 2018).[31] Such indexation solutions need to take into account their impact on the market equilibrium, including the incentives of households to borrow and repay their debt.[32] Empirically relevant informational asymmetries and other frictions may limit the set of state-contingent contracts that are sustainable in market equilibrium. Risk aversion and other constraints may also curtail the ability of financial intermediaries to insure the aggregate risk, limiting the effectiveness of state-contingent mortgages or debt relief policies. The mortgage design literature demonstrates that, even taking such complications into account, contracts and policies that temporarily reduce mortgage payments during recessions can potentially result in significant welfare gains by preventing costly foreclosures and providing consumption-smoothing to households. To the extent possible, it would be beneficial to index mortgage payments to measures that capture the state of the *local housing* and *labor* markets. This would allow mortgage payments to be lower in states of the world when *both* local labor markets and housing markets experience a downturn.[33] Interest rate indexation, such as adjustable-rate mortgages (ARMs), may also perform quite well in providing household debt relief during downturns, as long as such indices closely co-move with borrowers' house price and income.[34]

One should be careful, however, not to overstate the benefits of typical ARM contracts in providing effective household debt relief during economic downturns. First, the ability of mortgages indexed to national-level rate indexes to serve as effective debt relief also depends on the nature of monetary policy. In this regard, there were periods in the past, when interest rate indexes reached high levels during an economic downturn (e.g., the stagflation episode). A system with a larger share of ARMs could also complicate the central bank's price stability objective, given that increases in interest rates can be highly unpopular with homeowners, creating political pressure to keep rates low for an extended period (Campbell 2013). Moreover, the significant regional

[31] Such indexation programs need to take into account their impact on the market equilibrium, including the incentives of households to borrow and repay their debt. Empirically relevant informational asymmetries and other frictions may limit the set of state-contingent contracts that are sustainable in market equilibrium. Risk aversion and other constraints may also curtail the ability of financial intermediaries to insure aggregate risk, limiting the effectiveness of state-contingent mortgages or debt relief policies.

[32] Because debt relief solutions provide a form of insurance to households against economic downturns, the borrowers can respond to them by increasing their "ex-ante" debt levels and lowering their voluntary repayment rates, which can limit the effectiveness of such solutions.

[33] We note that current unemployment insurance programs implicitly provide a form of labor income indexation, which can help distressed households service their mortgage debt obligations (see Hsu et al. 2018).

[34] We note that interest rate indexation coupled with other options (e.g., ARMs with flexible mortgage repayments or FRMs convertible to ARMs) may further increase the effectiveness of such solutions (see, Piskorski and Tchistyi 2010, Eberly and Krishnamurthy 2014; Guren et al. 2017; Campbell et al. 2018).

heterogeneity indicates that one-size-fits-all contract indexation based on national-level variables may reduce the effectiveness of such solutions (see Piskorski and Seru 2018).[35]

An alternative approach to alleviate frictions related to the implementation of debt relief is to leave the structure of the mortgage contracts intact and instead rely on the design of large-scale post-crisis government programs that hope to spur refinancing and loan restructuring, such as HARP and HAMP, and on monetary policy. As we discussed above, however, various implementation frictions—including the nature of mortgage contracts and the ability of financial intermediaries to quickly implement debt relief as well as political constraints—can hamper the effectiveness of such ex post solutions.

Wide-scale refinancing programs, such as HARP, may be easier to implement because they stimulate a more routine activity like refinancing rather than loan renegotiation. However, because the implementation of such programs is through intermediaries, their effectiveness is impacted both by intermediary frictions, such as capacity constraints, and market design, such as competition in the refinancing market (Agarwal et al. 2015; Fuster et al. 2017). Such programs also critically rely on the ability of the government to guarantee mortgage debt during a crisis (for example, through the GSEs). A simple way to address some of the implementation frictions of such polices would be to allow contracts that automatically relax housing equity refinancing constraints in regions that experience sufficient declines in house prices.[36]

Similarly, programs aimed at stimulating mortgage renegotiation activity, such as HAMP, were hampered because it was difficult to transfer distressed mortgages to intermediaries who had the organizational capacity to conduct renegotiations. A simple way to address this issue would be to rely more heavily on “special servicers”, as is common in the commercial real estate market. Upon the occurrence of certain specified adverse events, contracts could automatically allow transfer of distressed loans to intermediaries that are better equipped to carry out renegotiations.

It is worth iterating that there is an important trade-off in the *design* and *implementation* challenges of ex-ante and ex-post debt relief solutions (Piskorski and Seru 2018). The ex-ante designed

[35] The quantitative life cycle models of households’ decisions also emphasize the importance of recognizing a specific nature of household risk for an appropriate mortgage contract choice (see Campbell and Cocco 2003 and 2015).
[36] An alternative approach to decrease the likelihood and costs of future housing crises is preventing households from becoming highly leveraged in the first place (see DeFusco et. 2017 for a recent analysis of such polices).

indexed mortgage contracts have the advantage of circumventing financial intermediary and other fictions and facilitating a quick ("automatic") implementation of debt relief during economic downturns. However, for such contracts to be effective, lenders, policymakers, and borrowers may need a good ex-ante understanding of the underlying distribution of risk and its relation to the indexes used when designing and choosing such state contingent contracts. Errors in beliefs about the structure of risk can reduce the benefits of such solutions. Given the documented vast heterogeneity in the nature of risk across space and time (e.g., Hurst et al. 2016; Beraja et al. 2017; Piskorski and Seru 2018), such errors are likely.[37]

On the other hand, ex-post debt relief solutions have the advantage of being more fine-tuned to the specific realization of economic risk. However, as our analysis and discussion illustrates, these solutions are subject to various implementation frictions that could significantly hamper the effectiveness of debt relief.

Our findings also suggest that macro-prudential polices should not only focus on monitoring and reacting to the buildup of risk in the economy. These polices should also recognize various factors and frictions in the household sector that can affect the transmission of debt relief and monetary policy to households and real economy after the crisis unfolds.

Finally, because GSEs are likely to dominate the residential lending market at least in the short to medium terms (Buchak et al. 2018a), a more resilient, redesigned mortgage system would likely require their active participation. They have certainly played a central role in financing the ever growing shadow bank sector that is dominated by "fintech" lenders such as Quicken (see Buchak et al. 2018a and Fuster et al. 2018). GSE presence in the lending landscape can also significantly alter the transmission of various shocks and macro-prudential stabilization polices through the housing sector (see Buchak et al. 2018b). Whether their presence would alleviate the various coordination and implementation hurdles of moving to a new mortgage market architecture remains an open area for discussion and research.

[37] In addition, a major change in the nature of mortgage contracts or housing policy can significantly alter relationships between market equilibrium outcomes on its own in a way that is potentially hard to quantify.

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Table 1: Descriptive Statistics

Panel (a) provides summary statistics for all consumers who are present in the data from Q2:2007 to Q4:2017. Columns (1)-(2) summarize all consumers, (3)-(6) summarize borrowers with single homes, and (7)-(10) summarize borrowers with multiple homes. Columns (5)-(6) and (9)-(10) summarize consumers who suffer foreclosure from June 2007 to December 2017 while columns (3)-(4) and (7)-(8) summarize consumers who do not experience foreclosure during this time period. Odd columns contain means while even columns contain standard deviations. All the variables are taken as of June 2007. Panel (b) shows a set of outcome variables for various subsets of consumers in this sample that occurred during Q2:2007 to Q4:2017. Panel (c) provides aggregate statistics on delinquencies and foreclosures in the U.S. economy from June 2007 to December 2017 implied by Panel (a) and (b). Column (1) estimates the total number of mortgage borrowers, mortgage borrowers with single homes, and mortgage borrowers with multiple homes in the U.S. economy. Columns (2) and (4) show the delinquency and foreclosure rates for each set of borrowers. Columns (3) and (5) estimate the total number of delinquencies and foreclosures in the economy. These numbers are calculated by multiplying the total number of borrowers by the corresponding delinquency or foreclosure rate. *Source:* Data comes from Equifax 10% representative sample of the U.S. credit population.

Panel A: Consumer-Level Summary Statistics

	All Consumers		Borrowers with Single Home				Borrowers with Multiple Homes			
			No Foreclosure		*Foreclosure*		*No Foreclosure*		*Foreclosure*	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Age	51.09	21.25	54.19	17.79	45.98	15.75	56.02	17.42	48.68	15.95
Income	40,941	17,150	48,960	16,387	41,939	13,429	60,110	22,117	54,093	19,339
Vantage	707.19	100.18	725.15	87.01	641.48	85.55	722.86	79.42	648.59	85.37
Fraction with Mortgage	0.3043	0.4601	-	-	-	-	-	-	-	-
Fraction of Borrowers with Multiple Homes	0.1315	0.3379	-	-	-	-	-	-	-	-
Number of First Mortgages (Borrowers)	1.1826	0.6335	-	-	-	-	2.3149	1.0082	2.6878	1.6495
First Mortgage Balance	185,440	222,852	147,772	136,462	190,509	145,887	372,090	404,266	608,539	597,717
Combined Mortgage Balance	187,098	237,069	160,299	150,448	212,413	167,169	398,543	435,014	212,413	167,169
Fraction with Nonzero Revolving Debt	0.7287	0.4447	0.7922	0.4057	0.7966	0.4025	0.8250	0.3800	0.8295	0.3761
Revolving Debt Balance (Nonzero Accounts)	5,625	9,444	6,886	10,430	9,815	13,356	8,817	13,300	11,920	16,357
Fraction with Nonzero Auto Debt	0.3241	0.4681	0.4460	0.4971	0.5493	0.4976	0.4638	0.4987	0.5370	0.4986
Auto Debt Balance (Nonzero Accounts)	15,747	14,524	16,664	14,551	20,018	16,627	19,728	19,506	23,419	22,843
Fraction with Nonzero Student Debt	0.1612	0.3677	0.1089	0.3115	0.1675	0.3734	0.1020	0.3013	0.1364	0.3432
Student Debt Balance (Nonzero Accounts)	19,946	26,889	22,310	29,285	22,891	29,018	24,345	31,218	25,171	32,015
Number of Consumers	13,558,277		3,274,209		309,767		434,704		107,756	

Table 1: Descriptive Statistics [Continued]

Panel B: Consumer-Level Outcome Variables

Outcome Variable	Mean
% Seriously Delinquent (All Consumers)	9.4%
% Seriously Delinquent (All Mortgage Borrowers)	24.3%
% Seriously Delinquent (Mortgage Borrowers with Single Home)	22.6%
% Seriously Delinquent (Mortgage Borrowers with Multiple Homes)	35.9%
% Seriously Delinquent (Mortgage Borrowers, Bottom 10% of Credit)	71.7%
% Foreclosed (All Consumers)	3.9%
% Foreclosed (All Mortgage Borrowers)	10.1%
% Foreclosed (Mortgage Borrowers with Single Home)	8.6%
% Foreclosed Delinquent (Mortgage Borrowers with Multiple Homes)	19.8%
% Foreclosed Delinquent (Mortgage Borrowers, Bottom 10% of Credit)	25.0%
Time to Foreclosure (All Foreclosed Borrowers)	18.0 months
Time to Foreclosure (Foreclosed Borrowers with Single Home)	17.7 months
Time to Foreclosure (Foreclosed Borrowers with Multiple Homes)	18.8 months
Time to Foreclosure (Foreclosed Borrowers, Bottom 10% of Credit)	26.4 months
% Moved (All Consumers)	40.6%
% Moved (Mortgage Borrowers with No Foreclosure)	30.3%
% Moved (Mortgage Borrowers with Foreclosure)	59.4%
% Regained Homeownership (Among Foreclosed)	22.7%
Time to Regain Homeownership (in months)	47.1 months

Panel C: Aggregate Delinquency and Foreclosure Statistics

	(1) Number	(2) Delinquency Rate	(3) Number of Delinquencies	(4) Foreclosure Rate	(5) Number of Foreclosures
Mortgage borrowers (All)	56,293,952	24.3%	13,714,086	10.1%	5,691,319
Mortgage borrowers with single home	48,893,567	22.6%	11,055,607	8.6%	4,224,404
Mortgage borrowers with multiple homes	7,400,386	35.9%	2,658,479	19.8%	1,469,717

Table 2A: Probability of Delinquency for Borrowers with a Single Home

This table reports the results from regressions of whether a borrower with a single home became delinquent on various borrower and ZIP code level variables. Delinquency is defined as 60 days past due on payment or worse. Column (1) contains all borrower level variables, except vantage score. Column (2) adds individual vantage score. Column (3) contains all variables from Column (2) and adds zip code fixed effects. Column (4) contains all borrower level variables from Column (2) and adds zip code level controls. Controls include zip code house price levels and CLTV in 2007, median household income, unemployment rate, median age, percent married with children, percent with college education, percent with high school education, percent white, percent Hispanic or Latino, and percent white. House price levels are taken as of 2007 and the remaining controls are averages of the years 2007 to 2011. Regression inputs are scaled to have a standard deviation of one. Standard errors are reported in parentheses. *Sources:* Individual delinquency status, income, age, and CLTV come from Equifax. House price data come from Zillow. The remaining variables come from the U.S. Census Bureau American Community Survey 5-Year Estimates.

	(1)	(2)	(3)	(4)
Individual Income	-0.181	-0.040	-0.032	-0.032
	(0.000)	(0.000)	(0.000)	(0.000)
Individual Age	-0.029	-0.001	-0.004	-0.003
	(0.000)	(0.000)	(0.000)	(0.000)
Combined Mortgage Balance	0.115	0.051	0.047	0.047
	(0.001)	(0.000)	(0.000)	(0.000)
Credit Card Debt	0.368	-0.573	-0.573	-0.570
	(0.006)	(0.005)	(0.005)	(0.005)
Auto Debt	0.032	0.007	0.007	0.006
	(0.000)	(0.000)	(0.000)	(0.000)
Student Debt	0.006	-0.002	-0.001	-0.002
	(0.000)	(0.000)	(0.000)	(0.000)
Vantage Score		-0.228	-0.224	-0.224
		(0.000)	(0.000)	(0.000)
Zip Code Fixed Effects	No	No	Yes	No
Zip Code Controls	No	No	No	Yes
Observations	1,234,247	1,234,247	1,234,247	1,234,247
Adjusted R-squared	0.152	0.348	0.365	0.361

Table 2B: Probability of Foreclosure for Borrowers with a Single Home

This table reports the results from regressions of whether a borrower with a single home suffered foreclosure on various borrower and zip code level variables. Column (1) contains all borrower level variables, except vantage score. Column (2) adds individual vantage score. Column (3) contains all variables from Column (2) and adds zip code fixed effects. Column (4) contains all borrower level variables from Column (2) and adds zip code level controls. Controls include zip code house price levels and CLTV in 2007, median household income, unemployment rate, median age, percent married with children, percent with college education, percent with high school education, percent white, percent Hispanic or Latino, and percent white. House price levels are taken as of 2007 and the remaining controls are averages of the years 2007 to 2011. Regression inputs are scaled to have a standard deviation of one. Standard errors are reported in parentheses. *Sources:* Individual foreclosure status, income, age, and zip code CLTV come from Equifax. House price data come from Zillow. The remaining variables come from the U.S. Census Bureau American Community Survey 5-Year Estimates.

	(1)	(2)	(3)	(4)
Individual Income	-0.066	-0.025	-0.020	-0.020
	(0.000)	(0.000)	(0.000)	(0.000)
Individual Age	-0.013	-0.005	-0.006	-0.0064
	(0.000)	(0.000)	(0.000)	(0.000)
Combined Mortgage Balance	0.050	0.031	0.031	0.030
	(0.000)	(0.000)	(0.000)	(0.000)
Credit Card Debt	0.386	0.111	0.107	0.108
	(0.004)	(0.0043)	(0.004)	(0.004)
Auto Debt	0.019	0.012	0.011	0.011
	(0.000)	(0.000)	(0.000)	(0.000)
Student Debt	0.005	0.0021	0.002	0.002
	(0.000)	(0.000)	(0.000)	(0.000)
Vantage Score		-0.0668	-0.064	-0.065
		(0.000)	(0.000)	(0.000)
CLTV				0.008
				(0.000)
Zip Code Fixed Effects	No	No	Yes	No
Zip Code Controls	No	No	No	Yes
Observations	1,234,247	1,234,247	1,234,247	1,234,247
Adjusted R-squared	0.057	0.094	0.109	0.103

Table 3A: Probability of Regaining Homeownership for Borrowers with a Single Home Who Suffered Foreclosure

This table reports the results from regressions of whether a borrower with a single home who suffered foreclosure regained homeownership on various borrower and zip code level variables. Column (1) contains all borrower level variables, except vantage score. Column (2) adds individual vantage score. Column (3) contains all variables from Column (2) and adds zip code fixed effects. Column (4) contains all borrower level variables from Column (2) and adds zip code level controls. Controls include zip code house price levels and CLTV in 2007, median household income, unemployment rate, median age, percent married with children, percent with college education, percent with high school education, percent white, percent Hispanic or Latino, and percent white. House price levels are taken as of 2007 and the remaining controls are averages of the years 2007 to 2011. Regression inputs are scaled to have a standard deviation of one. Standard errors are reported in parentheses. *Sources:* Individual homeownership status, income, and age come from Equifax and zip code CLTV comes from Equifax. House price data come from Zillow. The remaining variables come from the U.S. Census Bureau American Community Survey 5-Year Estimates.

	(1)	(2)	(3)	(4)
Individual Income	0.073	0.054	0.046	0.048
	(0.002)	(0.003)	(0.003)	(0.002)
Individual Age	-0.041	-0.043	-0.039	-0.039
	(0.001)	(0.001)	(0.002)	(0.002)
Combined Mortgage Balance	0.017	0.019	0.026	0.026
	(0.002)	(0.002)	(0.002)	(0.002)
Credit Card Debt	0.070	0.141	0.127	0.126
	(0.017)	(0.018)	(0.018)	(0.018)
Auto Debt	0.007	0.010	0.009	0.010
	(0.001)	(0.001)	(0.001)	(0.001)
Student Debt	-0.002	-0.0001	0.001	0.001
	(0.001)	(0.001)	(0.001)	(0.001)
Vantage Score		0.034	0.034	0.034
		(0.001)	(0.002)	(0.001)
Zip Code Fixed Effects	No	No	Yes	No
Zip Code Controls	No	No	No	Yes
Observations	110,421	110,421	110,421	110,421
Adjusted R-squared	0.024	0.028	0.036	0.034

Table 3B: Time to Regain Homeownership for Borrowers with a Single Home Who Suffered Foreclosure and Regained Homeownership

This table reports the results from regressions of the time it takes to regain a home for a borrower with a single home who suffered foreclosure and eventually regains homeownership on various borrower and zip code level variables. Column (1) contains all borrower level variables, except vantage score. Column (2) adds individual vantage score. Column (3) contains all variables from Column (2) and adds zip code fixed effects. Column (4) contains all borrower level variables from Column (2) and adds zip code level controls. Controls include zip code house price levels and CLTV in 2007, median household income, unemployment rate, median age, percent married with children, percent with college education, percent with high school education, percent white, percent Hispanic or Latino, and percent white. House price levels are taken as of 2007 and the remaining controls are averages of the years 2007 to 2011. Regression inputs are scaled to have a standard deviation of one. Standard errors are reported in parentheses. *Sources:* Time to regain homeownership, income, and age come from Equifax and zip code CLTV comes from Equifax. House price data come from Zillow. The remaining variables come from the U.S. Census Bureau American Community Survey 5-Year Estimates.

	(1)	(2)	(3)	(4)
Individual Income	-2.948	2.625	1.347	1.913
	(0.339)	(0.340)	(0.382)	(0.345)
Individual Age	-2.136	-1.692	-1.445	-1.405
	(0.258)	(0.245)	(0.272)	(0.246)
Combined Mortgage Balance	-3.459	-3.996	-4.054	-4.265
	(0.219)	(0.208)	(0.251)	(0.227)
Credit Card Debt	48.71	19.13	18.99	16.93
	(2.547)	(2.487)	(2.751)	(2.484)
Auto Debt	1.182	0.344	0.539	0.436
	(0.164)	(0.157)	(0.176)	(0.157)
Student Debt	-0.469	-0.701	-0.544	-0.605
	(0.152)	(0.144)	(0.158)	(0.144)
Vantage Score		-11.83	-11.66	-11.88
		(0.227)	(0.251)	(0.228)
Zip Code Fixed Effects	No	No	Yes	No
Zip Code Controls	No	No	No	Yes
Observations	25,610	25,610	25,610	25,610
Adjusted R-squared	0.036	0.129	0.143	0.136

Table 4: Slow Recovery of Regions after the Crisis

This table documents the rate and speed at which regions recovered from the financial crisis. Panel (a) shows the percent of regions recovered by year, where a region is "recovered" if its outcome variable is at or better than its pre-crisis level. The pre-crisis level is defined as the level in 2007, so the percent recovered in 2007 is 100% by definition. Column 1 shows the percent of zip codes recovered with respect to delinquency rates and Column 2 shows the percent of ZIP recovered with respect to foreclosure rates. Similarly, Column 3 shows the percent of zip codes that recovered in house prices and Column 4 shows the percent of zip codes recovered with respect to auto sales. Column 5 shows the percent of counties recovered with respect to unemployment rate. Panel (b) shows the means and standard deviations of the times from 2010 that regions below their pre-crisis levels in 2010 took to recover. *Sources:* Delinquency and foreclosure rates come from Equifax. House prices come from Zillow, unemployment rates come from the U.S. Census Bureau, Small Area Income and Poverty Estimates, and auto sales come from Polk.

Panel A: Percent of Regions Recovered by Year

	(1) Delinquency Rate	(2) Foreclosure Rate	(3) House Price Index	(4) Auto Sales	(5) Unemployment Rate
2007	100.00%	100.00%	100.00%	100.00%	100.00%
2008	44.63%	58.39%	32.64%	22.76%	12.40%
2009	35.61%	51.24%	27.12%	11.83%	0.70%
2010	34.27%	49.05%	16.92%	14.00%	1.18%
2011	37.53%	52.06%	13.95%	22.20%	1.62%
2012	41.25%	56.71%	13.73%	33.95%	2.80%
2013	49.06%	67.44%	16.62%	43.54%	4.43%
2014	57.31%	74.68%	21.24%	50.72%	15.67%
2015	65.16%	80.04%	27.95%	54.53%	33.08%
2016	70.62%	84.01%	37.34%	52.95%	41.36%
2017	74.46%	87.06%	48.44%	-	-

Panel B: Years to Recovery

	(1) Delinquency Rate		(2) Foreclosure Rate		(3) House Price Index		(4) Auto Sales Level		(5) Unemployment Rate	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Years to Recover	3.65	1.88	3.15	1.78	5.31	1.62	2.91	1.47	4.85	1.02

Table 5: Slow Recovery and the Pre-Crisis Housing Boom across Regions

This table provides the results of regressions describing whether a region recovered from the crisis in delinquency rate, foreclosure rate, house price level, auto sales level. Dependent variables are dummy variables that take on the value of 1 if a region recovered and 0 otherwise. Recovery of delinquency rates, foreclosure rates, and house price levels are taken as of 2017 and recovery of auto sales and unemployment are taken as of 2016. Unemployment rates are measured at the county level and all other variables are measured at the zip code level. The independent variable is the growth of annual house prices in a zip code from 2003 to 2007, where growth rates are measured as shares. Sources: House prices come from Zillow, auto sales come from Polk, delinquency rates and foreclosure rates come from Equifax, and unemployment rates come from the U.S. Census Bureau. Standard errors are reported in parentheses.

	Delinquencies Recovery (1)	Foreclosures Recovery (2)	House Prices Recovery (3)	Auto Sales Recovery (4)	Unemployment Recovery (5)
Pre-Crisis House Price Growth	-0.139 (0.016)	-0.124 (0.013)	-0.719 (0.016)	-0.0144 (0.016)	-0.644 (0.055)
Observations	13188	13188	13188	13188	1344
Adjusted R-squared	0.005	0.006	0.126	0.00001	0.090

Table 6: Regional Summary Statistics

This table provides summary statistics at the zip code level. Panel (a) summarizes socio-economic variables used in regional regressions. CLTV and house price levels are taken as of June 2007. All remaining variables are from the 2011 ACS 5-year estimate. Columns (1) to (3) provide summary statistics for all available zip codes, while Columns (4) to (6) are restricted to the zip codes used in our regional regressions. Panel (b) summarizes various financial variables. Again, Columns (1) to (3) provide summary statistics for all available ZIP codes, while Columns (4) to (6) are restricted to the zip codes used in our regional regressions. *Sources:* CLTV comes from the Equifax 10% sample, house price data come from Zillow. The remaining socioeconomic variables come from U.S. Census Bureau American Community Survey 5-Year Estimates. ARM shares come from Di Maggio et al. (2017), HARP eligible shares come from Agarwal et al. (2015), and high capacity shares come from Agarwal et al. (2017).

Panel A: Socio-Economic Variables

	All Zip Codes			Zip Codes Used in Regressions		
	(1)	(2)	(3)	(4)	(5)	(6)
	Mean	SD	# of Zip Codes	Mean	SD	# of Zip Codes
Median Income	51,277	21,996	33,120	59,452	22,880	2,920
Unemployment Rate	8.34	7.15	33,120	8.72	3.84	2,920
Median Age	41.02	8.56	33,120	39.33	6.14	2,920
% Married with Children	37.01	15.14	33,120	39.59	9.04	2,920
% High School Educated	84.8	11.38	33,120	88.10	6.82	2,920
% College Educated	21.57	16.05	33,120	30.97	16.09	2,920
% White	75.77	19.8	33,120	77.12	20.52	2,920
% Black	7.61	16.05	33,120	15.48	19.15	2,920
% Hispanic or Latino	8.5	16.3	33,120	8.63	12.43	2,920
CLTV	74.81	18.03	6,530	73.71	14.98	2,920
House Price Index	251,057	206,267	13,655	217,449	125,511	2,920

Panel B: Financial Variables

	All Zip Codes			Zip Codes Used in Regressions		
	(1)	(2)	(3)	(4)	(5)	(6)
	Mean	SD	# of ZIP Codes	Mean	SD	# of ZIP Codes
ARM Share	22.13	9.87	11,389	23.06	8.93	2,920
HARP Eligible Share	21.82	11.64	8,699	24.59	11.84	2,920
High Capacity Share	24.54	6.58	9,976	22.50	5.50	2,920

Table 7: Difference in the Average Zip Code Delinquency Rate Changes

This table reports the results from the regressions of the difference between mean annual changes in zip code quarterly delinquency rates after the major interventions in the housing market (2010-2016) and the preceding period (2007-2009) on various zip code level variables. Zip code controls include vantage, CLTV, percent with college education, percent with high school education, percent Hispanic or Latino, percent white, percent black, and percent married with children. The net gain in population is the difference between the percentage of people who moved into zip code *i* from June 2007 to December 2017 and the percentage of people who moved out of *i* during the same time period. Similarly, the net gain in population experiencing foreclosure is defined as the difference between the percentage of people who both moved into zip code *i* and experienced foreclosure and the percentage of people who moved out of *i* and suffered foreclosure. *Sources:* Vantage and CLTV are from Equifax and are taken as of June 2007. Mobility measures come are from the Equifax sample. Delinquency rates also come from Equifax. ARM shares come from Di Maggio et al. (2017), HARP eligible shares come from Agarwal et al. (2015), and high capacity shares come from Agarwal et al. (2017). The remaining zip code controls come from the U.S. Census Bureau American Community Survey 2011 5-year Estimates. Standard errors are reported in parentheses.

	(1)	(2)	(3)	(4)
ARM Share	-0.131			-0.107
	(0.004)			(0.004)
HARP Eligible Share		-0.059		-0.021
		(0.002)		(0.003)
High Capacity Share			-0.078	-0.035
			(0.0058)	(0.005)
Net Gain in Population	-0.010	-0.028	-0.036	-0.013
	(0.002)	(0.002)	(0.002)	(0.002)
Net Gain with Foreclosure	0.057	0.190	0.239	0.074
	(0.023)	(0.025)	(0.026)	(0.023)
Other Zip Code Controls	Yes	Yes	Yes	Yes
Observations	2,920	2,920	2,920	2,920
Adjusted R-squared	0.725	0.666	0.624	0.737

Table 8: Difference in the Average Zip Code Foreclosure Rate Changes

This table reports the results from the regressions of the difference between mean annual changes in ZIP code quarterly foreclosure rates after the major interventions in the housing market (2010-2016) and the preceding period (2007-2009) on various zip code level variables. Zip code controls include vantage, CLTV, percent with college education, percent with high school education, percent Hispanic or Latino, percent white, percent black, and percent married with children. The net gain in population is the difference between the percentage of people who moved into zip code *i* from June 2007 to December 2017 and the percentage of people who moved out of *i* during the same time period. Similarly, the net gain in population experiencing foreclosure is defined as the difference between the percentage of people who both moved into zip code *i* and experienced foreclosure and the percentage of people who moved out of *i* and suffered foreclosure. *Sources:* Vantage and CLTV are from Equifax and are taken as of June 2007. Mobility measures come are from the Equifax sample. Foreclosure rates also come from Equifax. ARM shares come from Di Maggio et al. (2017), HARP eligible shares come from Agarwal et al. (2015), and high capacity shares come from Agarwal et al. (2017). The remaining zip code controls come from the U.S. Census Bureau American Community Survey 2011 5-year Estimates. Standard errors are reported in parentheses.

	(1)	(2)	(3)	(4)
ARM Share	-0.079			-0.066
	(0.002)			(0.003)
HARP Eligible Share		-0.031		-0.007
		(0.002)		(0.002)
High Capacity Share			-0.056	-0.032
			(0.004)	(0.003)
Net Gain in Population	-0.015	-0.020	-0.006	-0.015
	(0.001)	(0.001)	(0.001)	(0.001)
Net Gain with Foreclosure	0.072	0.099	0.001	0.072
	(0.016)	(0.017)	(0.015)	(0.016)
Other Zip Code Controls	Yes	Yes	Yes	Yes
Observations	2,920	2,920	2,920	2,920
Adjusted R-squared	0.704	0.640	0.624	0.716

Table 9: Change in the Zip Code House Price Growth Rates

This table reports the results from the regressions of the difference between annual mean quarterly ZIP code house price growth rates after the major interventions in the housing market (2010-2016) and the preceding period (2007-2009) on various zip code level variables. Zip code controls include vantage, CLTV, percent with college education, percent with high school education, percent Hispanic or Latino, percent white, percent black, and percent married with children. The net gain in population is the difference between the percentage of people who moved into zip code *i* from June 2007 to December 2017 and the percentage of people who moved out of *i* during the same time period. Similarly, the net gain in population experiencing foreclosure is defined as the difference between the percentage of people who both moved into zip code *i* and experienced foreclosure and the percentage of people who moved out of *i* and suffered foreclosure. *Sources:* Vantage and CLTV are from Equifax and are taken as of June 2007. Mobility measures come are from the Equifax sample. House price growths come from Zillow. ARM shares come from Di Maggio et al. (2017), HARP eligible shares come from Agarwal et al. (2015), and high capacity shares come from Agarwal et al. (2017). The remaining zip code controls come from the U.S. Census Bureau American Community Survey 2011 5-year Estimates. Standard errors are reported in parentheses.

	(1)	(2)	(3)	(4)
ARM Share	0.059			0.040
	(0.001)			(0.001)
HARP Eligible Share		0.0336		0.020
		(0.001)		(0.001)
High Capacity Share			0.032	0.011
			(0.002)	(0.002)
Net Gain in Population	-0.001	0.007	0.012	0.002
	(0.001)	(0.001)	(0.001)	(0.001)
Net Gain with Foreclosure	-0.012	-0.066	-0.094	-0.022
	(0.008)	(0.008)	(0.009)	(0.007)
Other Zip Code Controls	Yes	Yes	Yes	Yes
Observations	2,920	2,920	2,920	2,920
Adjusted R-squared	0.6198	0.5780	0.3501	0.6970

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Table 10: Change in the Zip Code Consumption Growth Rates

This table reports the results from the regressions of the difference between mean annual ZIP code consumption growth rates (measured by auto sales) after the major interventions in the housing market (2010-2016) and the preceding period (2007-2009) on various zip code level variables. Zip code controls include vantage, CLTV, percent with college education, percent with high school education, percent Hispanic or Latino, percent white, percent black, and percent married with children. The net gain in population is the difference between the percentage of people who moved into zip code *i* from June 2007 to December 2017 and the percentage of people who moved out of *i* during the same time period. Similarly, the net gain in population experiencing foreclosure is defined as the difference between the percentage of people who both moved into zip code *i* and experienced foreclosure and the percentage of people who moved out of *i* and suffered foreclosure. *Sources:* Vantage and CLTV are from Equifax and are taken as of June 2007. Mobility measures come are from the Equifax sample. Auto sales growth come from Polk. ARM shares come from Di Maggio et al. (2017), HARP eligible shares come from Agarwal et al. (2015), and high capacity shares come from Agarwal et al. (2017). The remaining zip code controls come from the U.S. Census Bureau American Community Survey 2011 5-year Estimates. Standard errors are reported in parentheses.

	(1)	(2)	(3)	(4)
ARM Share	0.259			0.223
	(0.020)			(0.024)
HARP Eligible Share		0.116		0.047
		(0.012)		(0.014)
High Capacity Share			0.067	-0.023
			(0.027)	(0.028)
Net Gain in Population	0.032	0.069	0.082	0.034
	(0.010)	(0.011)	(0.011)	(0.011)
Net Gain with Foreclosure	0.333	0.072	-0.024	0.322
	(0.127)	(0.126)	(0.128)	(0.127)
Other Zip Code Controls	Yes	Yes	Yes	Yes
Observations	2,920	2,920	2,920	2,920
Adjusted R-squared	0.2954	0.2763	0.2557	0.2975

Table 11: Zip Code Unemployment Rate Changes

This table reports the results from the regressions of the difference between mean ZIP code unemployment rates after the major interventions in the housing market and the preceding period on various zip code level variables. Zip code level unemployment rates are only available as averages of the years 2007-2011 and 2012-2016, so for those regressions, we use the change of these time periods as dependent variables. Zip code controls include vantage, CLTV, percent with college education, percent with high school education, percent Hispanic or Latino, percent white, percent black, and percent married with children. The net gain in population is the difference between the percentage of people who moved into zip code *i* from June 2007 to December 2017 and the percentage of people who moved out of *i* during the same time period. Similarly, the net gain in population experiencing foreclosure is defined as the difference between the percentage of people who both moved into zip code *i* and experienced foreclosure and the percentage of people who moved out of *i* and suffered foreclosure. *Sources:* Vantage and CLTV are from Equifax and are taken as of June 2007. Mobility measures come are from the Equifax sample. ARM shares come from Di Maggio et al. (2017), HARP eligible shares come from Agarwal et al. (2015), and high capacity shares come from Agarwal et al. (2017). Unemployment rate and the remaining zip code controls come from the U.S. Census Bureau American Community Survey 2011 5-year Estimates.

	(1)	(2)	(3)	(4)
ARM Share	-0.071			-0.027
	(0.006)			(0.007)
HARP Eligible Share		-0.058		-0.048
		(0.004)		(0.004)
High Capacity Share			-0.043	-0.016
			(0.009)	(0.009)
Net Gain in Population	0.003	-0.003	-0.011	0.001
	(0.004)	(0.003)	(0.003)	(0.003)
Net Gain with Foreclosure	-0.033	0.007	0.065	-0.018
	(0.040)	(0.039)	(0.040)	(0.034)
Other Zip Code Controls	Yes	Yes	Yes	Yes
Observations	2,920	2,920	2,920	2,920
Adjusted R-squared	0.092	0.122	0.061	0.128

Figure 1: Timeline of the Crisis and Housing Stimulus Measures

This figure plots the FED funds rate, 1-Year treasury rate, and 6-month LIBOR from 2007 to 2017. It shows key events of the financial crisis, including New Century's Bankruptcy and Lehman's Collapse, and the implementation of debt relief stimulus, such as quantitative easing, HAMP, and HARP. *Sources:* FED funds rate, 1-Year treasury rate, and 6-month LIBOR rate come from FRED Economic Data, Federal Reserve Bank of St. Louis.

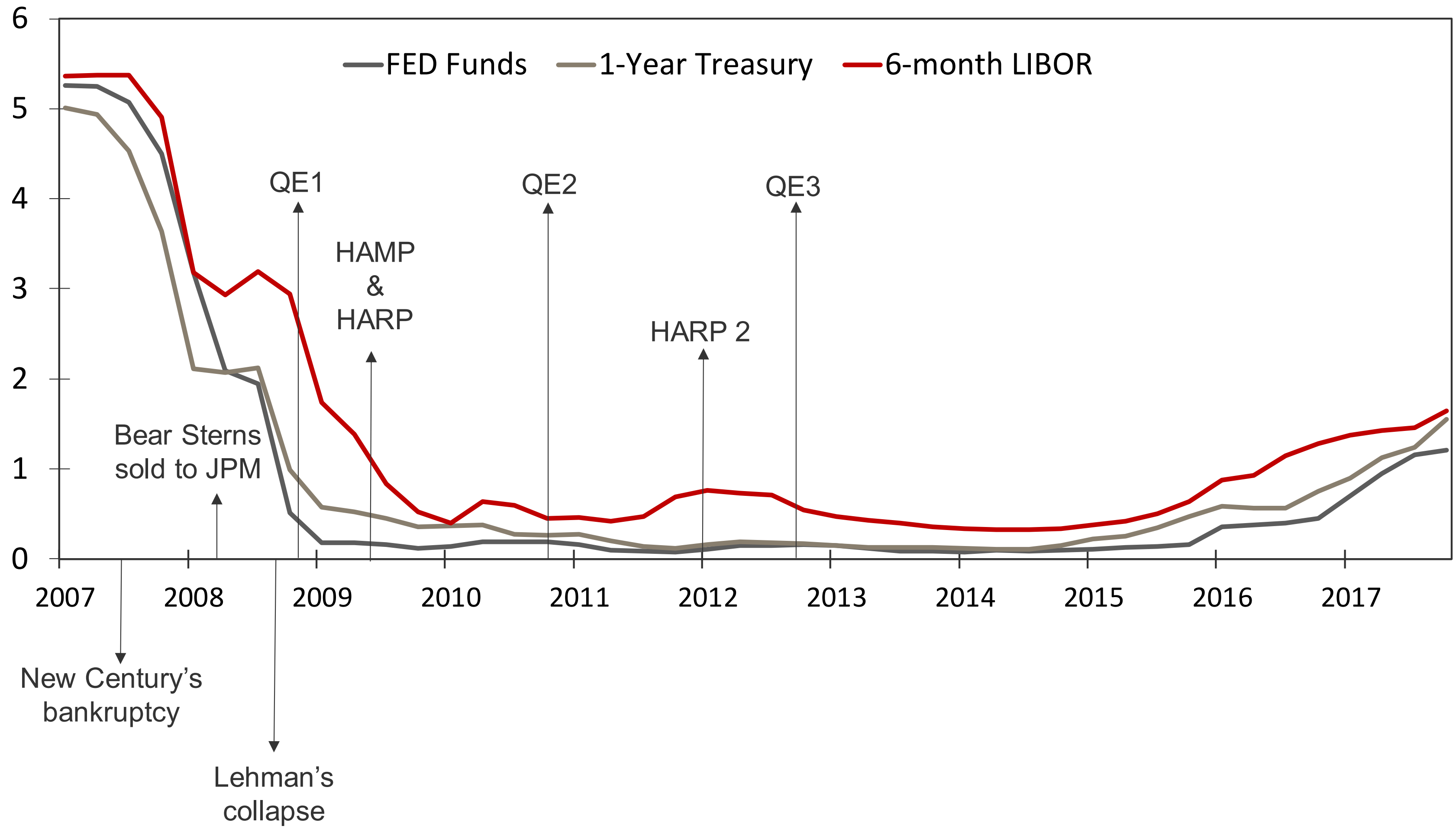


Figure 2: Foreclosure and Long-Term Borrower Creditworthiness

This figure plots mean vantage score of borrowers with single homes who suffered foreclosure for twelve quarters (three years) prior to foreclosure and twenty quarters (five years) after foreclosure, where Quarter 0 is the quarter in which the borrower experiences foreclosure. To investigate the recovery of vantage scores following foreclosure more formally, we calculate the percentage of borrowers with vantage scores at or above their original Period -12 level in each period. In Period 0 (when the borrower suffers foreclosure), the percentage of borrowers with vantage scores at least as high as their Period -12 level is 15.7%. This percentage increases steady throughout the remaining periods, though even five years after foreclosure only 51% of borrowers had recovered. *Source:* Equifax 10% representative sample of the U.S. credit population.

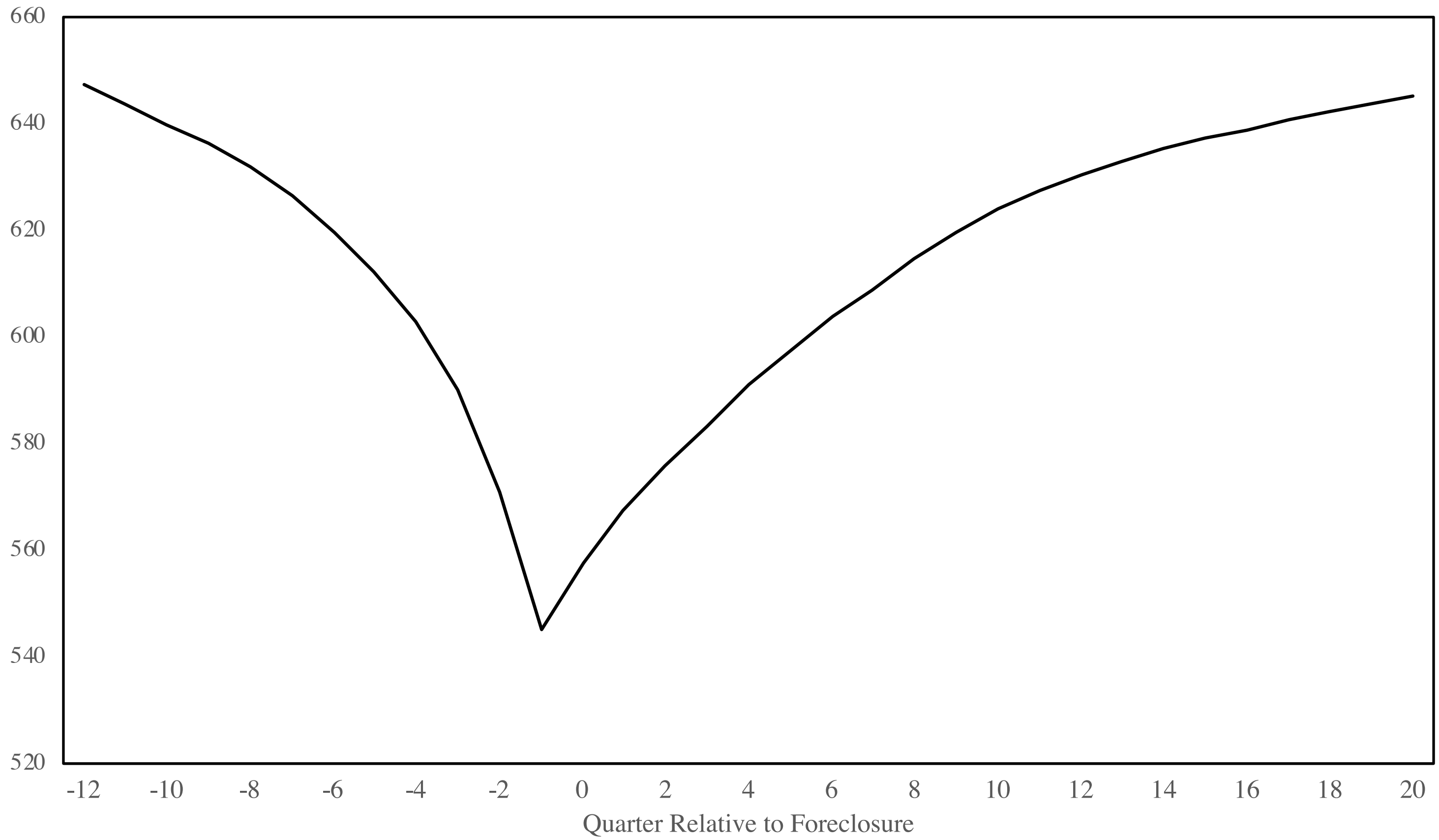
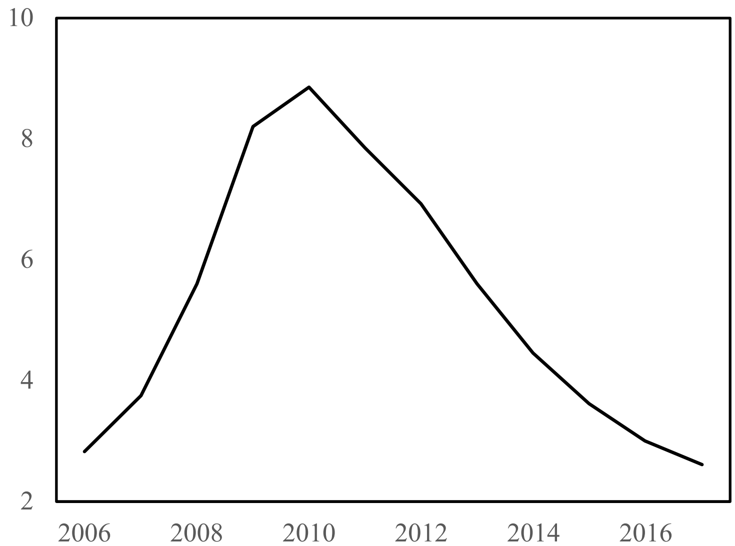
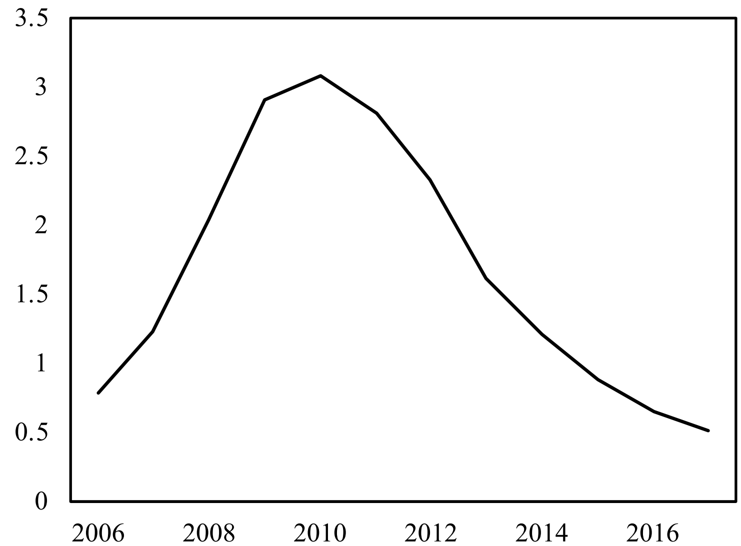


Figure 3: Delinquency and Foreclosure Rates

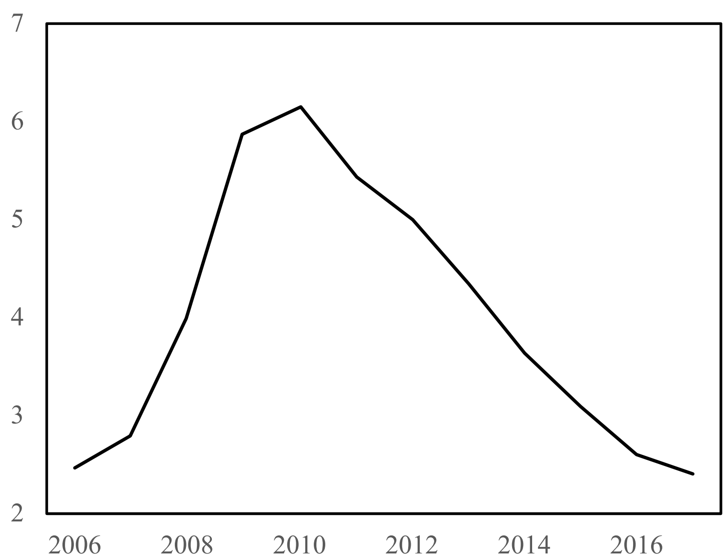
Panel (a) shows time-series of the mean of zip code serious delinquency rates from 2006 to 2017 across zip codes and Panel (b) shows the mean of zip code foreclosure rates during the same years. Panel (c) shows the standard deviation of delinquency rates across zip codes and Panel (d) shows the standard deviation of foreclosure rates. Calculations are population weighted by zip code. *Sources:* Equifax 10% representative sample of the U.S. credit population and U.S. Census Bureau zip code population estimates.



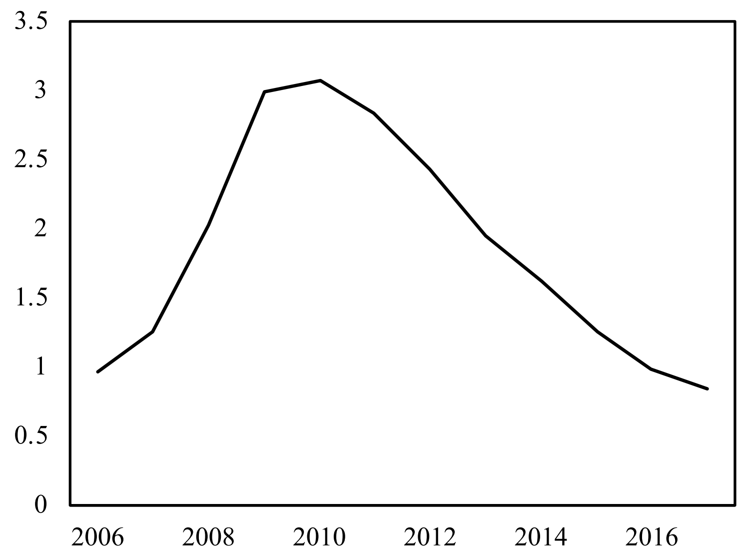
(a) Delinquency Rate (Mean)



(b) Foreclosure Rate (Mean)



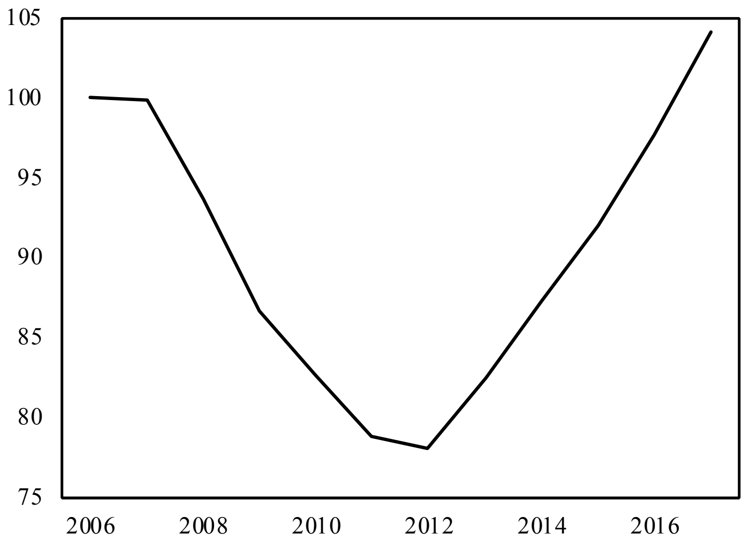
(c) Delinquency Rate (Standard Deviation)



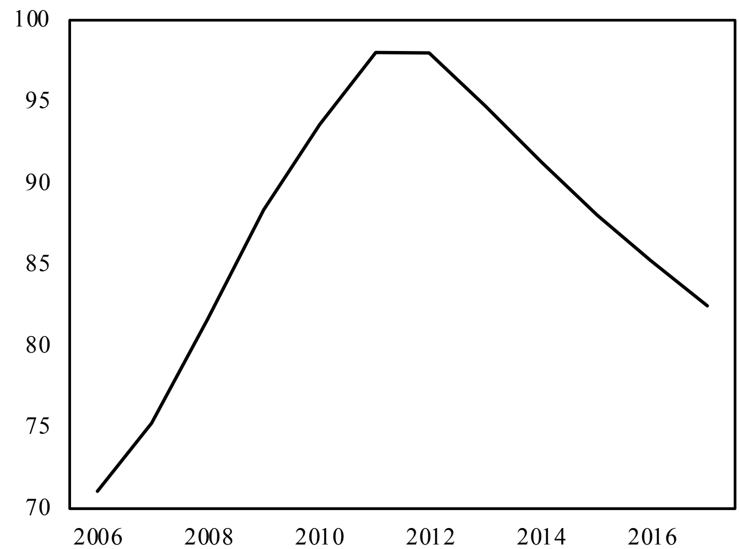
(d) Foreclosure Rate (Standard Deviation)

Figure 4: House Prices and CLTV

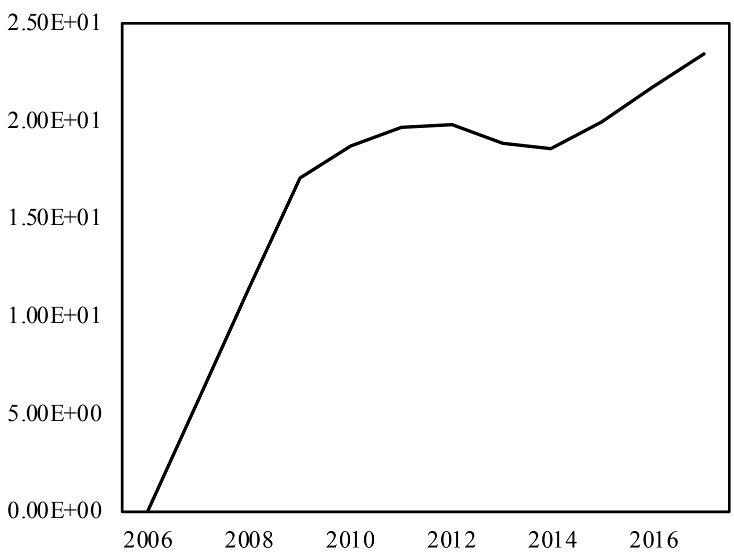
Panel (a) shows time-series of the mean of ZIP code house prices 2006 to 2017 across ZIP codes. Panel (b) shows the mean of CLTV during the same time period. Panel (c) shows the standard deviation of house price across ZIP codes from 2006 to 2017 and Panel (d) shows the standard deviation of CLTV during the same time. Calculations are population weighted by zip code. The house price index in each zip code is normalized to 100 in the first time period. *Sources:* House prices come from Zillow, CLTV is estimated from the Equifax 10% representative sample of the U.S. credit population, and ZIP code population data come from the U.S. Census Bureau ZIP code population estimates.



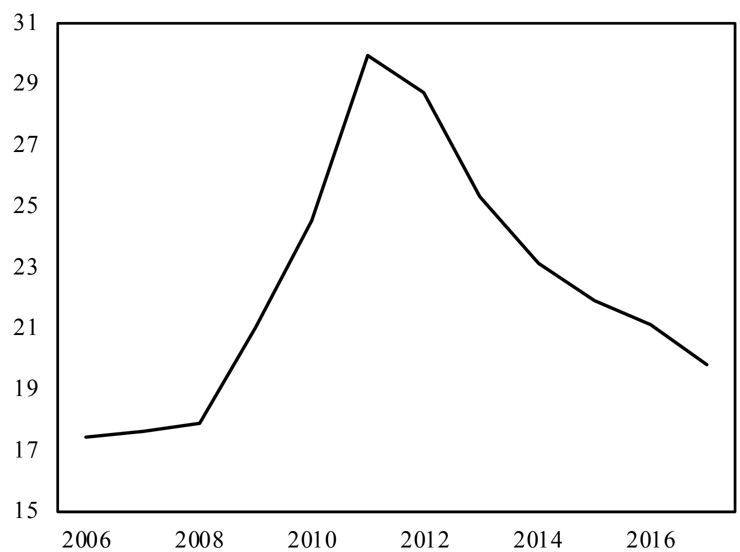
(a) House Price (Mean)



(b) CLTV (Mean)



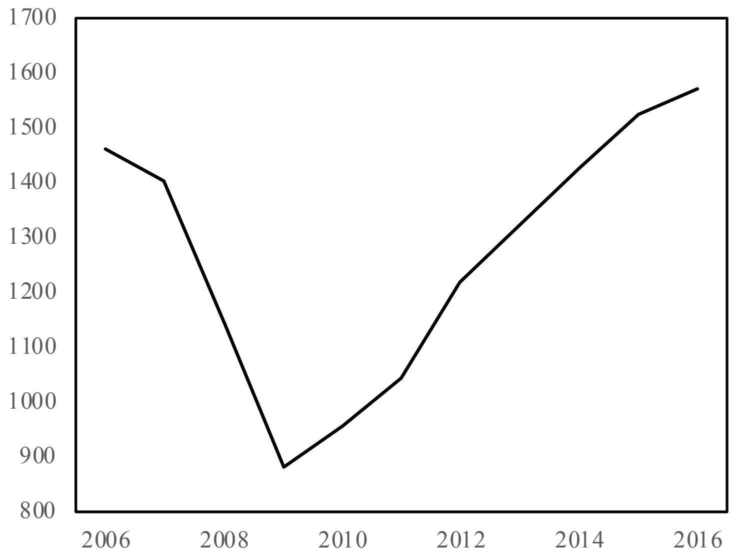
(c) House Price (Standard Deviation)



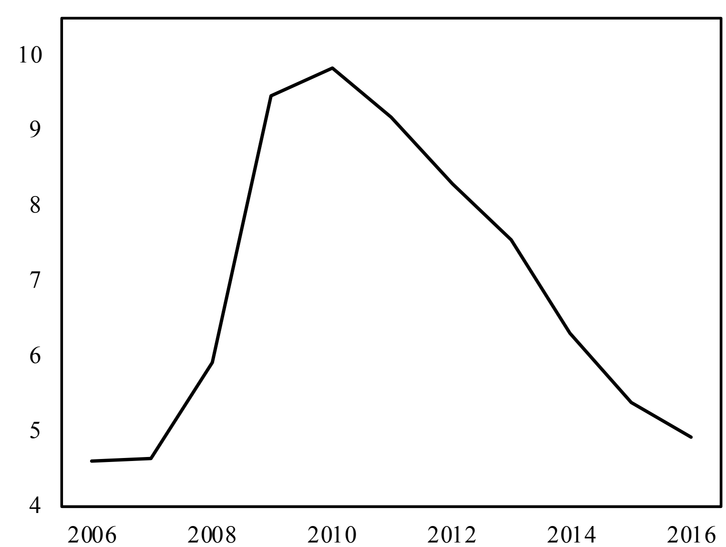
(d) CLTV (Standard Deviation)

Figure 5: Auto Sales and Unemployment Rate

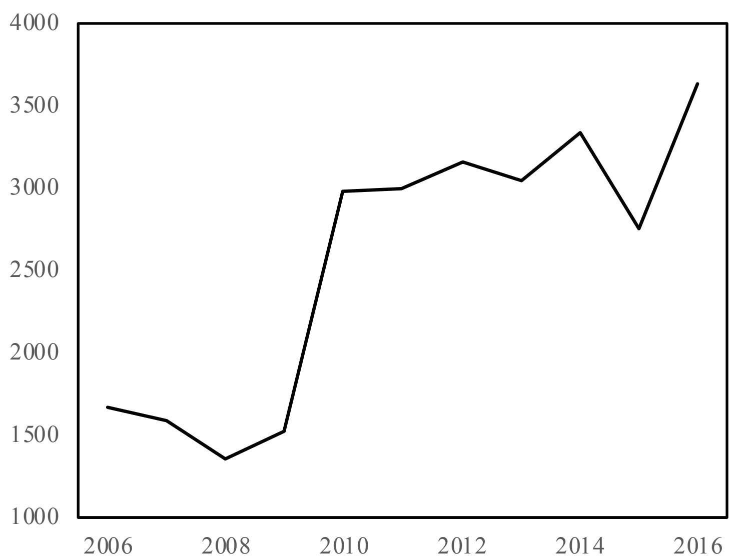
Panel (a) shows time-series of the mean of ZIP code auto sales from 2006 to 2016. Panel (b) shows mean county unemployment rate during the same time period. Panel (c) shows the standard deviation of auto sales across ZIP codes and Panel (d) shows standard deviation of unemployment rates across counties. Calculations are population weighted by region. *Sources:* Unemployment rate comes from the U.S. Census Bureau, Small Area Income and Poverty Estimates, auto sales come from Polk, and population data come from U.S. Census Bureau ZIP code and county population estimates.



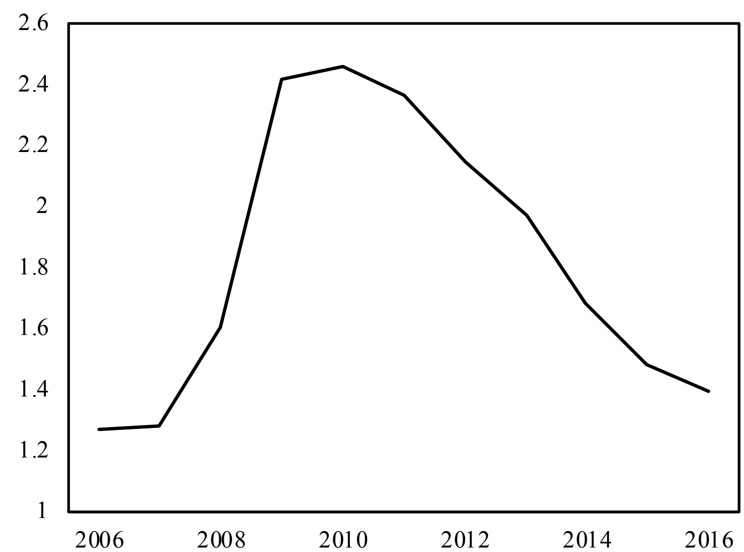
(a) Auto Sales (Mean)



(b) Unemployment Rate (Mean)



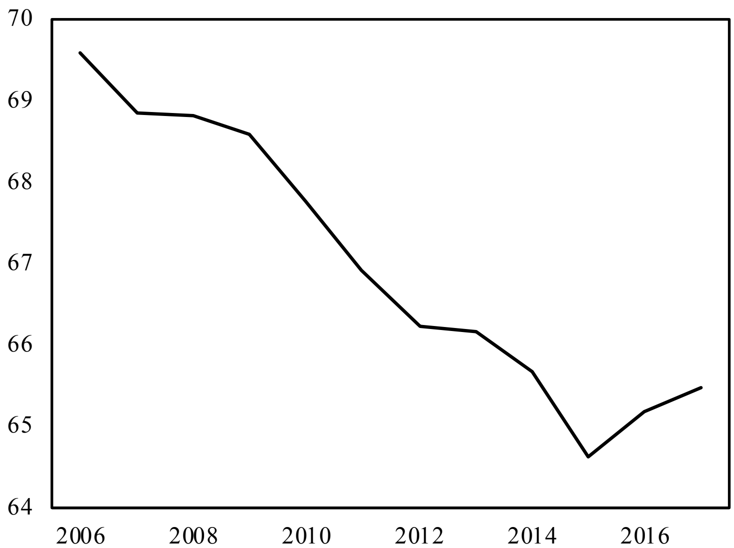
(c) Auto Sales (Standard Deviation)



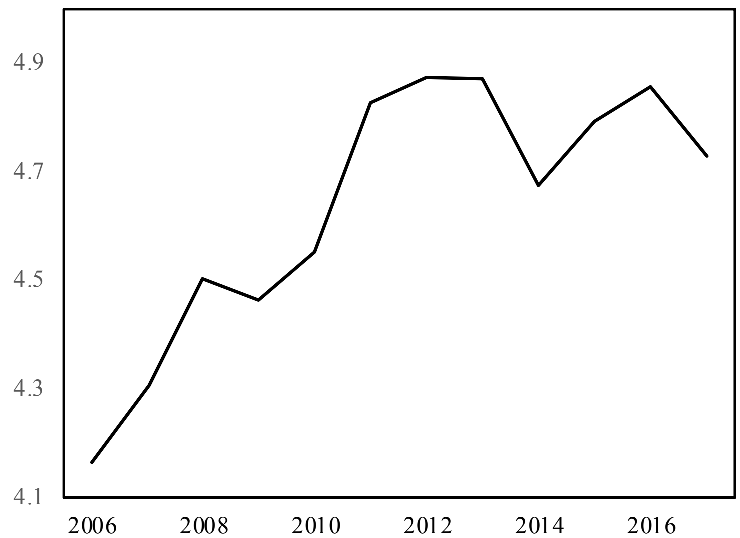
(d) Unemployment Rate (Standard Deviation)

Figure 6: Homeownership Rate

Panel (a) shows the time-series of the mean of homeownership rates across states from 2006 to 2016 and Panel (b) shows the standard deviation in each year. Calculations are population weighted by state. *Sources:* Homeownership rate comes from the U.S. Census Bureau Housing Vacancies and Homeownership statistics and populations U.S. Census Bureau population estimates.



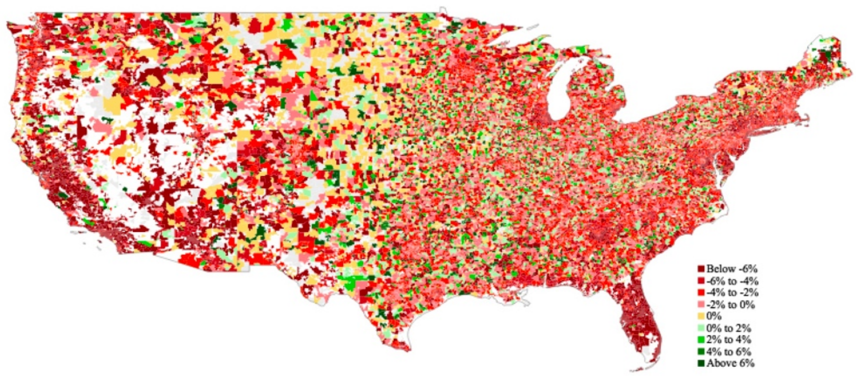
(a) Homeownership Rate (Mean)



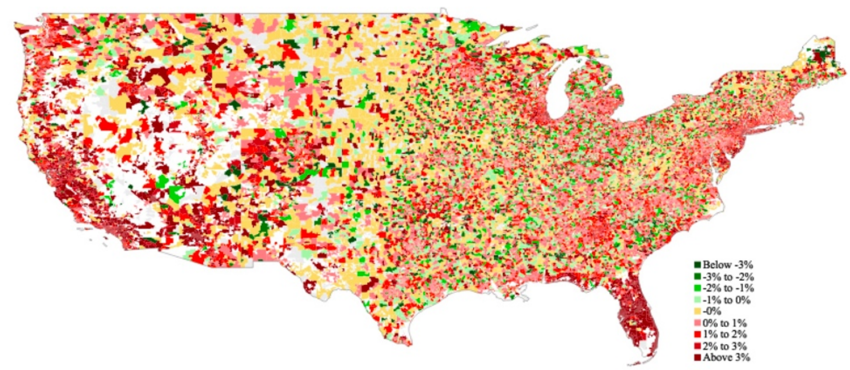
(b) Homeownership Rate (Standard Deviation)

Figure 7: Crisis Severity across Regions

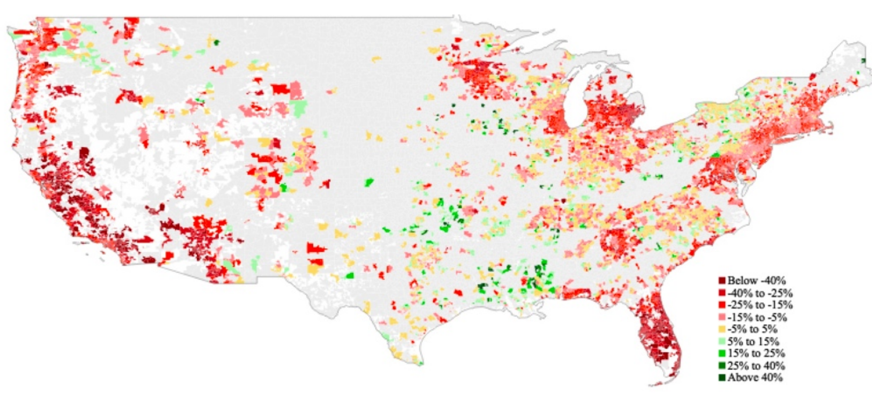
This figure shows changes or growth rates in delinquencies, foreclosures, house prices, auto sales, and unemployment rates from 2007 to 2010. Delinquencies, foreclosures, and unemployment rates are measured in changes, while house prices and auto sales are measured as growth rates. Delinquency rates, foreclosure rates, house prices, and auto sales are measured at the zip code level and unemployment rate is measured at the county level. *Sources:* Delinquency and foreclosure rates come from Equifax, auto sales data come from Polk, house prices come from Zillow, and unemployment rates come from the U.S. Census Bureau.



(a) Delinquency Rate

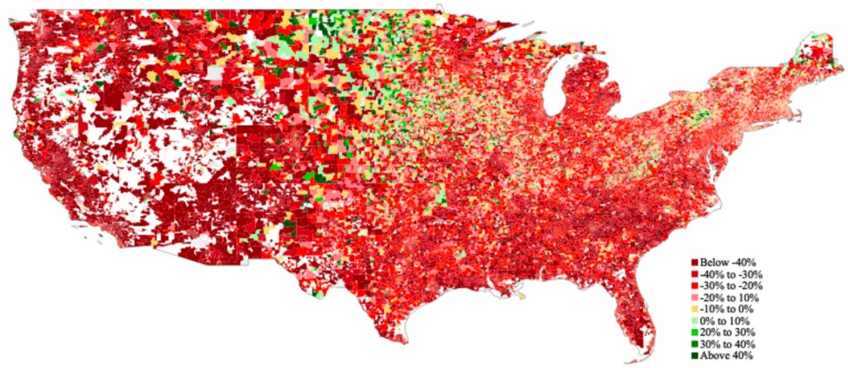


(b) Foreclosure Rate

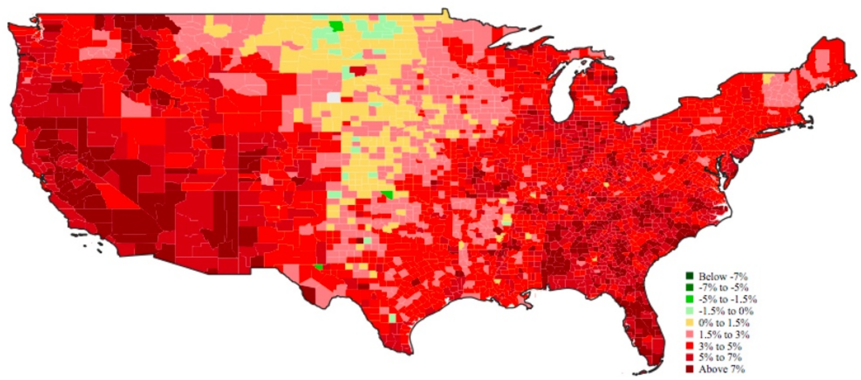


(c) House Prices

Figure 7: Crisis Severity across Regions [continued]



(d) Auto Sales



(e) Unemployment Rate

Figure 8: Slow Recovery: Share of Regions that Recovered to Pre-Crisis Level over Time

This figure shows the share of regions recovered to their pre-crisis levels over time. Pre-crisis levels are taken as of 2007, so 100% of regions are recovered in 2007 by definition. Delinquency rates, foreclosure rates, house prices, and auto sales are measured at the zip code level, while unemployment rates are measured at the county level. Delinquency rates, foreclosure rates, and house prices are measured from 2007 to 2017, while auto sales and unemployment rates are measured from 2007 to 2016. *Sources:* Delinquency and foreclosure rates come from Equifax, auto sales data come from Polk, house prices come from Zillow, and unemployment rates come from the U.S. Census Bureau.

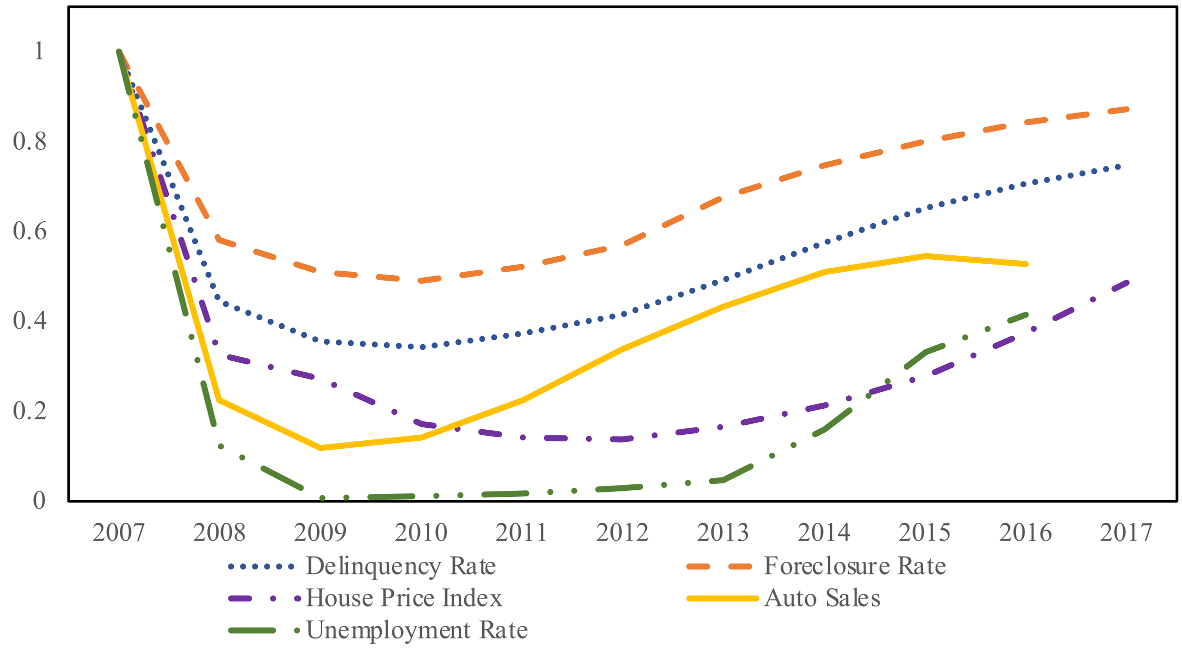
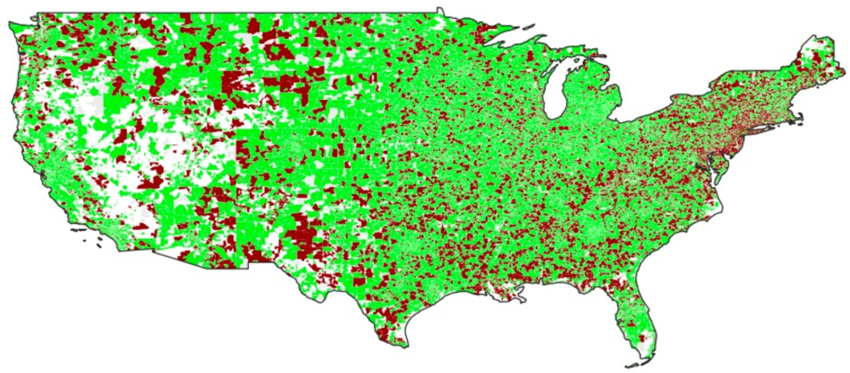
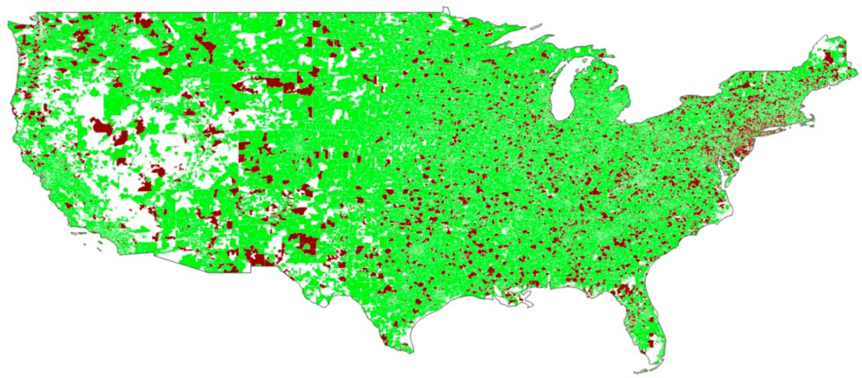


Figure 9: Regional Recovery after the Crisis

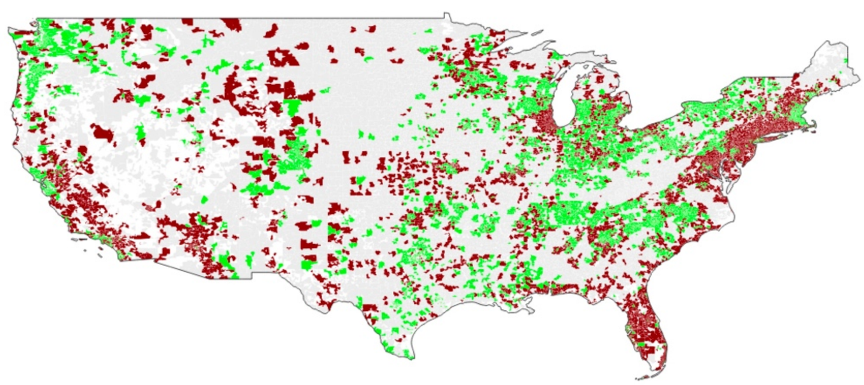
This figure illustrates the regional heterogeneity in the recovery of the crisis with respect to delinquency rates, foreclosure rates, house price levels, auto sales, and unemployment rate. Specifically, we consider whether a region recovered to its pre-crisis level. Dark color indicates that the region was below its pre-crisis (2007) level and light color indicates that the region recovered to its pre-crisis level. Delinquency rates, foreclosure rates, house prices, and auto sales are measured at the zip code level and unemployment rate is measured at the county level. Delinquency rates, foreclosure rates, and house prices are measured as of 2017, while auto sales and unemployment rates are measured as of 2016. *Sources:* Delinquency and foreclosure rates come from Equifax, auto sales data come from Polk, house prices come from Zillow, and unemployment rates come from the U.S. Census Bureau.



(a) Delinquency Rate

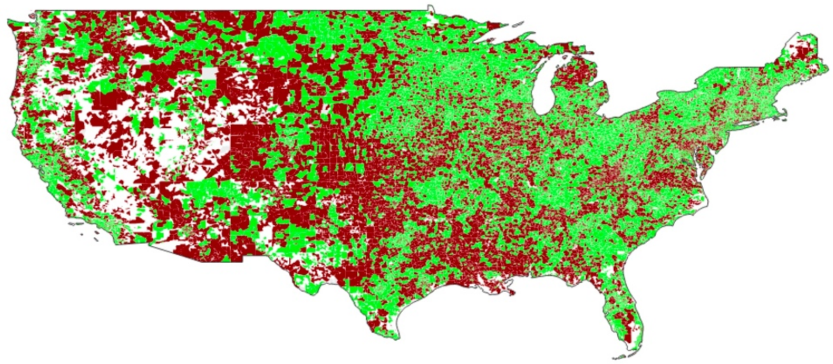


(b) Foreclosure Rate

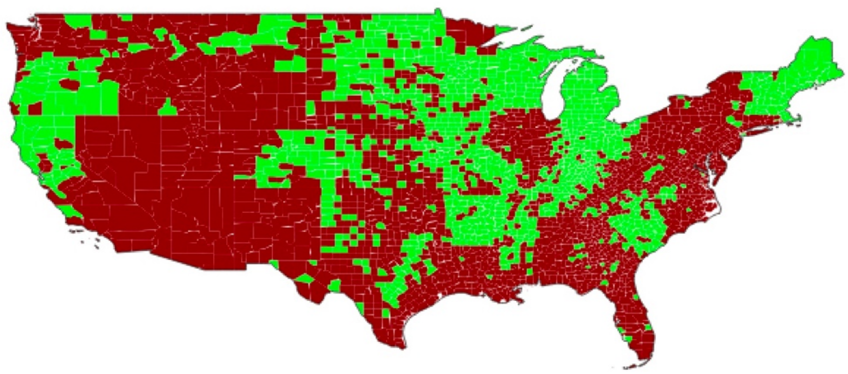


(c) House Prices

Figure 9: Regional Recovery after the Crisis [continued]



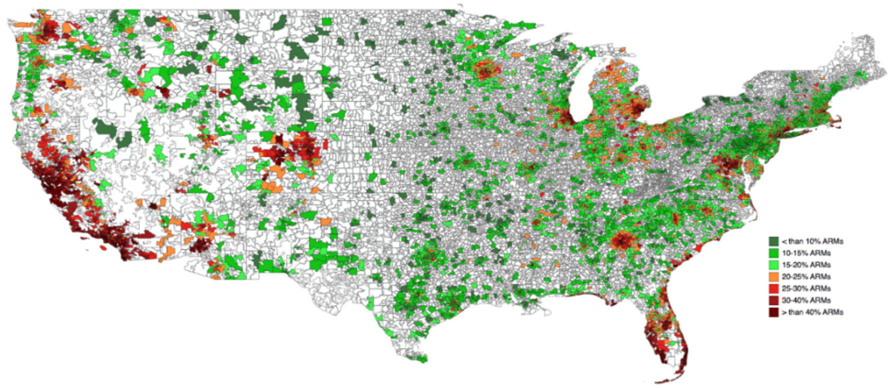
(d) Auto Sales



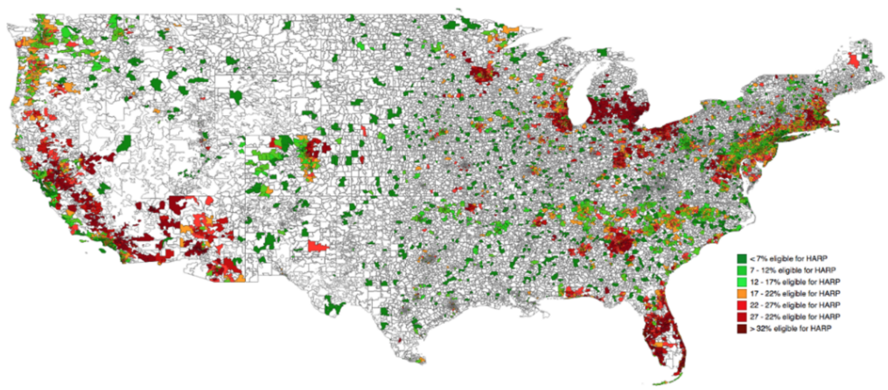
(e) Unemployment

Figure 10: Spatial Variation in the Implementation of Debt Relief

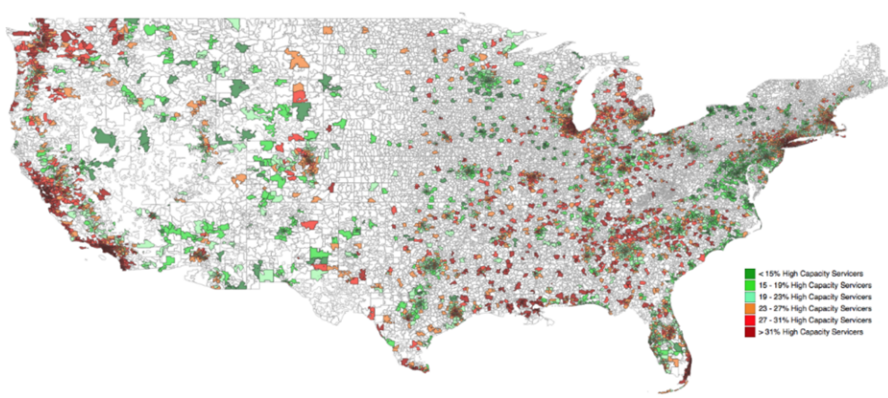
Panel (a) of this figure shows the spatial variation of zip code ARM share in the US (data from Di Maggio et al. 2017). We note that ARM loans can experience a quick "automatic" pass through of low interest rates. This share, however, needs to be interpreted with caution as many subprime ARM contracts feature various caps and floors that may limit the extent of adjustment of their rates. Panel (b) shows the share of loans in a zip code that were eligible for HARP (data from Agarwal et al. 2016) based on their LTV level and the presence of GSE guarantee. Panel (c) shows the share of loans in a zip code serviced by intermediaries with high organizational capacity to service and modify loans (data from Agarwal et al. 2017).



(a) ARM Share



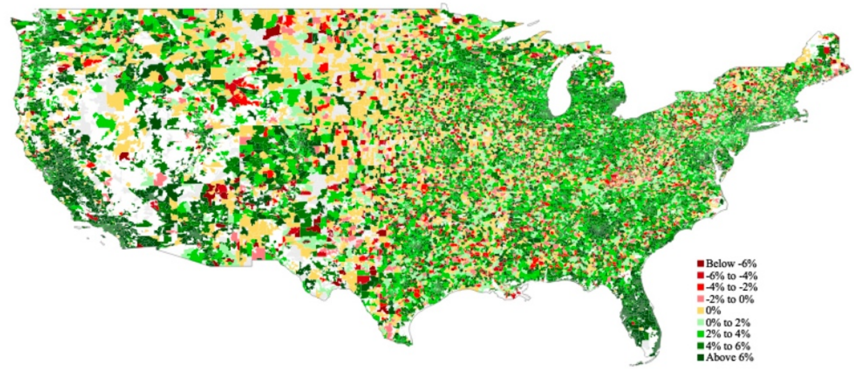
(b) HARP Eligible Share



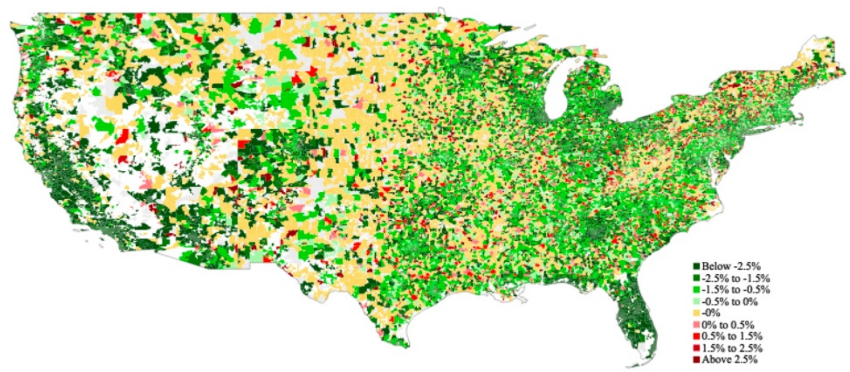
(c) High Capacity Share

Appendix A1: Recovery across Regions

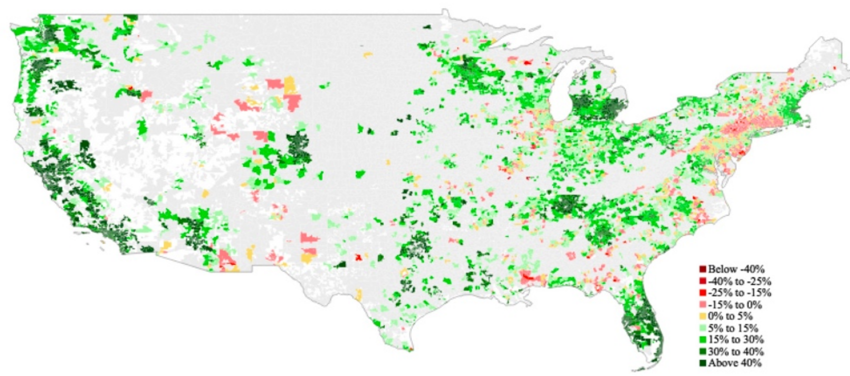
This figure shows changes or growth rates in delinquencies, foreclosures, house prices, auto sales, and unemployment rates from 2016 or 2017 to 2010. Delinquencies, foreclosures, and unemployment rates are measured in changes, while house prices and auto sales are measured as growth rates. Delinquency rates, foreclosure rates, and house prices are measured from 2010 to 2017, while auto sales and unemployment rates are measured from 2010 to 2016. Delinquency rates, foreclosure rates, house prices, and auto sales are measured at the zip code level and unemployment rate is measured at the county level. *Sources:* Delinquency and foreclosure rates come from Equifax, auto sales data come from Polk, house prices come from Zillow, and unemployment rates come from the U.S. Census Bureau.



(a) Delinquency Rate

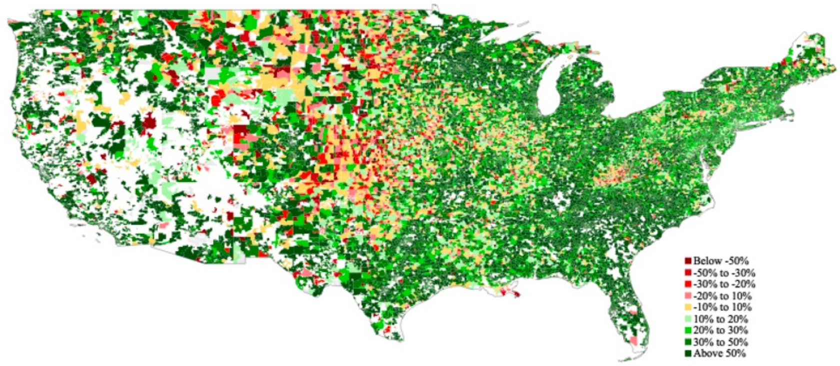


(b) Foreclosure Rate

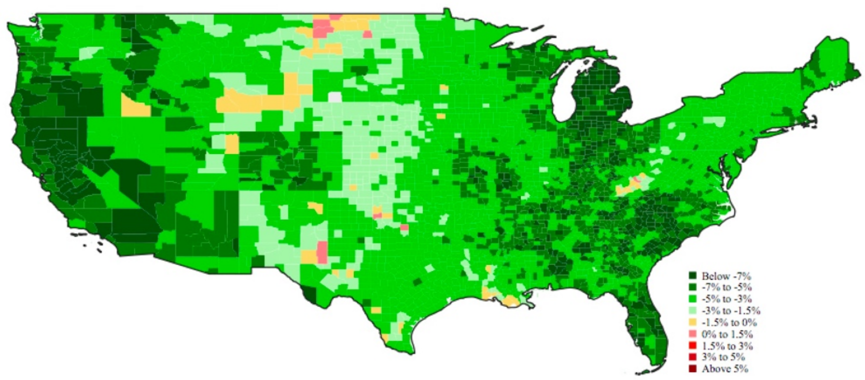


(c) House Prices

Appendix A1: Recovery across Regions [continued]



(d) Auto Sales



(e) Unemployment Rate