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# Mortgage market design: Lessons from the Great Recession

Tomasz Piskorski, Columbia University
Amit Seru, Stanford University

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# Mortgage Market Design: Lessons from the Great Recession

Tomasz Piskorski and Amit Seru[1]

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**Abstract**

Rigidity of mortgage contracts and a variety of frictions in design of the market and the intermediation sector hindered efforts to restructure or refinance household debt in the aftermath of the financial crisis. Using a simple framework that builds on mortgage design literature, we illustrate that automatically indexed mortgage contracts or debt relief polices can reduce borrower's debt burden during economic downturns, thereby leading to significant welfare gains. We show that benefits of such solutions are substantially reduced if there are errors in understanding the underlying structure of income and housing risk and their relation to the indices on which such contracts or polices are based. Empirical evidence reveals significant spatial heterogeneity and time-varying nature of the distribution of economic conditions. This poses a challenge to effective design of, ex-ante, automatically indexed mortgage contracts and debt relief polices. Policies implemented ex-post by financial intermediaries avoid this problem, but significant spatial heterogeneity of frictions differentially impacts their effectiveness. We conclude by discussing potential gains from indexing mortgage contract terms or debt relief polices to local economic conditions as well other mechanisms that may minimize adverse effects of ex-post implementation frictions.

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## 1. Introduction

The recent U.S. housing boom saw an unprecedented increase in household mortgage debt (Keys, Piskorski, Seru and Vig, 2013). This buildup of mortgage debt, held by vulnerable households, has been party attributed as having importantly contributed to the severity of aftermath (Mian and Sufi 2009, 2011, 2014a).[2] However, the characteristics of borrowers and loans originated prior to the crisis is not the only key factor that affected the severity of the housing downturn during the Great Recession. A series of papers have argued that a number of factors related to rigidity of contract terms, as well as a variety of frictions in design of the mortgage market and the intermediation sector hindered efforts to restructure or refinance household debt, exacerbating the foreclosure crisis (e.g., Piskorski, Seru, Vig 2010, Mayer et al. 2014, Di Maggio et al. 2017 and Fuster and Willen 2017).

In response, the central bank altered its monetary policy by lowering interest rates to historic lows. Also, the administration passed two unprecedented large-scale debt relief programs: the Home Affordable Refinancing Program (HARP), aimed to stimulate mortgage refinancing activity of up to eight million heavily indebted borrowers and the Home Affordable Modification Program (HAMP), aimed to stimulate mortgage restructuring effort for up to four million borrowers at risk of foreclosure. Research suggests that the implementation of the low interest rate policy and these debt relief programs had mixed success (e.g., Agarwal et al. 2015, 2017; Di Maggio et al. 2017,). What can we learn from extant research on the potential design of mortgages and more effective debt relief efforts in the future? The objective of this paper is to draw on lessons from prior research and provide evidence-based guidance on both these issues.

The paper starts by discussing the literature that documents potential frictions that hindered efforts to refinance or restructure mortgages during the Great Recession. The main frictions documented center around (i) contract rigidity, due to which most contracts that were fixed rate mortgages were locked in at high rates; (ii) equity refinancing constraints, due to which refinancing of mortgages was not feasible for many distressed borrowers with insufficient equity; (iii) intermediary organizational constraints, due to which refinancing or debt relief was not passed on to borrowers; (iv) agency conflicts in servicing of mortgages that were largely securitized that prevented restructuring; (v) lack of competition in the refinancing market that blunted the extent of pass through to borrowers, lowering their incentives to refinance; and (vi) ex-post moral hazard concerns of intermediaries, where offering debt

[2] See, among others, Landvoigt et al. (2015), Kaplan and Violante (2016), Guerrieri and Uhlig (2016), and Favilukis et al. (2017) for recent quantitative equilibrium models of housing booms and busts.

relief to distressed borrowers could alter the incentives of many solvent borrowers to continue making payments.

There is a large literature that shows that these frictions, each in part, might have prevented debt relief from reaching distressed households. Consequently, there is an ongoing debate regarding the reform of the mortgage market to alleviate the impact of such frictions in the future. At the center of this debate are a variety of proposals concerning the redesign of mortgage contracts, as well as future debt relief polices. In essence, these proposals argue for more efficient risk sharing between borrowers and lenders to lower the incidence of costly foreclosures and the severity of future housing downturns (e.g., Shiller 2008; Caplin et al. 2008; Piskorski and Tchistyi 2011; Campbell 2013; Keys et al. 2013; Mian and Sufi 2014b; Eberly and Krishnamurthy 2014). Since we want to use the lessons from the literature to assess the design of future mortgage contracts and debt relief policies, we start with the theoretical insights from the work on mortgage design. This allows us to think about various economic forces that should be in the consideration set as we make our assessment.

The main collective insights from this work (e.g., Piskorski and Tchistyi 2010, 2011, 2017; Eberly and Krishnamurthy 2014, Greenwald et al. 2017; Guren et al. 2017) are as follows. In general, contracts or polices that temporarily reduce mortgage payments during recessions can potentially result in significant welfare gains. This is especially the case for borrowers who face more income variability, buy high priced houses given their income level, or make little to no downpayment. To the extent possible, it would therefore be beneficial to design mortgages or debt relief programs that 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 local labor markets and housing markets experience a downturn. Such indexation schemes need to take into account their impact on the nature of 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 the aggregate risk, limiting the effectiveness of state-contingent mortgages or debt relief polices. Finally, contracts or debt relief polices based on other national indices -- e.g., interest rate indexation in the case of ARMs -- may perform quite well in providing household debt relief during the downturns, as long as the relevant indices to which these loans are tied closely co-move with local home prices and borrowers' income.

Next, we use a simple framework that builds on these insights to illustrate that automatically indexed mortgage contracts or debt relief polices can lead to significant welfare gains for borrowers. The main channel, as mentioned earlier, is by reducing the debt burden during economic downturns. Using this framework, we illustrate two points. First, and very intuitively, a mortgage contract or debt relief policy contingent on some index is more efficient if the index is highly correlated with variables capturing relevant (e.g., local) economic conditions for borrowers and if these variables co-move with each other. Second, we show that benefits of such solutions are substantially reduced if there are errors in understanding the underlying structure of income and housing risk and their relation to the indices on which such contracts or polices are based.

While the main insight behind why such contracts or debt relief might be efficient seems relatively straightforward, we spend the next part of the paper considering how to implement such a solution within the feasible set. A key insight of our framework is that successful implementation of such solutions rely on the correct understanding of the underlying structure of income and housing risk and its relation to the indices on which such contracts or polices will be based.[3] This observation is also consistent with the quantitative life-cycle models of households' mortgage decisions that emphasize the importance of recognizing a specific nature of household risk for appropriate mortgage contract choice (e.g., Campbell and Cocco 2003, 2015).

To better understand this aspect, we analyze simple measures of housing and income risk and their co-movements across time, regions, and borrowers. We document empirical evidence pointing to significant spatial heterogeneity and time-varying nature of the distribution of economic conditions. Our spatial analysis starts at the state level and shows that states' local business cycles have quite different frequencies. For instance, using principal component analysis we find that a national economic factor explains, on average, about 52% of the variation in the time series of a state economic factor and this association varies substantially across states. Moreover, while we find that all state economic factors decline sharply during the Great Recession, substantial dispersion remains. Consistent with this observation, we find that the state-level economic variables are on average more correlated with the local economic factor than the national ones. A direct implication of this analysis is that spatial heterogeneity may limit the effectiveness of mortgage contracts or debt relief policies based on the national-level indices.

[3] In particular, even the best designed automatically indexed mortgage contract can perform quite poorly ex-post if the lenders or policymakers have incorrect understanding of the true distribution of relevant economic risk.

Next, we zoom into more granular geographical regions and conduct analysis at the county level with variables that both capture risk of regions and that are available at high frequency. We find that, as within states, there is a large spatial variation in terms of delinquency rates and equity position of borrowers. At the one end, even during the depths of Great Recession, many counties have sizeable housing equity on average and relatively low levels of unemployment and mortgage delinquencies. At the other end, some counties consist of severely distressed pool of borrowers with depleted home equity.

We also consider the stability of relationships between county-level variables. We find that county-level mortgage defaults rates are positively related to increases in unemployment rate and negatively to house price growth. This is not surprising since the extensive empirical literature identifies these two factors as key drivers of mortgage default (Foote et al. 2008). However, we also find that the strength of these associations substantially varies over time. Moreover, the strength of the relationship between housing and income risk does not appear to be stable over time pointing to a time-varying distribution of these variables. This evidence is also broadly consistent with Hurst et al. (2016) and Beraja et al. (2017) who argue that regional shocks are an important feature of the US economy and that the regional distribution of housing equity and income substantially varies over time.

Zooming in further, we show that within county, there is significant heterogeneity at the zip code and individual level. For instance, we find that there is again large heterogeneity in distribution of negative equity and defaults in the US population across time. Importantly, this evidence also shows that even during the crisis there was a large variation among borrowers within county in terms of delinquency and their home equity position.

To investigate this issue more formally, we analyze how much variation in local variables – that might be used in ex ante and ex post policies -- can be explained by variables at different levels of geographic granularity. The first exercise we undertake is a simple statistical analysis of what fraction of local variation may be explained at various levels of aggregation by considering an upper bound to the informativeness of various economic variables by their level of geographic aggregation. In our analysis we focus on house prices, combined loan to value (CLTV), debt to income (DTI), delinquency rates, and foreclosures. We show that explained variation monotonically decreases as we consider coarser geographic areas. For example, the fraction of zip code mortgage delinquency and foreclosure rate that may be explained by the corresponding county level variables is about 43% and 35%. This pattern suggests a large local variation at the zip code level that is not captured by county, state or national data. We also assess the actual association of various national, county, and zip code variables with zip-code level delinquency and foreclosure rates and find similar evidence. We also examine predictability of local housing-related variables with corresponding lagged variables at different levels of geographic aggregation. We again find that predictability is worse as we consider coarser geographic areas.

Next, we ask what the evidence documented above implies for the design of mortgage contracts and debt relief policies. In particular, following insights from our framework and the analysis on significant spatial heterogeneity, we conclude that there might be significant gains from fine tuning debt relief solutions to more granular regional conditions and that "one size fits all" polices might not be that efficient. Indexing polices and contracts to variables capturing local component of housing market risk (e.g., zip code house price indices and other local variables) could be more effective than polices based on national indices.

Moreover, we argue that one needs to carefully consider potential costs of implementing such solutions relative to traditional contracts and polices. For instance, ignoring the heterogeneity in space, while ARM contracts indexed on national interest rate indices might be helpful during periods of low interest rates, they may also exacerbate distress during periods of higher interest rate, as was the case in the late 2006—early 2008 period.

The other consideration that emerges is that for solutions such as automatically index contracts or debt relief polices to be effective, one needs to have a good "ex-ante" understanding of the underlying distribution of relevant economic risk and its relation to indices on which such contracts or polices are based. We find that the benefits of such solutions are substantially reduced if there are errors in understanding these relationships. Thus, given the evidence of significant heterogeneity in space and time, along with limited data on crisis episodes, implementing such solutions can be quite challenging. Moreover, a major change in the nature of mortgage contracts or housing policy is likely to significantly alter market equilibrium including future joint distribution of economic outcomes such as house prices, housing supply, homeownership rate, and household debt levels (e.g., Piskorski and Tchistyi 2017, Guren el al. 2017, Greenwald et al 2017). This further complicates effective usage of historical data in the design and parametrization of future contracts or polices.[4]

We also discuss the challenge faced in implementing debt relief policies that may not be automatic and may confront frictions in the market and intermediary sector for implementation. We provide evidence that there is significant spatial heterogeneity of frictions that can differentially impact pass through of ex-post debt relief polices implemented by financial intermediaries. The presence of such factors and difficulty in identifying them ex-ante poses an additional challenge in designing effective debt relief polices. For instance, while HARP was largely indexed to local economic conditions of the borrower since it was based on CLTV, it was not as effective as anticipated. In particular,

[4] See also Rajan et al. 2015 that illustrates that changed nature of intermediation in the mortgage market (Keys et al. 2010, Purnanandam 2011) may alter the stability of statistical relationships between key variables.

since the implementation was through intermediaries, its effectiveness was hampered both by intermediary frictions – such as capacity constraints – as well as market design, such as competition in the refinancing market (Agarwal et al. 2016, Fuster, Lo and Willen, 2017).

We will conclude the paper by discussing the important trade-off when thinking about mortgage design or debt relief policies in the future. The indexed mortgage contracts have the advantage of circumventing financial intermediary and other fictions by facilitating a quick implementation of debt relief during economic downturns. However, for such contracts to be cost-effective, lenders, policymakers, and borrowers may need to have a good ex-ante understanding of the underlying distribution of relevant economic risk and its relation to the indices such contracts are based on. Given the evidence we discussed above, this can be challenging.

Ex-post debt relief solutions have the advantage of being more "fine-tuned" to the specific realization of economic risk. In other words, unlike pre-crisis designed contract or policies, ex-post policy interventions do not need to rely as much on a good "ex-ante" understanding of the underlying distribution of relevant economic risk and frictions and their relation to the severity of the crisis. However, ex-post policy interventions can also delay debt relief and subject it to various implementation frictions that could hinder their effectiveness. Finally, we also note that given our evidence both types of solutions (ex-ante or ex-post) would benefit from conditioning on more granular conditions (regional or individual) as opposed to "one-size-fits-all" indicators.

## 2. Frictions to Mortgage Debt Relief: Evidence from Great Recession

Recent literature has documented the effects of several frictions that impacted the effectiveness of debt relief, thereby exacerbating the foreclosure crisis. The first friction that impacted effectiveness of debt relief relates contract rigidity – i.e., the notion that most mortgage contracts were fixed rate mortgages that were locked in at high rates. DiMaggio et al. (2017) follow empirical design in Fuster and Willen (2017), and show that as monetary policy lowered the interest rates during the Great Recession, borrowers with certain types of Adjustable Rate Mortgages (ARMs) received an automatic debt relief.[5] This experiment is useful in quantifying the effects of debt relief since it was received by every borrower with ARM contracts, regardless of any other frictions in the market that potentially could hinder the extent of this debt relief.

In particular, exploiting variation in the timing of rate resets of ARMs during the aftermath of the financial crisis, authors show that the reduction in annual mortgage debt cost was substantial (between 20% to 50%). Importantly, consequent to the debt relief, households

[5] We note that subprime ARM contracts featuring the rate-adjustment floors limited the extent of debt relief received by these borrowers.

were substantially less likely to be delinquent on their loans and unsecured debt and more likely to purchase new automobiles, with substantially stronger responses among more indebted. This evidence is consistent with Fuster and Willen (2017) who show that downward resets on ARM loans substantially lowered the mortgage default rate of these borrowers.

In addition, DiMaggio et al. (2017) show that there was spatial variation in the response to the debt relief. Regions more exposed to mortgage rate declines -- those with larger share of ARM borrowers -- saw a decline in foreclosure rate, a relatively faster recovery in house prices, increased durable (auto) consumption, and increased employment growth. This evidence highlights the importance of contract rigidity – i.e., rigid fixed rate mortgages (FRM) versus flexible contracts such as ARM -- for understanding pass-through of debt relief during periods of low interest rates to the real economy. This evidence is also consistent with Auclert (2017), who provides a model evaluating the role of redistribution in the transmission mechanism of monetary policy to consumption and predicts that if all U.S. mortgages were of adjustable-rates type, the effect of monetary policy shocks on consumer spending would be significantly higher.

The next friction that potentially hampers deft relief relates to equity refinancing constraints – i.e., the notion that the refinancing of mortgages may not be feasible since many distressed borrowers may not have enough equity to refinance. This friction is particularly important for FRMs, the predominant financial obligation of households in the U.S.[6] For such borrowers, automatic debt relief, such as those provided to ARM borrowers, is not feasible. Instead, refinancing constitutes one of the main direct channels through which households can get debt relief from the low interest rate environment induced by monetary policy. As home prices dropped precipitously during the Great Recession, many borrowers with FRMs were left with little equity, making them ineligible for loan refinancing that requires a certain amount of borrower equity.

Agarwal et al. (2015) study how this constraint hampered effectiveness of debt relief by studying the effects of the Home Affordability Refinancing Program (HARP) – a government program that allowed for refinancing of insufficiently collateralized agency mortgages with government credit guarantees. The authors find that relaxing the equity constraint for refinancing led more than three million borrowers to refinance their loans. These borrowers, on average, experienced more than $3,000 in annual savings in debt relief. Many of these borrowers subsequently increased purchases of durable goods, such as autos, with a larger increase visible among more indebted borrowers who they find have much

[6] See Green and Wachter (2005) for discussion of the historical evolution of U.S. mortgage contracts.

higher MPC from rate reduction. A life-cycle model of refinancing quantitatively rationalizes these patterns and produces significant welfare gains from altering the refinancing market by removing the housing equity eligibility constraint.[7] There is again spatial heterogeneity in the effects. Regions more exposed to the program – based on the percentage of eligible borrowers in the region -- saw a relative increase in consumer spending, a decline in foreclosure rates, and a faster recovery in house prices. This evidence is also consistent with Beraja et al. (2017) who document that prior to HARP, low interest rates mainly benefited refinancing borrowers in regions with a relatively high housing equity, exacerbating regional economic inequality (see also Di Maggio, Kermani, and Palmer 2016).

The study also illustrates that lack of competition in the refinancing market blunted the extent of pass through to borrowers, lowering their incentives to refinance. The authors estimate that these frictions reduced the take-up rate among eligible borrowers by 10 to 20 percent and cost borrowers who refinanced their loans between $400 to $800 of annual savings from relief. Strikingly, the largest effects were among the most indebted borrowers -- the primary target of HARP – where competitive frictions had the most bite. As before, there was spatial variation in these effects depending on the degree of competitiveness in the refinancing market. These findings resonate well with Scharfstein and Sunderam (2016) and Drechsler et al. 2017, who show that the extent of pass through of low interest rates in the refinancing and bank deposit market is impacted by the degree of competition. They are also broadly connected with findings of Agarwal et al. (2018) and Benmelech et al. (2018) who demonstrate the importance of financial intermediaries for the pass-through of interest rate shocks in the credit card and auto loan market.

Refinancing is not the only way to offer debt relief to borrowers. Directly restructuring borrower debt through loan renegotiation is another feasible channel. Despite the surge in distressed borrowers, U.S. economy experienced very limited loan restructuring activity early in the crisis, significantly contributing to the high number of foreclosures (more than 5 million). Research attributes this lack of restructuring activity to lender concerns about future moral hazard by borrowers and 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). Motivated by such frictions and perceived negative externalities of debt overhang and foreclosures (Campbell,

[7] See, among others, Chen et al. (2014), Wong (2015), Greenwald (2016), Beraja et al. (2017) and Guren et al. (2017) for recent quantitative models emphasizing the importance of refinancing for household consumption.

Giglio, and Pathak 2011, Melzer 2017), the federal government implemented the Home Affordability Modification Program (HAMP). In brief, the program provided substantial financial incentives to financial intermediaries ("servicers") for renegotiating loans. Agarwal et al. (2017) study the effects of this program to understand the role of intermediary specific organizational frictions in implementation of debt relief.

The authors find that, when employed, the debt relief due to these renegotiations led to a lower rate of delinquencies and foreclosures for borrowers and higher consumer spending in more exposed regions. This evidence is also consistent with Ganong and Noel (2017) who further show that temporary mortgage rate reductions induced by HAMP played the major role in explaining these effects. However, the program reached just one-third of the eligible three to four million indebted households, thereby affecting the aggregate rate of foreclosures only modestly. Agarwal et al. 2017 show that there is large heterogeneity across the financial intermediaries in the effectiveness with which they passed debt relief to borrowers even after stripping away factors such as quality of the loans, the characteristics of the borrower, or regional differences – for instance, some intermediaries renegotiate at a rate more than twice as high as others. These differences strongly correlate with the organizational design of the banks before the program was introduced: banks that previously had fewer loans per employee, more training for staff, and shorter wait times for phone calls took more advantage of HAMP. Banks with weaker infrastructure previously—mostly the largest banks—did not participate intensively in the program. Because approximately 75% of loans were serviced by banks with low capability to restructure loans, the program's impact was severely curtailed.

Finally, as before there was spatial variation in the degree of effectiveness with which debt relief was passed to borrowers that relates to regional share of loans handled by banks with more conducive organization design. Thus, intermediary specific organizational factors can impact the ability of millions of households to reap the benefits of debt relief program that is moderated through the intermediaries. These findings resonate well with Fuster et al (2013) and Fuster, Lo, and Willen (2017) who argue that intermediary capacity constraints impacted the extent of pass through of debt relief though lower interest rates in the refinancing market.[8]

To summarize, there is large literature that shows that several frictions, each in part, might have prevented debt relief from reaching distressed households, thereby significantly

[8] 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 (see Keys, Pope, and Pope 2016 and Andersen et al. 2014 for the recent evidence on these factors.

exacerbating the foreclosure crisis. Moreover, there is large regional variation in how much debt relief was passed to borrowers. We next turn to understanding the key forces that should drive such policies in order to make them more effective. We will use insights from theoretical literature on mortgage design and build a simple illustrative framework.

## 3. Mortgage Design Literature and a Simple Framework

### *3.1 Implications from Mortgage Design Literature*

A key lesson of the research discussed so far is that the rigidity of mortgage contract terms, as well as a variety of other frictions, prevented effective renegotiation or refinancing of distressed borrowers' loans during the recent crisis. Consequently, there is an ongoing debate regarding the reform of the mortgage market to alleviate the impact of such frictions in the future. At the center of this debate are a variety of proposals concerning the redesign of mortgage contracts and debt relief polices that allow for more efficient sharing of risk between borrowers and lenders. The hope is that the new mechanisms will lower the incidence of costly foreclosures and the severity of future housing downturns (e.g., Shiller 2008; Caplin et al. 2008; Piskorski and Tchistyi 2011; Campbell 2013; Keys et al. 2013; Mian and Sufi 2014b; Eberly and Krishnamurthy 2014). There are also lessons related to design and implementation of debt relief policies that require the intermediary sector for implementation.

The debate on the first issue is informed by the growing literature that addresses the questions of mortgage contract design, mortgage choice, and their implications for the broader economy. In particular, Piskorski and Tchistyi (2010, 2011) characterize optimal long-term mortgage contracts in a partial equilibrium setting with costly foreclosure, stochastic interest rate, income, and house prices where a borrower who has variable and hard-to-verify income needs money to buy a house. They derive an optimal mortgage contract as a solution to a dynamic contracting problem between the borrower and the lender. The authors show that efficient mortgage contracts should generally depend on a combination of observable "local" house price and income indices in a manner that reduces debt payments during economic downturns (e.g., when house prices substantially decline).[9] They also show that this can be done in a manner that does not erode the borrower's "ex-ante" incentives to repay their debt. Finally, the authors show that the automatically indexed state-contingent mortgage contracts are particularly beneficial for borrowers who

[9] Such state-contingent contracts could be accompanied with refinancing penalties to enhance longer-term risk sharing between borrowers and lenders (see Dunn and Spatt 1985 and Mayer et al 2013 for analysis of benefits of such solutions).

face substantial income variability, buy high priced houses given their income level, or make little or no down payment.

Piskorski and Tchistyi (2010) show that in a setting where interest rates are a good measure of a relevant risk (“state of the economy”), the optimal contract takes the form of an adjustable rate mortgage (ARM) where the borrower can decide how much to pay until his balance reaches a certain limit (the so-called option ARM). The option to pay less than the minimum monthly interest owed on the loan is valuable for borrowers with fluctuating income. The borrowers can pay a little in lean income months and catch up in fat income months, helping them to avoid costly default. The fact that the loan is an ARM—namely, its rate fluctuates with market interest rates—is valuable as it reduces the chance of default when foreclosure is relatively costly (e.g., when interest rates are low). These findings underscore the importance of recognizing the interplay between mortgage contract form with the nature of labor income, house price, and interest rate risk. In this regard, they are also related to the quantitative life-cycle models of mortgage contract choice, such as Campbell and Cocco (2003, 2015), that study the implications of such factors for contract choice, consumer welfare, and default patterns.

It is worth noting that the studies above employ dynamic contracting tools or life-cycle models of mortgage contract choice in a partial equilibrium setting that takes some key variables, such as house prices, as given. A number of recent papers extend and study the implications of state-contingent mortgage contracts in a general equilibrium framework.

Piskorski and Tchistyi (2017) develop a tractable general equilibrium framework of housing and mortgage markets with aggregate and idiosyncratic risks, costly liquidity and strategic defaults, empirically relevant informational asymmetries, and endogenous mortgage design. They show that, intuitively, the equilibrium contract should depend on both local labor and housing market conditions, with mortgage payments being reduced when local labor markets and housing markets are performing poorly (and vice versa). However, if one takes into account the empirically relevant frictions – such as those discussed in Section 2, as well as inability of lenders to fully observe how much a given borrower values homeownership -- the equilibrium contract only depends on house prices. The equilibrium contract takes the form of a home equity insurance mortgage (HEIM) that eliminates the strategic default option imbedded in the FRM and insures the borrower's equity position. Interestingly, they also show that while beneficial for most borrowers, there are cases when HEIMs may decrease both the homeownership rate in the economy and the welfare of marginal homebuyers due to the general equilibrium effects.

The authors also note that a widespread adoption of HEIMs would require a timely and accurate regional house price index. Alternatively, appropriately structured ARM contracts may share some of the benefits of the state-contingent mortgage contracts as long as the relevant interest rate indices to which these loans are indexed closely co-move with home prices and borrowers' income. In such settings, rather than exposing borrowers to interest rate risk, ARMs can effectively provide households with valuable insurance against recessions by lowering mortgage payments in states when labor income and house prices are lower. This being said, the authors note that a significant regional heterogeneity in economic conditions, including the local housing markets, may limit the effectiveness of one-size fits all adjustments of mortgage terms based on the national indices. In this regard, the HEIM type-contracts indexed to local house price indices could be potentially more efficient in insuring households against housing downturns in such settings. Finally, they also show that unrestricted competition in mortgage design may lead to non-existence of equilibrium in some cases, suggesting a potential role of public policy in implementing new mortgage contracts. We will come back to this issue in Section 5.

It is worth emphasizing that the work discussed above is complementary to recent studies that focus on the role of mortgage contracts in quantitative dynamic equilibrium models of housing markets.[10] In particular, Guren, Krishnamurthy, and McQuade (2017) use a quantitative equilibrium life cycle model with aggregate shocks, long-term mortgages, and an equilibrium housing market, focusing in particular on mortgage designs that index payments to interest rates. They find that the welfare benefits are quantitatively substantial: ARMs improve household welfare relative to FRMs by the equivalent of 1.00 percent of annual consumption, if the central bank lowers interest rates in a bust. Recent empirical evidence is consistent with their quantitative findings. As noted in Section 2, Di Maggio et al. (2017) and Fuster and Willen (2017) show that mortgage rate declines during the Great Recession due to ARM contracts resetting to a low rate had a direct positive impact on borrowers and regions. The borrowers who experienced these reductions saw lower default rate and increased their consumption. Moreover, regions more exposed to mortgage rate declines due to ARM resets saw a relatively faster recovery in house prices, increased consumption, and decline in foreclosure rate. Guren et al. (2017) also find that among the potential alternatives they consider that reduce payments in a bust, the FRM convertible to the ARM, a contract similar to the one proposed by Eberly and Krishnamurthy (2014), may perform better than more standard contracts. However, they also point out that endogenous response of households to new mortgage designs can significantly reduce their benefits.

Greenwald, Landvoigt, and Van Nieuwerburgh (2017) study implications of shared appreciation mortgages (SAMs) that feature mortgage payments that adjust with house

[10] This line of work is also related to Kung (2015) who explores a number of counterfactuals related to credit availability and mortgage contract forms in a quantitative equilibrium model of the housing market.

prices in a quantitative general equilibrium model with financial intermediaries. These intermediaries channel savings from saver households to borrower households. They show that if financial intermediaries retain a significant share of mortgages on their balance sheets, the indexation of mortgage payments to aggregate house prices may increase financial fragility, reduce risk sharing, and lead to expensive financial sector bailouts. In contrast, they show that indexation to local house prices can reduce financial fragility and improve risk-sharing. The two types of indexation have opposite implications for wealth inequality.

Overall, taken together, there are number of key lessons that can be derived from the mortgage design literature. In general, contracts or polices that temporarily reduce mortgage payments during recessions can potentially result in significant welfare gains. To the extent possible, it would be beneficial to index mortgage payments to measures capturing the state of the local labor and housing markets, with mortgage payments being lower in states when these markets experience a downturn. Such indexation schemes need to take into account the impact of such contracts on the nature of mortgage market equilibrium, including the incentives of households to borrow and repay their debt. In addition, 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 limit the ability of financial intermediaries to insure the aggregate risk, limiting the effectiveness of state-contingent mortgages or debt relief polices. Finally, contracts or debt relief polices based on other indices not directly tied to the state of the local housing or labor markets (e.g., interest rate indexation in the case of ARM) may perform quite well in providing household debt relief during the downturns as long as the relevant indices to which these loans are indexed closely co-move with home prices and borrowers' income.

This discussion implies that one of the fundamental aspects in the successful implementation of state-contingent mortgage contracts or debt relief policies, is a thorough understanding of the underlying structure of economic risk faced by the mortgage borrowers. Moreover, one needs to understand how the nature of relevant economic risk relates to a variety of possible indices that can be used in the design of mortgage contracts or debt relief polices in practice. In the next subsection we illustrate the importance of these factors in a simple, stylized, illustrative framework. We will then provide empirical evidence on these issues as they relate to actual design of mortgage contracts and debt relief in Section 4.

### *3.2 A Simple Illustrative Framework*

#### *3.2.1 Setup*

We now discuss a simple illustrative framework that draws on insights from the literature we discussed earlier and will allow us to highlight the benefits of the automatically indexed mortgage contracts or debt relief polices relative to the simple FRMs. [11] We will use this framework to explore two issues. First, we will illustrate, through a few numerical examples, how the benefits of such indexed contracts or polices relate to the type of index used by lenders or policymakers and its relation to the underlying structure of economic risk. Second, we will also investigate how benefits of such solutions change if there are errors in understanding the underlying structure of income and housing risk and their relation to the indices on which such contracts or polices are based.

We consider a simple stylized partial equilibrium mortgage lending framework where a risk-neutral borrower with linear utility buys a home worth $P_0$ by borrowing D from a risk-neutral lender (hence down payment is $P_0 - D$). If $D = 0$, then the borrower pays zero down payment. The borrower can down-pay D equal to his initial personal wealth $W_0$ upon buying the house. For simplicity, we normalize the discount factor and risk-free rate to be 1. We first consider a FRM, the most commonly used residential mortgage contract in the US. Under the terms of FRM, the borrower faces a fixed-mortgage rate of $\bar{r}$.

The borrower derives utility of $\theta$ from living in the home. Next period, after the loan is made, the borrower realizes his income y drawn from normal distribution $f^y$ with $y \sim N(\bar{y}, \sigma_y^2)$. Furthermore, he sees the updated home price $P_1$ drawn from normal distribution $f^P$ with $P_1 \sim N(\overline{P}, \sigma_P^2)$. If the borrower sells his home at $P_1$ or defaults, he loses $\theta$ of utility. If the borrower defaults, the lender receives only $\delta \in (0,1)$ of $P_1$, where $\delta$ captures some liquidation costs and the borrower suffers utility cost of $\bar{v}$. We further assume that $\theta + \bar{v} > (1 + \bar{r})P_0$, implying that the borrower has incentive to repay his debt.

Given this setting the optimal strategy of the borrower can be described as follows:

(1) If realized income is such that $y < (1 + \bar{r})(P_0 - D)$ and realized house price is such that $P_1 < (1 + \bar{r})(P_0 - D)$, then the borrower has no choice but to default. His realized life-time utility will be $u(y, P_1) = y - \bar{v} - D$.

[11] Notably, our simple illustrative framework has number of important limitations. Among others, (i) we restrict the contract choice to a simple linear rule as a function of a given index; (ii) we only focus on liquidity driven defaults, neglecting strategic defaults that also accounted for defaults during the Great Recession; (iii) we do not incorporate some of the empirically relevant informational asymmetries between borrower and lender; (iv) we also do not model the long-term aspect of mortgage contracts and the possibility of loan refinancing; (v) we do not analyze the impact of borrower and lender risk-aversion on consumer welfare and mortgage terms; (vi) we also do not take into account general equilibrium effects of changes in contract terms and (vii) we set aside a question of what mortgage contracts would be sustainable in the competitive market equilibrium with empirically relevant frictions and whether there is a scope of welfare improving public policy intervention in such settings. The literature discussed in Section 3.1 addresses the design of mortgage contracts and its implications, capturing many of such factors and complications.

(2) If realized $y < (1+\bar{r})(P_0 - D)$ and $P_1 > (1+\bar{r})(P_0 - D)$, then the borrower cannot repay the loan but can sell the home. His realized lifetime utility will be $u(y, P_1) = y + P_1 - (1+\bar{r})(P_0 - D) - D$.

(3) If realized $y > (1+\bar{r})(P_0 - D)$ and $\theta \geq P_1$, then the borrower repays the loan without selling the house. His realized lifetime utility will be $u(y, P_1) = y + \theta - (1+\bar{r})(P_0 - D) - D$.

(4) If realized $y > (1+\bar{r})(P_0 - D)$ and $\theta < P_1$ then the borrower sells the home and his realized lifetime utility will be $u(y, P_1) = y + P_1 - (1+\bar{r})(P_0 - D) - D$.

We note that default happens if both house prices and income are sufficiently low, consistent with the "double trigger" notion in the literature (e.g., see Foote et al. 2008). The competitive FRM mortgage rate will be the lowest $\bar{r}$ -- since the lower $\bar{r}$, the higher the borrower utility -- such that the lender breaks even.

Formally, we formulate this problem as follows. First, we define the distribution of income and house price as follows:

$$X = \begin{bmatrix} y \\ P_1 \end{bmatrix}, \mu = \begin{bmatrix} \bar{y} \\ \bar{P} \end{bmatrix}, \Sigma = \begin{bmatrix} \sigma_y^2 & \rho_{yP}\sigma_y\sigma_P \\ \rho_{yP}\sigma_y\sigma_P & \sigma_P^2 \end{bmatrix}, \text{and } X \sim N(\mu, \Sigma).$$

Given the above discussion, under the fixed rate mortgage contract the consumer expected utility maximization problem subject to lender break even condition can be formulated as a function of defaulting, selling, and paying states as follows:

$$\max_{\bar{r}} \quad Pr_{def} * E(y - \bar{v}|def) + Pr_{sel} * E(y + P_1 - (1+\bar{r})(P_0 - D)|sel) + Pr_{pay} * E(y + \theta - (1+\bar{r})(P_0 - D)|pay) - D$$

$$\text{s.t.} \quad P_0 - D = Pr_{def} * E(\delta P_1|def) + Pr_{sel} * E\big((1+\bar{r})(P_0 - D)\big|sel\big) + Pr_{pay} * E\big((1+\bar{r})(P_0 - D)\big|pay\big),$$

where we define the probabilities above as follows:

$$Pr_{def} = Pr(y < (1+\bar{r})(P_0 - D), P_1 < (1+\bar{r})(P_0 - D)),$$

$$Pr_{sel} = Pr(y < (1+\bar{r})(P_0 - D), P_1 > (1+\bar{r})(P_0 - D)),$$

$$Pr_{pay} = Pr(y > (1+\bar{r})(P_0 - D)).$$

In the above calculations we assume that the borrower uses all its initial wealth for down payment. It is worth that in our simple stylized setting the borrower will generally have incentive to down-pay as much as possible since this reduces the expected mortgage cost, which is weakly higher than the riskless saving rate. In later discussion we will focus on two particular cases: (1) $D = 0$ (zero down − payment); (2) $D = 20\% *$

$P_0$ (20% down − payment). The former case is meant to represent the highly indebted borrowers with very little initial housing equity, while the latter represents more creditworthy prime borrowers that can afford substantial down-payment.

We next consider an indexed rate mortgage (IRM) contract of the form $r = \alpha_0 + \alpha_1 i$ where $i$ is an index drawn from standard normal distribution $f^i$ with $i \sim N(0,1)$. Hence $r \sim N(\alpha_0, \alpha_1^2)$ and the overall distribution of stochastic variables is defined as follows:

$$X = \begin{bmatrix} y \\ P_1 \\ r \end{bmatrix}, \mu = \begin{bmatrix} \bar{y} \\ \bar{P} \\ \alpha_0 \end{bmatrix}, \Sigma = \begin{bmatrix} \sigma_y^2 & \rho_{yP}\sigma_y\sigma_P & \rho_{yi}\sigma_y\alpha_1 \\ \rho_{yP}\sigma_y\sigma_P & \sigma_P^2 & \rho_{Pi}\sigma_P\alpha_1 \\ \rho_{yi}\sigma_y\alpha_1 & \rho_{Pi}\sigma_P\alpha_1 & \alpha_1^2 \end{bmatrix} \text{ and } X \sim N(\mu, \Sigma).$$

We note that the borrower optimal behavior and lifetime realized utility are the same as described above for the FRM contract, except replacing $\bar{r}$ with the realization of $r \sim N(\alpha_0, \alpha_1^2)$.

In offering this contract, the lenders optimally choose the parameters $\alpha_0$, and $\alpha_1$ while taking the distribution of the index as given. For example, we could think of the ARM contract as a special case of the IRM contract, where the index *i* is just some spread over realization of the interest rate index (e.g., 1-year Treasury or LIBOR). We could also think about the IRM as representing a state-contingent debt relief policy that depends on the policy index *i* coupled with simpler contracts (e.g., FRM).[12]

We further assume that the introduction of IRM contracts may be subject to a certain upfront fixed cost c per borrower that is faced by lenders relative to a setting with FRM contracts. This cost represents some additional unmodeled cost of issuing more complex contracts or implementing debt relief policy – such as potential costs of educating borrowers, costs of unmodeled uncertainty about the actual distribution of the index, some additional hedging costs for the lender, or some administrative costs of implementing a debt relief policy.

Given the above set-up under any particular correlation schedule $\rho_{yP}, \rho_{yi}$ and $\rho_{Pi}$, the competitive equilibrium IRM contract maximizes the consumer expected utility across the three states subject to lender break-even condition:

$$\max_{\alpha_0,\alpha_1} \quad Pr_{def} * E(y - \bar{v}|def) + Pr_{sel} * E(y + P_1 - (1+r)(P_0 - D)|sel) + Pr_{pay} * E(y + \theta - (1+r)(P_0 - D)|pay) - D$$

[12] Implementation of such debt relief policy with simpler contracts may require an ex-ante commitment from policymakers, lenders, and borrowers.

$$\text{s.t. } P_0 - D = \Pr_{def} * E(\delta P_1 | def) + \Pr_{sel} * E\big((1+r)(P_0 - D)\big| sel\big) + \Pr_{pay} * E\big((1+r)(P_0 - D)\big| pay\big) - c,$$

where:

$$\Pr_{def} = \Pr\big(y < (1+r)(P_0 - D), P_1 < (1+r)(P_0 - D)\big),$$

$$\Pr_{sel} = \Pr\big(y < (1+r)(P_0 - D), P_1 > (1+r)(P_0 - D)\big),$$

$$\Pr_{pay} = \Pr\big(y > (1+r)(P_0 - D)\big),$$

$$\text{and,} \quad r = \alpha_0 + \alpha_1 i.$$

This problem has no closed form solution, so we focus on numerical solutions for a set of parameters given in Table 1 to gain insights. We note that the main insights form our illustrative framework are valid across a wide range of parameters.

It is worth noting, as will become clear shortly, that if the additional cost of issuing IRM contracts is equal to zero, the IRM loans will always be weakly better for borrowers than the FRM . The reason is that IRM contracts nest the FRM ones. As we illustrate below with positive fixed cost of issuing a more complex mortgage, whether such a mortgage will be better than FRM depends on how closely $i$, y and $P_1$ co-move with each other.

*3.2.2 Benefits of Mortgage Debt Indexation*

First, let's consider the case of no fixed cost index mortgages compared to fixed rate mortgages. We start by showing the borrower's utility gain (in percentage terms) under IRM compared to FRM assuming (P,y) are perfectly correlated. Panel A of Figure 1 plots this result: on horizontal axis we have varying degrees of correlation of $i$ with y. Since y and P are perfectly correlated, this is also the correlation of $i$ with P.

Panel A of Figure 1 shows an important feature of our setting: IRM without fixed issuing cost would never do worse than FRM *provided that the lenders correctly assess the distribution of the underlying risk*. The reason is that by optimally choosing $r = \alpha_0 + \alpha_1 i$ in the contract, one can always reduce $\alpha_1$ to zero when the index correlation with y or P is approaching zero. In this sense, the FRM would simply be a special case of IRM. As soon as index correlation with y or P turn positive, there is always some benefit from reducing default probability. Hence, the optimal contract would also have $\alpha_1 > 0$, turning on the volatility of the index mortgage rate. Therefore, as is evident from Figure 1, generally the benefit of an index mortgage contract is larger when the correlation of the index with income or housing price is higher. We also note that in a setting with borrower risk aversion, state-contingent lending contracts may provide additional benefits to households by partially insuring their labor income risk and hence allowing them to better smooth their consumption profiles. This additional benefit should increase the value of state-contingent contracts relative to fixed-rate mortgages.

In reality house prices and household incomes may not be perfectly correlated. To understand how our insights might change due to this, we next consider two cases: (1) Corr(y,P)=0.25 (low correlation) and (2) Corr(y,P)=0.75 (high correlation). The results are shown in Panels A and B of Figure 2. The following results emerge: (1) IRM is never worse than FRM, as FRM is a special case of the IRM contract when $\alpha_1 = 0$; (2) Generally, the higher Corr(P,i) and Corr(y,i) are, the larger the gain from an indexed loan relative to FRM; (3) Corr(P,i) is quantitatively more important for the utility gain than Corr(y,i), as can be seen by the steeper slope along the dimension of Corr(P,i). This result is intuitive, as the borrower can avoid default by selling the home even when income is low; (4) Finally, the gains of utility under IRM are generally higher as Corr(P,y) is higher.

Next, we take into account the possibility of a down-payment in housing purchase. As formulated in the model, we consider the case of a 20% down-payment in both FRM and IRM. Panels C and D of Figure 2 show the corresponding results. We see that for the case of down-payment/significant positive home equity, gain from indexed contracts is smaller. This is intuitive, since down-payment lowers default probability and the associated deadweight losses from having a rigid contract.

Now, we consider the case where issuing IRM has a fixed cost to the lender, in particular 1% of the initial housing price. Again, we start by showing the utility gain (loss) of IRM compared to FRM, assuming house prices and income are perfectly correlated. Panel B of Figure 1 shows these results. Compared to Panel A, this figure shows that for our parameters with fixed cost of issuing an indexed loan, there is a range of correlations where utility under the indexed loan is lower than under the FRM. In general, this plot indicates that with additional cost of issuing an IRM loan, there may be a range of correlations where utility under the indexed loan may be lower than under the FRM.

To shed more light on this issue, Figure 3 reproduces the analysis in Figure 2, but with additional cost of indexation equal to 1% of the initial house price per borrower. This figure consistently shows that an IRM contract is more likely to benefit consumers when the index correlation with income and housing price is sufficiently high. When the index correlation with income and housing price is not sufficient, there can be a utility loss compared to FRM due to the IRM issuing cost.

Our simple framework shows that successful implementation of indexed-mortgages crucially relies on correct understanding of the underlying structure of income and housing risk and its relation to the indices on which such contracts or polices will be based. To illustrate this point, Figure 4 shows the borrower's utility -- in percentage terms -- under indexed-rate mortgage designed for incorrectly projected high correlation of income and house prices (equal to 0.75) and high projected correlation of index with income and house prices (equal to 0.60). These are compared to scenarios of indexed-mortgage that is correctly designed knowing that the actual correlation of income and house prices is low (equal to 0.25) and that the actual correlation of index with income and house prices is as shown on the figure. The computation assumes no down-payment and no indexation cost. As we observe, incorrect beliefs about the distribution of key economic variables result in substantial decline in efficiency relative to contract designed under the correct distribution of economic variables.

Based on our numerical results presented in Figure 1 to Figure 4, we summarize the main insights of our simple framework as follows:

(1) Without additional cost of indexation, the IRM contract is always weakly better than FRM contract;
(2) The higher the correlation of income and house prices with the index, the bigger the gain from an indexed loan relative to FRM;
(3) The utility gains under an indexed loan or an indexed debt relief policy are generally higher when the correlation between house prices and income is higher;
(4) With an additional cost of issuing an indexed loan, there are a range of correlations where utility under the indexed loan is lower than under the FRM. Besides, it is possible that when the index is sufficiently correlated with income and house price, the indexed contract is better than the FRM.
(5) Gains from indexed contracts are much higher for borrowers that make little or no down-payment (have little housing equity).
(6) Benefits of indexed-mortgages or debt relief polices crucially depend on the correct understanding of the underlying structure of income and housing risk and its relation to the indices on which such contracts or polices will be based. In the case of incorrect beliefs about these relationships, the benefits of such solutions can decrease substantially.

Our simple framework highlights the importance of understanding the underlying structure of income and housing risk and its relation to the indices on which contracts or debt relief polices will be based. More broadly, this includes an assessment of the expected degree of heterogeneity across regions and borrowers, the stability of such relations over time, and the relative value of polices based on national vs local indices.

**Section 4: Spatial and Individual Variation in Income and Housing Risk**

In this section we try to understand the structure of income and house price risk across regions and assess their relation to mortgage defaults and the home equity position of borrowers. We will also discuss how this risk relates to possible indices that could be used in future mortgage contracts or debt relief policies.

*4.1 Evidence from U.S. States*

To measure local economic conditions, we take a stance on variables that summarize business conditions. These variables include real GDP growth, personal income growth, unemployment, and house price growth. Real GDP growth measures the output of the economic area. Real personal income growth measures changes in wealth of local consumers. Both GDP and income data are from the Bureau of Economic Analysis. We deflate using CPI for all urban consumers from FRED (Federal Reserve Bank of St. Louis). Since unemployment is a permanent loss to income, we include the local unemployment rate. Unemployment data are from the Bureau of Labor Statistics. To measure expectations about future economic conditions, we use changes in the market value of real estate. When available, we use data from Zillow; otherwise, we use data from Freddie Mac House Price Index. For national housing data, we use the S&P/Case-Shiller U.S. National Home Price Index. Table 2 displays summary statistics for the national and state-level economic series.

We assume that the local business cycle influences output, income, unemployment, and house prices. For each state, we extract this common component through a principal component analysis (PCA). The first component explains on average 60% of the variation in these four series. This component loads positively on output, income, and house prices, but negatively on unemployment. Table 3 displays the summary statistics for the weights of the first component and its explained variation. The large explained variation and loadings are consistent with a proxy for local economic conditions. Figure 5 plots its mean and $10^{th}$-$90^{th}$ percentile range over time. Note that the economic factor declines sharply during the financial crisis of 2008, but dispersion remains rather stable.

To characterize further the cross-sectional heterogeneity of state-level economic conditions, we regress the local economic factor on a constant and the national economic factor. The data covers all 50 states and the District of Columbia spanning from 1980 to 2016. A national economic factor explains on average 52% of the variation in the time series of state. However, this explanatory power varies substantially across states.[13] Local economic conditions in Alaska are least represented by the national economic factor with an $R^2$ of near 0%, while Minnesota is most represented with 82% of variation explained. Appendix A1 illustrates the distribution of $R^2$. The fraction of variation explained is closely related to the correlation between local and national economic conditions. The heterogeneity in

[13] This national economic factor is constructed similarly to the state-level economic factors. The national economic factor is the first component of a PCA on real GDP growth, income growth, house price growth, and unemployment.

correlation is also illustrated by variation in the sensitivity of local economic conditions to that of the nation. A one standard deviation improvement to national economic conditions on average improves local economic conditions by 0.70 standard deviations. However, this varies substantially as illustrated in Appendix A1. For example, North Dakota has a beta of 0.08, while California has a beta of 0.94.

Other macroeconomic variables perform similarly in explaining the variation in state-level business cycles. We consider the underlying macroeconomic variables to the national factor (GDP growth, income growth, house price growth, and unemployment), macroprudential policy rates (Fed Funds rate), interest rates (nominal and real 1 year Treasury rate), and the 30 year mortgage rate. The Fed Funds rates, Treasury rates, and mortgage rates are sourced from FRED. For each state, we regress local economic conditions on a constant and the underlying macroeconomic variable iteratively. All of these national-level macroeconomic variables differ substantially in explanatory power and beta across states. Table 4 provides summary statistics detailing the variation.

Using local economic variables to explain local business conditions is both intuitive and more effective. For all economic series, the state-specific series are on average more correlated with the local economic factor. State-level change in unemployment correlates with the local economic factor by an average of -68%, but the national change in unemployment correlates on average -50%. For housing prices there is also a large gain: 67% for state-state and 58% for state-national. Figure 6 illustrates the cross-sectional distribution of correlations between state economic conditions and state economic variables (Panel A) and state economic conditions and national economic variables (Panel B). Notably, the distributions tend to be shifted toward positive one for real GDP growth, income growth, house price growth, and toward negative one for unemployment rate. Finally, Panel C of Figure 6 shows the substantial heterogeneity in correlation between changes in state economic conditions and national-level interest rate indices.

Overall, this simple analysis illustrates that the local economic conditions exhibit substantial heterogeneity, which is not that closely related to the national macroeconomic conditions or interest rate indices. Furthermore, state-level economic conditions vary in their correlation and sensitivity to national conditions. This regional heterogeneity may limit the ability of national macroprudential policy or mortgage contracts based on the national-level indices to comprehensively and effectively respond to local economic conditions.

### *4.2 Evidence from U.S. Counties and Zip Codes*

So far we have shown that states exhibited heterogeneous business cycles from 1980 to 2016. Now we turn to the county level to show that counties also experience substantial heterogeneity. Our data comes from a variety of sources. County unemployment rate is from the Bureau of Labor Statistics, county income is from the U.S. Census Bureau, county house prices come from Zillow's Home Value Index. We complement the county-level data with additional housing variables. County first mortgage serious delinquency rates combined loan-to-value ratios (CLTV) come from a 10% representative sample of the U.S. population provided by Equifax, covering sample period from 2005 to 2016.[14] For each county, we focus on local economic variables -- unemployment rate, change in unemployment rate, real income growth-- and housing variables – house prices, CLTV, and mortgage delinquency rates. We also complement our analysis by presenting some evidence on foreclosure rates, vantage credit scores, and debt payment to income ratios (all from Equifax data).[15]

We begin by examining the mean and standard deviation of real income growth and unemployment rate. Panel A of Figure 7 shows the mean of these variables. Unsurprisingly, there is a sharp decrease in mean income growth and a sharp increase in mean unemployment around 2008. Even more importantly, Panel B of Figure 7 shows the standard deviation of both variables. There is considerable variation in both income and unemployment across counties for the entire time series, with spikes at 2008. While the standard deviation of unemployment begins to decrease after 2010, the standard deviation of income growth increases substantially only from 2013 onwards.

Next, we examine the mean and standard deviation of housing variables. Panel A of Figure 8 shows the means of house price growth, CLTV, and delinquency rate. Again, the means vary substantially over time, with CLTV and delinquency rates reaching their maximum around 2010 and 2011 and HPI growth reaching its minimum in 2010. As Panel B of Figure 8 shows, the standard deviations also fluctuate throughout the time series, with volatility of all three variables reaching a peak during the period from 2009 to 2011. Overall, Figures 7 and 8 show that both the mean values of county variables and the variability of these values across counties vary significantly over time.

[14] We note that the Equifax data we use does not have a direct measure of current CLTV of mortgage borrowers. We compute this variable in a region (county or zip code) by diving the average combined mortgage debt level of borrowers with first mortgages on their credit files by the median house price in a region (from Zillow). We verified that our measure of average CLTV in a region is closely related to the CLTV measure from wieldy used Credit Risk Insight Servicing McDash (CRISM) data that covers approximately seventy percent of mortgage borrowers. We also note that our measure indicates slightly higher CLTV levels than CRISM data, likely due to the well-known underrepresentation of subprime borrowers in the CRISM data (see Appendix A2 for more details).

[15] The Equifax based debt payment to income ratio (DTI) should be interpreted with caution since the Equifax data does not report the actual income of the borrower and instead provides the estimated income based on credit variables.

Another way to view heterogeneity spatially is by presenting heat maps of county level variables before, during, and after the financial crisis. Figure 9 does so by plotting unemployment rate, while Figure 10 plots house price growth. Panels A of the maps illustrate that even before the recession, there was some heterogeneity across counties. We can see from Panels B that heterogeneity increased during the crisis. Panels C show that most counties recover across these two variables, but some remain in a distressed state. These figures illustrate the extent of the heterogeneity across counties in various time periods across income and house price risk. This evidence is also consistent with urban economics literature that documents significant heterogeneity in the local housing price movements (e.g., Glaeser et al. 2008; Sinai 2013).

Figure 11 similarly plots the heat map with CLTV and delinquency (in 2010). We note that areas with high CLTV level often correspond to the areas that experienced high house price growth prior to the crisis (see Panel A of Figure 10). This reflects, in part, a significant amount of home equity extraction in areas that experience a rapid house price growth prior to the bust (see Mian and Sufi 2011 and Buttha and Keys 2016). Figure 10 and 11 suggest that the heterogeneity in unemployment and house price growth implies a significant heterogeneity in housing equity and mortgage defaults during the peak of Great Recession. Many of the counties have high CLTVs, delinquency rates, and unemployment rates and low house price growth in 2010, but other counties continue to perform quite well. This evidence is consistent with Mian and Sufi (2014a) who show a strong link between household leverage and the extent of house price declines at the regional level and subsequent increase in unemployment during the Great Recession.  At the same time while many of the counties have high CLTVs, delinquency rates, and unemployment rates and low house price growth in 2010, other counties continue to perform quite well.

This heterogeneity exists across years, but especially so during the crisis. Figure 12 and 13 show similar evidence for U.S. zip codes.[16] Appendix A3 complements this evidence by showing similar heterogeneity in foreclosure rates, DTI, and vantage credit scores. Strikingly, at this more granular level the evidence of the heterogeneity becomes even more pronounced. Overall, this evidence indicates that the Great Recession did not affect regions uniformly and there is a substantial heterogeneity in housing equity and default that is also visible in the heterogeneity of unemployment and house price movements.

Thus far, we have visually examined heterogeneity in space and time through means and standard deviations.  Next, we will consider the stability of relationships between county level variables. We regress the dependent variable, such as mortgage default rate, on

[16] Our analysis of zip code level heterogeneity is limited as we do not have access to good unemployment data at this level.

another variable, such as unemployment rate, interacted with annual dummy variables for each year. In Figure 14, we show the coefficients of such regressions where we regress the change in the mortgage default rate on unemployment rate (Panel A) and house prices (Panel B), respectively. The figures also include 95% confidence intervals.

This figure confirms that the extent of mortgage defaults in a region is closely associated with change in unemployment rate and house prices with mortgage defaults being generally lower in areas experiencing lower levels of unemployment and higher house price growth. This is not surprising since the extensive empirical literature identifies this two factors as key drivers of mortgage default (see Foote et al. 2008, Keys et al. 2013). This is also consistent with the predictions of our simple illustrative framework from Section 3.2. Interestingly, while the relationships between these variables are quite strong, the strength of these relationships also varies over time. For example, the regression of mortgage default on unemployment rates is positive throughout the entire time series, but varies substantially (Panel A of Figure 14).

Figure 15 sheds additional light on this question by examining the stability of the relationship between house prices and change in unemployment (Panel A) and change in CLTV (adversely related to change in the housing equity) and change in unemployment rate (Panel B). The evidence points to a significant instability between these two key drivers of mortgage default. In other words, it appears that it is not always the case that regions experiencing substantial increase in house prices (or housing equity) also experience a substantial *simultaneous* decrease in unemployment. For example, the regression of house price growth on change in unemployment results in a strong negative relationship for most of the time series, but the strength of the relationship decreases from 2010 onwards and we even find positive results from 2013 to 2015. This evidence is also broadly consistent with Hurst et al. (2016) and Beraja et al. (2017) who show that regional shocks are an important feature of the US economy and that the regional distribution of housing equity and income varies over time.

### *4.3 Relative Importance of Local Economic Indicators*

The above evidence suggests that local regional economic conditions display considerable heterogeneity that is related to the state of the housing market. This suggests that indexing mortgage contract terms or debt relief polices to indices capturing the local component of economic conditions may improve the efficiency of such solutions. To shed more light on this issue, we now more formally assess the association of various national, county, and zip code variables. In particular, we now analyze how much variation in local variables – that might be used in ex ante and ex post policies -- can be explained by variables at different levels of geographic granularity. As will become clear, doing so allows us to better understand how to assess and predict these local variables.

The first exercise we undertake is a simple statistical analysis of what fraction of local variation may be explained at various levels of aggregation. In our analysis we will focus on five variables that we have discussed earlier: house prices, combined loan to value (CLTV), debt to income (DTI), delinquency rates, and foreclosures. We will analyze several levels of geographic granularity. At the most granular level, a local housing market will be defined by its zip code (14,250 zip codes). Similarly, we also assess geographic granularity at the level of city (7,600), county (1,000), metro-area (730), state (51), and national (1). Our analysis uses a sample that spans zip-codes over Jan 1997-Dec 2017 for housing prices and Jul 2005-Dec 2017 for CLTV, DTI, delinquency rates, and foreclosures. We will focus on variation in both the level of these variables and their growth rates. Additionally, we demean the series by zip code to absorb time-invariant cross-sectional heterogeneity. To make the analysis robust to outliers, we winsorize the tails at the 1% level. Appendix A4 reports the summary statistics of the housing market variables that we focus on.

To characterize the importance of local economic variables in capturing the state of the local housing market, we estimate the fraction of variation that may be explained by geography by time fixed effects. Formally, we regress

$$Y_{i,t} = Geography_{j(i)} \times Time_t + \varepsilon_{i,t}$$

where $Y_{i,t}$ is the housing market variable for zip code $i$ in period $t$. In particular, the housing market variables we consider include real house price, loan to value, debt to income, delinquency rates, and foreclosures, as discussed above in the data section. $Geography_{j(i)} \times Time_t$ is the geography by time fixed effects, where we measure $Geography_{j(i)}$ by different levels of aggregation: city, county, metro-area, state, and national level.

The set-up of this regression puts an upper bound on the variation of $Y_{i,t}$ that can be explained by any economic variable at aggregation level $j$. For example, suppose we included zip-code by time fixed effects. This specification soaks up all of the variation in $Y_{i,t}$, yielding an $R^2$ of 100%. Clearly, the upper bound to explanatory power is agnostic about what underlying economic variable explains variation in a given housing market variable. This effectively estimates an upper bound to $R^2$ that could be generated from a contemporaneously measured variable at the level of aggregation $j$. The regression results are reported in Table 5.

Panel A of Table 5 shows the results for the variation in the level of housing variables. It documents how the fraction of variation explained at the local level increases with the granularity of the geographic area. In each cell, we report the unadjusted $R^2$ of the zip code level housing variable regressed on different levels of geographic aggregation by time dummies, as in the above equation. First, when geographic aggregation is at the zip code level, the $R^2$ is 100%, as zip code by time dummies span the full panel dataset. Note that we report unadjusted $R^2$ because doing so provides a clear benchmark of 100% explained variation when we use the data with the highest level of granularity.

Next, consider aggregation at the city level to explain zip code level variation in housing markets. Looking across Columns (1) to (5), note that a city level variable can explain a significant amount of the variation (ranges between 71% and 85%) for local zip code housing variables. For example, 71% of the local variation of foreclosure growth rate can be explained by a city level variable (Column 5) while about 86% of the variation of zip-code level house prices can be explained by a city level economic variable (Column 1). However, note that at the city level we have on average less than 2 zip codes grouped together in our data. Hence this upper bound on $R^2$ would likely be tighter in the broader sample of zip codes.

Explanatory power monotonically decreases as we consider coarser geographic areas. For example, the fraction of mortgage delinquency and foreclosure rate that may be explained by county level aggregation is about 43% and 35%. This pattern suggests a large local variation at the zip code level that is not captured by county, state or national data.

Finally, we move to national level aggregation, which means using a national time series trend to explain the zip-code level time series pattern of housing market. We see that for housing price growth rate, this time series can explain about 34% of the local variation (Column 1). Though a decent faction, this still represents a significant drop from the county level result (80%). For delinquency and foreclosure rates, the national time series pattern can merely explain 13% to 26% of the local pattern (Columns 4 and 5).

As a robustness check, we also consider the heterogeneity of growth rates for housing variables. Panel B of Table 5 presents the corresponding results. As in the case of the level variables, the explanatory power substantially decreases as we consider coarser geographic areas. For example, the fraction of house price growth variation that may be explained by county level aggregation is 55.6%. Explained variation decreased by 21% when moving from city level aggregation (77%-55.6%). The drop is more extreme for other housing variables. For debt to income, loan to value, delinquency, and foreclosures, the variation explained drops significantly from around 60% to slightly above 10% when we move from city to county level. This interesting pattern suggests a large local variation at the city (or even finer) level that is not captured by county, state or national data.

Finally, when we move to national level aggregation we see that this time series can explain about 25% of the local variation for housing price growth rate (Column 5 of Panel B). Though a decent faction, this still represents a significant drop from the city level result. For all other variables including delinquency and foreclosure rates, the national time series pattern can merely explain 0.5% to 4.5% of the local pattern (Columns 1 through 4 of Panel B).

Overall, the upper bound to $R^2$ is uniformly lower for growth rates relative to levels of variables at all levels of aggregation. This decrease is likely because there is typically more variation in growth rates than level variables, which might be very persistent. This is especially true for variables such as delinquency rates and foreclosure rates. Finally, for robustness, Appendix A5 shows the results for the variables measured at monthly changes. We find very consistent evidence with our above analysis for the level and growth rates of housing variables.

The statistical exercise above identified an upper bound to the informativeness of various economic variables by their level of geographic aggregation. We next assess the actual association of various national, county, and zip code variables with zip-code level delinquency and foreclosure rates. We begin by investigating the association between zip code delinquency rates and lagged national variables, including average unemployment rate, house price growth, income growth, Fed Funds rate, CLTV, DTI ratio, and national vantage score. We consider four lags of each independent variable. All variables are measured at a quarterly frequency, with the exception of income growth. Income growth is only available on an annual basis, so each quarter is given the value of that year's annual income growth. That is, the lagged income growth for all four quarters of a year receives the value of annual income growth of the previous year.

More specifically we run the regression of the following form for the quarterly delinquency rate in zip code *i*:

$$delinquency_{i,t} = \alpha + \sum_{n \in N} \sum_{j=1}^{4} \beta_{n,j} X_{n,t-j} + \varepsilon_t.$$

We consider two variants of this regression: one without and one with non-linear (square) terms of the independent variables.

The first row of Column (1) of Table 6 shows the adjusted R-square from this regression. Column (2) shows the corresponding results from the specification with non-linear terms.

As we observe, national economic variables account for about 19% of in sample variation in the zip code delinquency rate.

We next estimate the above specification when instead we explore the association between quarterly zip code delinquency rate and the four quarterly lags of the county level variables to which a given zip code belongs to. The county level variables include unemployment rate, house price growth, CLTV, DTI ratio, and national average county credit score. Note that county unemployment rate is only available on an annual basis, so we convert it to quarters as we do with annual income data. The second row of Column (1) and Column (2) of Table 5 shows the adjusted R-square from these regressions. As we observe, county level economic variables account for about 39%-42% of in sample variation in the zip code delinquency rate, a substantial improvement over national indicators.

Next we move to an even more granular level and consider regressions with lagged zip-code level variables. Unfortunately, we do not have unemployment or income data at this level. The zip code level variables just include house price growth, CLTV, DTI ratio, and average zip code credit score of mortgage borrowers. The third row of Column (1) and Column (2) of Table 5 shows the adjusted R-square from these regressions. As we observe, zip code level variables account for 66% to 87% (with non-linear terms) of in sample variation in the zip code mortgage delinquency rate, a very substantial improvement over both national and county-level indicators. Moreover, fourth, fifth, and sixth rows of Column (1) and (2) of Table 5 show that adding national and county level indicators to zip code ones leads to only minor increases in the adjusted R-square.

Column (3) and (4) of Table 5 shows the corresponding analysis for the zip code foreclosure rate. Again as in the case of delinquency rate and consistent with our previous analysis, we see that zip code level indicators account for much larger variation of zip code foreclosure rates than county-level or national indicators.

We conclude this analysis by conducting additional robustness on our inferences. We do so by studying the predictability of local housing-related variables with corresponding lagged variables at different levels of geographic aggregation. Formally, we estimate a simple AR(12) process for each of the zip-code level local housing variables:

$$Y_{it} = \sum_{\tau=1}^{12} \beta_\tau Y_{j(i)t-\tau} + \varepsilon_{it}$$

Again, $Y_{it}$ refers to the monthly zip-code level housing variables: house prices combined loan to value, debt to income, delinquency rate, foreclosure rate, and real house price. All variables are measured as demeaned growth rates. We regression this on lagged 12 terms of $Y_{j(i)t-\tau}$ with different degrees of aggregation. In particular, $j$ is measured at zip-code and national level.

We measure the performance of predictability R-square, that is, the percentage of variation explained by the lagged 12 terms of the same variable. For ease of illustration, we compare the predictability performance between "zip-code on zip code" and "zip-code on national" levels. We measure the predictability of housing variables in growth rate measures rather than level measures. The primary reason for this, is that level variables exhibit strong auto-correlation. In this sense, a good fit of the level of housing market variables may not translate into good prediction of the change of variables.

In unreported regressions, we find that real house price growth exhibits high predictability at zip-code using lagged zip-code information. Zip-code lagged housing price growth explains 69% of the variation in house price growth with a RMSE of 0.56%. When using national house price growth, only 18% of the variation is explained. The other local housing variables are much more difficult to predict, even when using lagged local data. CLTV has an adjusted R-square of 2.64%, DTI (12.47%), delinquency (20%), and foreclosure (3.6%). At the national level, the explanatory power is approximately 0%.

For ease of illustration, we present these inferences in Appendix A6, where we illustrate the predictability at local (zip-code) and national level by plotting the 12 AR regression coefficients of local variable growth regressed at lagged local variable growth and lagged national variable growth, respectively. All of these local variables exhibit mean reversion except local housing price, which exhibit short-term momentum (see DeFusco, Nathanson, and Zwick 2017 for a recent comprehensive analysis of house price dynamics). For instance, an increase in the local delinquency rate growth of 1% predicts a subsequent decrease in the delinquency growth rate by 0.5% in the next month and 0.3% in the following month. Similar patterns of mean reversion are also found for DTI, CLTV, and foreclosure rates. In contrast, national level housing variables have little to no predictive power with $R^2 \approx 0$.

*4.4 Summary*

Overall, our evidence indicates that regional economic conditions display significant heterogeneity across US states, counties, and zip codes, and over time. This heterogeneity, along with our above analysis, suggests significant gains from using indices that capture the local component of economic conditions in assessing the state of the local housing markets relative to indices at coarser levels of geographic aggregation. We also find evidence of significant instability over time in the strength of relationship between key economic variables. In the next section we discuss the implications of these findings for the design of mortgage contracts or debt relief polices.

## 5. Implications for Mortgage Contract Design and Debt Relief Polices

In the prior section, we presented evidence of significant heterogeneity in local economic conditions across space and time. Moreover, the strength of the relationship between key economic variables affecting households, such as housing and income risk, does not appear to be that stable over time, pointing to a time-varying distribution of these variables. Recall that our simple framework in Section 3.2 illustrates that successful implementation of indexed mortgage contracts or debt relief polices crucially depend on the correct understanding of the underlying structure of income and housing risk and its relation to the indices on which such contracts or polices will be based. We now discuss the practical considerations in implementing temporary debt relief during economic downturns, drawing on insights from Section 3. We consider solutions that rely, respectively, on design of mortgage contracts, ex-post private renegotiation, and mortgage debt relief polices.

### *5.1 Mortgage Contract Design*

We start by considering implementation of debt relief through changes in mortgage contract terms. We focus on different methods of mortgage contract indexation. As noted earlier, such indexation effectively implements an "automatic" temporary debt relief during economic downturns and can potentially circumvent frictions discussed in Section 2.

#### *5.1.1 ARMs*

*National Interest Rate Indexation*

In practice, the most commonly used state-contingent mortgages are ARMs. Our discussion in Section 3 suggests that contracts indexed to national-level interest rate indices may implement debt relief efficiently, as long as the relevant interest rate indices to which these loans are indexed closely co-move with local home prices and borrowers' income. Having said that, there are two points worth emphasizing. First, as Panel A of Figure 17 shows, there is a large spatial variation in ARM share of mortgages in a zip code. This implies that "automatic" pass through of low interest rates would be differentially passed through across regions, to the extent FRMs would remain a popular contract choice.[17] Second, the empirical evidence we presented in Section 4 suggests that, due to significant regional heterogeneity, ARMs based on national indices may not be as effective, especially in some regions.

One could argue that the most relevant aspect in successfully implementing debt relief through this mechanism is the close co-movement of interest rates on which ARMs are

[17] 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 downward adjustment of their rates in response to a decline in interest rate indices.

indexed with relevant local economic variables during recessions. Indeed, Figure 4 shows that during the Great Recession, all US states experienced some decline in economic activity, though substantial heterogeneity remained in the strength of this effect. During this period, all main interest rate indices also reached historically low levels. Consistent with this observation, the empirical evidence finds that ARMs resetting to a low rate after 2009 had a direct positive impact across borrowers and regions by reducing default rate and increasing consumption, house prices, and local employment (see Di Maggio et al. 2017, Fuster and Willen 2017).

One should be careful, however, to not overstate the benefits of ARM contracts. First, there were periods in the past, such as the stagflation episode, when interest rate indices reached high levels during the economic downturn. In such an environment, a high share of ARMs in an economy could exacerbate the severity of the economic crisis. In particular, following a very substantial increase in interest rate indices along with the federal funds rate (see Appendix A7), the ARMs reset to much higher rates during the late 2006 to early 2008 period. As a consequence, these ARM borrowers faced substantial rate increases with vanishing refinancing opportunities due to the collapse of the subprime mortgage market by mid-2007. This aspect could have contributed to the mortgage default rate and the severity of the initial stage of the financial crisis.

To illustrate this more formally, we use the monthly loan-level panel data on more than 1.8 million of 2/28 subprime ARMs resetting during this period from BlackBox database. These 2-year ARM contracts are loans that were mainly originated during the 2004-2006 period. They faced a fixed initial rate for the first two years and subsequently a reset to the variable rate based on a short-term interest rate index (e.g., LIBOR rate). Panel A of Table 7 shows the summary statistics for these loans including the mortgage interest rate prior and after the first reset.

Column (1) and (2) of Panel B of Table 7 shows the regression results of the monthly mortgage interest rate and default rate of 2-year ARM borrowers on the time dummies for the three quarters before and four quarters after the change in the interest rate with the fourth quarter before the reset period servings as the excluded category. This specification controls for a variety of borrower, loan, and regional characteristics including the borrower's FICO credit score and the LTV ratio. As we observe from Panel A of Table 7 2-year ARM borrowers experience about 1.3 percentage point increase in their monthly interest rates after the reset amounting to more than 17% relative increase. Column (1) of Panel B of Table 7 finds shows similar effect. Panel A of Figure 16 shows the corresponding monthly mean default rate (serious delinquency rate) for these loans around the first reset date that happens after month 24 of the loan's life. Note that it would take at least two months to see the effects of the reset as for a loan to be considered seriously delinquent it needs to be 60 days or more past due on payments. We observe a very substantial increase in the default rate just after the first reset date. Column (2) of Panel B of Table 7 confirms this inference by showing that these borrowers experience an estimated 2.2 to 3% absolute increase in monthly default rate during the fourth quarters after the first reset, a very substantial effect (more than 100% relative increase).

One could worry that some of these effects reflect selection on unobservables due to refinances around the reset date. In particular, if better quality borrowers refinance their loans prior to the reset, the increase in default rate could reflect the change in the sample composition. To address this concern we also consider a sample of more than 180 thousand 3-year ARMs that were originated during March 2004 – January 2005 period when interest rates were at a historically low level (Panel A of Table 7 shows summary statistics for this sample). These loans experienced the first reset three years after their origination which corresponds to the period of April 2007 – January 2008. During this period interest rates were at relatively high level (see Appendix A7) inducing substantial rate increases after resets and the private label refinancing market virtually collapsed limiting refinancing opportunities. Column (3)-(4) shows that we also find a strong association between interest rate reset and increase in default rate in this sample (see also Panel B of Figure 16). In particular, 3-year ARM borrowers in our sample experienced an about 1.58 percentage point rate increase after reset (about 25% relative increase) and an associated 1.2 to 2 percentage point increase in monthly default rate (more than 100% relative increase in default rate). Overall this evidence suggests that an increase in interest rate indices at the outset of the Great Recession contributed to the high default rate among ARM borrowers possibly exacerbating the initial stage of the recent housing crisis. This effect could have been quite important given that majority of subprime loans originated prior to the crisis were of the ARM type.

The ability of mortgages indexed to national rate indices to serve as an effective debt relief also depends on the nature of monetary policy. In particular, policymakers could take into account ARM's potential role as an automatic stabilizer in setting the national interest rates indices. This, however, would require a careful and up-to-date assessment of economic conditions faced by mortgage borrowers as ARM contracts could also accelerate the pass-through of policy mistakes to households and real economy. Moreover, a system with a larger share of ARMs could also complicate the central bank price stability objective, as increases in interest rates can be highly unpopular with homeowners creating political pressure to keep interest rates low for an extended period of time (see Campbell 2013). Finally, in our analysis we have not considered inflation risk. In an environment with significant relative price instability, the FRM contracts may provide additional benefits to borrowers by insuring them against fluctuations in nominal interest rates and the associated potential increase in their debt payments relative to their incomes (see Campbell and Cocco 2003).

Regardless of such factors, the significant regional heterogeneity we documented in the prior section indicates that "one-size fits all" contract indexation based on national-level variables may reduce the effectiveness such solutions. Instead, there may be gains from pegging mortgage contracts to more granular regional conditions. Of course, such gains would need to be traded-off with potential costs of implementing such indexation, as noted above, including costs of introducing new contracts with limited prior market experience.

*House Price Indexation*

An alternative indexation form consists of mortgages that depend on local house price indices. Given significant regional heterogeneity, one of the key advantages of such contracts is that their terms can be more closely tied to the local economic conditions, as opposed to ARMs that are tied to national interest rates. Such "continuous workout mortgages" were long advocated by Robert Shiller (e.g., Shiller 2008). Piskorski and Tchistyi (2017) show that home equity insurance mortgages indexed to house prices, by alleviating incentives to default strategically, arise as an equilibrium contract in the private lending market equilibrium with empirically relevant frictions. Moreover, Greenwald et al. (2017) show that indexation to local house prices can reduce financial fragility and improve risk-sharing if financial intermediaries retain a significant portion of mortgages on their balance sheets.

The widespread adoption of house price indexed mortgages would require timely and accurate regional house price indices. Such indices were unavailable in the past. Zip-code level house price indices have only recently been developed and offered by data providers such as Zillow.com (see Appendix A8 for an example).

*Labor Income Indexation*

Our discussion in Section 3 suggests that conditioning mortgages on indexes capturing both local labor market conditions and house prices may provide additional efficiency. However, such arrangements would require timely and accurate regional local labor market indices that as of today are not commercially available. Having said that, current unemployment insurance programs implicitly provide a form of labor income indexation -- partly insuring households against income shocks – which helps distressed households service their mortgage debt obligations (see Hsu, Matsa, and Melzer 2018). Moreover, one could consider social transfer schemes that directly provide temporary subsidies, reducing mortgage payments of unemployed borrowers. Such schemes could condition the terms of the transfers on the specific financial position of the borrower (e.g., their debt burdens or DTI ratios). A potential downside of such approaches is that they could result in borrower's moral hazard risk (e.g., see Mayer et al. 2014 for recent evidence). For example, providing mortgage payment support to unemployed borrowers may erode their incentives to find a new job. The potential for such unintended consequences of social transfers to unemployed has long been recognized in the unemployment insurance literature.

*Discussion*

It is important to note that we have not suggested designing contracts just based on individual CLTV, house prices, or employment. While potentially more efficient in capturing the risk dynamics of individuals, such contracts may create moral hazard in terms of incentives to pay or maintain house going forward. For this reason, we focus our discussion on indices capturing these variables at the regional level (e.g., zip code).

It is worth discussing that such indexation forms have not been widely implemented in the past for several reasons. First, substantial government involvement in the mortgage market through a system of subsidies and regulations favors traditional contracts like FRMs or ARMs. This potentially suppresses adoption of new mortgage design.

Second, implementation of new design may require a significant amount of time due to private market inertia, learning, or low perceived value of such innovations from the ex-ante perspective. For example, prior to the Great Depression, mortgage contracts were predominantly short-term loans. The inability to roll these loans over was a major contributor to the collapse of the financial and housing markets. As a result, the government helped private market develop and standardize the fully-amortizing long-term contracts such as FRMs that currently dominate the US housing market.

Third, the widespread adoption of contracts index to local economic conditions would require timely and accurate regional indices. Such indices were unavailable in the past and only recently some of them have been developed and offered by data providers (e.g., house price indices). As we discussed in Section 4.3, given significant regional heterogeneity, lack of such indices at sufficient granular level may have significantly reduced the potential efficiency of such solutions stifling incentives for their development.[18]

Finally, it is not clear that private market innovation would lead to the successful development of such contracts. In particular, Piskorski and Tchistyi (2017) show that in the competitive equilibrium setting with empirically relevant frictions unrestricted

[18] In addition, Hartman-Glaser and Hebert (2016) point out that if there are informational asymmetries between borrowers and lenders about the ability of such indices to measure underlying states, the risk-sharing ability of state-contingent contracts based on such indices can be limited.

competition in mortgage design may lead in some cases to market instability (non-existence of equilibrium). Their findings highlight the potential understudied role of government sponsored enterprises (GSEs): by subsidizing a restricted contract choice through its guarantee system the GSEs may help facilitate the existence of a stable mortgage market by limiting private competition in mortgage design. In this regard, the government may also play a potentially important role in practical implementation of new mortgage designs by promoting certain contracts through its system of subsides. The downside of this approach is that it would require a continued operation of GSEs and the FHA – institutions plagued by political economy concerns surrounding implicit and explicit government. Such approach would also limit the ability to use market pricing for assessment of the cost of insurance imbedded in new mortgage designs.

*5.2 Leverage Regulation and Downpayment Limits*

Intuitively, as we discussed in Section 3, the benefits of indexed mortgage contracts or debt relief polices are much smaller for borrowers with significant housing equity. Hence, 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 al 2016 for a recent analysis of such polices). One way to implement this in practice would be to impose contract restrictions, like stricter minimum down payment limits, in the current mortgage market setting. Of course such polices, while potentially simpler to implement than other approaches, can result in additional welfare costs by delaying or preventing homeownership for some borrowers. There are also political economy considerations which might prevent such regulation from being imposed, especially when the housing market is booming. Finally, given significant evidence of misreporting the true extent of down payment and housing equity by financial intermediaries prior to the recent crisis (see Ben-David 2011; Piskorski et al. 2015;Griffin and Maturana 2016), such polices may face additional implementation hurdles.

*5.2 Private Mortgage Renegotiation*

Another approach to implementing debt relief is to rely on private renegotiation efforts. Since foreclosure can induce significant deadweight costs, there should be instances where both borrowers and lenders would find it beneficial to temporarily reduce their household debt burden during economic downturns.  As we discussed in Section 2, this approach faced a number of limitations during the Great Recession related to organizational frictions and capacity constraints in the intermediary sector, agency conflicts in securitization, ex-post moral hazard concerns of intermediaries, and the ability of intermediaries to identify instances when renegotiation might be beneficial for both borrowers and lenders. More broadly, private ex-post renegotiation may not take into account the positive externalities of debt relief and may also be of limited scope relative to solutions that rely on ex-ante committed changes in contract terms.

*5.3 Public Debt Relief Programs*

An alternative approach to implementing temporary debt relief polices is to leave the structure of the mortgage contracts intact and instead rely on large-scale government programs or monetary policy. Such programs rely on internalizing the negative externalities that are generated after delinquency or foreclosure in a neighborhood. Indeed, during the Great Recession the Federal Reserve reduced short-term interest rates and made large purchases of mortgage-backed securities in an attempt, among others, to support the prices of assets such as houses and lower the incidence of foreclosures. Moreover, in response to the recent crisis, the administration passed two unprecedented and large scale debt relief programs: Home Affordable Refinancing Program (HARP), aimed stimulating mortgage refinancing activity of up to eight million heavily indebted borrowers and Home Affordable Modification Program (HAMP), aimed at stimulating mortgage restructuring effort for up to four million borrowers at risk of foreclosure. Other notably programs during Great Recession included first-buyer tax credits aimed at stimulating house purchases (Berger et al. 2016) and programs aimed at stimulating consumer spending such economic stimulus payments (Parker et al. 2013) and subsidies for new car purchases (Mian and Sufi 2012).

As we discussed in Section 2 the effectiveness of such ex-post solutions crucially depends on the institutional features of mortgage market including the nature of mortgage contracts and the ability of financial intermediaries to quickly implement them. Di Maggio et al. 2017 show that a significant heterogeneity in the ARM share across regions (see panel A of Figure 17) resulted in significant differential pass-through of lower interest rates to households.

Unlike the "one-size fits all" monetary policy both programs mentioned above implemented a form of specific individual targeting. This, given the evidence of significant regional and borrower heterogeneity, could in principle increase the efficiency of such programs relative to polices or contracts based on national level indices. HAMP was mainly targeted at distressed borrowers with high debt to income ratios. However, the need to verify such program criteria coupled with limited organizational ability of financial intermediaries significantly hindered its effectiveness (see Agarwal et al. 2017). Figure 17 Panel B 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 would be differentially passed through across space.

Wide-scale refinancing program such as HARP may be easier to implement since they stimulate a more routine activity like refinancing rather than loan renegotiation. Moreover, a program like HARP, which was based on CLTV, implicitly indexed on a granular level (local house prices) relative to national indices. However, since the implementation of this program was through intermediaries, its effectiveness was hampered both by intermediary frictions – such as capacity constraints – as well as market design, such as competition in the refinancing market (see Agarwal et al. 2016 and Fuster et al. 2017). Moreover the program targeted only loans issued with prior GSE guarantees (agency loans), which usually correspond to more creditworthy borrowers than subprime borrowers. Panel C of Figure 17 illustrates a significant regional hetoregeinty in the fraction of loans eligible for HARP (see Agarwal et al. 2016). This suggests that debt relief through refinancing would be less likely in some regions than others.

To illustrate the importance of such factors, we conduct a simple analysis of the change in the zip code quarterly delinquency and foreclosure growth after the period starting from 2009 relative to the prior period. We note that 2009 coincides with the introduction of various debt relief programs, including HARP and HAMP, and with the firm commitment to the prolonged low interest rate policy. In particular, Table 8 shows the results of regressions of the difference in mean zip code delinquency or foreclosure growth on the zip code ARM share, high intermediary capacity share, and HARP eligible share. Panel A shows the results for change in zip code delinquency growth. Columns (1) through (6) regress the change in delinquency growth on each of the independent variables separately. We find that all coefficients in these columns are negative, indicating that zip codes with higher shares of ARM, high capacity servicer, and HARP eligible loans experience faster declines in delinquency growth. Columns (7) and (8) include all of these variables together and show that all coefficients remain negative. Panel B shows the results for zip code foreclosure growth. Consistent with Panel A, we find that zip codes with higher share of ARMs, higher share of loans serviced by high capacity intermediaries, and higher share of HARP eligible loans experienced faster declines in foreclosures after 2009. This evidence is consistent with Agarwal et al. (2016, 2017) and Di Maggio et al. (2017) who show that these institutional factors played an important role in the effectiveness of debt relief measures undertaken during the Great Recession and their differential impact across regions.

Overall, these findings provide guidance for designing large-scale debt relief programs in the future. First, in the case of programs aimed at stimulating mortgage renegotiation activity such as HAMP, it may have been productive for the program to have allowed the easy transfer of distressed mortgages from inefficient servicers to those more capable of conducting many renegotiations. One way to address this issue in the future is to rely more heavily on special servicers, as is common in the commercial real estate market. Upon the occurrence of certain specified adverse events, the non-performing loans would be automatically transferred to organizations better equipped to handle such assets. Moreover, there is a likely tradeoff between screening more intensively, which limits the potential costs of such programs including strategic defaults, and the reach and pace of the program.

Wide-scale refinancing program such as HARP may be easier to implement since they stimulate a more routine activity like refinancing rather than loan renegotiation. Moreover, a program like HARP, which was based on CLTV, implicitly indexed on a granular level (local house prices) relative to national indices. However, since the implementation of this program was through intermediaries, its effectiveness was hampered both by intermediary frictions – such as capacity constraints – as well as market design, such as competition in the refinancing market (see Agarwal et al. 2015 and Fuster et al. 2017) and its restricted eligibility to loans issued with prior GSE guarantees. Such programs critically rely on the ability of the government to guarantee mortgage debt during crisis (e.g., through GSEs). Their success also importantly depends on the speed and extent to which interest rates reach sufficiently low levels during housing downturns, which may impose additional constraints on the conduct of monetary policy. HARP-like polices could also become a part of permanent market arrangement by automatically relaxing housing equity refinancing constraints in regions that experienced sufficient declines in house prices.

## 6. Conclusion

Our discussion highlights an important trade-off that warrants more comprehensive analysis. The indexed mortgage contracts have the advantage of circumventing financial intermediary and other fictions by facilitating a quick ("automatic") implementation of debt relief during economic downturns. However, as illustrated in Section 3.2, for such contracts to be cost-effective, lenders, policymakers, and borrowers may need a good "ex-ante" understanding of the underlying distribution of risk and its relation to indices being used when designing and choosing such contracts. Given the evidence of significant time-varying regionally heterogeneity this can be challenging. Moreover, our simple framework illustrates that error in beliefs about the structure of risk can reduce the benefits of such solutions. Given the vast heterogeneity in nature of risk across space and time, such errors are likely, especially as a major change in the nature of mortgage contracts or housing policy can on its own significantly alter relationships between market equilibrium outcomes in potentially hard to quantify way. As a result, one may have to rely on an ex-post debt relief solutions as well.

An ex-post debt relief solution has the advantage of being more "fine-tuned" to the specific realization of economic risk, at the possible cost of delaying debt relief and subjecting it to various implementation frictions that could hinder its effectiveness.

More broadly, our evidence suggests that effective mortgage design approach to debt relief requires more in depth analysis of the nature of relevant income and housing risk and its evolution across regions and borrowers. This could include the development of new and sufficiently granular indices on which such contracts could be based. The recent "big-data" revolution is promising in this regard. Such analysis could also identify mortgage designs that effectively implement debt relief across a range of possible environments. Finally, the approach relying on public debt relief programs should focus on alleviating frictions that may hinder the effective implementation of such polices. This should also include development of effective and "easy to verify" set of eligibility criteria regarding debt relief policies.

## Table 1

## Simple Framework: Base Parameter Values

This table describes a set of base parameter values used in numerical examples in Section 3.2.

| **Parameters** | **Definition** | **Values** |
|---|---|---|
| $y$ | Income average | 200 |
| $\sigma_y$ | Income standard deviation | 70 |
| $P_1$ | House price average | 150 |
| $\sigma_P$ | House price standard deviation | 50 |
| $\delta$ | Recovery rate when default | 0.7 |
| $P_0$ | Initial house price | 100 |
| $\bar{v}$ | Loss of utility when default | 50 |
| $\theta$ | Utility of living in a house | 200 |
| c | Fixed cost of index mortgage contract | 0 or $1\% * P_0$ |
| D | Down-payment of house | 0 or $20\% * P_0$ |

## Table 2

## National and State-Level Economic Variables: Summary Statistics

This table presents summary statistics of the economic series used in the principal components analysis to extract a proxy for national and local economic conditions. Both GDP and income data are from the Bureau of Economic Analysis. Both series are deflated using CPI for all urban consumers from FRED (Federal Reserve Bank of St. Louis). Growth rates are measured at the annual level. Unemployment rate data are from the Bureau of Labor Statistics. House price growth data is from Zillow when available; otherwise, we use data from Freddie Mac House Price Index. Using growth rates avoids the issue of merging two separate datasets because growth rates are computed from the same series and then appended. For national housing data, we use the S&P/Case-Shiller U.S. National Home Price Index.

Panel A: National-Level Summary Statistics

| Variable | Mean | Std. Dev. | Min | Max |
|---|---|---|---|---|
| GDP Growth | 2.28% | 2.14% | -4.78% | 7.50% |
| Income Growth | 2.46% | 2.22% | -5.95% | 6.21% |
| Unemployment Rate | 6.35% | 1.66% | 3.90% | 10.80% |
| Housing Price Growth | 0.97% | 5.46% | -11.97% | 9.96% |

Panel B: State-Level Summary Statistics

| Variable | Mean | Std. Dev. | Min | Max |
|---|---|---|---|---|
| GDP Growth | 2.25% | 3.69% | -27.49% | 31.12% |
| Income Growth | 2.43% | 2.95% | -14.77% | 20.25% |
| Unemployment Rate | 6.02% | 2.13% | 2.20% | 18.30% |
| Housing Price Growth | 0.55% | 6.42% | -43.72% | 47.99% |

## Table 3: Principal Comment Analysis: Summary Statistics

This table displays the summary statistics about the weight on the economic variables in the first factor of the principal component analysis. The weight represents the relative loading of the local economic conditions proxy on local economic variables. We present the mean, standard deviation, min and max of the weights for the state level PCA.

| Weight | Mean | Std. Dev. | Min | Max |
|---|---|---|---|---|
| GDP Growth | 56% | 4% | 46% | 69% |
| Income Growth | 53% | 5% | 45% | 73% |
| Unemployment Rate | -44% | 8% | -54% | -1% |
| Housing Price Growth | 43% | 11% | -8% | 53% |
| Explained Variation | 60% | 9% | 32% | 73% |

## Table 4: State Level Economic Factor Heterogeneity

This table reports the results from the OLS regression of the form $EF_t = \alpha + \beta X_t + \epsilon_t$, where $EF_t$ is the economic factor for a given state at time $t$ and $X_t$ is one of the national macroeconomic variables listed in the tables below. This regression is estimated separately for each state iteratively, one X at a time. Panel A reports the fraction of variation explained and Panel B reports the coefficient $\beta$.

Panel A: Fraction of Variation Explained

| R^2 | Mean | Std. Dev. | Min | Max |
|---|---|---|---|---|
| Economic Factor | 52.04% | 24.10% | 0.00% | 82.11% |
| GDP Growth | 42.53% | 21.15% | 1.05% | 68.77% |
| Unemployment | 27.95% | 14.10% | 0.08% | 59.19% |
| Unemployment Change | 18.17% | 12.03% | 0.15% | 53.40% |
| Income Growth | 35.37% | 15.40% | 3.71% | 65.08% |
| House Price Growth | 21.51% | 15.90% | 0.00% | 55.91% |
| Fed Funds Rate | 5.62% | 6.50% | 0.02% | 26.83% |
| Treasury Rate | 4.74% | 4.92% | 0.06% | 21.43% |
| Real Treasury Rate | 13.97% | 12.78% | 0.00% | 45.78% |
| Δ Real Treasury Rate | 2.95% | 3.78% | 0.00% | 14.89% |
| Δ Real Treasury Rate (t-1) | 1.24% | 1.37% | 0.00% | 5.81% |
| Mortgage Rate | 5.77% | 6.08% | 0.01% | 26.06% |

Panel B: Coefficient Estimates

| Beta | Mean | Std. Dev. | Min | Max |
|---|---|---|---|---|
| Economic Factor | 0.70 | 0.24 | 0.00 | 0.94 |
| GDP Growth | 44.91 | 15.72 | 5.37 | 62.23 |
| Unemployment | -46.96 | 17.55 | -77.48 | 15.24 |
| Unemployment Change | -53.94 | 31.02 | -109.69 | 31.77 |
| Income Growth | 40.15 | 11.29 | 12.38 | 55.71 |
| House Price Growth | 11.44 | 7.23 | -5.29 | 22.27 |
| Fed Funds Rate | -2.69 | 8.31 | -18.12 | 12.93 |
| Treasury Rate 1Y | -0.46 | 9.13 | -18.08 | 16.76 |
| Real Treasury Rate | 18.49 | 17.81 | -22.97 | 47.54 |
| Δ Real Treasury Rate | 11.96 | 10.29 | -14.78 | 35.33 |
| Δ Real Treasury Rate (t-1) | 6.55 | 8.24 | -13.09 | 23.67 |
| Mortgage Rate | -4.33 | 10.14 | -23.26 | 15.46 |

## Table 5: The Importance of Local Economic Variables: Upper Bound to $R^2$

This table shows the upper bound to $R^2$ of local zip-code level variables that can be explained by different levels of aggregation. In particular, the local zip-code level housing variables are regressed on contemporaneous geography by time fixed effects at the city, county, metro, states and national level and the unadjusted $R^2$ is reported in each cell. All housing variables are measured as levels (Panel A) or growth rates (Panel B). Further, all housing variables are demeaned at zip-code level and winsorized at 1%. Real house price data are from Jan 1997-Dec 2017; loan to value, debt to income, delinquency rates, and foreclosures data are from Jul 2005-Dec 2017.

Panel A: Levels

| Aggregation\Variable | House Price | CLTV | DTI | Delinquency Rate | Foreclosure Rate |
|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) |
| National | 34.44% | 39.39% | 13.00% | 26.57% | 13.81% |
| States | 67.17% | 58.45% | 21.24% | 37.52% | 28.73% |
| Metro | 80.48% | 69.02% | 29.64% | 43.51% | 35.45% |
| County | 80.32% | 67.86% | 30.42% | 43.85% | 35.36% |
| City | 85.93% | 83.04% | 68.84% | 76.05% | 71.45% |
| ZIP Code | 100% | 100% | 100% | 100% | 100% |

Panel B: Growth Rates

| Aggregation\Variable | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| | House Price Growth | CLTV Growth | DTI Growth | Delinquency Growth | Foreclosure Growth |
| National | 24.91% | 4.45% | 1.13% | 1.06% | 0.58% |
| States | 36.88% | 6.89% | 1.83% | 1.92% | 1.50% |
| Metro | 52.23% | 14.47% | 8.75% | 8.36% | 9.25% |
| County | 55.67% | 16.60% | 10.75% | 10.49% | 12.01% |
| City | 77.05% | 62.17% | 60.41% | 60.59% | 56.93% |
| ZIP Code | 100% | 100% | 100% | 100% | 100% |

## Table 6: Relative Importance of Local Economic Indicators in Accounting for Variation in Mortgage Delinquency and Foreclosure Rates (R-squares)

This table analyzes the association of various national, county, and zip code variables with zip-code delinquency and foreclosure rates. In order to do so we carry out a series of simple linear regressions. We begin by investigating the association between zip code delinquency rates and lagged national variables, including average unemployment rate, house price growth, income growth, Fed Funds rate, CLTV, DTI ratio, and national vantage score. We consider four lags for each independent variable. All variables are measured at a quarterly frequency, with the exception of income growth. Income growth is only available on an annual basis, so each quarter is given the value of that year's annual income growth that is the lagged income growth for all four quarters of a year receives the value of annual income growth of the previous year. More specifically we run the regression of the following form for the quarterly delinquency rate in zip code *i*:

$$delinquency_{i,t} = \alpha + \sum_{n \in N} \sum_{j=1}^{4} \beta_{n,j} X_{n,t-j} + \varepsilon_t.$$

We consider two variants of this regression: one without and one with non-linear (square) terms of the independent variables. We next estimate the above specification when instead we explore the association between quarterly zip code delinquency rate and the four quarterly lags of the county level variables to which a given zip code belongs to. The county level variables include unemployment rate, house price growth, CLTV, DTI ratio, and national average county credit score. Note that county unemployment rate is only available on an annual basis, so we convert it to quarters as we do with annual income data. Next we move to an even more granular level and consider regressions with lagged zip-code level variables. The zip code level variables just include house price growth, CLTV, DTI ratio, and average zip code credit score of mortgage borrowers. The table below shows the adjusted R-squares from these regressions with various sets of controls discussed above. Column (1) and (2) shows the results for zip code mortgage default rate (serious delinquency rate) while Column (3) and (4) shows the results for zip code foreclosure rate.

| | Dependent Variable: Zip Code Delinquency Rate | | Dependent Variable: Zip Code Foreclosure Rate | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| National variables | 0.19 | 0.19 | 0.08 | 0.08 |
| County variables | 0.39 | 0.42 | 0.54 | 0.54 |
| Zip variables | 0.66 | 0.87 | 0.74 | 0.75 |
| Zip and county variables | 0.70 | 0.88 | 0.76 | 0.77 |
| Zip, county, and national variables | 0.71 | 0.89 | 0.78 | 0.79 |
| Non-linear terms | No | Yes | No | Yes |
| Number of observations | 262,258 | 262,258 | 262,258 | 262,258 |

## Table 7: Impact of ARM Resets on Mortgage Default at the Outset of Great Recession

Panel A shows the summary statics for the sample of 2-year (2/28) ARMs and 3-year (3/27) ARMs used in our analysis (from BlackBox data). The sample of 2-year ARMs consists of loans that were mainly originated during the 2004-2006 period. They faced a fixed initial rate for the first two years and subsequently a reset to the variable rate based on a short-term interest rate index (e.g., LIBOR rate). The sample of 3-year ARMs consist of loans that were originated during March 2004 – January 2005 period when interest rates were at a historically low level (Panel A of Table 7 shows summary statistics for this sample). These loans experienced the first reset three years after their origination which corresponds to the period of April 2007 – January 2008. During this period interest rates were at relatively high level (see Appendix A7) inducing substantial rate increases after resets and the private label refinancing market virtually collapsed limiting refinancing opportunities. Column (1) and (2) of Panel B shows the regression results of the monthly mortgage interest rate and default rate of 2-year ARM borrowers on the time dummies for the three quarters before and four quarters after the change in the interest rate due to the first rest with the fourth quarter before the reset period servings as the excluded category. The specifications controls for a variety of borrower, loan, and regional characteristics including the borrower's FICO credit score and the LTV ratio. Panel B shows the corresponding results for 3-year ARMs. Column (3) and (4) of Panel B shows the corresponding results for 3-year ARM borrowers. Standard errors are in the parentheses.

**Panel A:** Summary Statistics

| | 2-Year ARM Sample | | 3-Year ARM Sample | |
|---|---|---|---|---|
| | Mean | S.D | Mean | S.D |
| FICO | 622.8 | 58.1 | 682.0897 | 64.35078 |
| Loan Balance | 199,435 | 130,569 | 221965.9 | 172645.7 |
| Initial LTV | 82.25 | 10.96 | 78.71714 | 14.78156 |
| Initial Interest Rate | 7.80 | 1.67 | 6.308084 | 1.425647 |
| Interest Rate after Reset | 9.13 | 2.10 | 7.897143 | 2.225515 |
| N. of Observations | 1,815,178 | | 146, 078 | |

**Panel B:** Impact on Mortgage Interest Rates and Defaults

| | 2-Year ARM Sample | | 3-Year ARM Sample | |
|---|---|---|---|---|
| | Interest Rate | Default Rate | Interest Rate | Default Rate |
| | (1) | (2) | (3) | (4) |
| Three Quarters Before | -0.0672 | 0.164 | -0.0109 | 0.110 |
| | (0.001) | (0.014) | (0.004) | (0.032) |
| Two Quarters Before | -0.183 | 0.296 | -0.0151 | 0.236 |
| | (0.002) | (0.015) | (0.004) | (0.033) |
| One Quarter Before | -0.268 | 0.679 | 0.0345 | 0.417 |
| | (0.002) | (0.016) | (0.004) | (0.034) |
| One Quarter After | 1.502 | 2.226 | 2.117 | 1.213 |
| | (0.002) | (0.018) | (0.004) | (0.041) |
| Two Quarters After | 1.426 | 3.081 | 1.901*** | 1.968 |
| | (0.002) | (0.021) | (0.005) | (0.045) |
| Three Quarters After | 1.600 | 2.500 | 1.455*** | 1.816 |
| | (0.002) | (0.025) | (0.005) | (0.047) |
| Four Quarters After | 1.546 | 2.314 | 1.323*** | 2.009 |
| | (0.003) | (0.030) | (0.006) | (0.050) |
| Other Controls | Yes | Yes | Yes | Yes |
| N. of Observations | 13,036,083 | 13,036,083 | 1,089,761 | 1,089,761 |
| R-square | 0.278 | 0.0130 | 0.564 | 0.0284 |

## Table 8: The Association between Mortgage Contract Type and Financial Intermediary Factors and the Housing Recovery

This table reports the results from the OLS regressions of the difference between mean zip code delinquency growth and foreclosure growth after the major interventions in the housing market (2009-2016) and the preceding period (2006-2008) on various zip code level variables. The regressions are of the form $Y_{i,after}-Y_{i,before} = \alpha + \beta X_i + \epsilon_i$, where $Y_i$ is mean zip code delinquency growth or mean foreclosure growth and $X_i$ is the variable for zip code $i$. We consider the following variables at the zip code level: "ARM Share" that captures share of loans that are of ARM type (from Di Maggio et al 2017), "High Capacity Share" that captures share of loans serviced by high organizational capacity intermediaries (from Agarwal et al. 2017), and "HARP Eligible Share" that captures share of loans that are HARP eligible (from Agarwal et al. 2016). Controls include zip code DTI, CLTV at the zip code level. Panel A shows the results for zip code delinquency growth and Panel B shows the results for zip code foreclosure growth. Standard errors are in the parentheses.

Panel A: Change in the Zip Code Delinquency Growth Rate

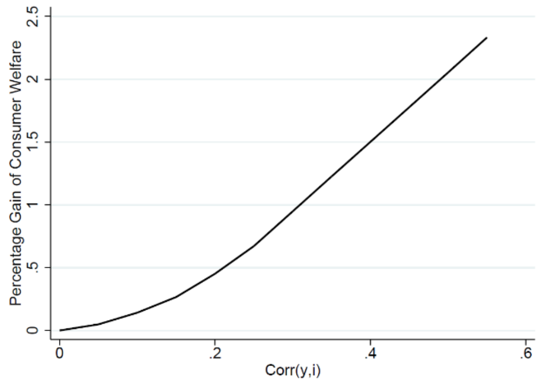
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|---|---|---|---|---|---|---|---|---|
| ARM Share | -0.00194 | -0.00119 | | | | | -0.00164 | -0.00092 |
| | (0.00012) | (0.00013) | | | | | (0.000143) | (0.000143) |
| High Experience Share | | | -0.193 | -0.0634 | | | -0.0833 | -0.0242 |
| | | | (0.0207) | (0.0202) | | | (0.0233) | (0.0219) |
| HARP Eligible Share | | | | | -0.061 | -0.0906 | -0.0354 | -0.0727 |
| | | | | | (0.0113) | (0.0109) | (0.0116) | (0.0114) |
| Control | No | Yes | No | Yes | No | Yes | No | Yes |
| Observations | 6739 | 6739 | 6739 | 6739 | 6739 | 6739 | 6739 | 6739 |
| Adjusted R-squared | 0.035 | 0.163 | 0.012 | 0.153 | 0.004 | 0.161 | 0.037 | 0.167 |

Panel B: Change in the Zip Code Foreclosure Growth Rate

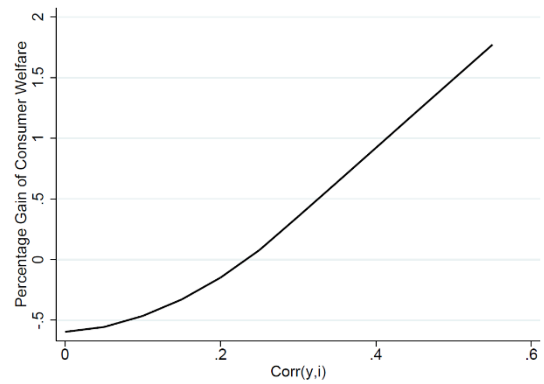
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|---|---|---|---|---|---|---|---|---|
| ARM Share | -0.00706 | -0.00587 | | | | | -0.00535 | -0.00395 |
| | (0.00034) | (0.00037) | | | | | (0.000393) | (0.000412) |
| High Experience Share | | | -0.681 | -0.549 | | | -0.369 | -0.39 |
| | | | (0.0579) | (0.0591) | | | (0.0641) | (0.0631) |
| HARP Eligible Share | | | | | -0.401 | -0.424 | -0.323 | -0.361 |
| | | | | | (0.0313) | (0.0317) | (0.0320) | (0.0328) |
| Controls | No | Yes | No | Yes | No | Yes | No | Yes |
| Observations | 6739 | 6739 | 6739 | 6739 | 6739 | 6739 | 6739 | 6739 |
| Adjusted R-squared | 0.059 | 0.106 | 0.02 | 0.085 | 0.024 | 0.097 | 0.074 | 0.123 |

## Figure 1: Simple Framework: Utility Gains from Mortgage Indexation (Perfectly Correlated Income and House Price Risk)

This figure shows the borrower's utility gain (in percentage terms) under indexed-rate mortgage (IRM) compared to FRM for various degrees of correlation of rate index with income and assuming house price and income shocks are perfectly correlated. Panel A shows the results for the case of no indexation cost. Panel B shows the results for the case of mortgage indexation cost. Base parameters are as in Table 1.



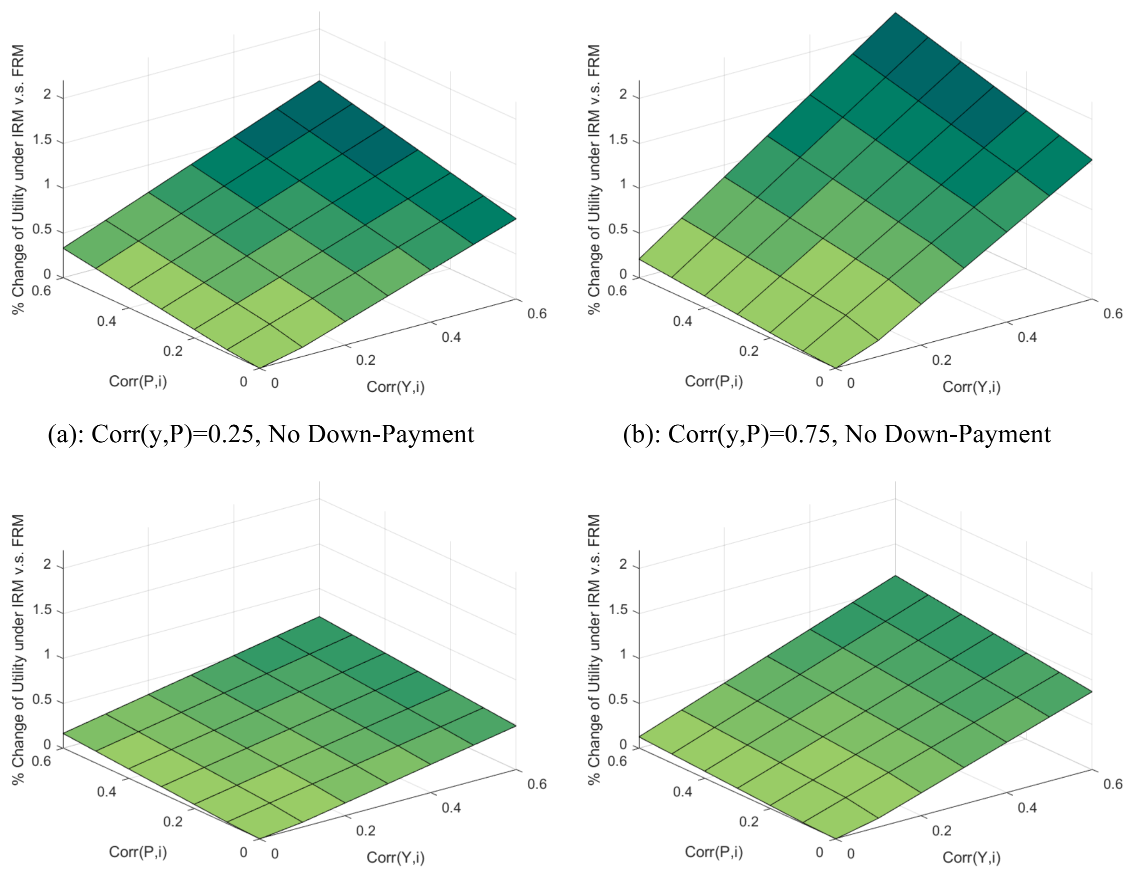

(a): No indexation cost




(b): With indexation cost

**Figure 2: Simple Framework: Utility Gains from Mortgage Indexation**
**(No Indexation Cost, Imperfectly Correlated Income and Housing Risk)**

This figure shows the borrower's utility gain (in percentage terms) under indexed-rate mortgage (IRM) compared to FRM for various degree of correlation of index with income and house prices. Panel A shows the results for correlation of income and house prices equal to 0.25 (low correlation) while Panel B shows the corresponding results for correlation of income and house prices equal to 0.75 (high correlation). Both cases assume no down payment. Panels C and D shows the corresponding figures for the case of 20% down payment. Other parameters are as in Table 1.




(a): Corr(y,P)=0.25, No Down-Payment

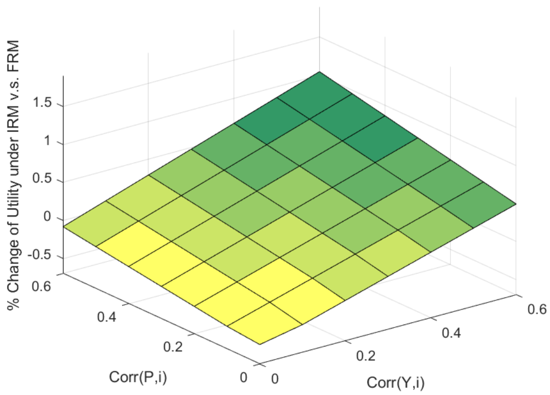
(b): Corr(y,P)=0.75, No Down-Payment

(c): Corr(y,P)=0.25, 20% Down-Payment

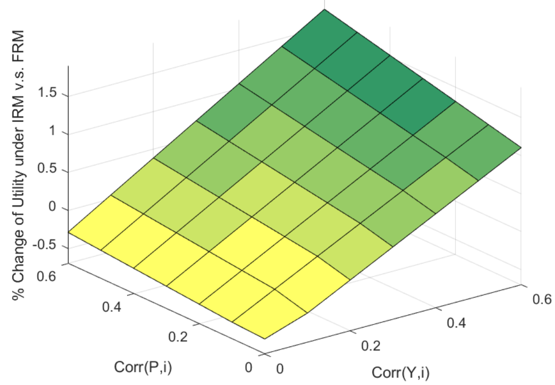
(d): Corr(y,P)=0.75, 20% Down-Payment

## Figure 3: Simple Framework: Utility Gains from Mortgage Indexation (Positive Indexation Cost, Imperfectly Correlated Income and Housing Risk)

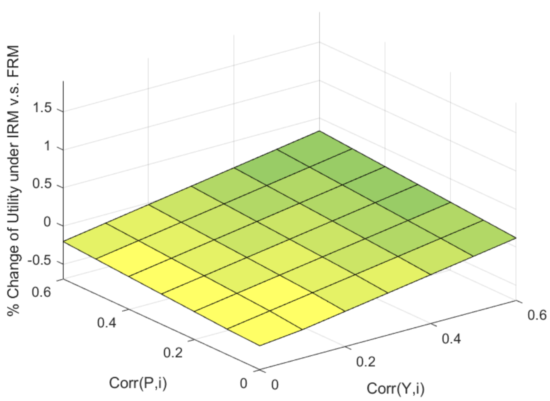
This figure shows the borrower's utility gain (in percentage terms) under indexed-rate mortgage (IRM) compared to FRM for various degree of correlation of index with income and house prices assuming positive indexation cost. Panel A shows the results for correlation of income and house prices equal to 0.25 (low correlation) while Panel B shows the corresponding results for correlation of income and house prices equal to 0.75 (high correlation). Both cases assume no down-payment. Panel C and D shows the corresponding figures for the case of 20% down-payment. Other parameters are as in Table 1.



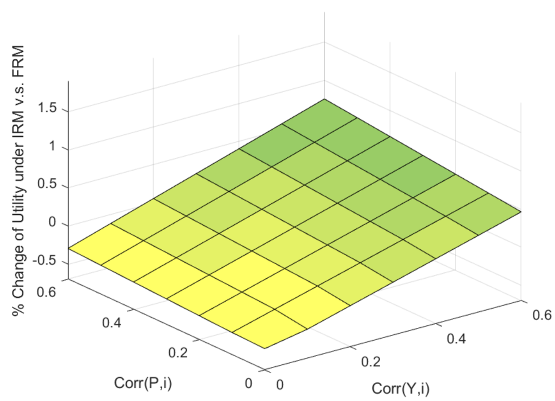

(a): Corr(y,P)=0.25, No Down-Payment




(b) Corr(y,P)=0.75, No Down-Payment



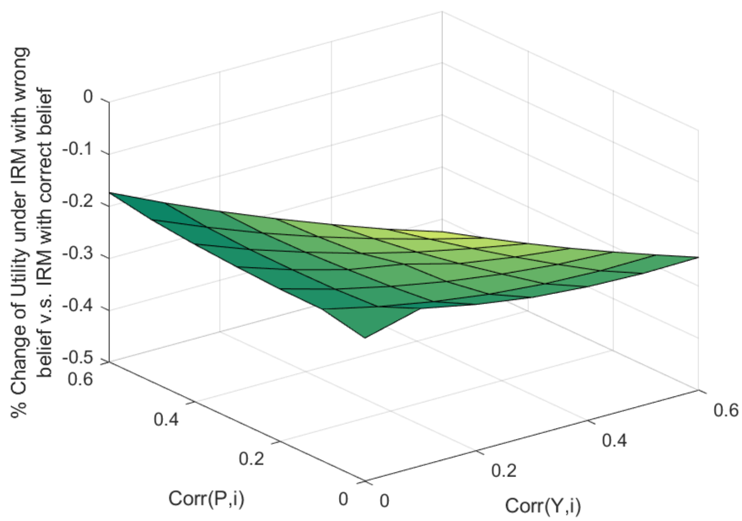

(c): Corr(y,P)=0.25, 20% Down-Payment




(d): Corr(y,P)=0.75, 20% Down-Payment

## Figure 4: Simple Framework:
## Impact of Incorrect Beliefs about Distribution of Relevant Economic Risk

This figure shows the borrower's utility (in percentage terms) under indexed-rate mortgage (IRM) designed for incorrectly high correlation of income and house prices (equal to 0.75) and high correlation of index with income and house prices (equal to 0.6) relative to the indexed-mortgage correctly designed knowing that the actual correlation of income and house prices is low (equal to 0.25) and the actual correlation of index with income and house prices is as shown in the figure. The computations assume no down-payment and no indexation cost. Other parameters are as in Table 1.

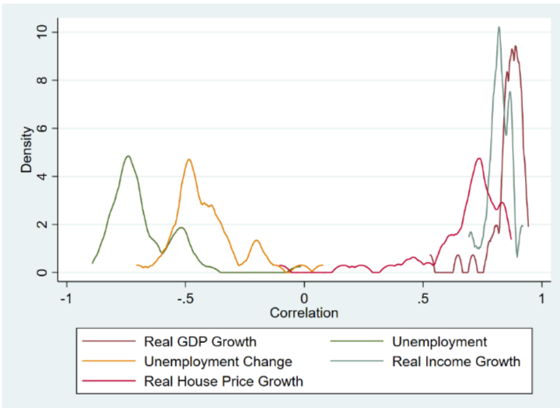


## Figure 5: Regional Heterogeneity: Evolution of State Economic Factor over Time

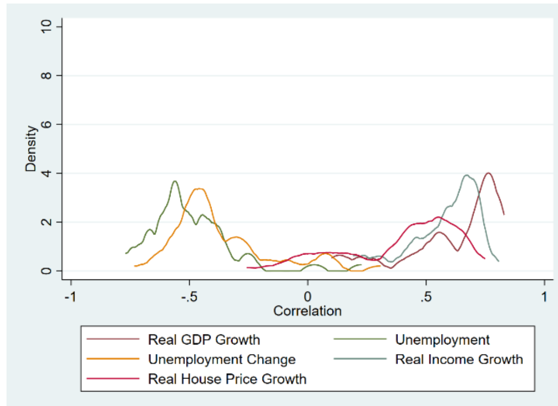
This figure illustrates the time series variation for the distribution of local economic conditions from 1980 to 2016. The black solid line is the average local economic conditions across all 50 states and the District of Columbia. The two gray lines are the 10th and 90th percentile, displaying the extent of cross-sectional variation.

**Figure 6: State Economic Factor and National and State-Level Variables**

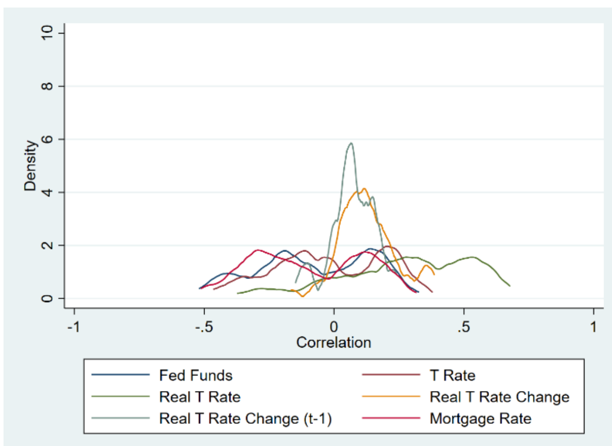
Panel A of this figure displays the kernel densities of the correlation between the state economic factors with various state economic variables. Panel B displays the corresponding kernel densities of the correlation between state economic factors with national economic conditions and various national-level macroeconomic variables. Panel C displays the corresponding kernel densities of the correlation between state economic factor with national-level interest rate indices.




(a) Correlation with State-Level Variables



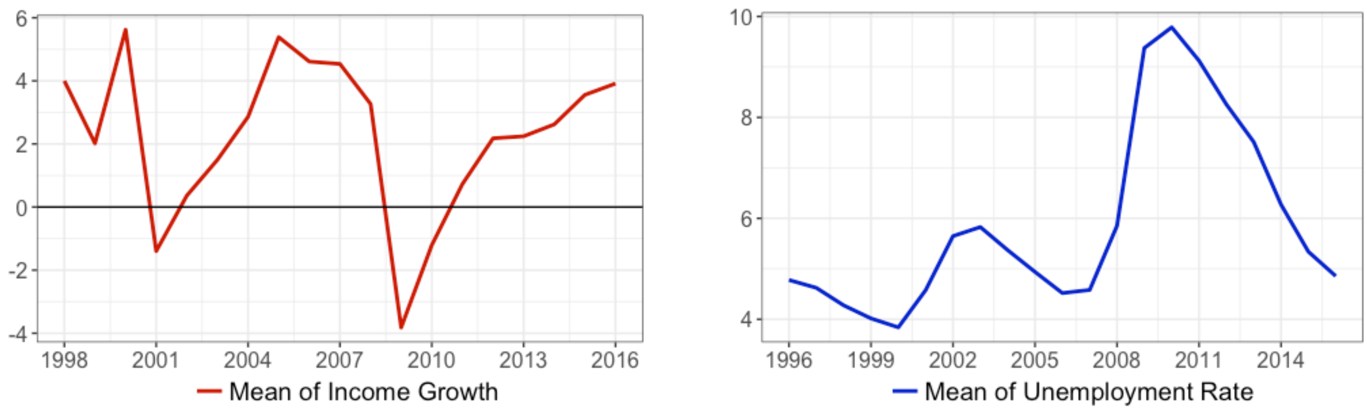

(b) Correlation with National-Level Variables



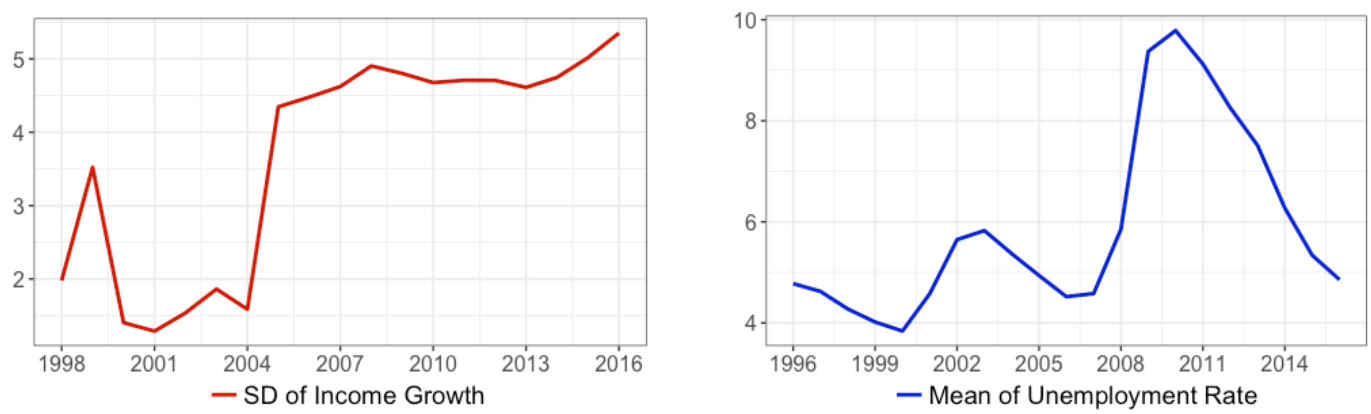

(c) Correlation with Interest Rate Indices

## Figure 7: County-Level Income and Unemployment Rate

Panel A shows time-series of the means of county-level real income growth from 1998 to 2016 and unemployment rate from 1996 to 2016. Calculations are population weighted by county. Panel B shows the standard deviation of these variables across counties in each year. County income data comes from U.S. Census Bureau, Small Area Income and Poverty Estimates. County unemployment data comes from the Bureau of Labor Statistics, Local Area Unemployment Statistics.



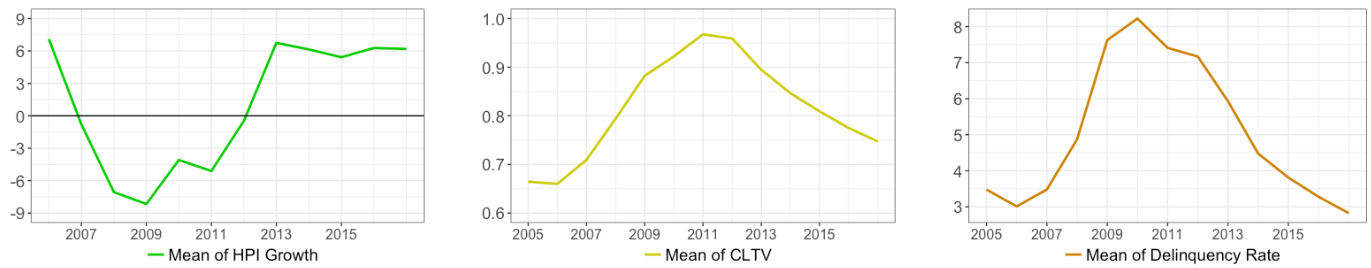

(a): Means



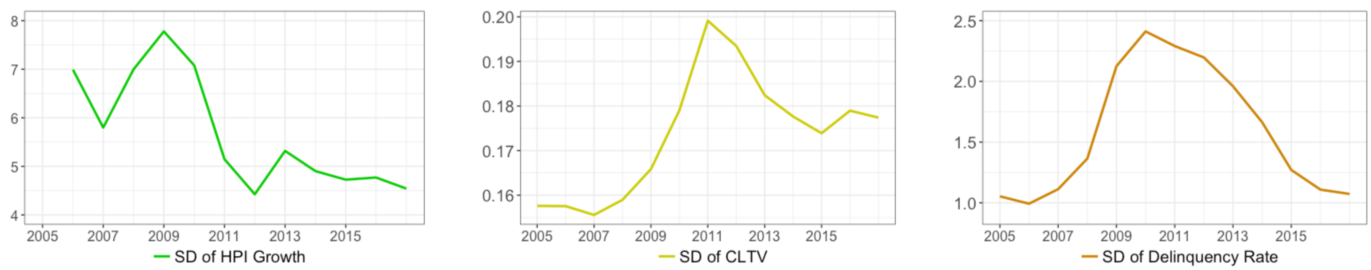

(b): Standard Deviations

## Figure 8: County-Level Housing Variables

Panel A shows time-series of the means of county-level house price growth, CLTV, and delinquency rate from 2005 to 2016. Panel B shows the standard deviation of these variables across counties in each year. Calculations are population weighted by county. HPI data comes from county level Zillow Home Value Index and CLTV and delinquency rate from Equifax.



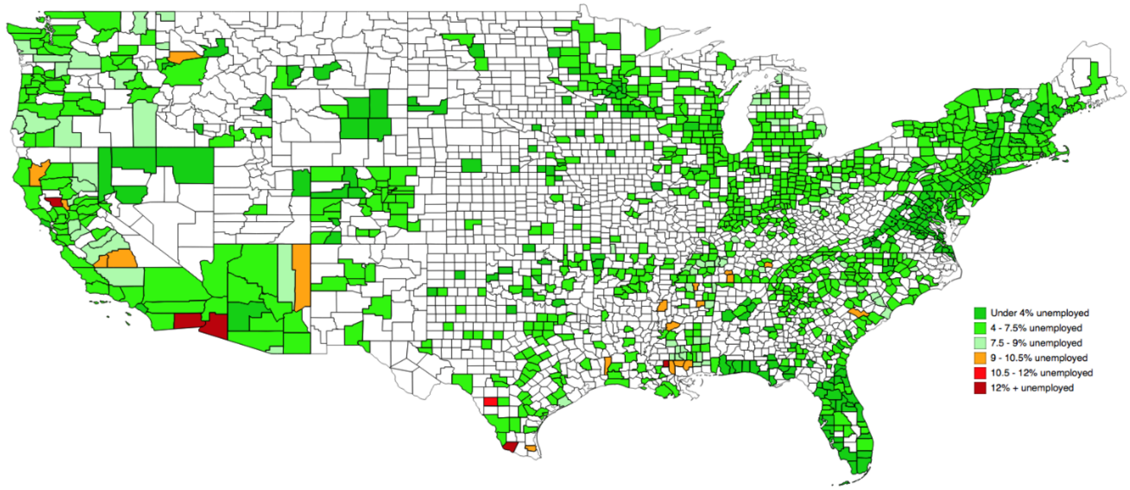

(a): Means



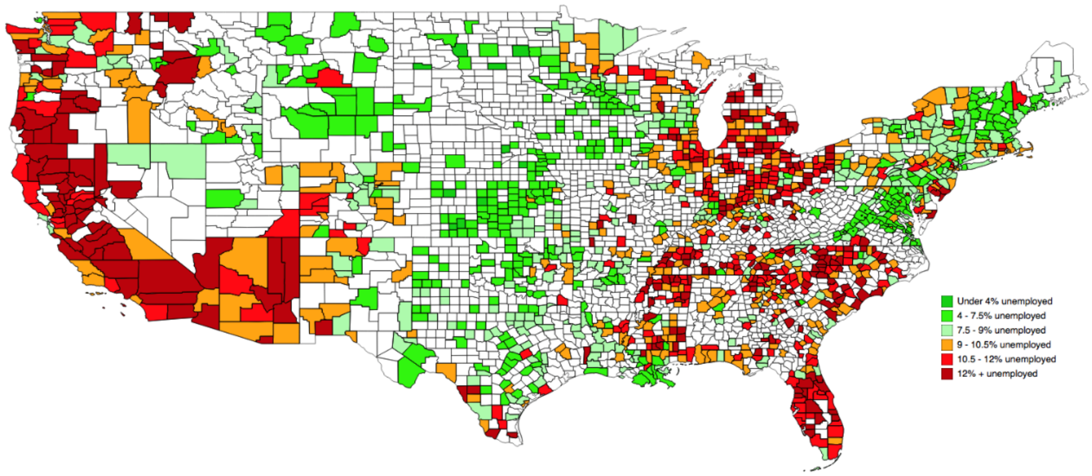

(b): Standard Deviations

## Figure 9: County Heterogeneity: Unemployment Rate Maps

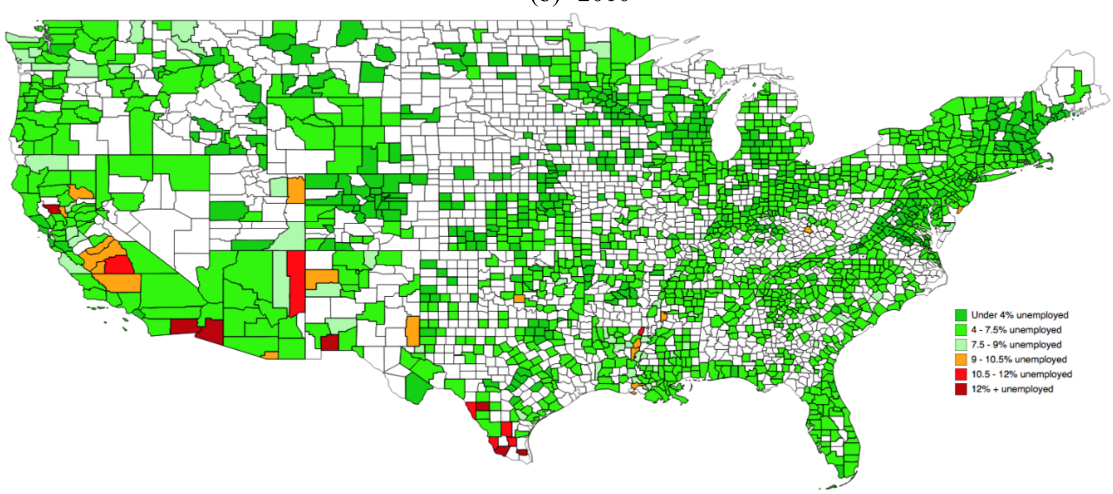
Panel A shows county-level unemployment rate in 2005, Panel B shows unemployment rate in 2010, and Panel C shows unemployment rate in 2016. Data comes from Equifax sample. County unemployment data comes from the Bureau of Labor Statistics, Local Area Unemployment Statistics.




(a) 2005



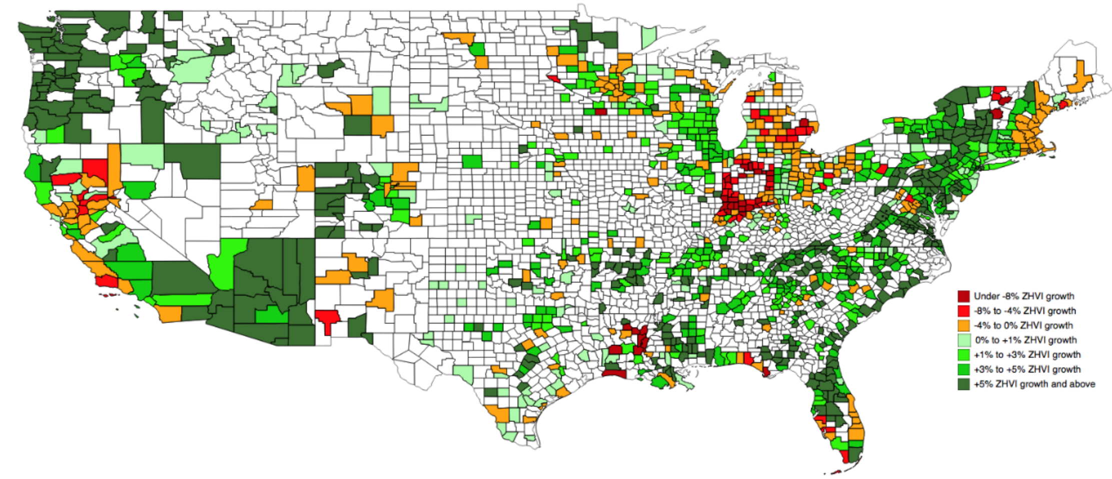

(b) 2010



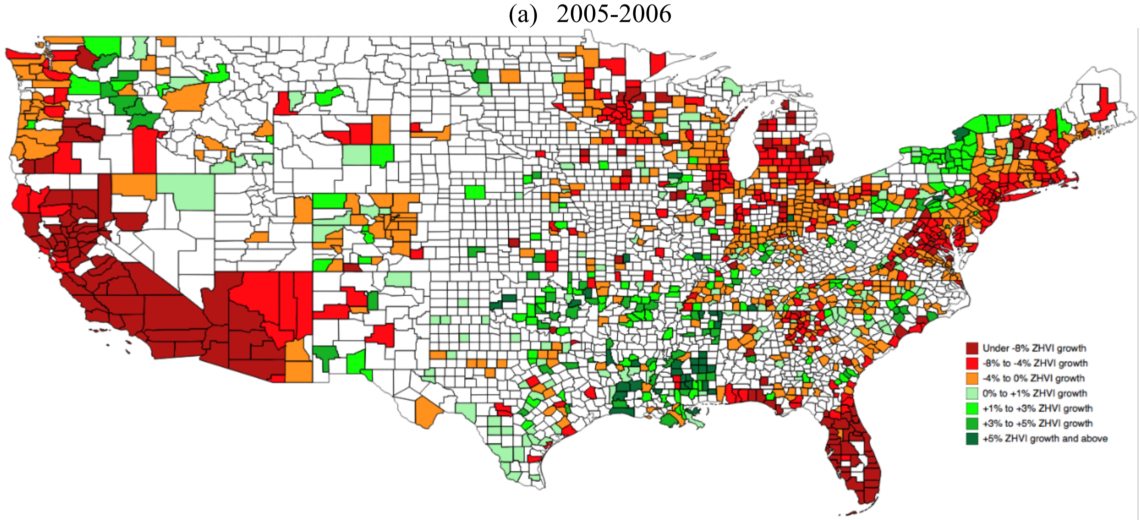

(c) 2016

## Figure 10: County Heterogeneity: House Price Growth

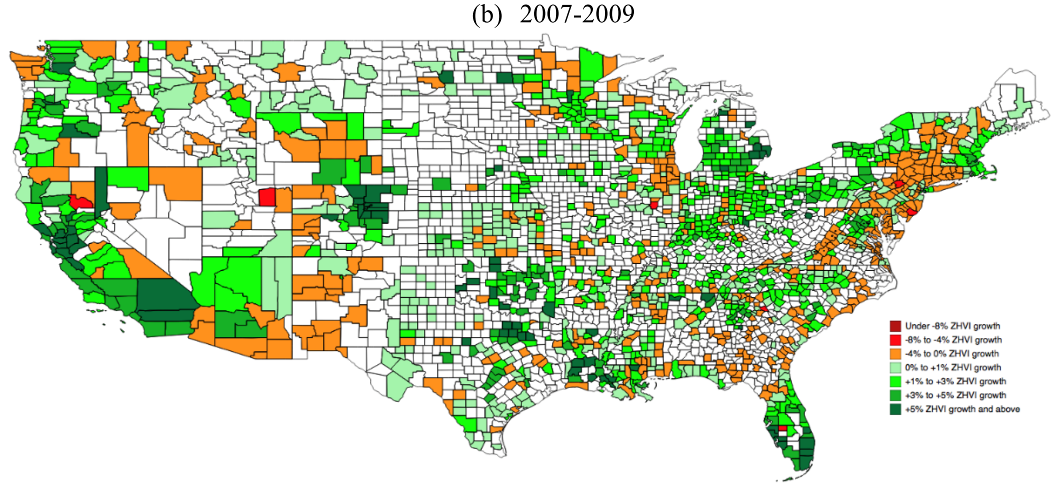
Panel A shows average annual county-level house price growth from 2005 to 2006, Panel B shows house price growth from 2007 to 2009 and Panel C shows house price growth from 2010 to 2016. Data comes from county level Zillow Home Value Index.




(a) 2005-2006



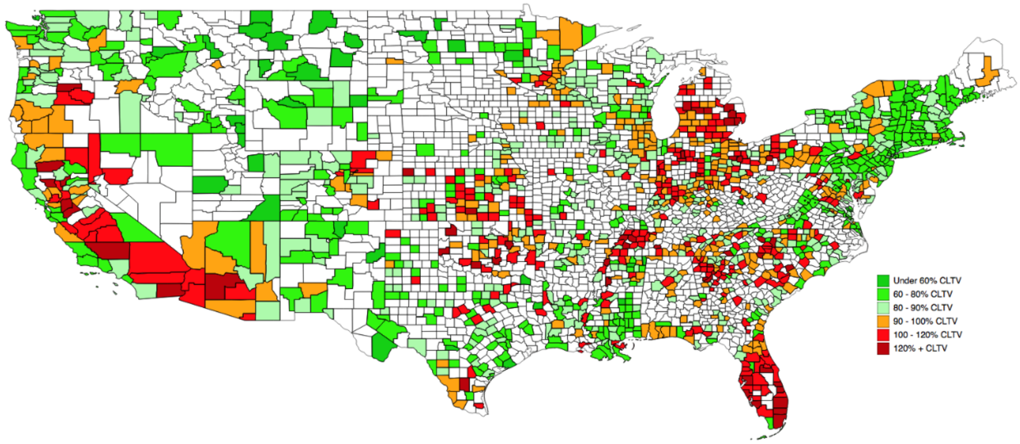

(b) 2007-2009



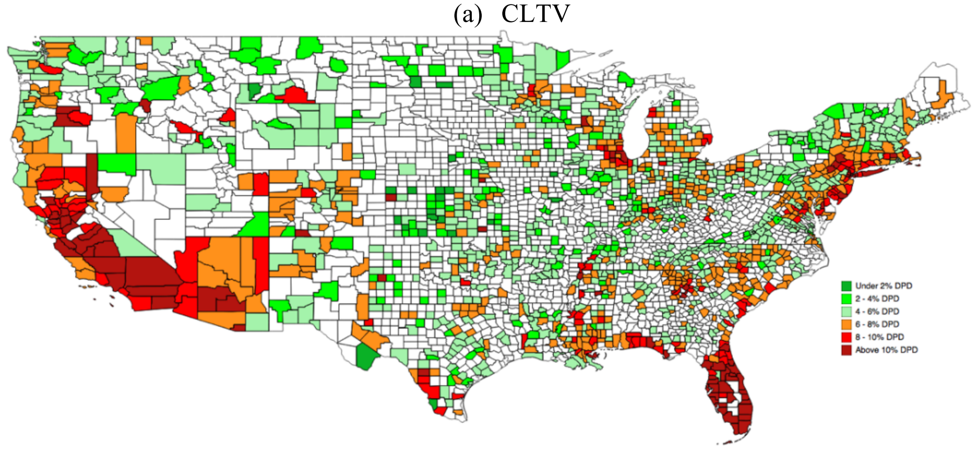

(c) 2010-2016

## Figure 11: County Heterogeneity: Housing Equity (CLTV) and Mortgage Default during the Great Recession

Panel A shows average annual county-level CLTV in 2010. Panel B shows average serious mortgage delinquency rate in 2010 in a county. Data comes from the Equifax representative panel of 10% of US population.



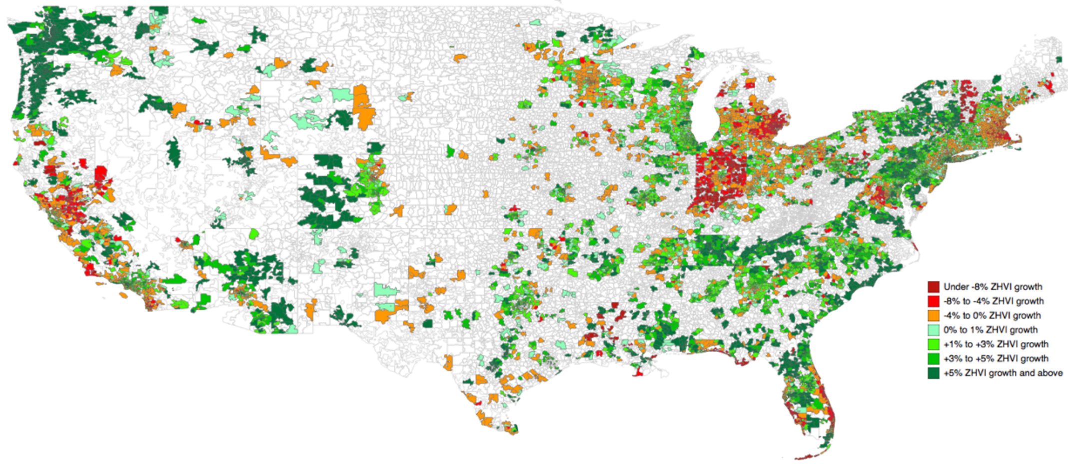

(a) CLTV



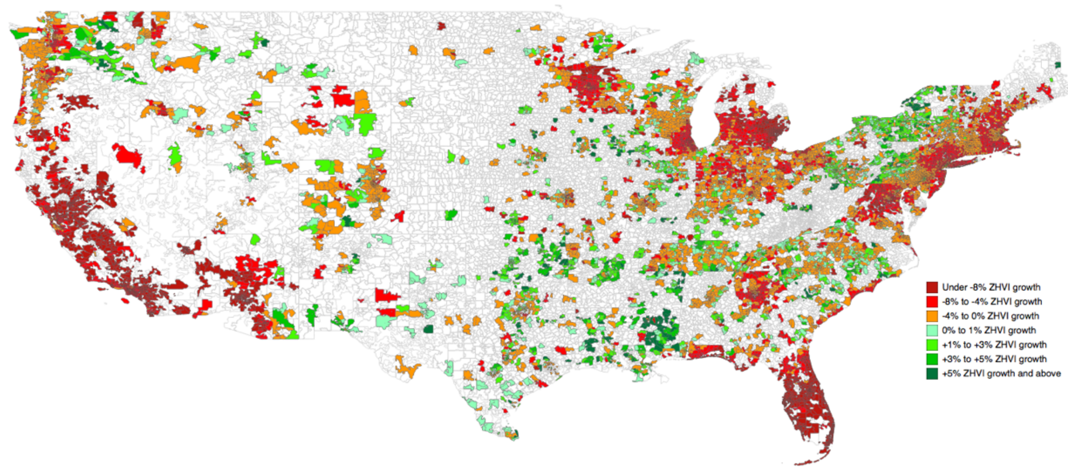

(b) Mortgage Default

## Figure 12: Zip Code Heterogeneity: House Price Growth

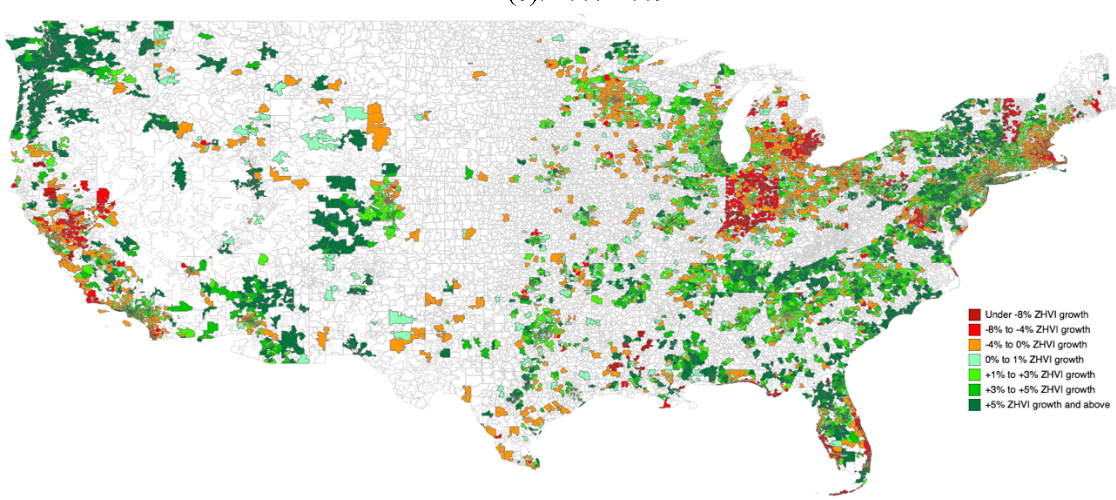
Panel A shows average annual zip-code level house price growth from 2005 to 2006, Panel B shows house price growth from 2007 to 2009 and Panel C shows house price growth from 2010 to 2016. Data comes from zip-code level Zillow Home Value Index.




(a): 2005-2006



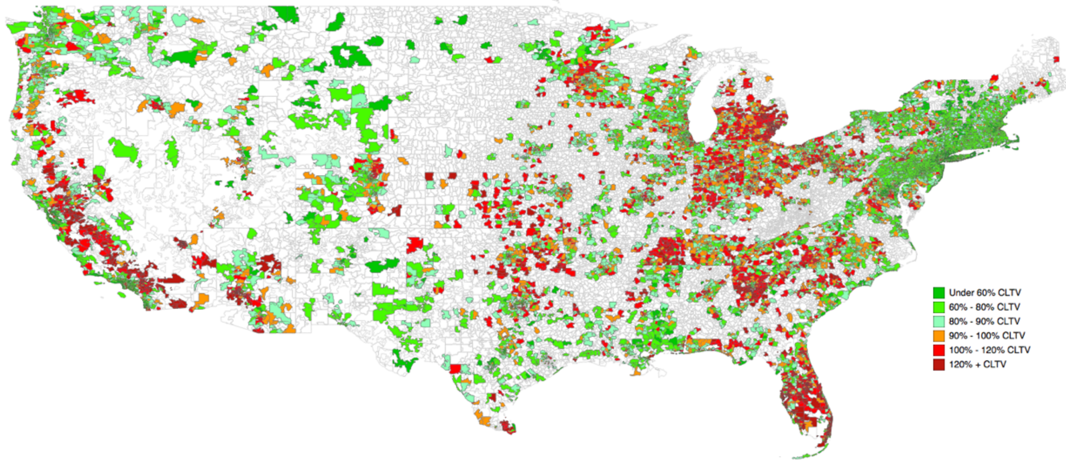

(b): 2007-2009



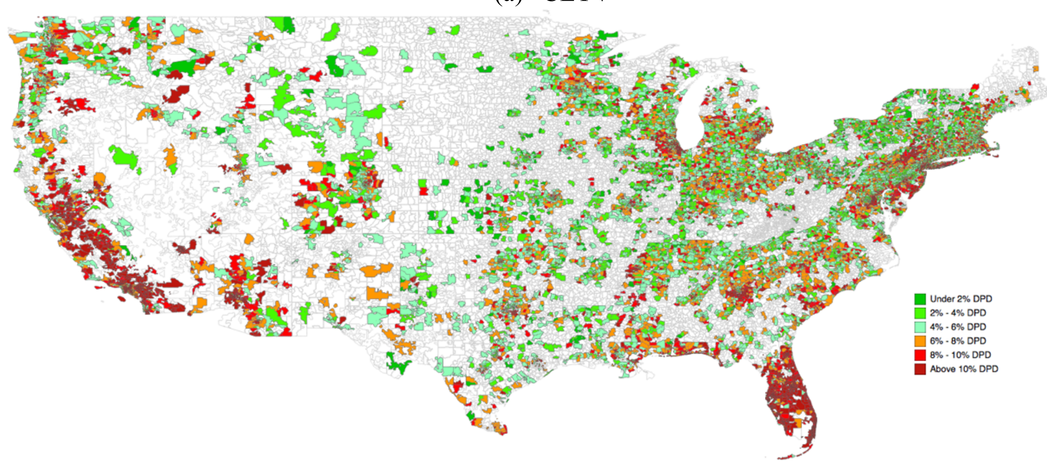

(c): 2010-2016

## Figure 13: Zip Code Heterogeneity: Housing Equity (CLTV) and Mortgage Default during the Great Recession

Panel A shows average annual zip code CLTV in 2010. Panel B shows average serious mortgage delinquency rate in 2010 in a zip code. Data comes from the Equifax representative panel of 10% of US population.



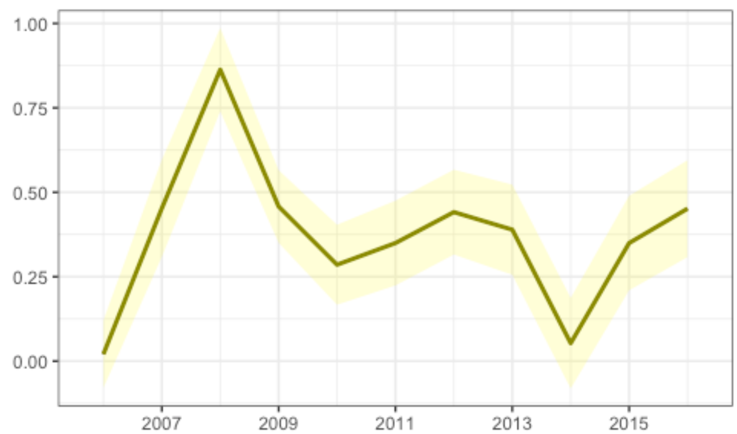

(a) CLTV



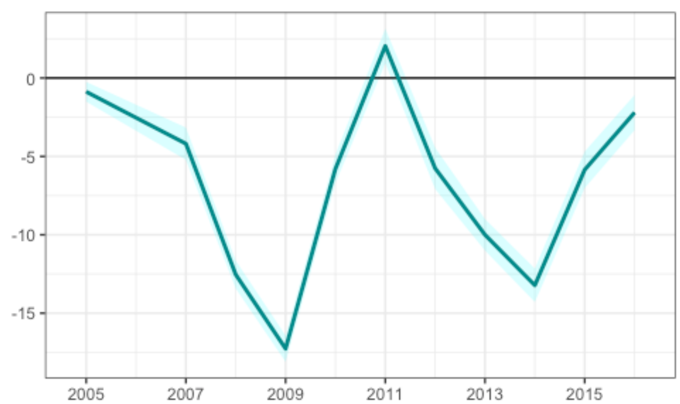

(b) Mortgage Default

## Figure 14: County-Level Evidence: Mortgage Default, House Prices, and Unemployment

This figure examines the relationships between county level variables through simple linear regressions. Dependent variables are regressed on county level independent variables that are interacted with annual dummies for each year from 2005 to 2016. Regressions are population weighted by county. Panel A shows the estimated relationship between annual change in the serious mortgage delinquency rate and annual change in unemployment rate along with 95% confidence interval. Panel B shows the estimated relationship between annual change in the delinquency rate and house price growth rate along with 95% confidence interval.




(a) Mortgage Default and Unemployment Relationship




(b) Mortgage Default and House Price Relationship

## Figure 15: County-Level Evidence:
## House Prices, Housing Equity, and Unemployment over Time

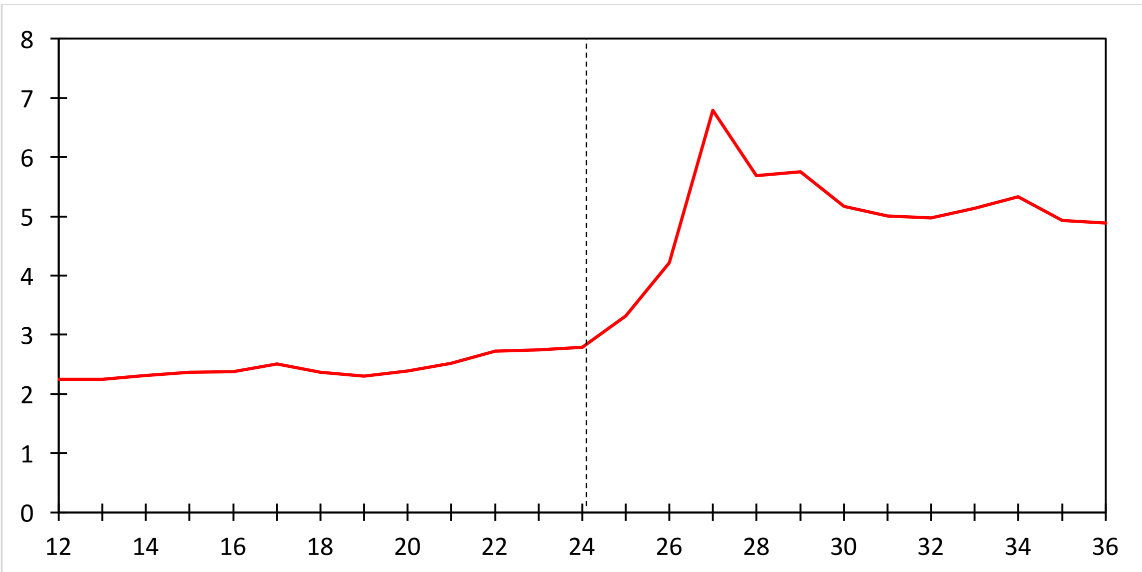
This figure examines the relationships between county level variables through simple linear regressions. Dependent variables are regressed on county level independent variables that are interacted with annual dummies for each year. Regressions are population weighted by county. Panel A shows the estimated relationship between annual growth in house prices and unemployment rate change along with 95% confidence interval for years 1997 to 2016. Panel B shows the estimated relationship between annual change in the CLTV and annual change unemployment rate along with 95% confidence interval for years 2006 to 2017.


(a) House Prices and Unemployment Relationship

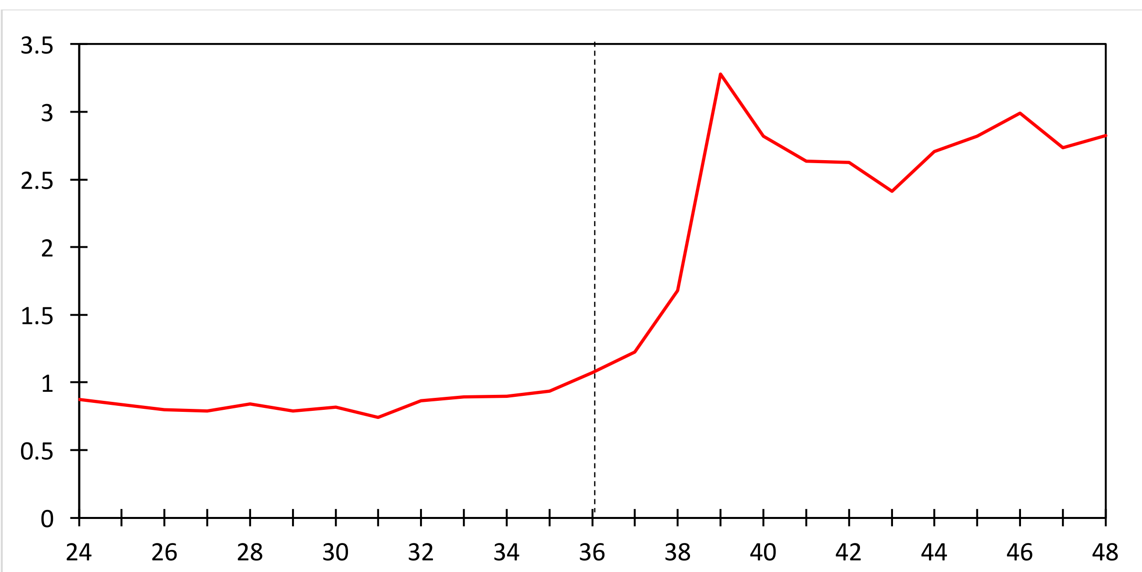

(b) Change in CLTV and Change in Unemployment Relationship

## Figure 16: Impact of ARM Resets on Defaults during Mid 2006 – Early 2008

Panel A of this figure shows the mortgage default rate for 2-year (2/28) subprime ARMs originated during the 2004-2006 period. These 2-year ARM contracts faced a fixed initial rate for the first two years and subsequently a reset to the variable rate based on a short-term interest rate index (e.g., LIBOR rate) during the late 2006-early 2008 period. Panel B of this figure shows the mortgage default rate for 3-year (3/27) ARMs originated from March 2004 – January 2005. These 3-year ARM contracts faced a fixed initial rate for the first three years and subsequently reset over the period of April 2007 – January 2008 based on a short-term interest rate index (e.g., LIBOR rate). The x-axis shows the loan life in months. The dashed line shows the timing of the first reset date. Source: 2/28 and 3/27 ARMs from BlackBox Logic Data.



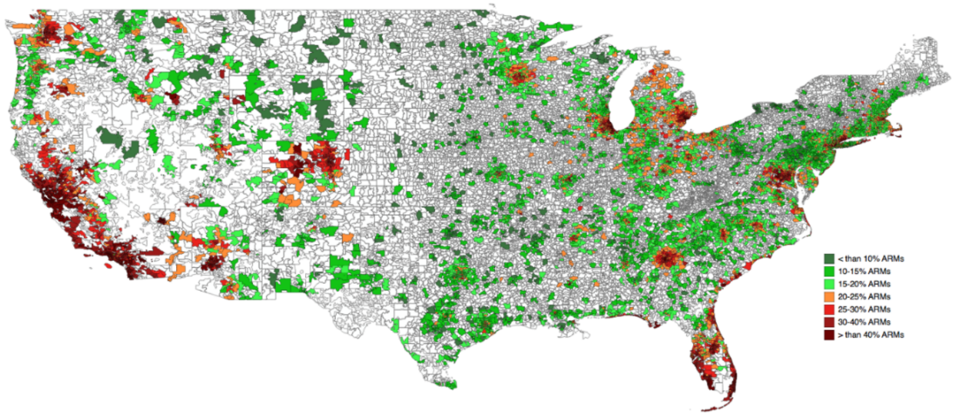

(a) Mortage default rate (2-year ARMs)



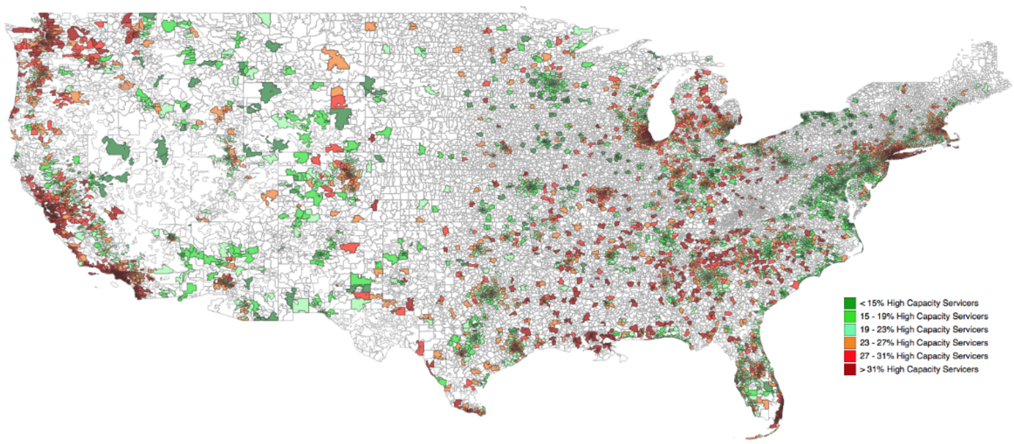

(b) Mortgage default rate (3-year ARMs)

## Figure 17: Spatial Variation in Implementation of Debt Relief

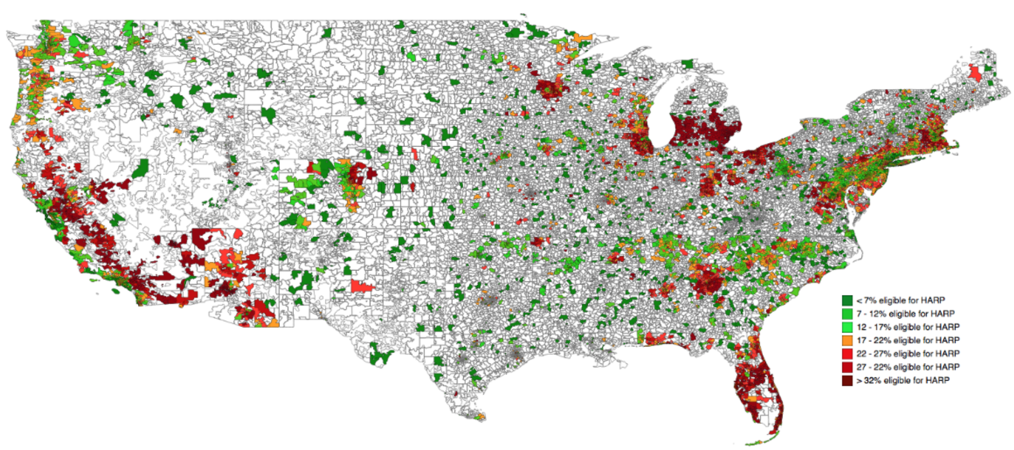
Panel A of this figure shows the spatial variation of zip code ARM share in the US (data from Di Maggio et al. 2017). We note that ARM loans can experience a quick "automatic" pass through of low interest rates. This share, however, needs to be interpreted with caution as many subprime ARM contracts 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 serviced by intermediaries with low organizational capacity to service and modify loans (data from Agarwal et al. 2017). Panel C 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.




(a) ARM Share




(b) Share of Loans Serviced by High Organizational Capacity Intermediaries




(c) HARP Eligible Share

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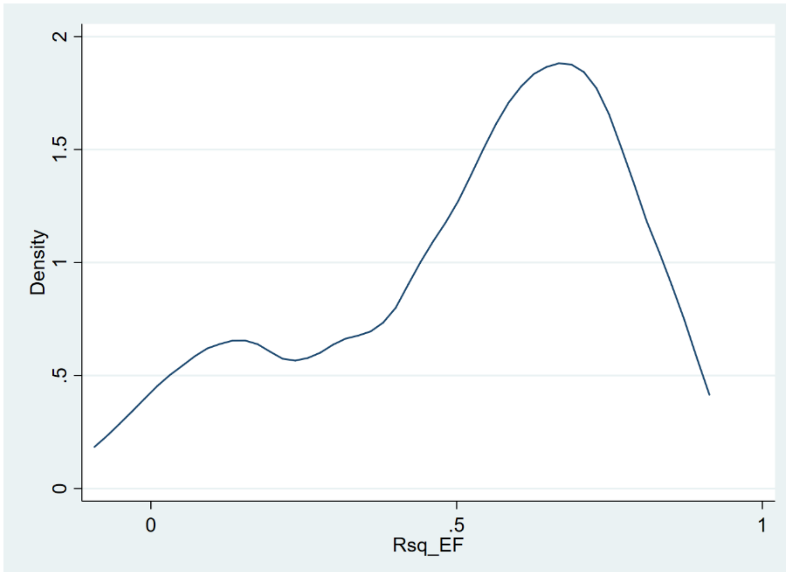
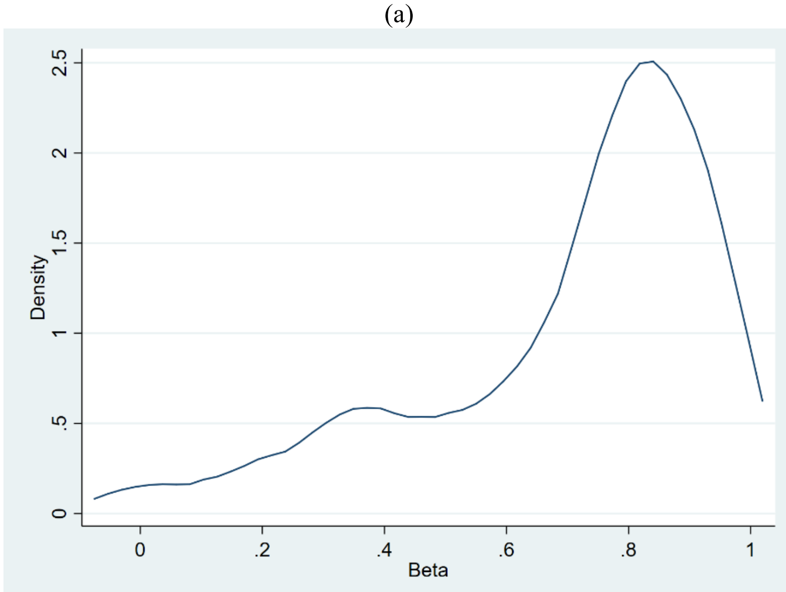
## Appendix A1: Distribution of State Economic Factor $R^2$ and Beta

Panel A shows the kernel density of the explained variation in 51 separate regressions of local economic conditions on a constant and national economic conditions as discussed in Section 4. Panel B shows the kernel density of the coefficients on national economic conditions in the aforementioned regression.



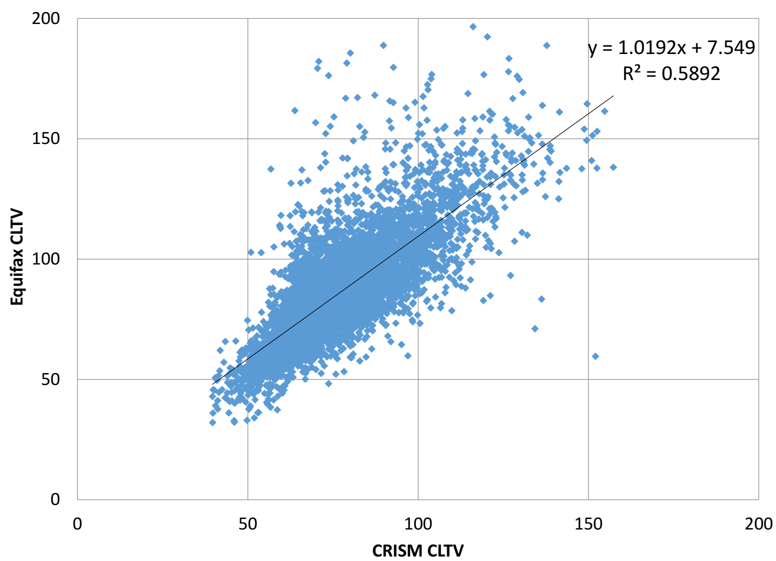

(a)




(b)

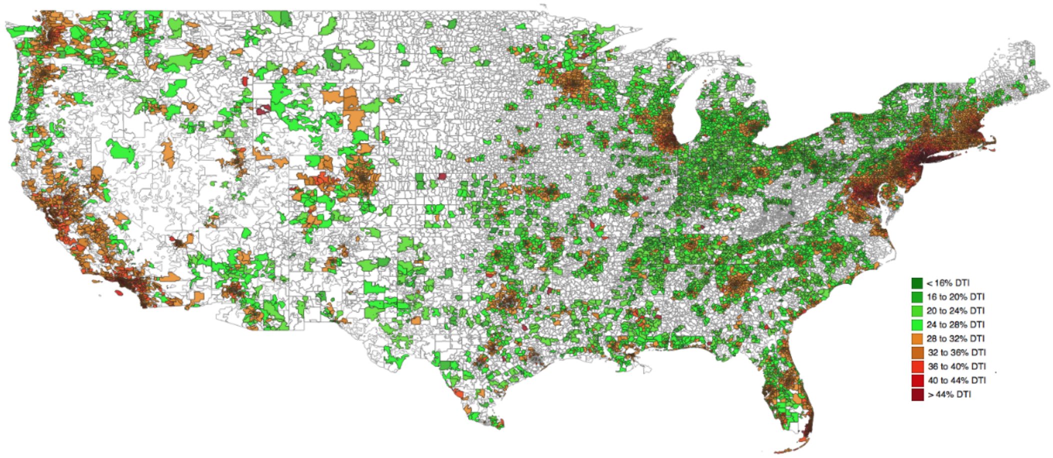
## Appendix A2: Relationship between Equifax CLTV and CRISM CLTV

We note that the Equifax data we use does not have a direct measure of current CLTV of mortgage borrowers. We compute this variable in a region (county or zip code) 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 (from Zillow). The plot below verifies that our (Equifax-based) measure of average CLTV in a zip code is closely related to the CLTV measure from wieldy used Credit Risk Insight Servicing McDash (CRISM) data that covers approximately seventy percent of mortgage borrowers. It shows the relationship between zip CLTV in the CRISM data (x-axis) and the Equifax data (y-axis) during the depth of the crisis (in 2009). As we observe the estimated slope of this relationship is very close to unity. We note that our measure indicates slightly higher CLTV levels than CRISM data, likely in part due to underrepresentation of subprime borrowers in the CRISM data.

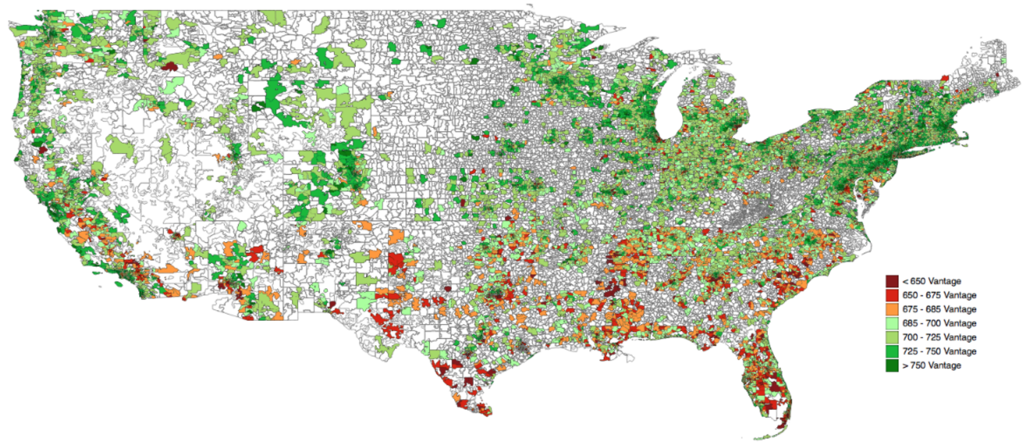


## A3: Zip Code Heterogeneity: DTI, Credit Score (Vantage), and Foreclosures during the Great Recession

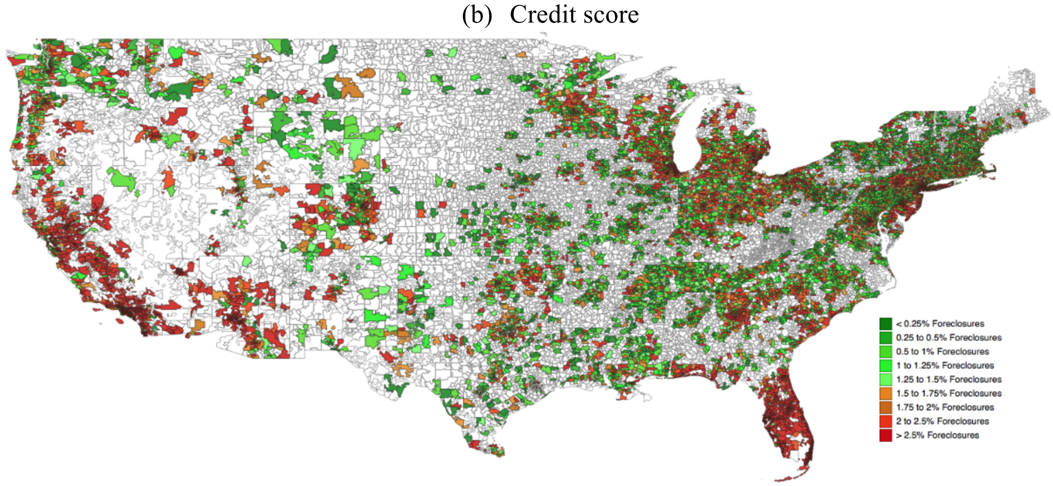
Panel A shows the spatial distribution of average annual zip code mortgage debt payment to income ratio (DTI) in 2010. Panel B shows average zip code vantage in 2010. Panel C shows the percentage of loans in foreclosure in zip code in 2010. Data comes from the Equifax representative panel of 10% of US population.




(a) DTI




(b) Credit score




(c) Foreclosure rate

## Appendix A4: Summary Statistics for the Analysis of the Importance of Local Economic Variables and the Upper Bound to $R^2$

This table shows the summary statistics of major housing variables at zip-code level used in the analysis shown in Table 5. Panel A shows the statistics for levels while Panel B shows the corresponding statistics for the monthly growth rates. Combined loan to value, debt to income, delinquency rates, and foreclosures data are from Jul 2005-Dec 2017 (form Equifax); real house price data are from Jan 1997-Dec 2017 (from Zillow).

Panel A: Levels

| Variable | Obs. | Mean | Std. Dev. |
|---|---|---|---|
| Real House Price | 3,378,242 | $235,118 | $170,804 |
| CLTV | 2,001,211 | 81% | 7% |
| DTI | 2,135,081 | 29% | 4% |
| Delinquency Rate | 2,101,678 | 5% | 4% |
| Foreclosure Rate | 2,082,162 | 2% | 2% |

Panel B: Growth Rates

| Variable | Obs. | Mean | Std. Dev. |
|---|---|---|---|
| Real House Price | 3,378,005 | 0.10% | 1% |
| CLTV | 2,001,211 | 0.11% | 3% |
| DTI | 2,135,081 | 0.12% | 3% |
| Delinquency Rate | 2,101,678 | 3.43% | 46% |
| Foreclosure Rate | 2,082,162 | -0.05% | 34% |

## Appendix A5: Robustness: The Importance of Local Economic Variables and Upper Bound to $R^2$

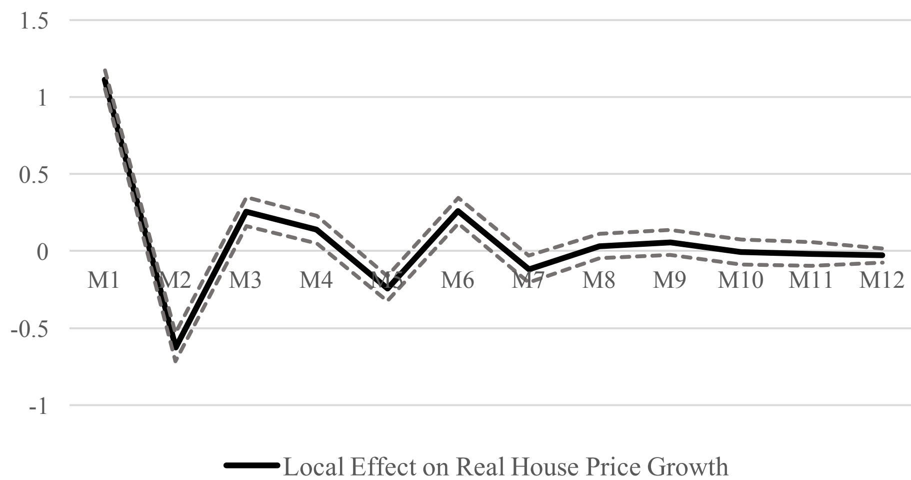
This table shows similar analysis to the one presented in Table 5 where all housing variables are measured at monthly changes. In particular, the table shows the upper bound to $R^2$ of local zip-code level variables that can be explained by different levels of aggregation. The local zip-code level housing variables are regressed on contemporaneous geography by time fixed effects at the city, county, metro, states and national level and the unadjusted $R^2$ is reported in each cell. Further, all housing variables are demeaned at zip-code level and winsorized at 1%. CLTV, DTI, delinquency rates, and foreclosures data are from Jul 2005-Dec 2017; real house price data are from Jan 1997-Dec 2017.

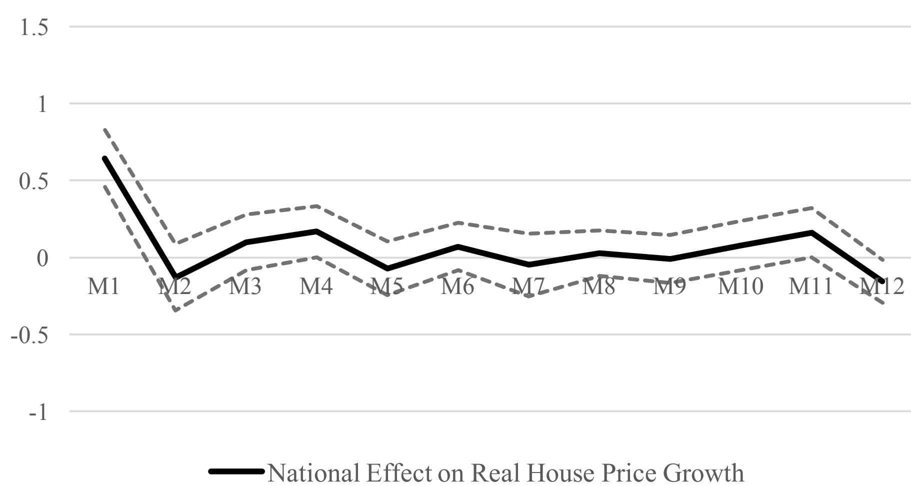
| | CLTV Change | DTI Change | Delinquency Change | Foreclosure Change | Real House Price Change |
|---|---|---|---|---|---|
| Aggregation\Variable | (1) | (2) | (3) | (4) | (5) |
| National | 3.91% | 1.23% | 1.05% | 0.46% | 23.17% |
| States | 6.52% | 2.02% | 1.75% | 1.31% | 25.71% |
| Metro | 14.61% | 8.06% | 7.79% | 6.44% | 39.85% |
| County | 16.62% | 10.18% | 9.68% | 8.43% | 45.13% |
| City | 60.36% | 58.85% | 62.68% | 57.45% | 73.19% |
| ZIP Code | 100% | 100% | 100% | 100% | 100% |

## Appendix A6: Predictability of Housing Variables and the Importance of Local Indicators

The two figures plot the AR(12) coefficients form a regression of a given zip-code level variable (in the monthly growth rate) on twelve lags of that variable measured at the zip code level (top figure) and the national level (bottom figure). Panel A shows the results for house price growth, Panel B for CLTV growth, Panel C for DTI growth, Panel D for delinquency rate growth, and Panel E for foreclosure rate growth. Two grey lines indicate the 95% confidence intervals.

Panel A: House Price Growth

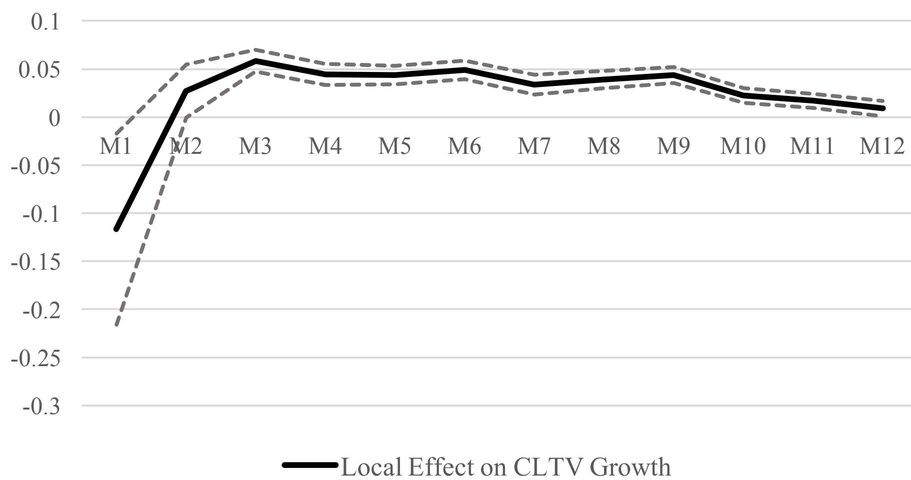


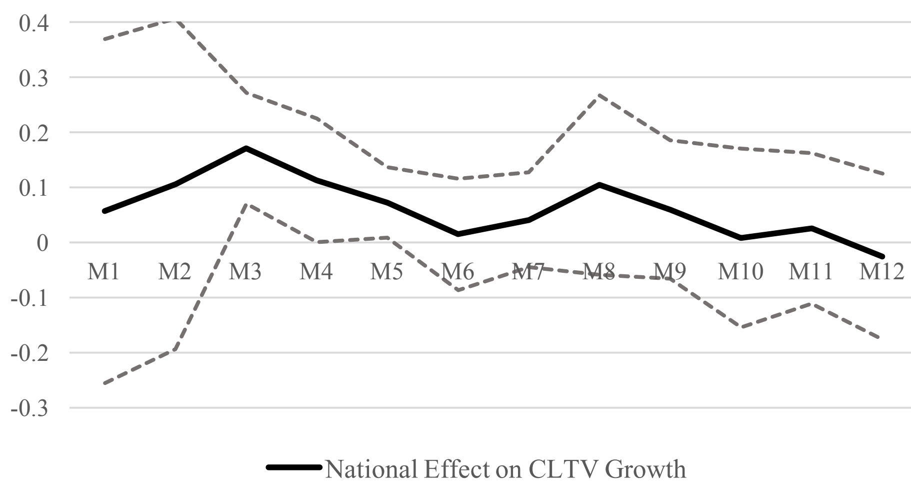



## Appendix A6: Predictability of Housing Variables and the Importance of Local Indicators (continued)

The two figures plot the AR(12) coefficients of zip-code level loan to value ratio (CLTV) growth on lagged zip-code level CLTV growth (upper panel) and lagged national level CLTV growth (lower panel). The underlying CLTV data are from Jul 2005-Dec 2017 at monthly frequency. The two grey lines indicate the 95% confidence intervals.

Panel B: CLTV Growth

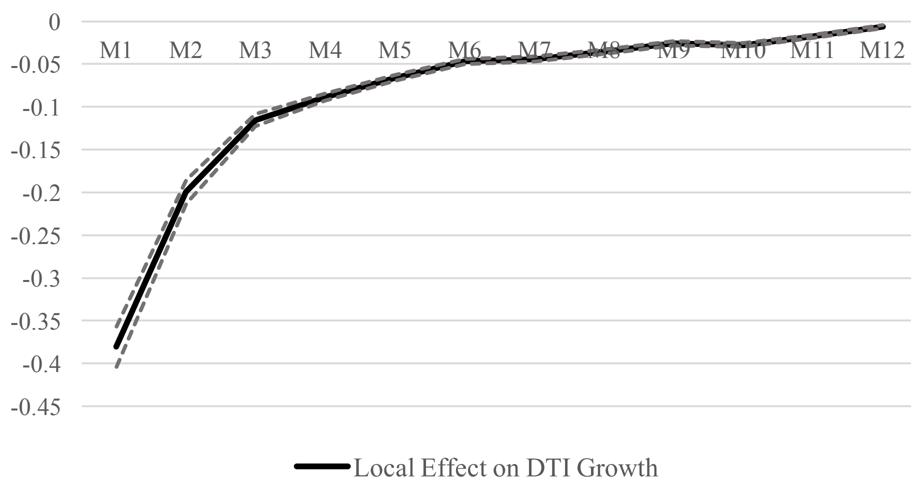


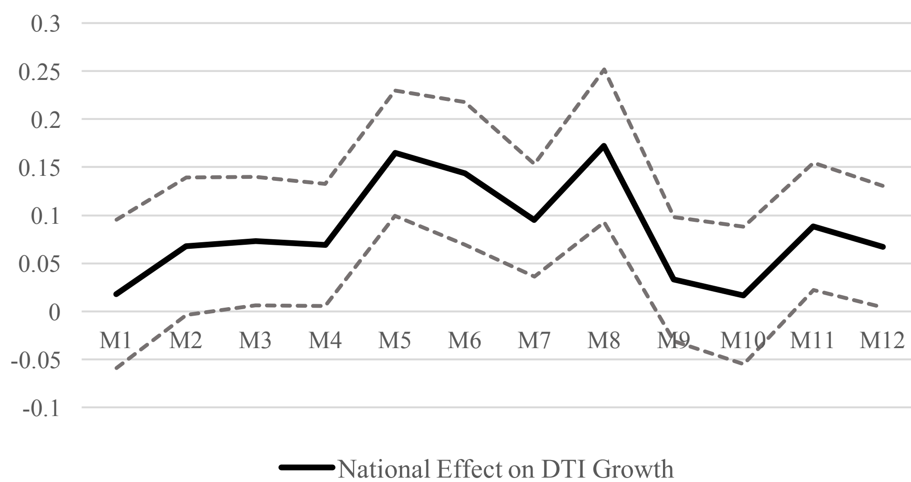



## Appendix A6: Predictability of Housing Variables and the Importance of Local Indicators (continued)

The two figures plot the AR(12) coefficients of zip-code level debt to income ratio (DTI) growth on lagged zip-code level DTI growth (upper panel) and lagged national level DTI growth (lower panel). The underlying DTI data are from Jul 2005-Dec 2017 at monthly frequency. The two grey lines indicate the 95% confidence intervals.

Panel C: Debt to Income Growth

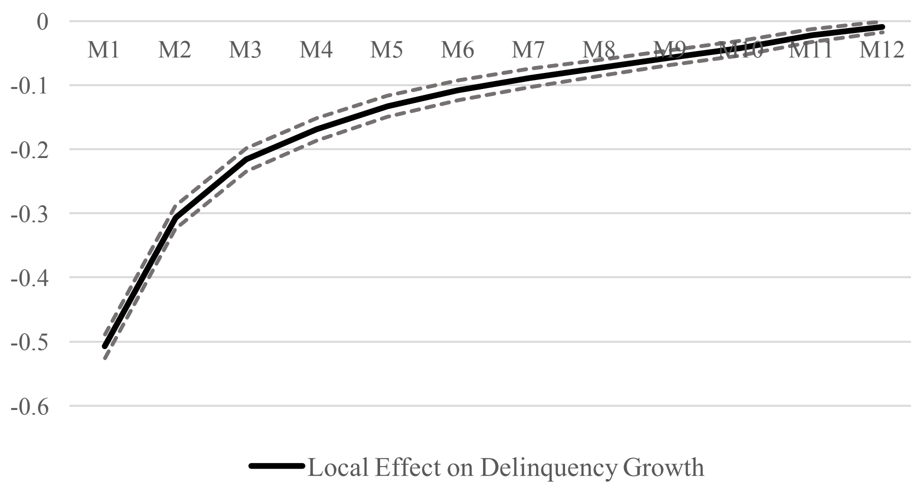


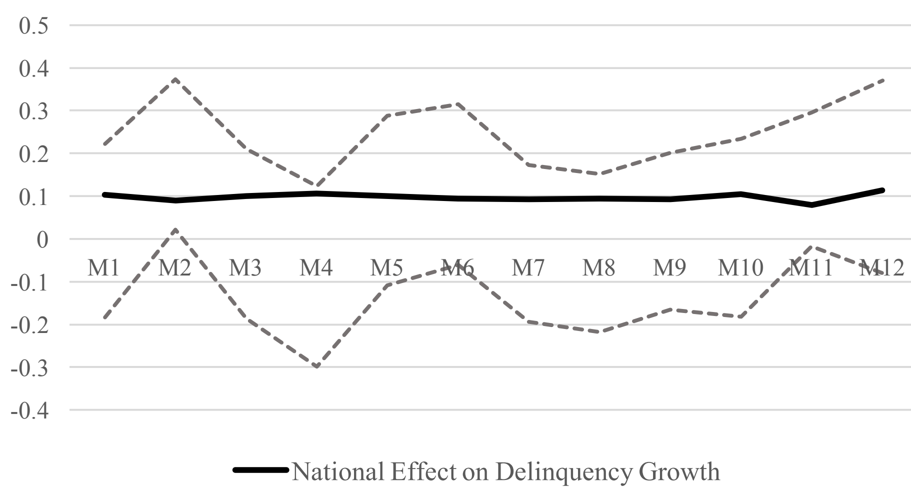



## Appendix A6: Predictability of Housing Variables and the Importance of Local Indicators (continued)

The two figures plot the AR(12) coefficients of zip-code level delinquency growth on lagged zip-code level delinquency growth (upper panel) and lagged national level delinquency growth (lower panel). The underlying delinquency data are from Jul 2005-Dec 2017 at monthly frequency. The two grey lines indicate the 95% confidence intervals.

Panel D: Delinquency Rate Growth

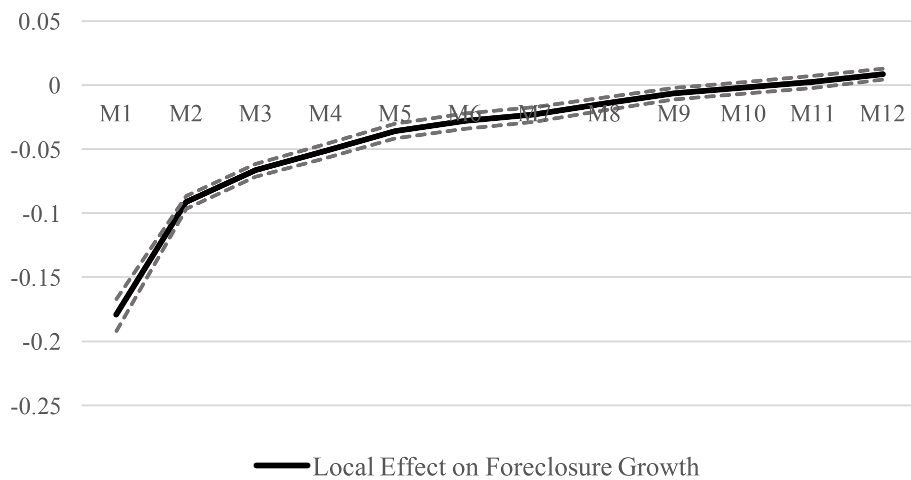


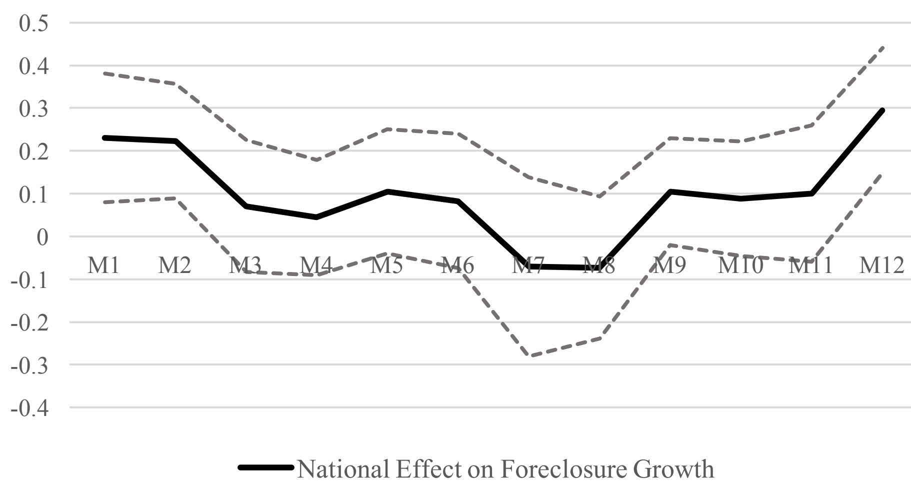



## Appendix A6: Predictability of Housing Variables and the Importance of Local Indicators (continued)

The figures plot the AR(12) coefficients of zip-code level foreclosure growth on lagged zip-code level foreclosure growth (upper panel) and lagged national level foreclosure growth (lower panel). The underlying foreclosure data are from Jul 2005-Dec 2017 at monthly frequency. The two grey lines indicate the 95% confidence intervals.

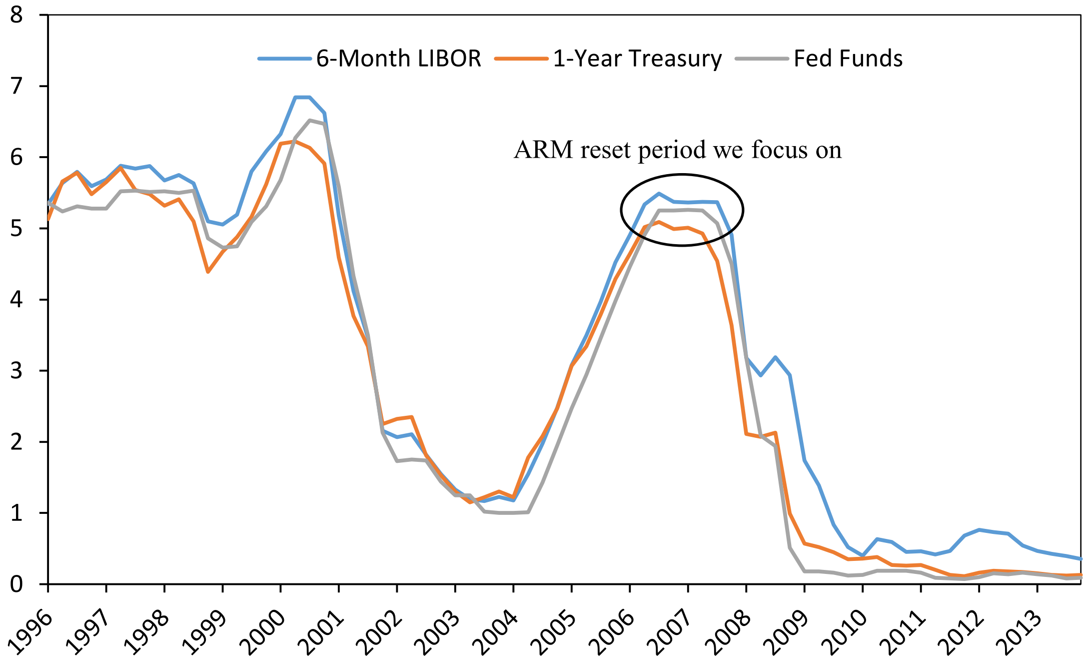
Panel E: Foreclosure Rate Growth



## Appendix A7: Major Interest Rate Indices

This figure shows major interest rate indices (6 month LIBOR and 1-Year Treasury) to which ARM loans reset along with the Fed funds rate. We also mark on this figure the ARM reset period we focus on in our analysis in Section 5.1.1.



## Appendix A8: Example of Zip Code Zillow Index

This figure shows average house price index for the zip code 85023 in Phoenix, Arizona. *Source:* Zillow.com.