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Tracking and Stress-Testing U.S. Household Leverage

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Abstract

Borrowers' housing equity is an important component of their wealth and a critical determinant of their vulnerability to shocks. In this paper, we create a unique data set that enables us to provide a comprehensive look at the ratio of housing debt to housing values—what we refer to as household leverage—at the micro level. An advantage of our data is that we are able to study the evolution of household leverage over time and locations in the United States. We find that leverage was at a very low point just prior to the large declines in house prices that began in 2006, and rose very quickly thereafter, despite reductions in housing debt. As of early 2016, leverage statistics are approaching their pre-crisis levels, as house prices have risen more than 30 percent nationally since 2012. We use our borrower-level leverage measures and another unique feature of our data—updated borrower credit scores—to conduct "stress tests": projecting leverage and defaults under various adverse house price scenarios. We find that while the riskiness of the household sector has declined significantly since 2012, it remains vulnerable to very severe house price declines.

Key words: mortgages, leverage, stress testing

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1 Introduction

High household debt is widely perceived to be one of the main causes of the Great Recession and the slow recovery from it. Over the first half of the 2000s, US household debt, particularly mortgage debt, rose rapidly along with house prices, leaving consumers very vulnerable to house price falls. Indeed, Figure 1 illustrates that as house prices fell nationwide over the course of 2007 to 2010, and unemployment rates soared, mortgage defaults and foreclosures skyrocketed as many households were "underwater" – meaning their outstanding home loans exceeded the current value of their properties. To assess and lean against the risk of a similar event occurring again in the future, it is crucial to track household leverage, especially on home loans (first-lien mortgages as well as home equity loans/lines of credit). Furthermore, it is imperative to not only consider homeowner leverage at the current level of house prices, but also under realistic scenarios involving negative house price shocks. In this paper, we combine different datasets to track and stress-test the leverage of US homeowners in a representative way.

The main source of information we rely on is a newly-available dataset, Equifax's Credit Risk Insight Servicing McDash (CRISM), which combines mortgage servicing records of about two thirds of outstanding US first-lien mortgages (the McDash component, which is also known as LPS) with credit record information on the mortgage holder (from Equifax). The credit record component allows us to observe second liens (home equity loans and lines of credit) likely associated with a first mortgage, so that we can construct an updated combined loan-to-value (CLTV) ratio for properties with a first mortgage in our sample (something that is typically impossible with mortgage servicing data alone, since it generally does not provide a method for connecting second liens with first liens on the same property). We also observe borrowers' updated FICO credit scores, giving us a further dimension along which we can evaluate potential default risk. Since the CRISM sample does not cover the full population of US mortgages, we ensure its representativeness by weighting observations based on the distribution of loan characteristics in the Federal Reserve Bank of New York's Consumer Credit Panel (CCP), which tracks credit records of a representative sample of the US population.[1]

We use the resulting CLTV estimates to document the changing pattern of leverage of US homeowners over the last ten years, both nationwide and also across different regions. In addition to showing average CLTVs, we focus in particular on the fraction of properties with CLTV exceeding 80% or 100%. We also quantify the strong relation between CLTVs and the rate at which borrowers become seriously delinquent (meaning they are 90 days or more behind on their mortgage payments). Furthermore, we assess what

[1] See Lee and van der Klaauw (2010) or http://www.newyorkfed.org/microeconomics/ccp.html for additional information on the CCP. Note that the CCP alone would be insufficient to track leverage, since credit records do not contain information about the value of the collateral underlying a loan.

would happen to CLTVs and delinquency rates under a variety of more or less severe shocks to local house prices, based either on a reversal of recent growth rates, or on a repetition of the house price drop that occurred during the recent bust. This analysis thus provides an early warning indicator of risks to the financial system emanating from housing finance. It is therefore related to the stress-testing of banks (for instance, the Federal Reserve's Comprehensive Capital Analysis and Review, or CCAR), though our analysis is conducted at the property level (and then aggregated to regional and national levels) rather than at the lender level.[2]

Our main findings are the following: as of 2016:Q1, nationwide, household leverage has declined substantially relative to 2008-2012, and is approaching its pre-crisis levels. Consequently, and also due to an improvement in credit scores among households with outstanding mortgages, the household sector's vulnerability to a modest house price decline has decreased, although for very severe house price declines (approaching the magnitude of those observed during the crisis) vulnerability remains elevated. At a more disaggregated level, the time series of our leverage measures clearly reflect the dramatic regional home price dynamics that others have observed, with the widest swings in prices found in the "sand states": Arizona, California, Florida and Nevada. Studying these states illustrates one of the key lessons from our analysis: looking at measures of leverage based on concurrent housing values will often lead one to misestimate the vulnerability of a housing market to shocks. Homeowners in the sand states were much less levered in 2005 than those in other regions, yet as home prices mean-reverted, their leverage rapidly increased and extremely high mortgage defaults followed. While not perfect, stress tests such as the one proposed in this paper allow one to anticipate such potential dynamics and provide a better view of how vulnerabilities vary over time and across locations.

Our motivation for tracking and stress-testing household (and specifically homeowner) leverage comes from various strands of the academic literature.[3] First, higher leverage, and in particular a household being underwater on their mortgage(s), is a strong predictor of mortgage default and foreclosure (see, for example, Foote et al. 2008; Corbae and Quintin 2015; Ferreira and Gyourko 2015). Foote et al. describe negative equity as a "necessary condition" for mortgage default. Negative equity loans represent a pool of default risks: if the borrowers are hit with liquidity shocks resulting from, say, a lost job, then default may

[2] We also present the evolution of leverage, as well as our delinquency stress test projections, across different funding sources for the loan (Fannie Mae/Freddie Mac; FHA/VA; privately securitized; or held in bank portfolios).
[3] Geanakoplos and Pedersen (2014) discuss why monitoring leverage is important also in other asset markets.

be the only viable option. Positive equity borrowers faced with liquidity shocks, on the other hand, are generally able to sell the property and avoid default.[4]

Understanding the risk of an increase in mortgage defaults is important because of the potential for losses by banks and other holders of mortgage assets (as illustrated by the recent crisis); because of the negative consequences for defaulting borrowers, such as the negative impact on their creditworthiness (Brevoort and Cooper 2013); and because foreclosures may have negative externalities on the value of other properties (Campbell et al. 2011, Anenberg and Kung 2014, Gerardi et al. 2015).

Beyond defaults, household leverage is also important from a macroeconomic perspective because highly levered households may cut back consumption more in response to a negative shock, in part because they do not have “debt capacity” that could help them smooth consumption (e.g. Dynan 2012; Mian et al. 2013) and are typically unable to refinance to take advantage of lower mortgage rates (Caplin et al. 1997; Beraja et al. 2015). Underwater households may reduce expenses on property maintenance or investments (Melzer 2013; Haughwout et al. 2013) and may exhibit lower mobility (Ferreira et al. 2010, 2012). Even if a household is not quite underwater, downpayment requirements on a new home may mean that high leverage reduces transaction volume and prices, thereby generating self-reinforcing dynamics (Stein 1995). Lamont and Stein (1999) document that in cities where more homeowners are highly leveraged, house prices are more sensitive to shocks (such as city-specific income shocks).

We believe that our approach significantly improves upon existing measures that researchers and policymakers have used to track household leverage. One common measure of household leverage that researchers rely on is the aggregate ratio of housing (or total consumer) debt to the value of residential housing, based on the Flow of Funds data, or the ratio of debt to GDP or income (see, for instance, Claessens et al. 2010, Glick and Lansing 2010, Justiniano et al. 2013, or Vidangos 2015). Aggregate leverage only provides an incomplete picture of potential household vulnerability, since an economy where half the households have a 100% LTV and the other half 0% is very different from an economy where everybody has a 50% LTV.[5]

Moving to the micro level, some researchers have relied on local (e.g. zip-code or county level) measures of the ratio of total debt to total income as a measure of household leverage (see, for instance, Mian and Sufi 2010). This provides a useful measure of potential vulnerability, especially when house prices and debt increase at a faster pace than incomes; however, unlike the CLTV on a property, this measure of

[4] Because selling a home takes time and involves transaction costs, and because home prices are estimated with error, some defaults do occur even in cases where the borrower appears to not be underwater. See Low (2015) for further discussion.
[5] This is illustrated, for instance, by the model of Eggertsson and Krugman (2012).

"leverage" ignores the role of the house as collateral for mortgage loans, and thus does not directly correspond to a quantity that captures a homeowner's incentive to default or ability to refinance. Furthermore, recent work by Adelino et al. (2015) has illustrated that looking at aggregates can yield different conclusions from looking at individual-level data (where the latter is preferable); we measure leverage at the individual loan level and then study distributions at more aggregated levels.

As an alternative to using mortgage servicing and credit record data, as we do here, other researchers (such as Ferreira and Gyourko 2015) have used deeds records, which have the advantage of being comprehensive for the areas and time periods in the sample; however, mortgage balances are only observed at origination and thus have to be imputed for subsequent time periods. Similarly, it is difficult to accurately track equity withdrawal based on deeds records, especially when it occurs through home equity lines of credit (as was common during the 2000s boom – see e.g. Lee et al. 2012; Bhutta and Keys 2016). Finally, deeds records contain no information on credit scores (or other borrower characteristics).[6]

Closest to our measures of leverage are quarterly reports published by real estate data firms such as CoreLogic or Zillow, who also provide timely measures of the fractions of homeowners that are in or near negative equity. Aside from our innovation of making the mortgage data at our disposal representative of the population of borrowers, the main new aspects in our analysis relative to these reports are that we jointly consider leverage and updated credit scores, and the link of these variables with defaults, and that we subject households to a stress test consisting of local house price drops of different severities. We further discuss the relation between our estimates and existing ones in Section 3.[7]

One limitation of our analysis is that we do not track or stress-test the affordability of loans (as could be measured for instance by the ratio of monthly required payments divided by income, known as "debt service ratio"), even though the literature on mortgage default suggests that affordability or liquidity shocks are important drivers of default (see, for instance, Elul et al. 2010, Fuster and Willen 2012, Gerardi et al. 2013, or Hsu et al. 2014). The main reason for this is that updated measures of individual income are not available. This implies that when we project default rates under our stress test scenarios, we implicitly assume that liquidity drivers of default would evolve in a way similar to the recent crisis. In other words, one can think of affordability/liquidity shocks as an omitted variable in our delinquency analysis, the effect of which will be picked up by our measure of leverage, which is likely quite strongly

[6] Glaeser et al. (2013) and Ferreira and Gyourko (2015) also use the deeds records to characterize the evolution of downpayment fractions on newly originated mortgages, i.e. the *flow*; throughout this paper, we instead focus on snapshots of the *stock* of outstanding mortgages.

[7] One could also conduct an analysis similar to ours using publicly available datasets such as the Survey of Consumer Finances or the Panel Study of Income Dynamics. However, these are available at much lower frequency and have much smaller sample sizes than the data used in this paper.

correlated with liquidity shocks at the local level (since areas that saw the largest house price declines during the crisis were also those were unemployment rates increased the most; see e.g. Beraja et al. 2015). This is not a problem for prediction if the correlation between changes in leverage and affordability is stable, but may lead our projections to be biased if, for instance, a negative house price shock were to occur without an increase in unemployment. Clearly, an extension of our analysis to include a separate consideration of liquidity shocks would provide an important next step in this line of work.[8]

Another potential shortcoming of our approach is that our delinquency projections do not take into account variation in borrower characteristics (other than FICO score) or loan features (such as whether loans have “exotic” features such as an interest-only period). In particular, since underwriting has been stricter in recent years and exotic loan features are increasingly rare relative to the boom years of the early 2000s, one could argue that a future house price drop would cause a smaller increase in defaults than we project based on the crisis experience. Although this is possible (and indeed desirable), we note that Ferreira and Gyourko (2015) forcefully argue that while negative equity has very strong explanatory power for defaults, “neither borrower traits nor housing unit traits appear to have played a meaningful role in the foreclosure crisis.” Thus, it appears rightfully conservative to assume that default rates would be just as bad as during the crisis if CLTV ratios reached the same levels again.

In sum, our analysis, which we plan to periodically update going forward, provides a timely measure of households’ leverage through home loans, providing policy makers and market participants with the potential to assess potential vulnerabilities of household finances and the macro economy to housing market shocks. The rest of this paper is organized as follows: we describe the unique data that enable us to produce comprehensive disaggregated household leverage estimates, along with our methods for doing so, in the next section. We present our basic results in Section 3, where we report points in the distribution of borrower-level loan-to-value ratios for the period 2005-2016, and provide details on the evolving role of junior liens over time. This section also provides data on variation in leverage across states and regions. Finally, we characterize how leverage and creditworthiness jointly affect delinquency. Section 4 combines the pieces developed in Section 3 to provide the results of our “household stress test,” in which we estimate the effect on leverage and delinquencies of various unfavorable house price trajectories. Section 5 concludes.

[8] Household stress tests conducted by regulators or central banks in other countries often primarily focus on affordability, in part because larger fractions of mortgages in these countries have adjustable rates (whereas in the US, the bulk of outstanding mortgages have fixed rates). See Anderson et al. (2014), Bilston et al. (2015), and Finansinspektionen (2015) for examples of household stress tests in the UK, Australia, and Sweden, respectively. More broadly, a google search for “household stress testing” reveals related analyses conducted in at least 14 countries, but not the US.

2 Data and methodology for estimating leverage

This section describes our methodology for estimating leverage, the datasets used, and how we make our sample representative of US mortgaged properties.

2.1 Definitions and datasets

Our measure of the leverage of a property i at time t is the updated combined loan-to-value ratio, or CLTV:

$$\text{CLTV}_{it} = \frac{(\text{balance first mortgage + balance junior lien(s)})_{it}}{(\widehat{\text{home value}})_{it}}.$$

We first describe how we measure the numerator, and then turn to the denominator.

Our primary source of data on mortgage balances is a rich transaction-level dataset called Equifax Credit Risk Insight Servicing McDash (CRISM), which is constructed by Equifax using a proprietary matching algorithm to link loans appearing in the McDash Analytics loan-level mortgage performance data from Black Knight Data & Analytics (formerly known as LPS) with the borrower's Equifax consumer credit file. Our analysis is based on a 5% random sample of CRISM.

CRISM contains monthly data starting in June 2005. Each McDash loan is visible from either: (i) the time of origination, (ii) June 2005 for earlier originations, or (iii) the time a loan began being serviced by a firm contributing data to McDash. Monthly observations recording loan performance appear until a loan is terminated.[9] CRISM does not include recent mortgage originations due to data requirements for this algorithm and therefore we supplement the CRISM data with recent originations (currently, for the period since July 2015) from McDash. Henceforth for brevity, references to "the CRISM dataset" include CRISM and appended McDash components unless explicitly stated otherwise.

Our unit of analysis is properties with first mortgages in CRISM.[10] The dataset contains the origination details of the loan (origination date, amount and other loan characteristics), the location (zip code) and appraisal value of the property the loan is secured against, and monthly performance details of this loan (outstanding balance and delinquency status), as recorded in McDash.[11] McDash contains loan-level information on both first mortgages and home equity loans/lines of credit; however, coverage of the latter

[9] Loans can be terminated due to the loan being repaid, refinanced, a default event (such as foreclosure), or the servicing being transferred to a different entity.
[10] A property is included in our analysis if there is a loan with a "lien_type" value of 1 in the McDash component of our CRISM sample.
[11] McDash also contains other information on the loan, such as its interest rate and maturity, but we do not use this information in the analysis discussed here.

is much less extensive and junior and senior liens are not matched at the property level, so we only use first mortgage data from this dataset. Thus, throughout we do not include properties in the analysis if the only loan secured against them is a home equity line of credit; this is relatively infrequent and the borrowers in question tend to have low leverage and low risk of default. (Note that throughout the paper we refer to home equity loans or lines of credit as "second" or "junior" liens, even though in cases where there is no "regular" mortgage they are effectively in the first lien position.)

Instead, we use information on second liens from CRISM's Equifax credit record component.[12] The credit record includes tradeline data containing the origination amount and date plus subsequent performance of all secured loans of the same borrower (including first mortgages, closed-end second liens, and home equity lines of credit), as well as the outstanding amounts and performance of unsecured and secured non-housing debt (not used in this paper). It also contains a variety of credit scores, in particular borrowers' updated FICO score (which we will use in our delinquency analysis) and the Equifax riskscore (used for weighting to the CCP, as explained below). It is frequently the case that more than one borrower's credit record is associated with the same McDash first mortgage (for instance when two spouses jointly take out a mortgage); in this case we use information from the designated "primary" borrower in CRISM. Credit record data is observed for each month between origination and termination of the McDash mortgage as well as six months before and after.

The Equifax credit file variables are at the individual level and do not contain location information for the property that real estate loans secure. As a result, simply adding all of a borrower's second liens to a McDash first mortgage might overestimate leverage for borrowers who have mortgages on multiple properties. We therefore develop an algorithm to decide which second liens to match to the McDash mortgage; this is explained in detail in the Appendix.

In order to calculate updated CLTVs, we also need an estimate of the current value of a property against which loans are secured. One approach to valuing properties is using hedonic models which estimate individual properties' values based on their location and other attributes. CRISM does not contain property information required to create a hedonic model; however, it does contain appraisal values at origination and information on the location of the property, which we can use to update this valuation over time. We thus use a home price index (HPI) to estimate home values after origination (time 0):

[12] For the most recent originations, where we rely on McDash for first mortgages, we match second liens from the FRBNY Consumer Credit Panel (CCP). 100% of recent originations in McDash and CCP are used for this matching process, which is based on zip code, origination amount and month, current quarter, and current remaining balance. Origination amount and current balance are rounded to the nearest 1,000. These characteristics match to a single loan in 97.9% of cases. We match with the CCP using these characteristics and keep only matched loans (corresponding to 5.8% of the recently originated loans in McDash).

$$\widehat{(\text{home value})}_{it} = (\text{home value})_{i0} \cdot \frac{HPI_t}{HPI_0}$$

We do this for each property using the most granular single-family HPI from CoreLogic that we are able to match to the property. For the majority of properties, this means that estimated home values are updated using a zip code-level HPI, but for those where zip code-level HPIs do not exist, we go to (in this order) county, MSA or state-level indices instead.[13] We match roughly 78% of observations to zip-level HPIs. We use the combined single-family HPI, which includes distressed sales.

This updated-appraisal valuation approach will include some measurement error at the property level, for a variety of reasons. First, we rely on the recorded appraisal amounts for the home value at the time of origination, even though there is evidence that these appraisals are frequently inflated relative to true values for refinance loans (e.g., Agarwal et al. 2015). Second, this approach assumes that house price growth moves in lockstep for all properties in an area whereas in reality there is of course substantial variation, even within a zip code. The value of some properties will rise faster than average due to improvement in their quality, for instance due to renovations or the arrival of nearby amenities. Conversely, some properties will experience falls in valuations due to property degradation or the arrival of undesirable nearby features. As LTV ratios are a convex function of asset valuations, we expect the effect of using the average local HPI rather than the actual, unobserved heterogeneous property-level house price to lead to an underestimate of CLTV ratios (see e.g. Korteweg and Sorensen 2016).[14] In addition, previous research indicates that underwater borrowers reduce their housing maintenance and investment, suggesting that our procedure may overestimate home values for borrowers at or near the underwater mark (Melzer 2013, Haughwout et al. 2013). These considerations may also explain why our estimates of the fractions of borrowers that are underwater tend to be lower than those of CoreLogic and Zillow, who use finer valuation models for individual properties, as discussed in more detail in Section 3.2.1.

In addition, our estimated leverage distributions below will display seasonality, coming from the seasonality in HPIs. We do not adjust the HPIs for seasonality, based on the view that a non-seasonally-adjusted index provides an indication for what a property could be sold for at a given point in time, which is the relevant value in case a borrower considers default due to liquidity problems or needs to sell the home quickly to move for a job elsewhere.

[13] Loans which do not have appraisal amounts, dates or location information or where the appraisal date is before 1976 (when HPI starts) are dropped. This affects under 1% of loans.
[14] More generally, HPIs may provide less accurate estimates of a property's value when there are low volumes of transactions and few repeat sales – an effect which was likely pronounced during the housing bust period.

2.2 Coverage and weighting

Over our sample period, CRISM covers approximately two thirds of outstanding first mortgages balances, though this coverage has changed over time, for instance with servicers joining McDash at different times. As a result, there are some differences in the distribution of loans from that observed in the nationally-representative FRBNY Consumer Credit Panel (CCP).

It is important to ensure our leverage estimates are representative of the US properties with positive first mortgage balances as otherwise we could get a misleading picture – for example, if our dataset oversampled prime customers relative to the population we would expect to get lower leverage estimates than prevail in reality. CRISM is based on data from large mortgage servicers; since they are not a random sample, one might expect the loans serviced by these companies to not be completely representative of all outstanding mortgages.[15] To make our dataset representative of the population of US properties with positive first mortgage balances, we weight observations such that the distribution of certain loan characteristics is identical to the distribution in the CCP. This weighting process is done by taking the population of observations from the CCP tradeline data where first mortgages have positive outstanding balances. We then construct a series of weighting buckets in the CCP (as described below) such that each month in CRISM is weighted to that quarter's CCP and the distribution of loans matches within 51 states (states plus Washington D.C.) and 38 large MSAs.[16] The largest MSAs were chosen to ensure the distribution of mortgages was accurate within the more populous states where non-MSA areas can have significantly different leverage patterns relative to MSAs.[17]

Within each of these state-MSA-month combinations, loans in both datasets are first split into delinquent and non-delinquent, where delinquency is defined as 60+ days delinquent.[18] We then sequentially compute balance-weighted quantiles in the CCP, first by outstanding first-mortgage balance and then by Equifax riskscore, with the thresholds for these quantiles varying within each state-MSA-month-delinquency status combination.[19] Having computed these thresholds in the CCP we weight the CRISM

[15] At one time all the top 10 mortgage servicers were included; now there are fewer due to mergers.
[16] Henceforth references to 'states' cover the 50 states and Washington D.C. unless stated otherwise. 38 MSAs produce 42 MSAs-state combinations as some MSAs cross state lines. This produces 93 state-MSA combinations as observations not in the largest MSAs are solely weighted to the state-level rather than at both the MSA and state level.
[17] MSAs were chosen with 1m+ population in 2010 census and where there were sufficient observations in CCP and CRISM to be able to accurately weight at both state and MSA level.
[18] This is done because reporting practices result in severely delinquent loans staying in the two datasets for different durations. As delinquency is a relatively rare event (especially early in our sample period), using finer buckets would produce thinly-filled buckets which we want to avoid.
[19] Observations with origination amounts greater than $5m or observations that likely contain erroneous data are dropped to ensure balance-weights are not thrown off. This affects less than 0.05% of observations. For very recent originations we weight by origination FICO as we do not observe current Equifax riskscore in McDash.

data by the ratio of CCP to CRISM observations in each state-MSA-month-delinquency status-outstanding balance-riskscore bucket.[20] Having more buckets ensures that the weighted dataset exactly matches the CCP population at a more granular level; however, doing so results in thinner buckets and therefore more observations given relatively extreme weights. Observations with very large weights are particularly undesirable as they can make overall results fragile and produce misleading results as we are not weighting on every dimension (for instance appraisal amount, or loan age). We therefore strike a balance (using 5 buckets of outstanding balance and 4 of current riskscore within each state-MSA-month-delinquency status combination) in order to ensure the weighting achieves a distribution matching the population while keeping it extremely rare for a bucket to consist of only a few observations in either CCP or CRISM.

One issue with both mortgage servicing and credit record datasets is that some loans enter the data with a delay of a few months (this is known as "seasoning"). This could distort our estimates of leverage since, at any given time, the newly originated loans tend to be among the most highly levered (especially during a period of price increases). To address this problem, in CRISM/McDash we "backfill" the monthly observations of loans to their origination date, interpolating the balance in between the first monthly observation and the original balance. We only backfill the CCP one quarter and only for loans where the seasoning is less than three months, since this covers the vast majority of loans.

The result of the above process is producing a nationally-representative dataset of CLTVs on properties with positive outstanding first mortgage balances over 2005-2016. In addition to CLTVs, in some of the analysis below we also display "mortgage LTVs" (MLTVs) that are based only on the first mortgage as recorded in McDash. These ratios are used to estimate whether a mortgaged-property is in negative equity – defined as when the MLTV or CLTV is greater than or equal to 100%. We display a range of thresholds of being 'near' negative equity (e.g. 80% or 90% CLTV) as doing so provides a range of estimates to account for potential mis-measurement.

[20] One potential source of noise in this method is that the location reported in the CCP is that of the borrower, while the location in CRISM/McDash is that of the property.

3 Results: Leverage and delinquency across time and space

3.1 Time-series patterns in the full sample

After weighting the CRISM dataset to the CCP, we produce a time series of aggregate mortgage debt balances as displayed in panel (a) of Figure 2.[21] A significant share of total CCP second lien balances are held by properties without positive first mortgage balances outstanding and therefore total second lien balances in the figure are lower than those presented in Lee et al. (2012). Relative to total mortgage debt, second liens are relatively small, peaking at just under 9% of first mortgage balances; however, the relative growth in these between 2005 and 2007-08 was substantial, with home equity lines of credit (HELOC) balances and closed-end seconds (CES) increasing by $138bn and $189bn, respectively. These second lien balances are especially important to consider given that they are not equally distributed across first mortgage holders. Indeed, as shown in panel (b) of Figure 2, only a minority of properties with first mortgages also feature a second lien, peaking at 29% in 2007 and now down to 14% (as of 2016:Q1). For those borrowers, ignoring the second liens could lead us to substantially understate their leverage and vulnerability to house price shocks.

Figure 3 displays the nationwide distribution of leverage over the last decade, both unweighted (that is, each property with an outstanding first-lien mortgage is given the same weight) and balance-weighted. Panel (a) shows that average leverage increased between 2005 and 2009, plateaued until 2012, and has been decreasing since. Average leverage is higher when we balance-weight observations, as one would expect since small outstanding balances are frequently associated with low CLTVs.

The figure also illustrates the effect of including second liens by displaying both CLTVs (solid lines), which include all liens that we assign to a property, and MLTVs (dotted lines), which only includes the first mortgage. The largest difference occurs in 2009:Q1, when second lien balances were adding 5.1 percentage points (or 6%) to mean (balance-weighted) leverage.

Panels (b) and (c) show the 25th, 50th, 75th and 90th percentile of the CLTV and MLTV distributions over time, again unweighted and weighted. We see that there is substantial heterogeneity in leverage across borrowers throughout our sample period. For instance, at the beginning of our sample period, the median

[21] Our estimates of aggregate debt balances differ slightly from those reported in the NY Fed's *Household Debt and Credit Report* (HHDC) for two main reasons. First, our method is intended to capture only those junior liens associated with positive-balance first liens. Thus, for example, HELOCs with no associated first lien are excluded from our calculations by design. Second, our backfilling approach effectively introduces a timing difference with the HHDC, which counts mortgages as they appear in credit reports. In aggregate these differences are small: the quarterly absolute difference between the two series averages 3.5% of total balances outstanding (according to the HHDC) over our sample period.

CLTV was around 0.6, yet already then the top decile of borrowers had CLTVs around 90%. We also see that the difference between MLTV and CLTV grows toward the upper tail of the distribution of leverage, especially during the period of high LTVs between 2009 and 2012.

Figure 4 directly shows the share of loans (panel a) or balances (panel b) in different CLTV bands, thereby providing an easy way to see what fraction of loans have CLTVs above certain values at different points in time. For instance, the combination of the bottom two bands shows the estimated fraction of borrowers that are in negative equity or "underwater" (CLTV>1). The figure indicates that almost no properties were in negative equity at the start of the dataset in 2005:Q2. Towards the end of 2006 the proportions in negative equity started to increase rapidly as house prices started falling. By 2008:Q2, we estimate that 16% of loans accounting for 21% of balances were in negative equity – over ten times the proportions two years earlier and triple the figure only a year before. These proportions continued to rise, peaking at 26% of loans and 33% of balances in 2009:Q1 before remaining stubbornly close to those levels, with some volatility due to seasonality in house prices as well as potential noise due to relatively few transactions taking place. CLTVs started falling in 2011:Q4, as house prices started to rise. This process has been continuing to the latest available data from 2016:Q1, showing a negative equity share of 4.1% (equal-weighted), respectively 4.4% (balance-weighted) – levels not seen since early 2007. The proportions near negative equity have also been declining and are now near their early 2007 levels; as of 2016:Q1, the balance-weighted shares of properties with CLTV above 90% and above 80% are at 12.1% and 24.9%, respectively.

3.2 Regional patterns

The richness of our data enables us to examine leverage at different disaggregations. A disaggregation of particular interest is splitting the data by regions given the substantial heterogeneity in the evolution of house prices and borrowing observed during the boom over the first half of the 2000s, as well as the bust that followed.

Figure 5 and Figure 6 show the evolution of average CLTVs, as well as the balance-weighted fraction of loans with CLTV above 0.8, 1, or 1.2, for different groups of US states:

1. 'Sand states': AZ, CA, FL, NV.
2. 'East North Central' ("ENC") census division: IL, IN, MI, OH, WI
3. 'West South Central' ("WSC") census division: AR, LA, OK, TX
4. 'Northeast' ("NE") census region: CT, MA, ME, NH, NJ, NY, PA, RI, VT

The figures illustrate that the time series patterns of leverage across these groups of states display substantial variation. Most strikingly, at the beginning of our sample period, leverage is the lowest in the 'sand states', which had been experiencing rapid house price growth. Even though many homeowners were actively cashing out home equity, this house price growth meant that only few of them had high CLTVs – according to our estimates, the balance-weighted share of properties with a CLTV above 0.8 was only about 8% as of mid-2005. However, once house prices started falling, this fraction rapidly increased, peaking near 70%, whereas the fraction of underwater homes (CLTV>1) exceeded 50% at its peak in 2009.

In the ENC states, leverage started out much higher (since the house price boom was more modest) but then reached similar highs. Interestingly, while the fraction of loans with CLTV>0.8 was higher than in the sand states over much of the sample period, the share of underwater loans (and especially severely underwater loans with CLTV>1.2) peaked at much lower levels. This comparison thus illustrates the value of considering the entire distribution of leverage, rather than just a single statistic such as the average.

The WSC states provide a stark contrast to the previous two groups: while the fraction of loans with CLTV>0.8 started at a fairly high level in mid-2005, it fell over the following two years, and then during the crisis period never rose much above 50%.[22] Even more importantly, the fraction of underwater borrowers never rose above 17%, and there were essentially no severely underwater borrowers.

Finally, the time-series pattern of CLTVs in the Northeast is in the middle relative to the other groups – leverage never increased to levels as high as in the most cyclical areas, but the fraction of underwater borrowers nevertheless was around 15-20% for a substantial period of time, and has been decreasing more slowly than elsewhere (possibly reflecting slow departures of underwater properties through judicial foreclosure).

These regional patterns illustrate that looking at leverage at a point in time, while informative, gives an incomplete picture of potential vulnerabilities. For instance, as of mid-2005, very few households in the sand states were highly leveraged based on prevailing house prices; to see the potential risk associated with housing debt one would have had to consider stress scenarios like the ones we discuss in the next section.

[22] One potential explanation why leverage remained lower in this census division is that in Texas, there are restrictions on equity extraction: CLTVs at origination of a refinance loan or a second lien cannot exceed 80%. See Kumar (2014) for additional discussion and evidence on the default-reducing effects of these restrictions.

As a first step to this forward-looking exercise, Figure 7 displays the proportions of households that we estimate to be in or near negative equity as of 2016:Q1, by state. Figure 8 compares these estimated fractions to their peak values over our sample period**.**

We estimate that Nevada is still the state with the highest proportion of borrowers in negative equity, ahead of Florida and, perhaps more surprisingly, Rhode Island. Among the states worst hit by the bust, California has made the strongest recovery, due to rapid house price increases; we estimate that as of 2016:Q1, only 2.7% of Californian borrowers are underwater and only 12.6% have a CLTV>0.8 (both statistics are balance-weighted). In all states, negative equity fractions are much lower than they were during the worst of the housing bust, though there is heterogeneity in the extent of the recovery, as can be seen in Figure 8 – the states that are further to the upper left of these scatter plots have recovered relatively less from the peak of the crisis in terms of the fraction of highly levered borrowers.

3.2.1 Comparison to other estimates

We are able to benchmark our regional estimates against external negative equity estimates provided by CoreLogic and Zillow.[23] These firms use different datasets and empirical methodologies and therefore we would not expect these to exactly match our estimates. Figure 9 compares our estimated fractions of loans with CLTV>0.8 and CLTV>1 in 2016:Q1 to those published by CoreLogic and Zillow. We see that our estimated underwater fractions are systematically lower than those from the other sources (especially Zillow's). However, our estimated shares of loans with CLTV>0.8 tend to be much closer, suggesting that the differences in underwater fractions may come from relatively small differences in estimated home valuations that can put borrowers just above or below the CLTV=1 threshold.

Also, we note the high correlation between our estimates and those from the other sources: for the CLTV>0.8 share, the correlations are 0.72 between our estimates and Zillow's and 0.86between our estimates and CoreLogic's; for the CLTV>1 share the respective correlations are 0.59 and 0.90. The results of this external benchmarking are therefore encouraging at validating our methodology.

3.3 Delinquencies

One of the main reasons why leverage is important to track is its strong correlation with a borrower's propensity to become seriously delinquent. Figure 10 shows the fraction of loans in different CLTV bands that are seriously (90 days or more) delinquent over the time period covered by our data (2005-2016). We note the strong relation between CLTV and delinquency – for instance, the delinquency rate for loans

[23] These are available at http://www.corelogic.com/about-us/researchtrends/homeowner-equity-report.aspx and http://www.zillow.com/research/data/#additional-data.

with estimated CLTV above 120% peaked at 30% whereas for loans with CLTV between 80 and 100% it peaked around 7%. We also note that there is time-series variation of delinquency within a CLTV band (especially for the highest CLTV category). This could occur for various reasons: variation in how high the CLTVs are within the band; variation in other factors causing default (such as the rate of job losses); or exit of loans from the sample due to foreclosures (since the chart shows the stock of delinquencies, not the flow into delinquencies).

That said, leverage is of course not the only variable that is predictive of delinquency. As discussed earlier, evidence suggests that "liquidity shocks" such as job loss are an important trigger for default. Since borrowers' updated income or employment status are not observable to us, we rely on a widely used indicator that correlates with individual liquidity constraints, namely the credit score (FICO). One major advantage of our dataset is that the FICO is observed not just at the time of loan origination, but throughout the life of the loan. In the second and third panel of Figure 10, we show serious delinquency rates by CLTV band separately for "prime" and "subprime" borrowers, where we define the latter as having a 12-month lagged FICO score of below 660. We use the lagged FICO because using the contemporaneous FICO would mechanically lead to a correlation with delinquency (since entering delinquency leads to a drop in a borrower's FICO). The figure illustrates that for a given CLTV band, delinquency rates are substantially higher for borrowers with low FICO scores, often by an order of magnitude. That said, within both groups CLTV remains a strong predictor of delinquency.

Given the strong relation between CLTV, FICO, and delinquency, it is important to track not only the distribution of leverage, but also its correlation with FICO scores. In Figure 11 we do so for different CLTV and FICO buckets, focusing on non-seriously-delinquent (meaning current or less than 90 days past due) loans. We see that the balance-weighted fraction of loans where the borrower has a low current FICO score is much lower now than it was before and during the crisis: for instance, as of 2016:Q1 only 14% of borrowers in non-delinquent loans have current FICO scores below 660, whereas from 2005 to 2010 this number was around 20%. Similarly, conditional on being underwater (CLTV>100%), the share of loans with current FICOs below 660 is lower than it was during the crisis; as of 2016:Q1, it is at 25%, compared to 36% in 2008:Q1 and 32% in 2010:Q1 (all fractions balance-weighted). This suggests a lower default risk today not only because of a reduction in leverage, but also because of improved borrower characteristics. We will return to this assessment in the next section, when we consider potential delinquency rates under different stress scenarios.

4 Stress-testing household leverage and delinquencies

Understanding how the current stock of outstanding mortgage debt would be affected by a house price downturn can provide valuable insight into how the household and banking sectors, and thus the economy as a whole, would be affected by such an event. To "stress test" the mortgage-borrowing households, we first construct simple scenarios for house prices, and apply these to the outstanding stock of loans to see how the distribution of leverage would change under these scenarios. We then use the historical relationship between leverage, credit scores and delinquency to estimate transition probabilities in order to estimate potential delinquency rates under the shock scenarios. Importantly, we present the results from our analysis both at the aggregate (nationwide) level and also at the state level in order to highlight which parts of the country are particularly vulnerable to house price shocks.

4.1 Stress-testing part I: House price scenarios and the effects on leverage

Our scenarios shock house prices, thus changing the estimated asset valuation of properties and altering leverage. Although the relationship between house prices and leverage is mechanical, it is also non-linear, meaning that heuristic rules such as "an X% drop in house prices would increase everybody's CLTV by X percentage points" tend to give misleading results.[24] Thus, there is value in quantifying by how much exactly the CLTV distribution would shift as a consequence of house price shocks of different magnitude.

The house prices scenarios we consider are local, rather than uniform across the US, reflecting the substantial heterogeneity in house price volatility across different markets (due, for example, to differences in housing supply elasticities). Rather than attempting to construct house price scenarios based on some measure of local fundamentals, or valuation measures such as price-to-rent ratios, we simply consider the possibility of a reversal of house prices to their level 2 or 4 years ago. This assumption of a reversal in recent growth is based on the experience during the recent crisis, where local house price changes over 2007-2011 were strongly negatively correlated with the changes over 2000-2006, as illustrated in Figure 12. At the county level, the correlation between house price changes during the bust period and house price changes during the boom was -0.57. Nationwide, the fall in prices between mid-2006 and early 2011 corresponded approximately to a reversal of house prices to late 2002 levels, that is, 3.5 years before the peak.[25] As of 2016:Q1, a return of prices to their level of 4 years ago is a particularly

[24] For instance, it is indeed the case that if one starts out with a CLTV of 80% and then applies a 20% house price drop, the CLTV increases by 20 percentage points. But if instead the assumed house price drop was 60%, then the CLTV would increase by 120 percentage points; similarly, if one started out with a CLTV of 40%, a 20% house price drop only increases the CLTV by 10 percentage points.

[25] Normalizing the CoreLogic national home price index to 100 in January 2000, its peak was reached in April 2006, at 193.7; it then fell to a local trough of 128.6 in March 2011, corresponding approximately to the level of November 2002.

severe scenario, since this wipes out practically all of the price gains that have been recorded since the 2011 trough.

In addition, we consider a drop in house prices equal to the largest local "peak-to-trough" (abbreviated P2T) decline in house prices from January 2000 to today.[26] This becomes an especially harsh scenario for regions where house prices have not recovered from their troughs. On the other hand, it is arguably more realistic for areas of the country where house prices have substantially recovered or even reached new peaks.[27] Another reason why aggregate leverage and delinquency may be overstated by this scenario is that we assume the P2T drop occurs in all areas simultaneously, whereas in reality there would be some dispersion in the timing of a house price drop (Ferreira and Gyourko 2012).

Our shocks are always applied at the county level (or MSA or state level in cases where we do not have HPI information for a county). Figure 13 displays the 10th, 50th and 90th percentile of assumed house price changes across scenarios and how they would have changed over time if applied to historical outstanding debt. There is substantial variation in how "harsh" the different scenarios are, both over time and in the cross-section of outstanding loans at a point in time. This of course reflects the differential house price growth in different areas and time periods. Note also that (except for P2T) these scenarios do not always imply negative house price growth – indeed, if house prices fell over a recent period (leading to relatively high leverage), these scenarios would involve a recovery.

Figure 14 shows what the different scenarios would imply for the distribution of CLTVs (holding outstanding loan balances fixed), both in the aggregate and across states, for the latest available quarter (2016:Q1). Panel (a) shows that across the US, we estimate that 4% of borrowers (balance-weighted) are underwater, while 75% have a CLTV below 80%. However, the following two columns illustrate that if house prices reverted back to their level two or four years ago, the share of underwater properties would increase quite dramatically, to 10% and 26% respectively. The final column shows that a repetition of the peak-to-trough house price drop would have an even more dramatic effect: an estimated 41% of borrowers would be underwater, many of them substantially so, and only 35% would have a CLTV below 80. Unsurprisingly, this would be worse than at the height of the bust, since in many areas of the country house prices have not yet recovered to the same peaks from which they fell.

Panel (b) looks across different states, focusing on the estimated fraction of underwater borrowers under the different scenarios. The first column shows that at current house prices, as of 2016:Q1, most states

[26] This scenario is bounded such that any region which only experienced house price growth has its home values unchanged.
[27] Out of 1,306 counties for which we have HPIs, 33% have reached their (nominal) peak in 2016, and another 35% are within 10% of their peak HPI level (data as of mid-2016).

have estimated balance-weighted underwater shares below 10%; the regional patterns were already discussed above (in the context of Figure 7). Looking across the other columns reveals substantial differences in vulnerability to a reversal of recent house price changes. For example, were house prices to return to their levels as of 2014:Q1, we estimate that Nevada would return to a high underwater share of 27%, whereas in Rhode Island (which has a similar current underwater fraction) the share would go to "only" 19%. Were house prices to return to their levels four years ago, the "sand states" would see their underwater fractions soar again, with Nevada at 62%, Arizona at 46%, Florida at 41%, and California at 34%. Other states where underwater shares would rise substantially include Georgia and Michigan.

The fourth column of the table shows that if house prices were to repeat their worst peak-to-trough drop, predicted underwater shares would closely correlate with those experienced during the crisis (the highest experienced underwater fraction is shown in the final column), and in many cases exceed them.

In Figure 15, we illustrate the usefulness but also the limitations of our stress testing approach by asking what it would have predicted (in terms of leverage distribution and underwater shares) had we applied it in 2006:Q1, right before (national) house prices peaked. The first column of panel (a) illustrates that, as we also saw earlier, leverage at concurrent house prices was generally modest and barely any borrowers were underwater. However, the following two columns illustrate that, if one had considered a return of house prices to their levels two or four years earlier, one would have predicted that CLTVs would become much higher and a substantial fraction of borrowers could end up underwater – 19% if house prices went back to the 2004:Q1 level and 40% if they went back to the 2002:Q1 level. The latter estimate is quite close to the peak nationwide negative equity share in our data of 33% (with the overestimate coming from the fact that house prices did not end up falling quite to their 2002:Q1 level).

Panel (b) repeats this analysis at the state level, looking at underwater fractions. We see that considering these house price reversal scenarios would have correctly identified some states that later indeed saw high underwater fractions, in particular the sand states. However, we also see that one would not have projected the large fraction of underwater borrowers in some states such as Michigan, where house prices fell 25 percent below their level in 2000. Overall, the correlation between the predicted underwater fractions across states and the peak underwater fraction during the bust is 0.61 for the "HPI 2 years ago" scenario and 0.48 for the "HPI 4 years ago scenario." The 2-year scenario understates average realized peaks during the bust, while the 4-year scenario slightly overstates them; nevertheless, considering these scenarios as of 2006:Q1 would clearly have been very useful in anticipating what would happen under a negative house price shock.

The final column of the table shows that if, at that time, one had been able to foresee the local peak-to-trough house price drops, and conduct our analysis based on those, one would have come very close on average to forecasting the realized underwater fractions (the correlation is 0.96).[28] This is of course not surprising but nevertheless useful in validating our methodology.

4.2 Stress-testing part II: Predicting delinquencies

Next, we want to predict the effect on delinquencies that different house price scenarios would have on the currently outstanding loans. Doing so requires calculating delinquency transition rates to apply to our data. There is significant uncertainty associated with calculating such rates, as they are highly variable over time even for given observed loan characteristics (and macro conditions). Rather than parametrically modelling the relationship between loan characteristics and delinquency rates, for simplicity and transparency, we use a simple non-parametric approach.[29]

We focus on the transition of initially non-seriously-delinquent loans into 90+ days delinquency. Our approach splits outstanding loans into five buckets by updated FICO risk score (under 600, 600-659, 660-699, 700-739, 740+). We then look at the delinquency status of these loans 24 months later (or, if they exit the sample sooner due to default, at their last observation), and also record their updated CLTV at that time, grouping loans into four CLTV buckets (under 80%, 80-100%, 100-120%, and over 120%). We do not include loans that voluntarily prepay in our transition calculations.

We calculate the transition rates for loans that are outstanding in 2007-8, meaning that we follow them until 2009-10.[30] The resulting transition rates are shown in Figure 16, where all fractions are balance-weighted within each cell. The matrix indicates that, for instance, a borrower with updated FICO below 600 at the beginning of the observation period had a 55% probability of transitioning into serious delinquency if his estimated updated CLTV at the end of the observation period was over 120%, but "only" 16% if his updated CLTV was below 80%. For any CLTV bin, delinquency rates are monotonically falling in FICO score, as expected.

Once armed with this transition matrix, we can apply it to the outstanding loans at a point in time and under the different house price scenarios described in the previous subsection. Essentially, we re-calculate the distribution matrices shown in Figure 11 under the three alternative house price scenarios described

[28] States with relatively larger divergences tend to be those where house prices started falling the latest.
[29] Our approach is related to Li and Goodman's (2014) way of tracking the riskiness of originated mortgages over time.
[30] We conduct the analysis for each month Jan 2007-Dec 2008, and then take an equal-weighted average of transition probabilities over those 24 months. We purposefully chose to focus on the highest-delinquency period over the bust to make our projections conservative.

above (but holding current FICO scores fixed) and then multiply these matrices by the transition matrix from Figure 16 to get the predicted delinquency transition rate (obtained by taking the sum across all cells).[31]

The resulting projections at the economy-wide level, and their change over time, are shown in Figure 17. For instance, as of 2016:Q1, our method projects that under unchanged house prices, 4.4% of mortgage balances will transition over the following 24 months under a "baseline" scenario of unchanged home prices. (Note that this is almost certainly an overstatement; we discuss the reasons further below.) If house prices were to go back to their level 2 years earlier, the delinquency transition rate is predicted to be 0.9 percentage points (or roughly 20%) higher, while house prices falling back to their 2012:Q1 levels would lead to predicted delinquency transitions of 7.8%, or 77% higher than under the base scenario. Finally, a repetition of the peak-to-trough home price decline is predicted to lead to a 10.4% transition rate to serious delinquency, more than twice what it is under the baseline.

The figure illustrates that over the past three years, the portfolio of outstanding mortgages seems to have become more resilient either under constant home prices, or under the peak-to-trough drop (which is also held constant over time within each location). This has occurred thanks to the realized home price growth, which has improved households' equity position, and also the improvement in credit scores of mortgagors. At the same time, the third column in particular illustrates that the vulnerability to a reversal in home prices (to their level 4 years earlier) has remained relatively constant over time – this is because in 2012, such a reversal would in many places have meant a price increase, while now in practically all places it would mean an often substantial price decrease (see Figure 13).

Figure 18 shows the distribution of predicted delinquency transitions across states as of 2016:Q1. We note that under the base scenario (with constant house prices) there is relatively little dispersion in predicted delinquency transition rates. If prices were to go back to their levels two or four years ago, or if they suffered another peak-to-trough drop, however, the dispersion across states would be substantial, with the "sand states" Arizona, Nevada and Florida generally being most vulnerable (while California is in the middle of the pack).

At this point we remind the reader of some of the caveats to our analysis, which are perhaps most clearly reflected in our "estimate" that with unchanged house prices 4.4% of current mortgage balances will transition into serious delinquency in the next 24 months. This figure is above the current rate of delinquency transitions shown, for example, in the New York Fed's *Quarterly Report on Household Debt*

[31] The "base" scenario is that house prices stay at their current levels, so for that scenario, we can directly use the distribution matrix as shown in Figure 11.

and Credit, primarily reflecting the fact that we use transitions from the worst period of mortgage delinquency in modern history – 2007-2010. As discussed above, conditional on the characteristics of the outstanding stock of loans, delinquency transitions during the crisis were very high and our scenarios effectively assume a return to those unusually high delinquency transitions. Other factors also push our projected delinquency transitions upward, including the fact that we ignore the leverage-reducing effects of loan amortization, and our exclusion of loans that voluntarily prepay. The latter is equivalent to assuming that borrowers who prepay (either by refinancing or by moving to a new home and getting a new mortgage) are subsequently as likely to default as borrowers who do not prepay.

Some sources of uncertainty in our estimates are more difficult to sign: for example, our estimates of the value of individual houses are imprecise, and correlations of those errors with mortgage balances, credit scores or house price changes could add error to our leverage and default estimates. While on balance we believe our results are likely to overstate delinquencies in benign economic circumstances, these limitations suggest that our stress test results should be used with some caution.

4.3 Leverage patterns and delinquency stress test by funding source

While we are primarily interested in tracking and stress testing the evolution of leverage across different locations, we can also group loans in other ways. One that is particularly relevant is by the channel through which the loan is funded, which also determines who holds the credit risk on the loan. We distinguish between the following four channels:

- GSE: loans securitized through the government-sponsored enterprises Fannie Mae and Freddie Mac, or held in portfolio by these firms.
- Government: loans originated through programs by the Federal Housing Administration (FHA) or the Veterans' Administration (VA), generally securitized through the government entity Ginnie Mae.
- Privately securitized: loans securitized through investment banks, with the credit risk being held by the investors in the securities (or the originating entities). This includes in particular many subprime, Alt-A, and jumbo mortgages.
- Portfolio: loans held in portfolio by financial institutions.

In our (weighted) data, as of 2016:Q1, the GSEs have the largest share among outstanding loans, at 57%, followed by government (19%), portfolio (16%), and privately securitized (9%). The total outstanding amounts in our data for GSE, government and privately securitized loans are roughly in line with other sources (for instance, the statistics compiled by SIFMA[32]).

Panel (a) of Figure 19 shows the evolution of average CLTVs across the four funding sources. GSE loans are the least highly levered throughout the sample period, followed by portfolio loans. Government loans (FHA/VA) are generally originated with high LTVs (between 95 and 100%) and thus it is not surprising that the average updated CLTV on those loans tends to be at or above 80%. Interestingly, privately securitized loans, which were particularly common in areas with pronounced boom-bust patterns in house prices, started the sample period with a relatively low average CLTV. However, over 2005-2009, the average CLTV on these loans increased dramatically, eventually exceeding 100%. As house prices have recovered, the average CLTV on the remaining privately securitized loans has fallen quite rapidly and is now back around 70%.

Panel (b) zooms in on 2016:Q1 and looks at the distribution of CLTVs across the four funding types, which reveals interesting patterns that were not reflected in the averages. In particular, it is notable that only about half of all government loans are estimated to be backed by 20% equity or more, while even for privately securitized loans, almost 70% are now above that threshold. At the same time, however, the share of loans that are underwater (CLTV>100%) is still largest for this category, at 9%. In contrast, only a small share of GSE and portfolio loans are in or near negative equity (approximately 8% have a CLTV above 90%).

Finally, in panel (c) we show the delinquency stress test results as of 2016:Q1 for the different funding sources. Unsurprisingly, since the GSE and portfolio loans are the least levered, they have the lowest projected delinquency rates across scenarios; this is further enhanced by the fact that FICO scores tend to be higher for those loan types than for government and privately securitized loans. Across scenarios, the projected transition into delinquency is more than twice as high for government loans as for GSE and portfolio loans. Nevertheless, it is interesting to note that the relative increase across columns is largest for portfolio loans: for instance, dividing the projected delinquency rate from the last column by the one from the first column yields a ratio of 2.7 for portfolio loans compared to "only" 2.2 for government loans. Thus, in that sense, loans held in the portfolios of financial institutions may be relatively more sensitive to a drop in house prices than securitized loans (although their projected delinquency rates remain much lower even in the peak-to-trough scenario).

[32] http://www.sifma.org/research/statistics.aspx.

5 Conclusion

In this paper, we have described a new methodology for tracking the housing-related leverage of US households. We rely on multiple sources of data that, combined, allow us to study the distribution of leverage over time and across different regions, and to project the likely consequences of house price shocks of different severities. We document the history of our measures over time and geography, and then use our current estimates to project the response of the sector to a variety of adverse price shocks. After a substantial increase due to the housing bust, as of early 2016 our leverage measures based on outstanding mortgage debt and current house valuations are approaching levels last seen a decade ago. Our scenario analyses indicate that the household sector remains vulnerable to severe house price declines, although the higher level of credit-worthiness among today's borrowers serves to mitigate that effect.

As we plan to update and potentially refine our measures going forward, we hope they will be useful to policy makers, businesses, and households alike in assessing housing-related vulnerabilities due to excessive leverage.

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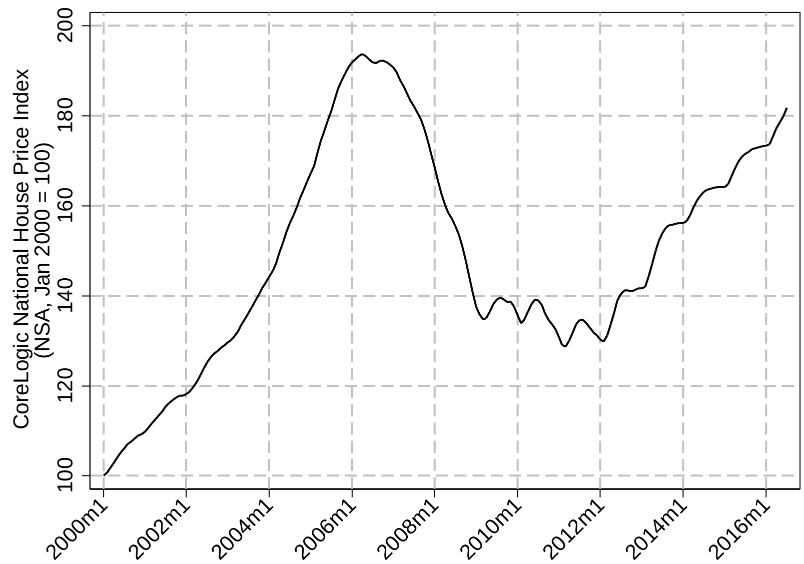
7 Figures and Tables

Figure 1: US house prices and mortgage delinquencies, 2000-2016

(a) CoreLogic National House Price Index (nominal)



(b) Mortgage delinquencies (source: FRBNY CCP)

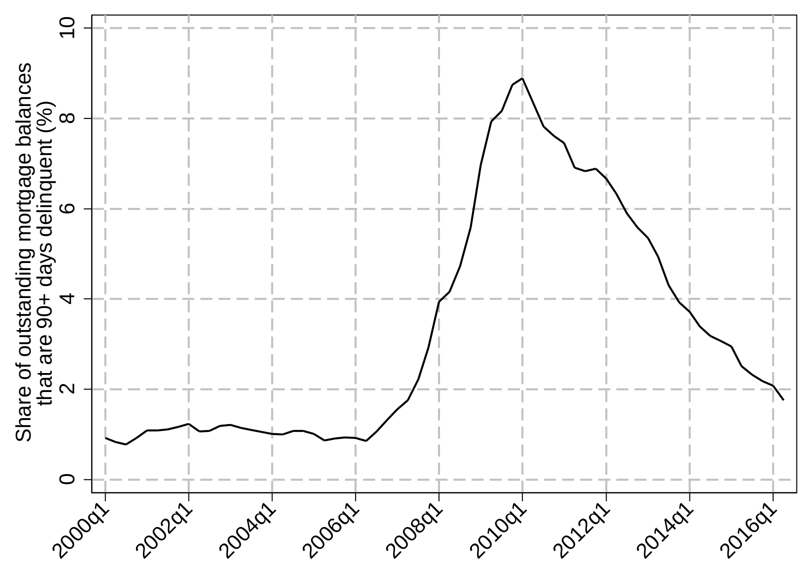
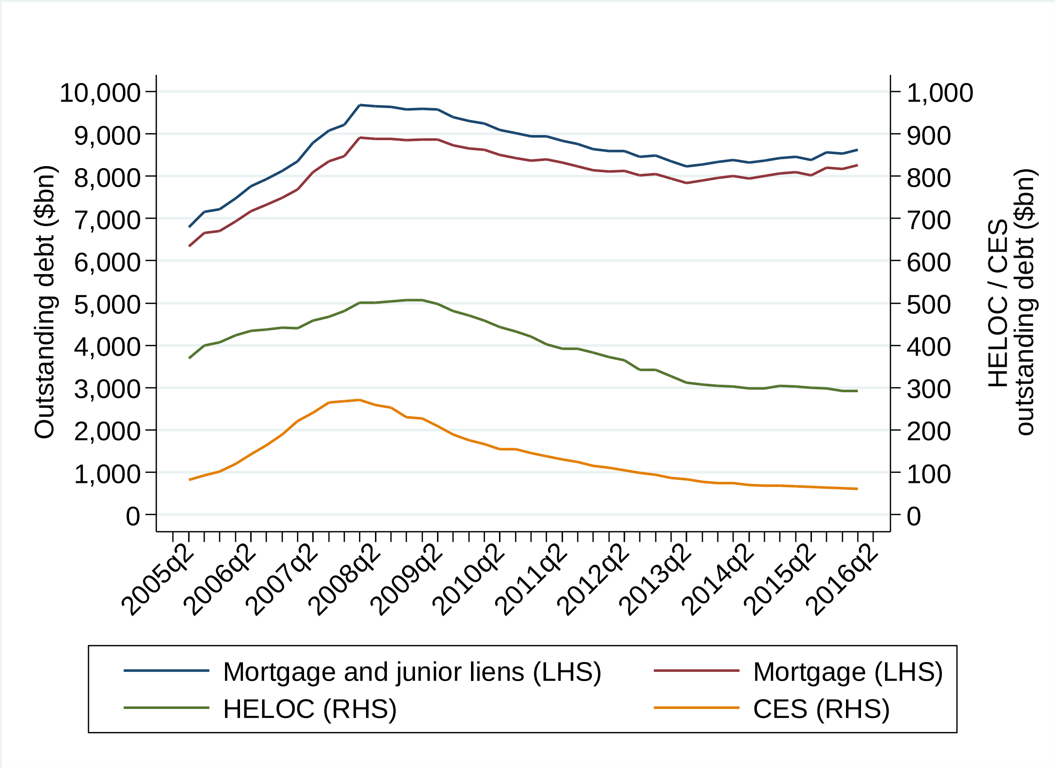


Figure 2: Nationwide mortgage and junior lien debt for properties with positive outstanding first mortgage balances, 2005-2016

(a) Outstanding debt



(b) Fraction of properties with second lien

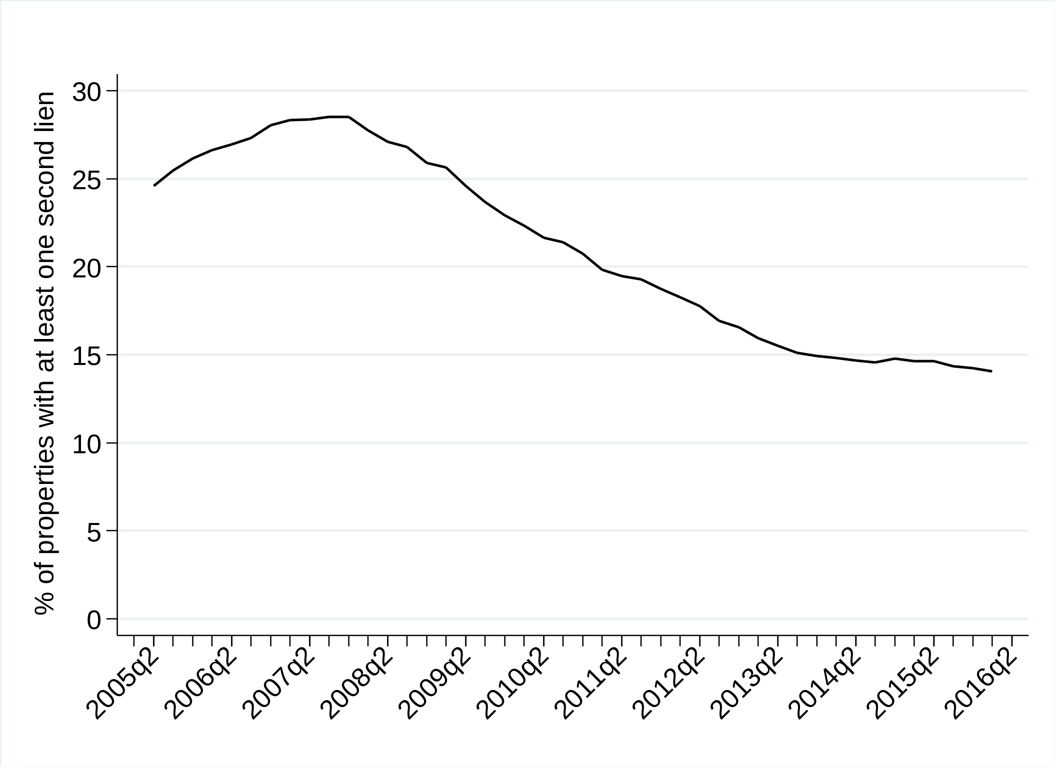
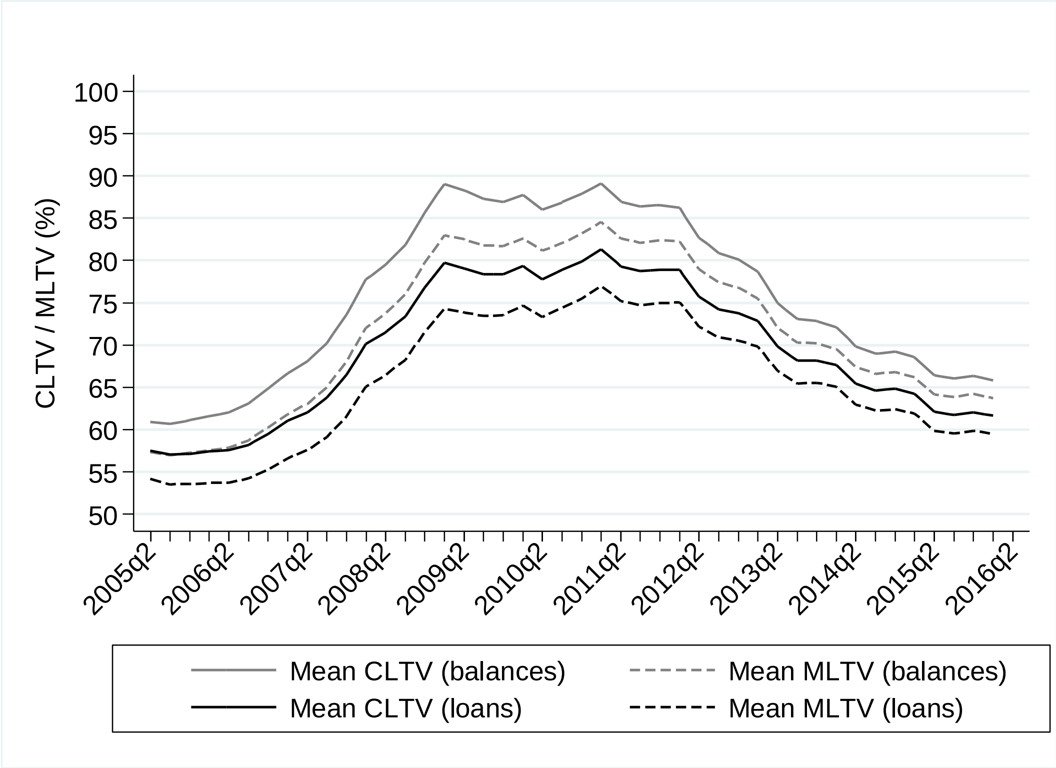
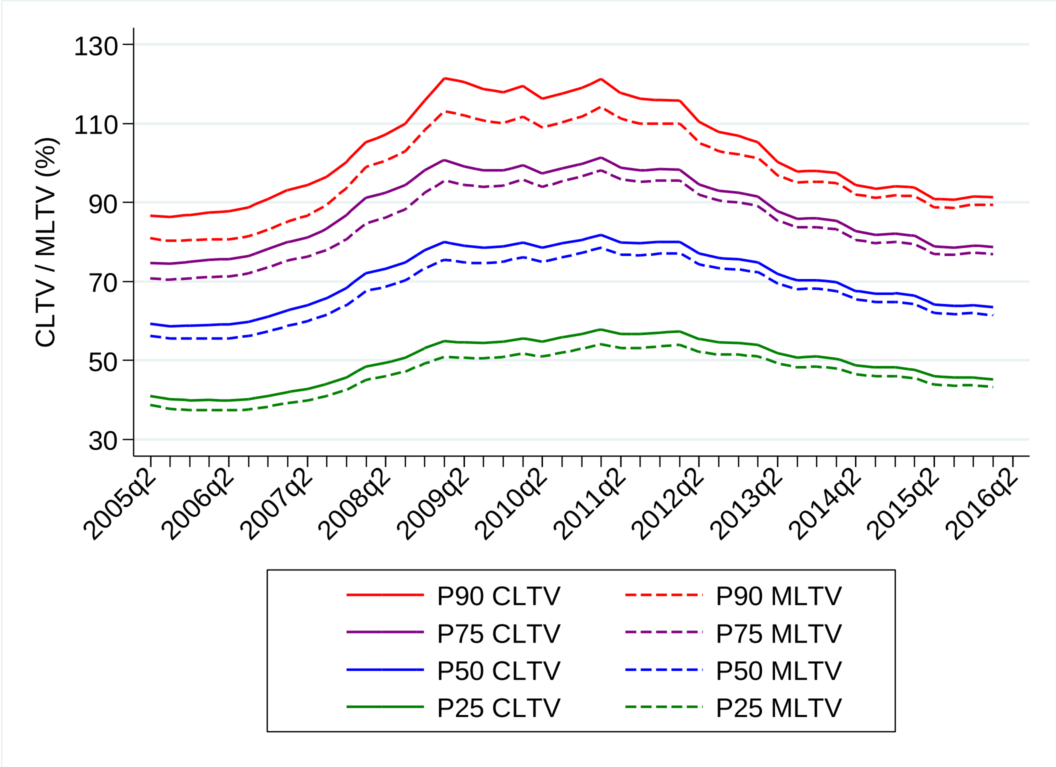


Figure 3: Nationwide distribution of leverage, 2005-2016

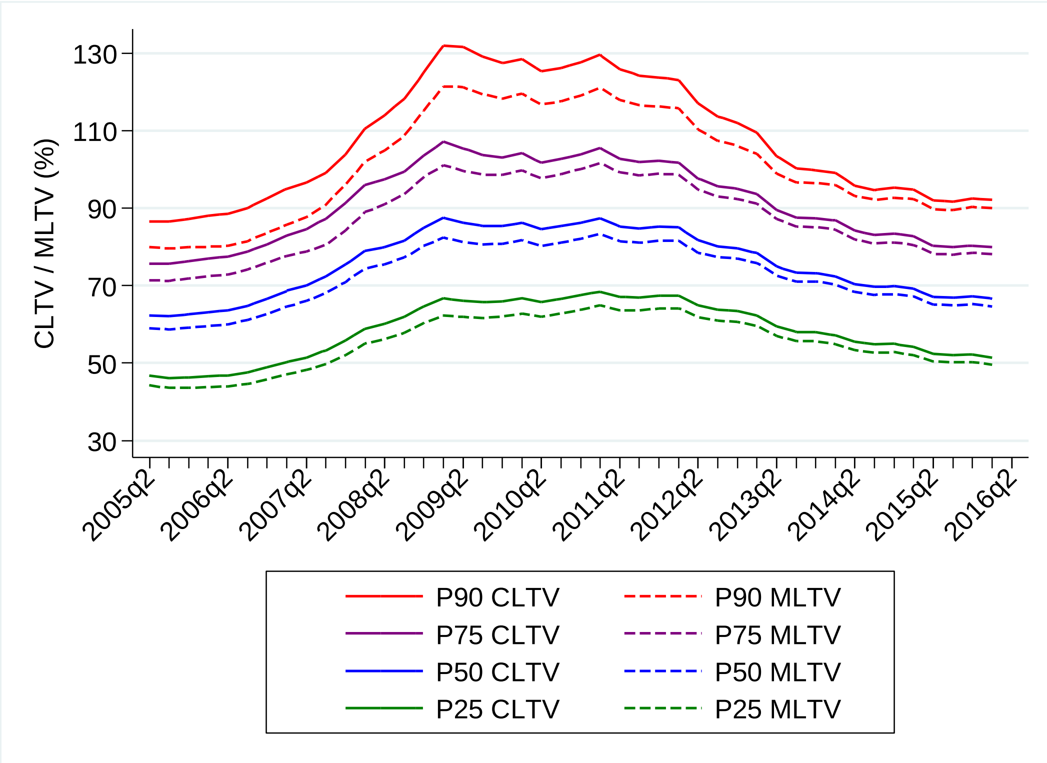
(a) Averages



(b) Distribution by loans



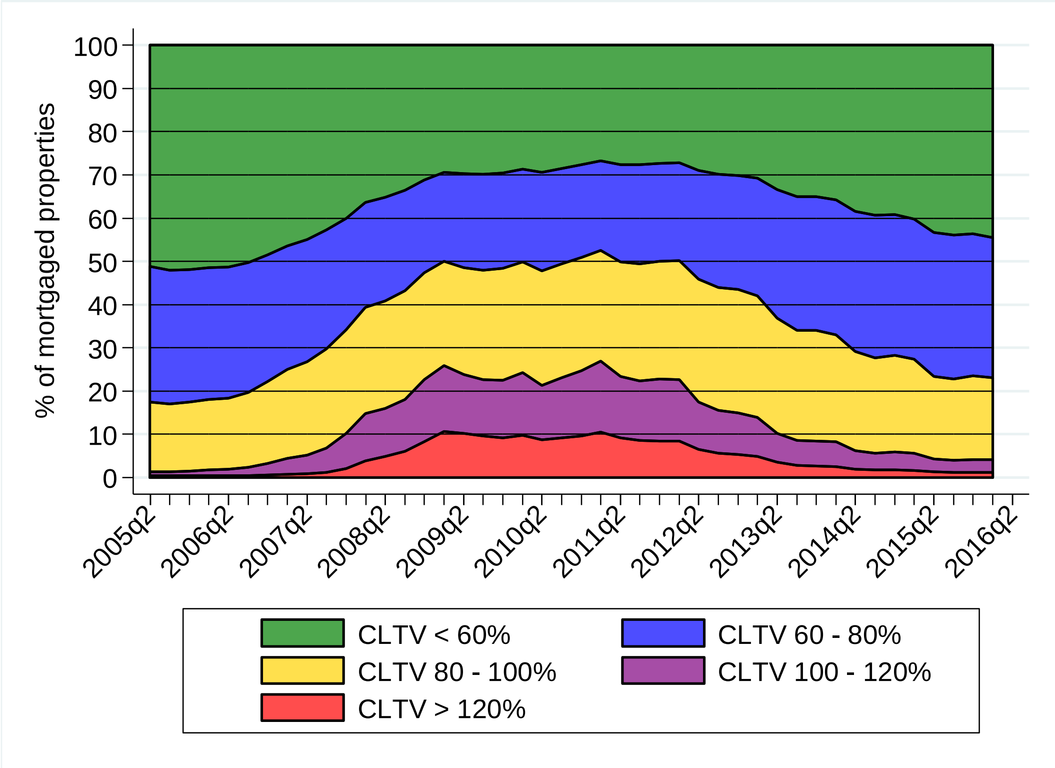
(c) Distribution by balance-weighted loans



Note: in panels (b) and (c), P“X” means the Xth percentile of the CLTV (or MLTV) distribution.

Figure 4: Nationwide distribution of CLTVs for properties with a first mortgage, 2005-2016

(a) Distribution of loans (equal-weighted)



(b) Distribution of balance-weighted loans

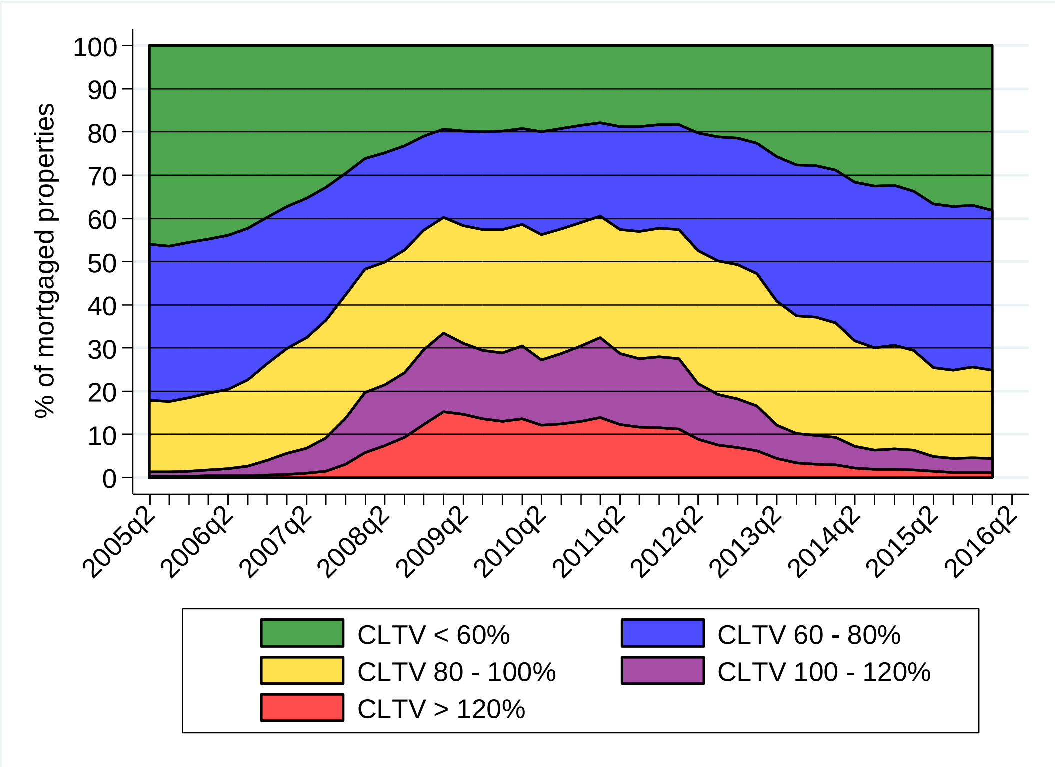


Figure 5: Mean CLTV for selected regions, 2005-2016

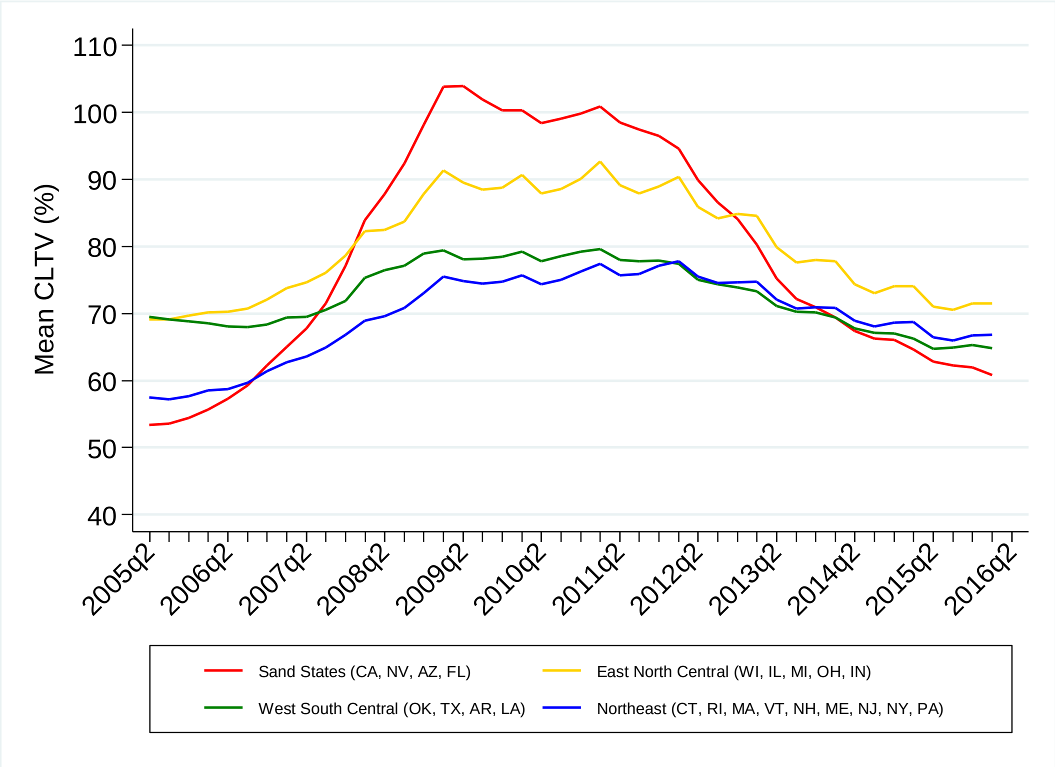


Figure 6: Distribution of CLTVs for selected regions, 2005-2016; distributions are balance-weighted.

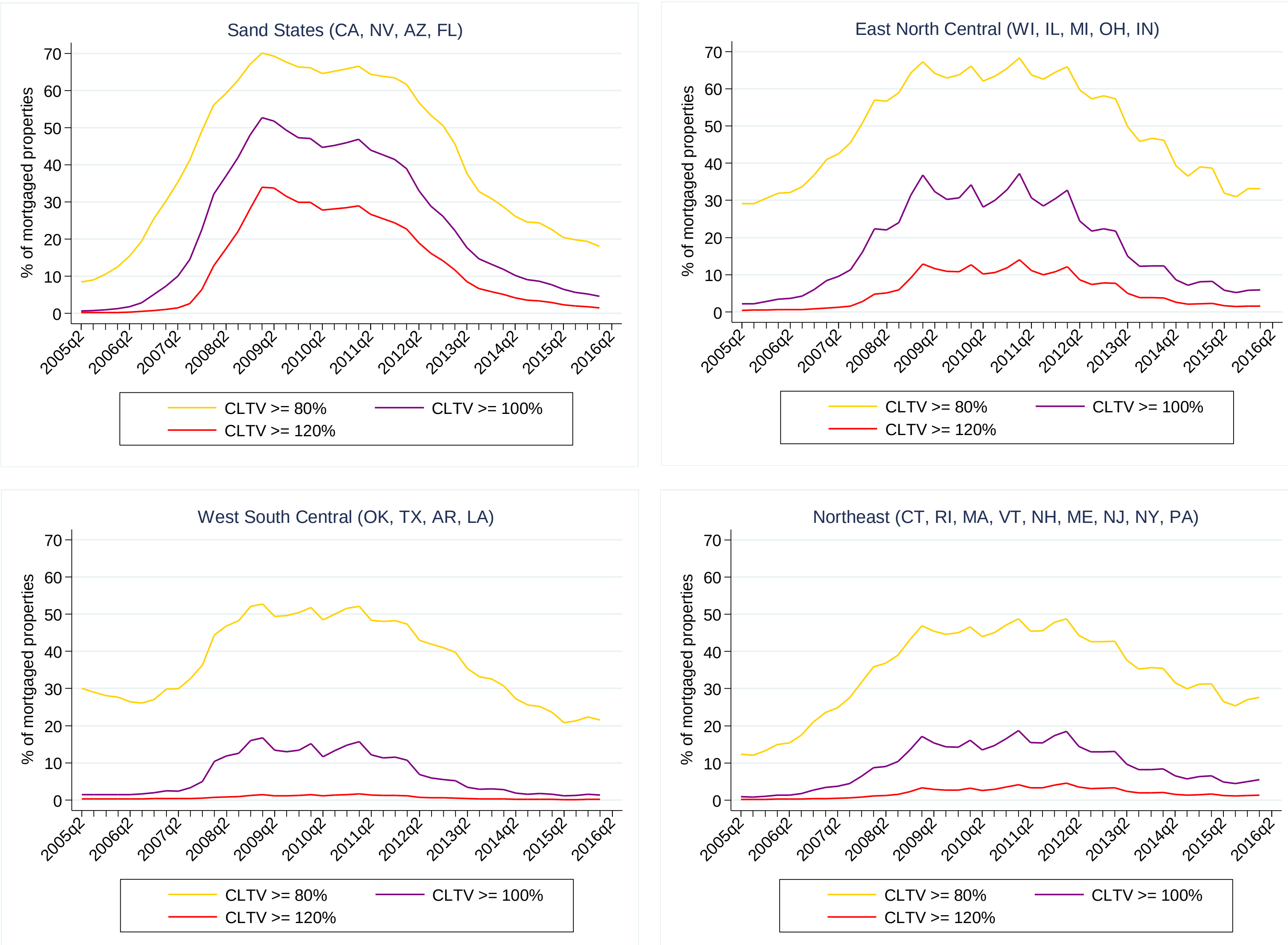


Figure 7: Estimated balance-weighted share of properties with positive first mortgage debt and CLTV ≥ 0.8 or ≥ 1, as of 2016:Q1, by state

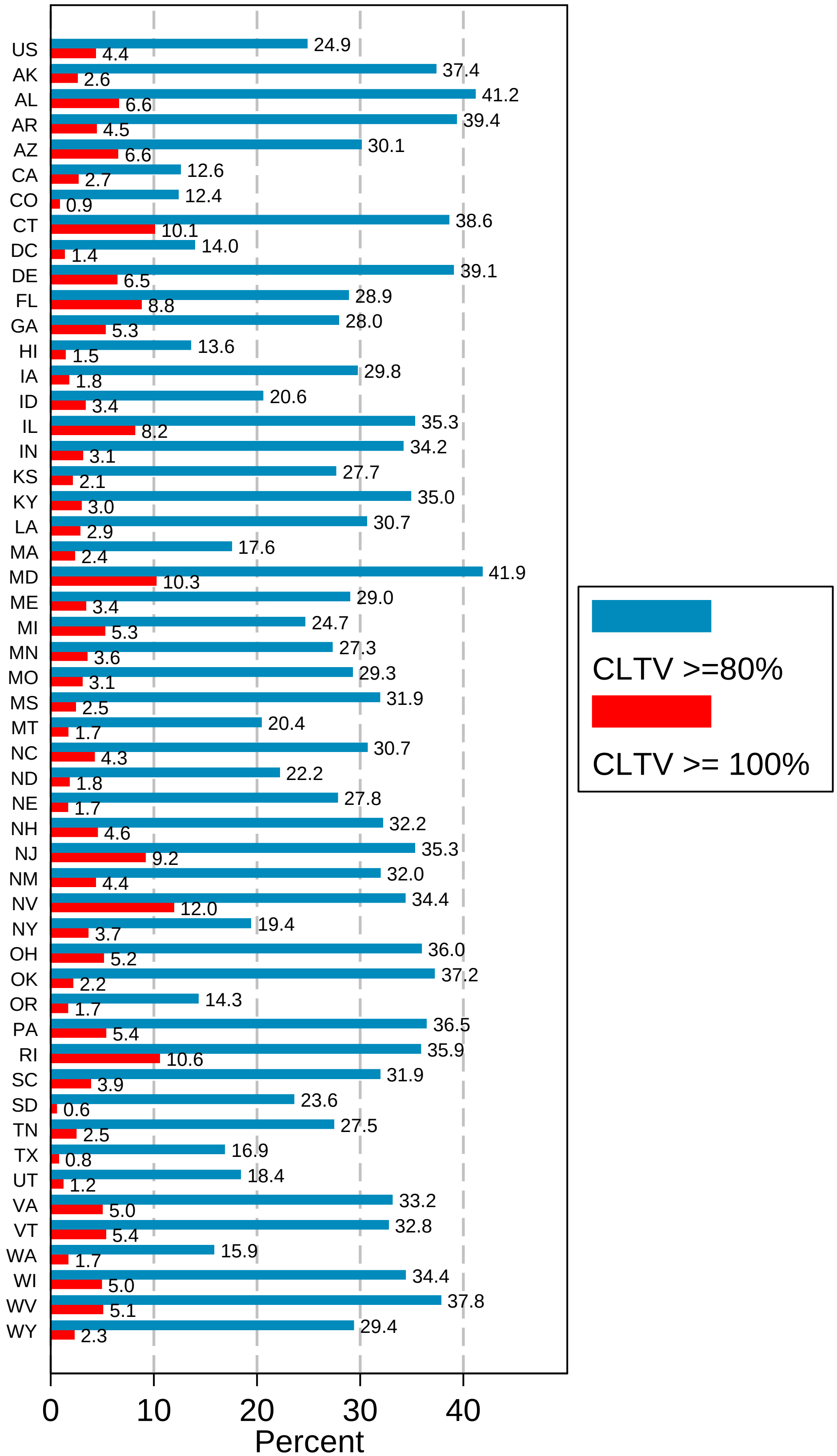
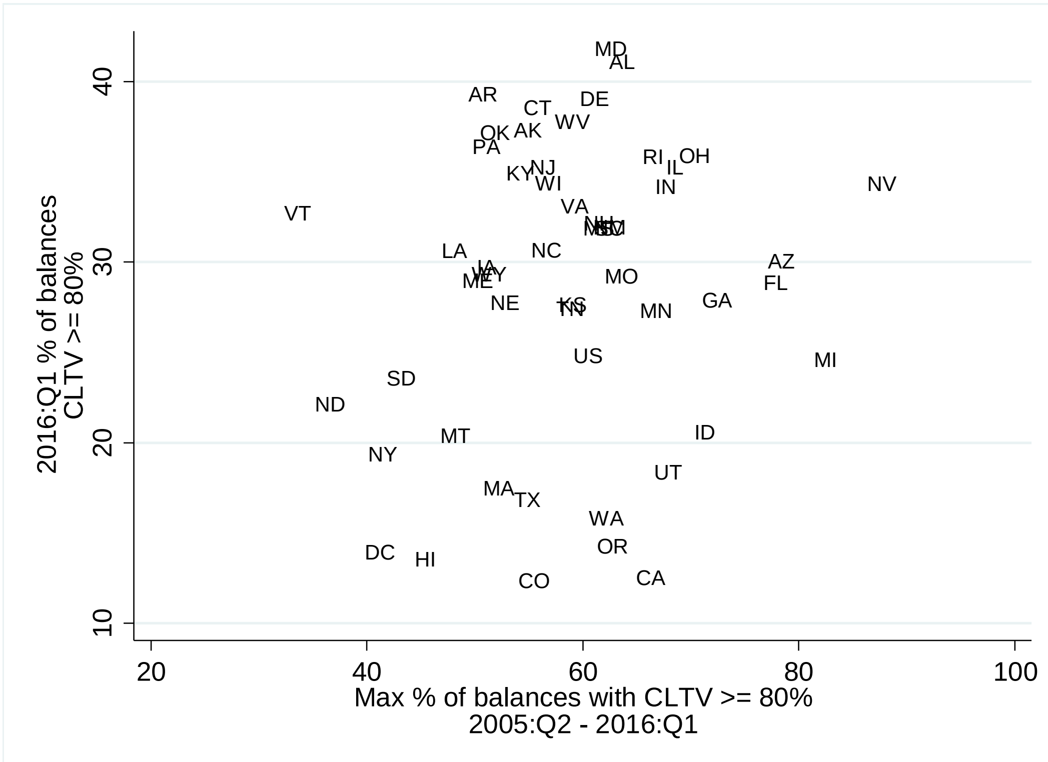


Figure 8: Estimated balance-weighted share of properties with positive first mortgage debt and CLTV ≥ 0.8 or ≥ 1, 2016:Q1 vs. peak over 2005-2016, by state



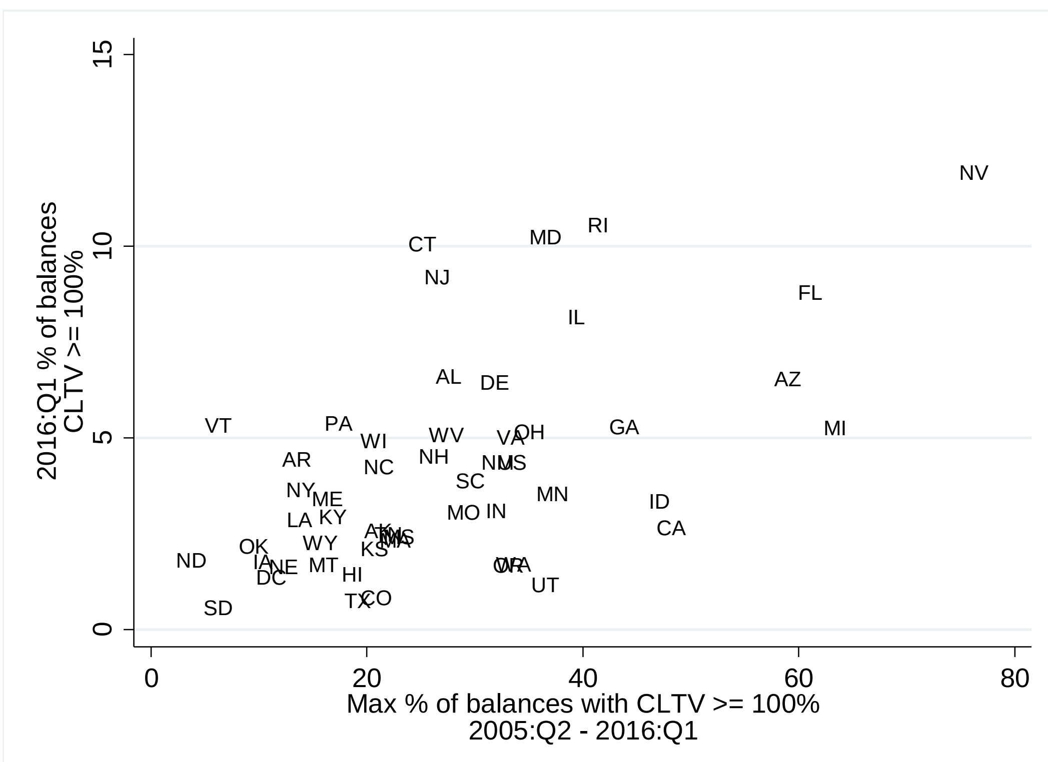
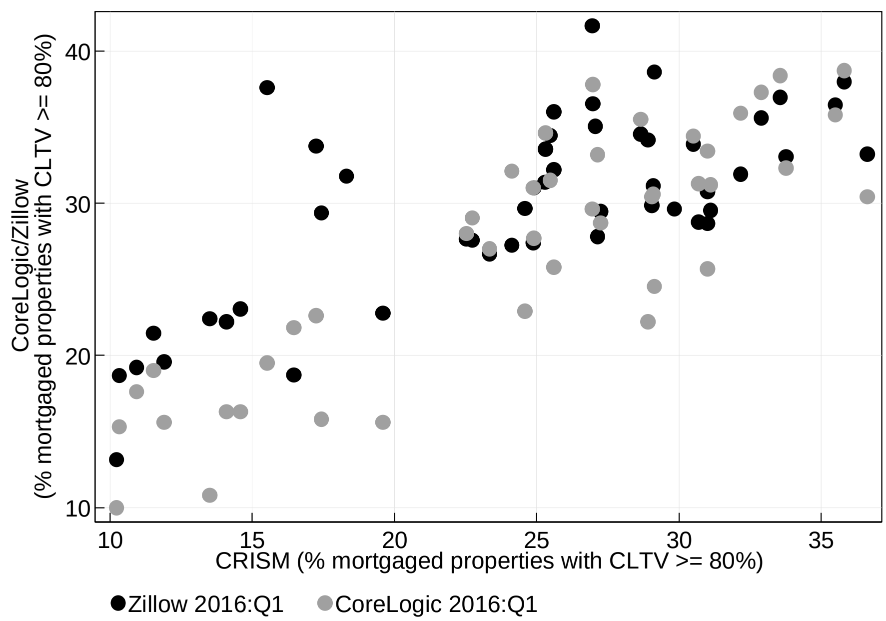
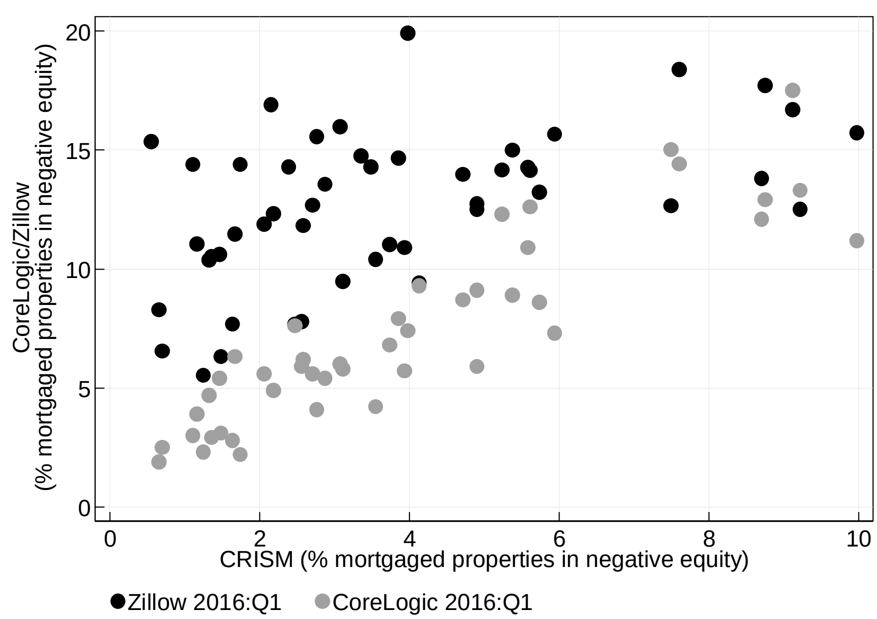


Figure 9: Proportions of properties with positive first mortgage debt and CLTV ≥ 0.8 or ≥ 1 compared with CoreLogic and Zillow estimates, as of 2016:Q1, by state

(a) Percent of properties[33] with CLTV >=80%



(b) Percent of properties with CLTV >=100%

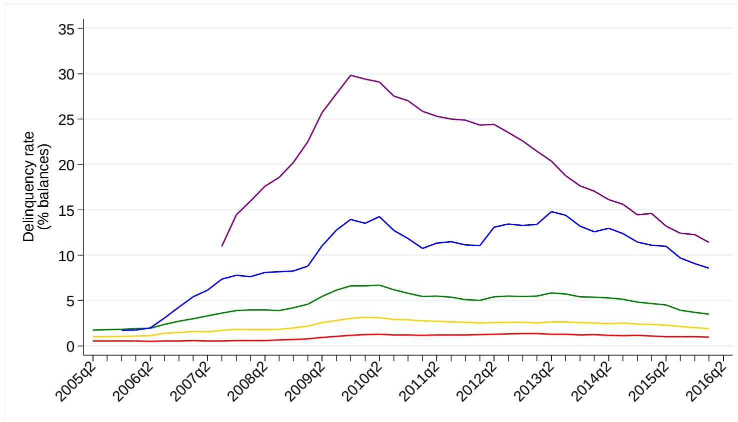


[33] Zillow and CoreLogic estimate the percentage of properties in negative equity so we compare this to our estimates of loans rather than balance-weighted estimates we use in the rest of the paper.

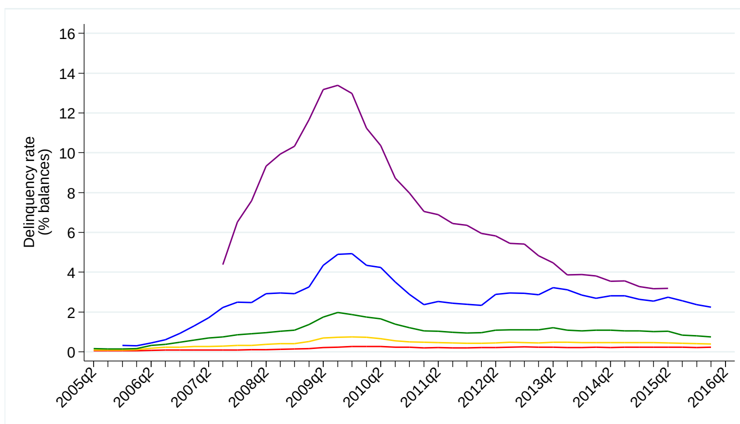
Figure 10: Nationwide serious delinquency rates by CLTV buckets, 2005-2016

(Serious delinquency defined as 90 days delinquent or worse. Charts only include CLTV buckets representing at least 1% of total balances.)

a) All loans (balance-weighted)



b) Prime loans (12-month-lagged FICO >= 660)



c) Subprime loans (12-month-lagged FICO < 660)

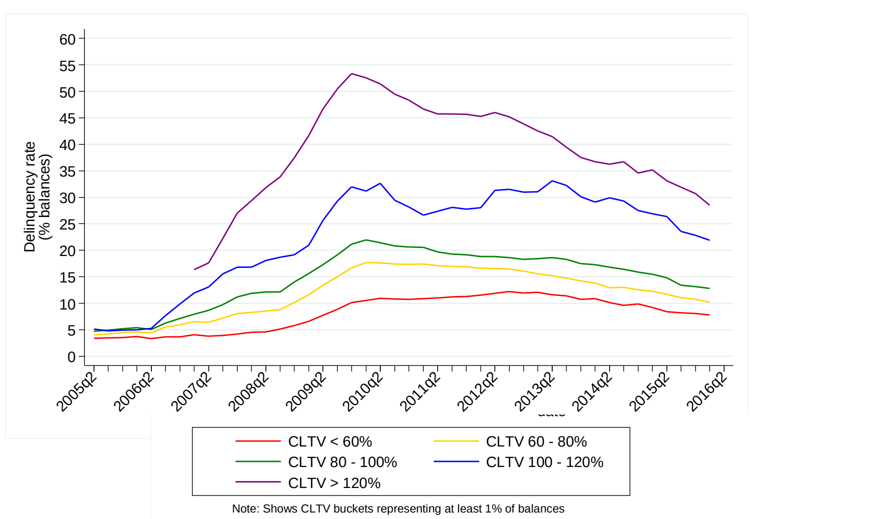


Figure 11: Share of non-seriously-delinquent balances by CLTV-FICO buckets 2005:Q3 – 2016:Q1

(Non-seriously-delinquent refers to loans that are current or less than 90 days past due.)

2006:Q1	<80%	80-100%	100-120%	>120%	*Subtotal*
<600	5.8%	2.5%	0.2%	0.0%	*8.5%*
600-659	7.7%	3.2%	0.3%	0.1%	*11.1%*
660-699	10.4%	3.3%	0.3%	0.1%	*14.1%*
700-739	12.8%	3.2%	0.3%	0.1%	*16.3%*
>=740	44.1%	5.4%	0.4%	0.1%	*50.0%*
Subtotal	*80.7%*	*17.5%*	*1.4%*	*0.4%*	

2008:Q1	<80%	80-100%	100-120%	>120%	*Subtotal*
<600	3.6%	3.8%	2.4%	1.1%	*10.9%*
600-659	3.9%	3.8%	2.2%	0.8%	*10.6%*
660-699	5.5%	4.4%	2.3%	0.9%	*13.1%*
700-739	7.5%	4.8%	2.3%	0.8%	*15.5%*
>=740	32.7%	11.7%	4.2%	1.3%	*49.9%*
Subtotal	*53.2%*	*28.5%*	*13.3%*	*5.0%*	

2010:Q1	<80%	80-100%	100-120%	>120%	*Subtotal*
<600	2.4%	3.1%	2.6%	2.2%	*10.4%*
600-659	2.5%	3.1%	2.2%	1.4%	*9.1%*
660-699	3.6%	3.9%	2.4%	1.4%	*11.3%*
700-739	5.6%	4.6%	2.6%	1.7%	*14.5%*
>=740	30.3%	14.2%	6.4%	3.9%	*54.8%*
Subtotal	*44.4%*	*29.0%*	*16.1%*	*10.5%*	

2012:Q1	<80%	80-100%	100-120%	>120%	*Subtotal*
<600	2.0%	2.6%	2.1%	1.6%	*8.2%*
600-659	2.5%	3.3%	2.2%	1.4%	*9.5%*
660-699	3.6%	4.1%	2.4%	1.4%	*11.4%*
700-739	5.5%	4.9%	2.6%	1.4%	*14.3%*
>=740	31.3%	15.6%	6.3%	3.3%	*56.5%*
Subtotal	*44.8%*	*30.5%*	*15.5%*	*9.1%*	

2014:Q1	<80%	80-100%	100-120%	>120%	*Subtotal*
<600	3.0%	2.6%	0.8%	0.4%	*6.7%*
600-659	4.2%	3.3%	0.9%	0.4%	*8.8%*
660-699	6.2%	4.2%	1.0%	0.4%	*11.7%*
700-739	8.7%	4.5%	1.0%	0.4%	*14.6%*
>=740	43.4%	11.6%	2.2%	0.9%	*58.1%*
Subtotal	*65.5%*	*26.1%*	*5.8%*	*2.5%*	

2016:Q1	<80%	80-100%	100-120%	>120%	*Subtotal*
<600	3.4%	1.6%	0.3%	0.1%	*5.5%*
600-659	5.1%	2.5%	0.5%	0.1%	*8.2%*
660-699	7.5%	3.4%	0.6%	0.2%	*11.6%*
700-739	10.5%	3.7%	0.6%	0.2%	*14.9%*
>=740	49.2%	9.1%	1.1%	0.4%	*59.9%*
Subtotal	*75.7%*	*20.2%*	*3.0%*	*1.0%*	

Figure 12: County level house price growth over 2006-2011 vs. 2000-2006.

Correlation coefficient is -0.6.

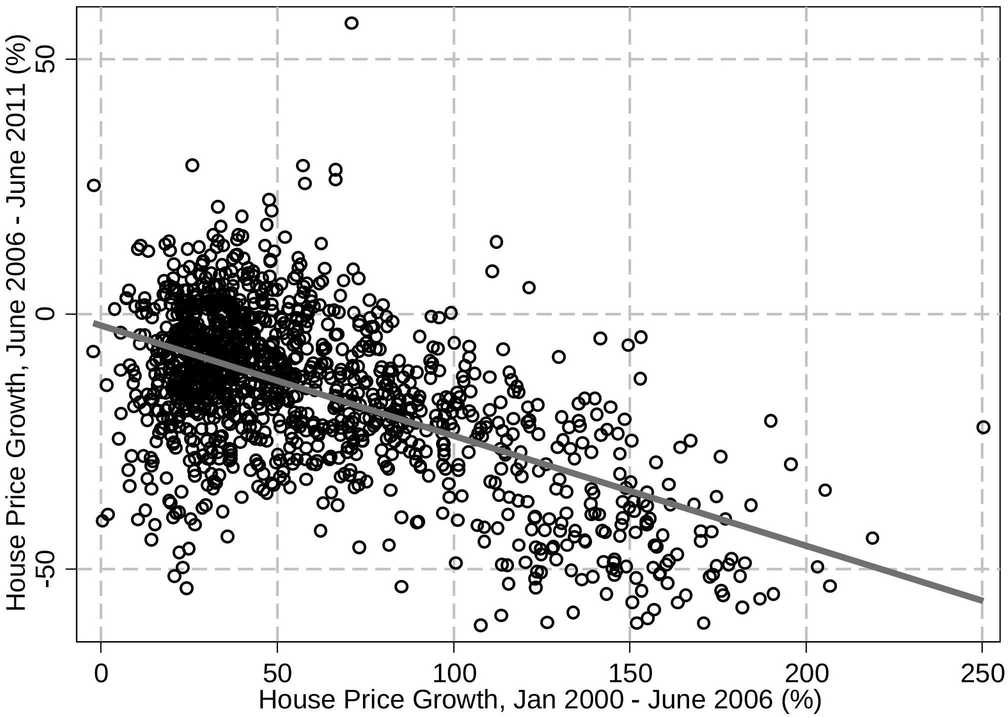


Figure 13: Scenarios for house price shocks, distribution across mortgaged properties in our sample, 2005-2016

	HPI 2 years ago			HPI 4 years ago		
	p10	p50	p90	p10	p50	p90
2006m3	-34.4%	-18.4%	-6.4%	-51.0%	-31.2%	-11.6%
2007m3	-20.7%	-8.6%	1.9%	-43.1%	-27.1%	-9.7%
2008m3	-4.9%	7.1%	36.5%	-26.7%	-11.2%	5.3%
2009m3	4.2%	19.9%	70.4%	-8.7%	10.8%	52.9%
2010m3	2.7%	13.9%	39.6%	1.3%	20.6%	89.4%
2011m3	-0.6%	5.4%	16.2%	7.4%	28.5%	88.3%
2012m3	-2.3%	4.3%	12.1%	3.4%	19.2%	45.3%
2013m3	-15.7%	-6.5%	1.3%	-12.8%	-0.4%	12.4%
2014m3	-24.7%	-12.1%	-3.3%	-22.3%	-9.0%	3.0%
2014m3	-24.7%	-12.1%	-3.3%	-22.3%	-9.0%	3.0%
2016m3	-15.4%	-8.7%	-1.8%	-34.4%	-20.1%	-6.4%

Peak-to-trough (as of 2016:Q1)		
p10	p50	p90
-51.8%	-25.9%	-10.5%

Figure 14: Effects of different house price scenarios on CLTV distribution (balance-weighted), 2016:Q1

(a) Aggregate

	Scenario			
CLTV	As of 2016m3	HPI-2yr	HPI-4yr	Peak-to-trough
<80%	75%	62%	43%	35%
80-90%	13%	17%	16%	12%
90-100%	8%	11%	16%	12%
100-120%	3%	8%	17%	19%
>120%	1%	2%	9%	22%

(b) State level: estimated balance-weighted fraction of borrowers in negative equity

	Base	2yr	4yr	P2T	Max crisis
US	4%	10%	26%	41%	33%
AK	3%	7%	14%	17%	21%
AL	7%	10%	17%	42%	28%
AR	4%	8%	12%	21%	14%
AZ	7%	15%	46%	81%	59%
CA	3%	8%	34%	46%	48%
CO	1%	8%	25%	11%	21%
CT	10%	10%	13%	49%	25%
DC	1%	3%	10%	6%	11%
DE	6%	9%	23%	51%	32%
FL	9%	20%	41%	78%	61%
GA	5%	15%	40%	49%	44%
HI	1%	6%	19%	15%	19%
IA	2%	5%	11%	8%	10%
ID	3%	10%	31%	59%	47%
IL	8%	14%	27%	62%	39%
IN	3%	9%	19%	33%	32%
KS	2%	8%	17%	21%	21%
KY	3%	7%	13%	18%	17%
LA	3%	8%	14%	15%	14%
MA	2%	6%	16%	26%	23%
MD	10%	12%	23%	60%	37%
ME	3%	7%	15%	24%	16%
MI	5%	15%	42%	67%	63%
MN	4%	10%	29%	49%	37%
MO	3%	9%	20%	37%	29%
MS	2%	9%	11%	25%	23%
MT	2%	6%	16%	15%	16%
NC	4%	9%	16%	25%	21%
ND	2%	10%	26%	3%	4%
NE	2%	6%	13%	8%	12%
NH	5%	9%	21%	43%	26%
NJ	9%	10%	15%	49%	27%
NM	4%	8%	15%	51%	32%
NV	12%	27%	62%	89%	76%
NY	4%	5%	10%	18%	14%
OH	5%	11%	24%	42%	35%
OK	2%	6%	13%	8%	10%
OR	2%	9%	31%	30%	33%
PA	5%	7%	12%	26%	17%
RI	11%	19%	30%	66%	41%
SC	4%	11%	21%	35%	30%
SD	1%	6%	17%	3%	6%
TN	3%	10%	20%	20%	22%
TX	1%	8%	23%	11%	19%
UT	1%	9%	30%	42%	37%
VA	5%	7%	18%	52%	33%
VT	5%	3%	6%	18%	6%
WA	2%	9%	29%	33%	34%
WI	5%	10%	16%	33%	21%
WV	5%	9%	21%	45%	27%
WY	2%	8%	20%	22%	16%

Figure 15: Effects of different house price scenarios on CLTV distribution (balance-weighted), 2006:Q1 (before house price decline)

(a) Aggregate

CLTV	Scenario: As of 2006m3	Scenario: HPI-2yr	Scenario: HPI-4yr	Scenario: Peak-to-trough
<80%	81%	52%	34%	39%
80-90%	12%	15%	13%	12%
90-100%	6%	13%	13%	12%
100-120%	1%	14%	19%	18%
>120%	0%	5%	21%	19%

(b) State level: estimated balance-weighted fraction of borrowers in negative equity

	Base	2yr	4yr	P2T	Max crisis
US	2%	19%	40%	37%	33%
AK	2%	27%	50%	12%	21%
AL	2%	16%	29%	29%	28%
AR	2%	13%	27%	13%	14%
AZ	1%	40%	57%	60%	59%
CA	1%	24%	54%	45%	48%
CO	4%	12%	19%	26%	21%
CT	1%	11%	35%	23%	25%
DC	1%	18%	52%	5%	11%
DE	1%	17%	46%	24%	32%
FL	1%	34%	58%	59%	61%
GA	3%	14%	25%	56%	44%
HI	1%	23%	52%	9%	19%
IA	3%	11%	19%	13%	10%
ID	1%	25%	40%	47%	47%
IL	1%	13%	33%	50%	39%
IN	3%	12%	21%	37%	32%
KS	3%	12%	25%	26%	21%
KY	3%	10%	19%	18%	17%
LA	1%	11%	24%	8%	14%
MA	2%	8%	31%	25%	23%
MD	1%	25%	56%	28%	37%
ME	2%	13%	40%	16%	16%
MI	6%	8%	17%	79%	63%
MN	2%	12%	34%	43%	37%
MO	2%	13%	29%	35%	29%
MS	2%	15%	28%	25%	23%
MT	1%	17%	38%	12%	16%
NC	3%	15%	24%	25%	21%
ND	2%	12%	22%	4%	4%
NE	4%	11%	23%	14%	12%
NH	2%	11%	39%	32%	26%
NJ	1%	14%	44%	24%	27%
NM	1%	19%	35%	32%	32%
NV	2%	43%	70%	83%	76%
NY	1%	12%	37%	11%	14%
OH	5%	10%	21%	47%	35%
OK	3%	14%	25%	8%	10%
OR	1%	21%	37%	27%	33%
PA	2%	14%	36%	12%	17%
RI	2%	14%	55%	47%	41%
SC	2%	19%	33%	26%	30%
SD	4%	11%	25%	9%	6%
TN	2%	15%	27%	24%	22%
TX	1%	12%	21%	18%	19%
UT	1%	23%	33%	45%	37%
VA	1%	27%	53%	30%	33%
VT	1%	10%	30%	7%	6%
WA	1%	21%	38%	30%	34%
WI	2%	11%	28%	25%	21%
WV	1%	22%	43%	25%	27%
WY	2%	19%	42%	17%	16%

Figure 16: 24-month transition rates of loans into serious delinquency (90 days or more past due), by CLTV-FICO buckets

Derived from loans that started out non-seriously-delinquent (meaning current or less than 90 days past due) over 2007-8 and are then followed for 24 months. Rates are balance-weighted within each cell. See text for details.

FICO \ CLTV	<80%	80-100%	100-120%	>120%
<600	16.2%	28.6%	37.2%	54.6%
600-659	8.2%	17.1%	25.4%	43.9%
660-699	4.4%	10.6%	17.4%	33.9%
700-739	2.4%	6.9%	12.3%	25.7%
>=740	0.6%	2.8%	6.1%	15.3%

Figure 17: 24-month serious delinquency forecasts (balance-weighted) under different house price scenarios, and for different as-of dates

"Base" = house prices stay constant at the level of the as-of date; "HPI-2" / "HPI-4" = local house prices return to their level 2 (or 4) years ago; "P2T" = local house prices experience a drop similar to the drop from their peak to their trough during the period since 2005, measured again at the local (mostly county) level.

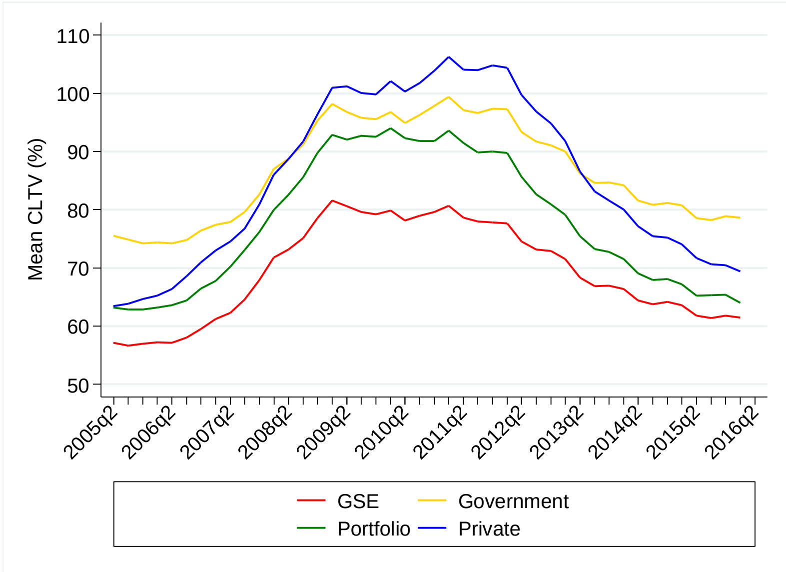
	Base	HPI-2	HPI-4	P2T
2012m3	8.8%	8.0%	5.7%	16.0%
2012m6	7.9%	7.6%	5.9%	15.1%
2012m9	7.5%	7.7%	6.1%	14.8%
2012m12	7.4%	8.0%	6.8%	14.7%
2013m3	7.1%	8.3%	7.3%	14.3%
2013m6	6.3%	7.9%	7.1%	13.3%
2013m9	5.9%	7.8%	7.0%	12.8%
2013m12	5.8%	8.0%	7.0%	12.8%
2014m3	5.7%	8.0%	7.2%	12.6%
2014m6	5.2%	7.1%	6.9%	11.8%
2014m9	5.0%	6.8%	7.1%	11.6%
2014m12	5.1%	6.8%	7.5%	11.7%
2015m3	4.9%	6.5%	7.8%	11.4%
2015m6	4.6%	5.8%	7.4%	10.7%
2015m9	4.5%	5.5%	7.6%	10.6%
2015m12	4.5%	5.5%	7.8%	10.7%
2016m3	4.4%	5.3%	7.8%	10.4%

Figure 18: 24-month serious delinquency forecasts (balance-weighted) under different house price scenarios as of 2016:Q1 – state level

	Base	HPI-2	HPI-4	P2T
US	4.4%	5.3%	7.8%	10.4%
AK	4.7%	5.3%	6.0%	6.3%
AL	6.1%	6.8%	7.7%	11.4%
AR	5.6%	6.1%	6.5%	7.7%
AZ	4.8%	6.0%	11.1%	18.7%
CA	3.1%	4.1%	8.2%	10.6%
CO	2.9%	4.2%	6.5%	4.5%
CT	5.6%	5.6%	6.2%	11.5%
DC	2.8%	3.1%	4.2%	3.5%
DE	5.7%	6.2%	7.7%	12.2%
FL	5.7%	7.5%	11.3%	19.4%
GA	5.4%	7.0%	11.2%	12.9%
HI	2.9%	3.7%	5.7%	5.1%
IA	4.2%	4.9%	5.6%	5.2%
ID	4.0%	5.2%	8.5%	13.7%
IL	5.1%	6.1%	8.0%	13.8%
IN	5.4%	6.4%	7.7%	9.5%
KS	4.3%	5.3%	6.4%	6.8%
KY	5.3%	6.1%	6.7%	7.3%
LA	5.8%	6.7%	7.6%	7.6%
MA	3.5%	4.3%	5.8%	7.1%
MD	6.1%	6.4%	8.1%	14.4%
ME	4.7%	5.3%	6.3%	7.7%
MI	4.7%	6.3%	10.7%	15.8%
MN	3.8%	4.7%	7.2%	10.2%
MO	4.7%	5.8%	7.1%	9.4%
MS	6.4%	7.6%	7.9%	9.6%
MT	3.5%	4.2%	5.7%	5.7%
NC	5.1%	6.0%	7.0%	8.2%
ND	3.3%	4.3%	6.7%	3.4%
NE	3.8%	4.7%	5.5%	4.9%
NH	4.7%	5.4%	6.9%	9.9%
NJ	5.2%	5.3%	6.1%	11.4%
NM	5.1%	5.8%	6.7%	11.8%
NV	5.9%	8.0%	15.5%	21.9%
NY	3.9%	4.2%	5.2%	6.2%
OH	5.4%	6.4%	8.0%	10.6%
OK	5.6%	6.3%	7.0%	6.5%
OR	3.0%	4.3%	7.3%	7.4%
PA	5.2%	5.5%	6.1%	8.0%
RI	5.7%	7.1%	8.8%	15.8%
SC	5.3%	6.5%	7.8%	9.7%
SD	3.5%	4.5%	5.7%	4.0%
TN	4.8%	6.1%	7.6%	7.6%
TX	4.3%	5.6%	8.1%	6.0%
UT	3.5%	4.6%	8.0%	9.7%
VA	4.5%	4.9%	6.2%	11.5%
VT	4.4%	4.0%	4.4%	6.1%
WA	3.2%	4.6%	7.2%	8.0%
WI	4.6%	5.3%	6.0%	8.6%
WV	6.3%	7.1%	8.6%	13.4%
WY	4.2%	5.0%	6.3%	6.6%

Figure 19: CLTV distributions and delinquencies by funding source

a. Average CLTVs, 2005-2016



b. CLTV categories by funding source, 2016:Q1

	Funding Source			
CLTV Category	**GSE**	**Government**	**Portfolio**	**Private**
<80%	82%	51%	83%	69%
80-90%	10%	25%	9%	13%
90-100%	5%	19%	5%	9%
100-120%	2%	5%	3%	7%
>120%	1%	1%	1%	2%
Share of Total Outstanding	*57%*	*19%*	*16%*	*9%*

c. Delinquencies in stress testing scenarios, 2016:Q1

	Scenario			
Funding source	**Base**	**HPI-2**	**HPI-4**	**P2T**
GSE	3.2%	3.9%	5.6%	7.9%
Government	8.0%	9.6%	13.3%	17.6%
Portfolio	3.3%	4.2%	6.8%	8.8%
Private	6.5%	7.9%	11.9%	14.8%

8 Appendix

8.1 Additional details on CRISM data

Whereas McDash loans are linked to a specific property for which there is an appraisal value, Equifax credit files are person-level records and therefore can cover loans secured to multiple dwellings. The Equifax section of CRISM includes tradeline data on the balances and performance of the largest secured loans held, aggregate data on secured and unsecured debts and other metrics such as risk scores and an indicator for whether an individual appears in the FRBNY's Consumer Credit Panel (CCP).

In Equifax credit files we observe the total, largest and second largest loan held at each point in time for each category of: first mortgage (FM), closed-end second (CES) and home equity line of credit (HELOC). We are able to use the difference between the total and largest plus second largest loan in each category to calculate a 'remainder loan' – for individuals with exactly three loans in a category this remainder is their third loan. Unlike the largest and second largest loans in the credit files we do not observe the origination amount or time for this 'remainder loan' – these are estimated using the outstanding balance and date of the first observation which appears in CRISM.

As CRISM does not record which Equifax loan (as described in the preceding paragraph as largest, second largest and remainder loans for FM, CES and HELOC) a McDash loan is matched to, we construct an algorithm to identify this. This algorithm first looks for exact matches by outstanding balance and origination balance. If no match is found it then looks for loans with a $5,000 or less absolute difference in outstanding balances and origination balances. If no match is found the algorithm looks for matches from other observations for this same McDash loan. The result of this algorithm is that 97% of the McDash loan observations are matched to an Equifax first mortgage; those unmatched (or found to closely match to a second lien) are dropped.

We then need to decide which second lien(s) to match to our first mortgage of interest since, if either of the following criteria are met, it is possible that a borrower's recorded second liens could be associated with a mortgaged property other than the one we observe in McDash:

(i) The individual's Equifax credit file records a first mortgage other than the McDash mortgage;

(ii) Prior observations for this McDash loan recorded this individual holding a first mortgage other than the current McDash loan.[34]

[34] CRISM includes Equifax data from six months preceding the time of McDash loan origination. However, as the first CRISM observation is in June 2005, six months of data before origination is not always available.

For observations meeting the above criteria we then apply the following rules to determine when to *not* allocate a second lien balance from an Equifax tradeline to a McDash first mortgage:

- If the second lien balance at origination is greater than or equal to the McDash mortgage origination balance;
- If the second lien's origination date is closer to the origination date of an Equifax first mortgage tradeline of the same borrower other than the one corresponding to the McDash loan;
- If the second lien's origination date is more than two months before the origination date of the first mortgage and we have three or fewer months of data for the second lien subsequent to the origination of the first mortgage;
- If the second lien's origination date precedes the McDash mortgage origination date and the first mortgage is marked as a purchase mortgage.

Our findings are robust to tweaking these rules, and comparison with CCP data indicates that the distribution of second liens relative to first mortgages is plausible.