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Tracking and Stress-Testing U.S. Household Leverage

- Borrowers' ability to withstand economic shocks depends importantly on housing equity. This dynamic played a key role in the 2007-09 recession, when surging mortgage debt followed by falling home prices put many homeowners "underwater" on their mortgages.
- To monitor risks emanating from the housing sector, the authors track the evolution of household leverage—the ratio of housing debt to housing values—over time and across states and regions, using a unique new data set.
- They find that leverage was low before 2006, rose rapidly through 2012, and then—as home prices recovered—fell back toward pre-crisis lows by early 2017.
- "Stress tests" predicting future leverage and defaults under scenarios of declining home prices reveal that the household sector is still vulnerable to severe house-price declines, although it has become steadily less risky in recent years.

1. Introduction

High household debt is widely considered one of the main causes of the Great Recession and the slow recovery that followed. Over the first half of the 2000s, U.S. household debt, particularly mortgage debt, rose rapidly along with house prices, leaving consumers very vulnerable to house price declines. Indeed, as house prices fell nationwide from 2007 to 2010 and unemployment rates soared, mortgage defaults and foreclosures skyrocketed because many households were "underwater," meaning the outstanding amount of their home loans exceeded the then-current value of their properties (see Chart 1). To assess the risk of a reoccurrence of this scenario (or of a similar event taking place) in the future, and to guard against such an event, it is crucial to track household leverage, especially on home loans (first-lien mortgages as well as home equity loans and lines of credit). Furthermore, it is imperative to consider homeowner leverage not only at the current level of house prices but also under realistic scenarios involving negative house price shocks. In this article, we combine different data sets to track and stress-test the leverage of U.S. homeowners in a representative way.

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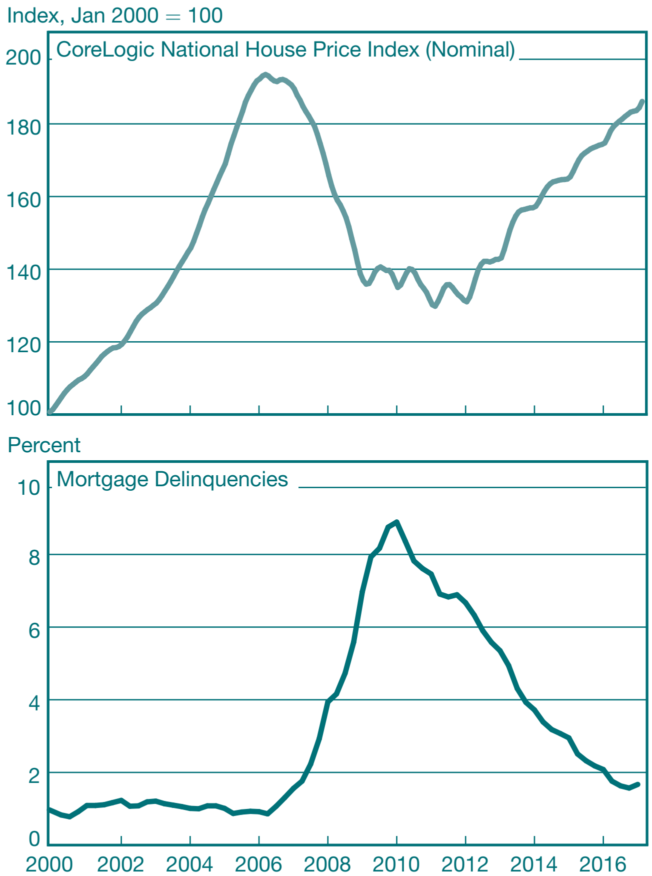
Chart 1
U.S. House Prices and Mortgage Delinquencies, 2000-17



Sources: CoreLogic; New York Fed Consumer Credit Panel.

Notes: Indexes are not seasonally adjusted. Delinqencies reflect the share of outstanding mortgage balances that are ninety or more days delinquent.

The primary source of information used in our analysis is a newly available data set, Equifax's Credit Risk Insight Servicing McDash (CRISM), which combines the mortgage-servicing records of about two-thirds of outstanding U.S. first-lien mortgages (the McDash component[1]) with credit record information on the respective mortgage holders (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. Such a calculation is typically impossible using mortgage servicing data alone, because there is no way to connect second liens with first liens on the same property. We also observe borrowers' updated FICO credit scores, giving us a further dimension along which to evaluate potential default risk. Since the CRISM sample does not cover the full population of U.S. mortgages, we ensure its representativeness by weighting observations based on the distribution of loan characteristics in the New York Fed Consumer Credit Panel (CCP), which tracks the credit records of a representative sample of the U.S. population.[2]

We use the resulting CLTV estimates to document the changing pattern of U.S. homeowners' leverage over the last ten years, both nationwide and across regions. In addition to showing average CLTVs, we focus in particular on the fraction of properties with CLTVs exceeding 80 percent or 100 percent. We also quantify the strong relationship between CLTVs and the rate at which borrowers become seriously delinquent (meaning they are behind on their mortgage payments by ninety days or more). Furthermore, we assess what would happen to CLTVs and delinquency rates under a variety of more- or less-severe shocks to local house prices, with those shocks reflecting either a reversal of recent growth rates or a repetition of the drop in house prices that occurred during the 2007-10 bust. This analysis thus provides an early warning indicator of risks to the financial system emanating from housing finance, and 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.[3]

Our key findings are the following: As of the first quarter of 2017, nationwide, household leverage has declined substantially compared with 2008-12 and is approaching pre-crisis levels. Consequently, and also because of an improvement in credit scores among households with outstanding mortgages, the household sector's vulnerability to a modest decline in house prices has decreased. However, for very severe house price declines (approaching the magnitude of those observed during the crisis), vulnerability remains elevated. At a more

[1] McDash is a set of loan-level mortgage performance data from Black Knight Data and Analytics, which was formerly known as Lender Processing Services (LPS). LPS had earlier acquired McDash Analytics.

[2] See Lee and van der Klaauw (2010) or https://www.newyorkfed.org/microeconomics/hhdc/background.htm 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.

[3] 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, Federal Housing Administration/Veterans Administration, privately securitized, or held in bank portfolios).

disaggregated level, the time series of our leverage metrics 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 contemporaneous 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 reverted to their mean, the leverage of these homeowners rapidly increased and extremely high mortgage defaults followed. While not perfect, stress tests like the one proposed in this article allow one to anticipate such potential dynamics and also 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.[4] Most importantly, higher leverage, and in particular a household being underwater on its mortgage(s), is a strong predictor of mortgage default and foreclosure (see, for example, Foote, Gerardi, and Willen [2008], Corbae and Quintin [2015], and Ferreira and Gyourko [2015]). Foote, Gerardi, and Willen 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 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.[5]

Understanding the risk of an increase in mortgage defaults is important because of (1) the potential for losses by banks and other holders of mortgage assets, as illustrated by the recent crisis; (2) the negative consequences for defaulting borrowers, such as the impact on their creditworthiness (Brevoort and Cooper 2013); and (3) the negative externalities that foreclosures may have on the value of other properties (Campbell, Giglio, and Pathak 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 than less-levered households in response to a negative shock, in part because they do not have "debt capacity" that could help them smooth consumption (for example, Dynan [2012] and Mian, Rao, and Sufi [2013]) and they are typically unable to refinance to take advantage of lower mortgage rates (Caplin, Freeman, and Tracy 1997; Beraja et al. 2015). Underwater households may reduce expenditures on property maintenance or investments (Melzer 2013; Haughwout, Sutherland, and Tracy 2013) and may exhibit lower mobility (Ferreira, Gyourko, and Tracy 2010, 2012). Even if a household is not quite underwater, down payment 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 used by researchers and policymakers to track household leverage. One such commonly used measure is the aggregate ratio of housing (or total consumer) debt to the value of residential housing, based on the Federal Reserve's 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, Primiceri, and Tambalotti [2015], or Vidangos [2015]). However, aggregate leverage provides only an incomplete picture of potential household vulnerability, since an economy where half the households have a loan-to-value ratio (LTV) of 100 percent and the other half 0 percent is very different from an economy where everybody has a 50 percent LTV.[6]

Moving to the micro level, some researchers have relied on local (for example, based on zip code or county) measures of the ratio of total debt to total income to estimate household leverage (see, for instance, Mian and Sufi [2010]). This approach 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 "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, Schoar, and Severino (2016) has illustrated that looking at aggregates can yield different conclusions than those based on 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 deed records, which have the advantage of being comprehensive for the areas

[4] Geanakoplos and Pedersen (2014) discuss why monitoring leverage is also important in other asset markets.

[5] 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.

[6] This is illustrated, for instance, by the model of Eggertsson and Krugman (2012).

and time periods in the sample; however, with deed records, mortgage balances are observed only at origination and thus have to be imputed for subsequent time periods. Similarly, it is difficult to accurately track equity withdrawal based on deed records, especially when it occurs through home equity lines of credit (as was common during the 2000s boom—see, for example, Lee, Mayer, and Tracy [2012] and Bhutta and Keys [2016]). Finally, deed records contain no information on credit scores (or other borrower characteristics).[7]

Closest to our measures of leverage are quarterly reports published by real estate data firms such as CoreLogic or Zillow, which also provide timely measures of the fractions of homeowners who 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 primary new aspects of our analysis relative to these reports are that we jointly consider leverage and updated credit scores as well as the link between these variables and default, and we subject households to a stress test consisting of local house price drops of different severities. We further discuss the relationship between our estimates and existing estimates in Section 3.[8]

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 to monthly income, known as the "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 [2017], Gerardi et al. [forthcoming], or Hsu, Matsa, and Melzer [2018]). The central reason for not considering affordability is that updated measures of individual income are not available. As a result, 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 or 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 correlated with liquidity shocks at the local level (since areas that saw the largest house price declines during the crisis were also those where unemployment rates increased the most; see, for example, Beraja et al. [2015]). This assumption is not a problem for prediction if the correlation between changes in leverage and affordability is stable, but it 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.[9]

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 compared with the boom years of the early 2000s, one could argue that a future drop in house prices 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 again reached the same levels.

In sum, our analysis, which we plan to update periodically, produces a timely measure of households' leverage through home loans, enabling policymakers and market participants to assess potential vulnerabilities of household finances and the macroeconomy to housing market shocks.

The rest of this article 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. Our basic results are presented in Section 3, where we report points in the distribution of borrower-level LTV ratios for the period 2005-17 and provide details on the evolving role of junior liens over time. We also provide data on the variation in leverage across states and regions, and characterize how leverage and creditworthiness jointly affect delinquency. Section 4 combines the pieces developed in Section 3 to report the results of our "household

[7] Glaeser, Gottlieb, and Gyourko (2013) and Ferreira and Gyourko (2015) also use deed records to characterize the evolution of down payment fractions on newly originated mortgages—that is, the flow; throughout this article, we instead focus on snapshots of the stock of outstanding mortgages.

[8] One could also conduct an analysis similar to ours using publicly available data sets such as the Federal Reserve's Survey of Consumer Finances or the University of Michigan's Panel Study of Income Dynamics. However, these sources are available at much lower frequency and have much smaller sample sizes than the data used in this article.

[9] 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 United States, the bulk of outstanding mortgages have fixed rates). See Anderson et al. (2014), Bilston, Johnson, and Read (2015), and Finansinspektionen (2015) for examples of household stress tests in the United Kingdom, Australia, and Sweden, respectively. More broadly, a Google search for "household stress-testing" reveals related analyses conducted in at least fourteen countries, but not the United States.

stress test," in which we estimate the effect on leverage and delinquencies of various unfavorable house price trajectories. We present our conclusions in Section 5.

2. Data and Methodology for Estimating Leverage

This section describes our methodology for estimating leverage, the data sets used, and how we make our sample representative of U.S. mortgaged properties.

2.1 Definitions and Data Sets

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

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

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

Our primary source of data on mortgage balances is the rich transaction-level data set Equifax CRISM. CRISM 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 and Analytics with the borrower's Equifax consumer credit file. Our analysis is based on a 5 percent random sample of CRISM.

CRISM contains monthly data starting in June 2005. Each McDash loan is visible from either: (1) the time of origination, (2) June 2005 for earlier originations, or (3) the time at which a firm contributing data to McDash began servicing a loan. Monthly observations recording loan performance appear until a loan is terminated.[10] CRISM does not include recent mortgage originations owing to data requirements for the algorithm matching the mortgage performance data with the consumer credit files, and therefore, we supplement the CRISM data with recent originations (currently, for the period since September 2015) from McDash. Henceforth for brevity, references to "the CRISM data set" include both CRISM and the appended McDash components unless explicitly stated otherwise.

[10] Loans can be terminated because the loan has been repaid or refinanced, a default event (such as foreclosure) has occurred, or the servicing has been transferred to a different entity.

Our unit of analysis is properties with first mortgages in CRISM.[11] The data set contains the origination details of the loan (origination date, amount, and other loan characteristics), the location (zip code) and appraisal value of the property that secures the loan, and monthly performance details of the loan (outstanding balance and delinquency status), as recorded in McDash.[12] McDash contains loan-level information on both first mortgages and home equity loans/lines of credit; however, coverage of the latter is much less extensive, and junior and senior liens are not matched at the property level, so we use only first mortgage data from this data set. Thus, throughout, we do not include properties in the analysis if the only loan secured against the property 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 article, 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.[13] The credit record includes "tradeline" data for each loan containing the origination amount and date plus the subsequent performance of all secured loans of the same borrower (including first mortgages, closed-end second liens, and home equity lines of credit[14]), as well as the outstanding amounts and performance of unsecured and secured non-housing debt (not used in this article). It also contains a variety of credit scores, in particular the borrower's updated FICO score (which we will use in our delinquency analysis) and Equifax risk score (used for weighting to the CCP, as explained below). Often, 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

[11] 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.

[12] 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.

[13] For the most recent originations, where we rely on McDash for first mortgages, we match second liens from the CCP. We use 100 percent of recent originations in McDash and the CCP 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 thousand. These characteristics match to a single loan in 97.9 percent of cases. We match with the CCP using these characteristics and keep only matched loans (corresponding to 5.8 percent of the recently originated loans in McDash).

[14] A closed-end second-lien mortgage is for a fixed amount, while with a home equity line of credit, the lender agrees to give the borrower a line of credit up to some maximum amount. See Lee, Mayer, and Tracy (2012) for additional discussion.

designated "primary" borrower in CRISM. Credit record data are 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 properties that secure the real estate loans. 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 the property that secures the loan(s). One approach to valuing properties is to use "hedonic" models, which estimate the value of individual properties based on their location and other attributes. CRISM does not contain the 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):

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

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, metropolitan statistical area (MSA), or state-level indices instead.[15] We match roughly 78 percent of observations to zip-level HPIs. We use the combined single-family HPI, which includes distressed sales.

This valuation approach based on updated appraisal values 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 (for example, Agarwal, Ben-David, and Yao [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 because of improvements in their quality—for instance, because of renovations or the arrival of nearby amenities. Conversely, some properties will experience a fall in valuation owing to property degradation or the arrival of undesirable features nearby. Since LTV ratios are a convex function of asset valuations, we expect that using the average local HPI rather than the actual unobserved heterogeneous property-level house price will lead to an underestimate of CLTV ratios (see, for example, Korteweg and Sorensen [2016]).[16] 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, Sutherland, and Tracy 2013). These considerations may also explain why our estimates of the fractions of borrowers who are underwater tend to be lower than those of CoreLogic and Zillow, which use finer valuation models for individual properties, as discussed in more detail in the subsection "Comparison with Other Estimates" in Section 3.

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

2.2 Coverage and Weighting

For our sample period, CRISM covers approximately two-thirds of outstanding first mortgage balances, though this coverage has changed over time, for instance, with servicers joining McDash at different times. As a result, the distribution of loans is somewhat different from that observed in the nationally representative CCP.

It is important to ensure that our leverage estimates are representative of the U.S. properties with positive first mortgage balances because, otherwise, we could get a misleading picture. For example, if our data set oversampled prime customers relative to the population, we would expect

[15] We drop loans that do not have appraisal amounts, dates, or location information or loans for which the appraisal date is before 1976 (when HPI starts). This affects less than 1 percent of loans.

[16] More generally, HPIs may provide less accurate estimates of a property's value when transaction volumes are low and there are few repeat sales, an effect that was likely pronounced during the housing bust.

to get leverage estimates lower than those that prevail in reality. CRISM is based on data from large mortgage servicers; since these data are not a random sample, it is plausible that the loans serviced by these companies are not completely representative of all outstanding mortgages.[17] To make our data set representative of the population of U.S. 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. We achieve that weighting 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 in the next paragraph) such that each month in CRISM is weighted to that quarter's CCP and the distribution of loans matches within fifty-one states (the states plus Washington, D.C.) and thirty-eight large MSAs.[18] The largest MSAs were chosen to ensure that the distribution of mortgages was accurate within the more populous states, where non-MSA areas can have significantly different leverage patterns from those of MSAs.[19]

Within each of these state-MSA-month combinations, loans in both data sets are first split into delinquent and nondelinquent, where delinquency is defined as sixty or more days behind on payments.[20] We then sequentially compute balance-weighted quantiles in the CCP, first by outstanding first mortgage balance and then by Equifax risk score, with the thresholds for these quantiles varying within each state-MSA-month-delinquency-status combination.[21] Having computed these thresholds in the CCP, we weight the CRISM data by the ratio of CCP to CRISM observations in each state-MSA-month-delinquency-status-outstanding-balance-risk-score bucket.[22] The use of more buckets ensures that the weighted data set exactly matches the CCP population at a more granular level; however, it also results in thinner buckets and, therefore, more observations given relatively extreme weights. Observations with very large weights are particularly undesirable, because large weights can make overall results fragile and produce misleading outcomes, since we are not weighting on every dimension (for instance, appraisal amount or loan age). We therefore strike a balance (using five buckets of outstanding balance and four of current risk score within each state-MSA-month-delinquency-status combination) in order to ensure that the weighting achieves a distribution that matches the population while keeping it extremely rare for a bucket to consist of only a few observations in either the CCP or CRISM.

One issue with both mortgage servicing and credit record data sets is that some loans enter the data with a delay of a few months (this is known as "seasoning"). This delay 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 backfill the CCP only one quarter and only for loans where the seasoning is less than three months, since this covers the vast majority of loans.

The process described above yields a nationally representative data set of CLTVs on properties with positive outstanding first mortgage balances over 2005-17. 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 having an MLTV or CLTV greater than or equal to 100 percent. We display a range of thresholds of being "near" negative equity (for example, 80 percent or 90 percent CLTV), since doing so provides a range of estimates to account for potential mismeasurement.

[17] At one time, all of the top ten mortgage servicers were included in CRISM; now there are fewer because of mergers.

[18] Henceforth, references to "states" cover the fifty states and Washington, D.C., unless stated otherwise. Thirty-eight MSAs produce forty-two MSA-state combinations, since some MSAs cross state lines. This approach produces ninety-three state-MSA combinations, since observations not in the largest MSAs are solely weighted to the state level rather than at both the MSA and the state level.

[19] We chose MSAs with populations of one million or more in the 2010 census and for which there were sufficient observations in the CCP and CRISM data sets to be able to accurately weight at both the state and MSA level.

[20] We do so because reporting practices result in severely delinquent loans staying in the two data sets for different durations. Since delinquency is a relatively rare event (especially early in our sample period), using finer buckets would produce thinly filled buckets, a situation we want to avoid.

[21] Observations with origination amounts greater than $5 million or observations that likely contain erroneous data are dropped to ensure that balance weights are not thrown off. This affects less than 0.05 percent of observations. For very recent originations, we weight by origination FICO, since we do not observe current Equifax risk scores in McDash.

[22] 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 Geography

3.1 Time Series Patterns in the Full Sample

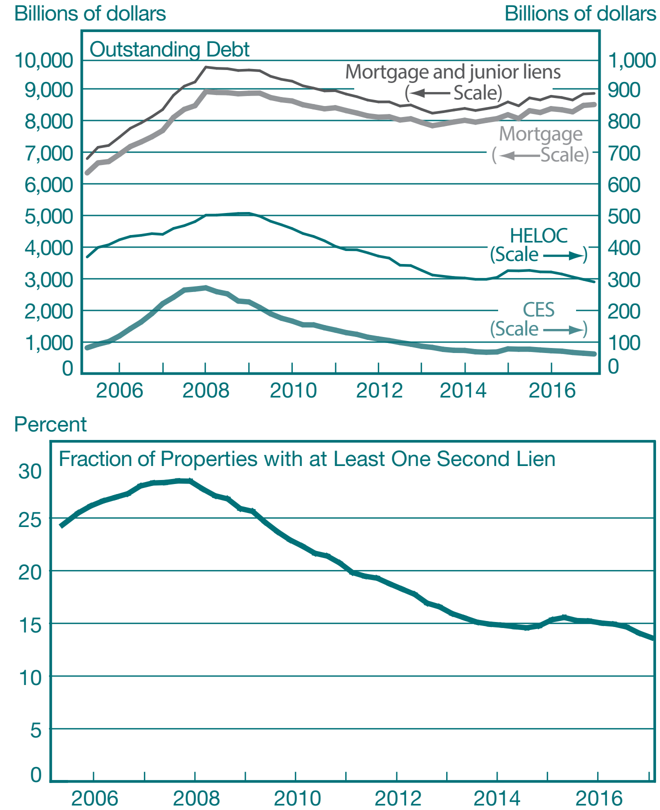
After weighting the CRISM data set to the CCP, we produce a time series of aggregate mortgage debt balances as displayed in the top panel of Chart 2.[23] A significant share of total CCP second-lien balances is associated with properties without positive first mortgage balances outstanding, and therefore total second-lien balances in the figure are lower than those presented in Lee, Mayer, and Tracy (2012). Relative to total mortgage debt, second liens are relatively small, peaking at just under 9 percent of first mortgage balances; however, the growth in second liens between 2005 and 2007-08 was substantial, with home equity line of credit (HELOC) balances and closed-end second mortgages (CES) increasing by \$138 billion and \$189 billion, 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 the bottom panel of Chart 2, only a minority of properties with first mortgages also feature a second lien, with that figure peaking at 29 percent in 2007 and falling to 14 percent as of the first quarter of 2017. For those borrowers, ignoring the second liens could lead us to substantially understate their leverage and vulnerability to house price shocks.

Chart 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. The top panel 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 top panel of Chart 3 also illustrates the effect of including second liens by displaying both CLTVs (solid lines), which include all liens that we assign to a property,

Chart 2

Nationwide Mortgage and Junior Lien Debt for Properties with a First Mortgage, 2005-17



Source: Equifax Credit Risk Insight Servicing McDash (CRISM).

Notes: HELOC is home equity line of credit. CES is closed-end second mortgage.

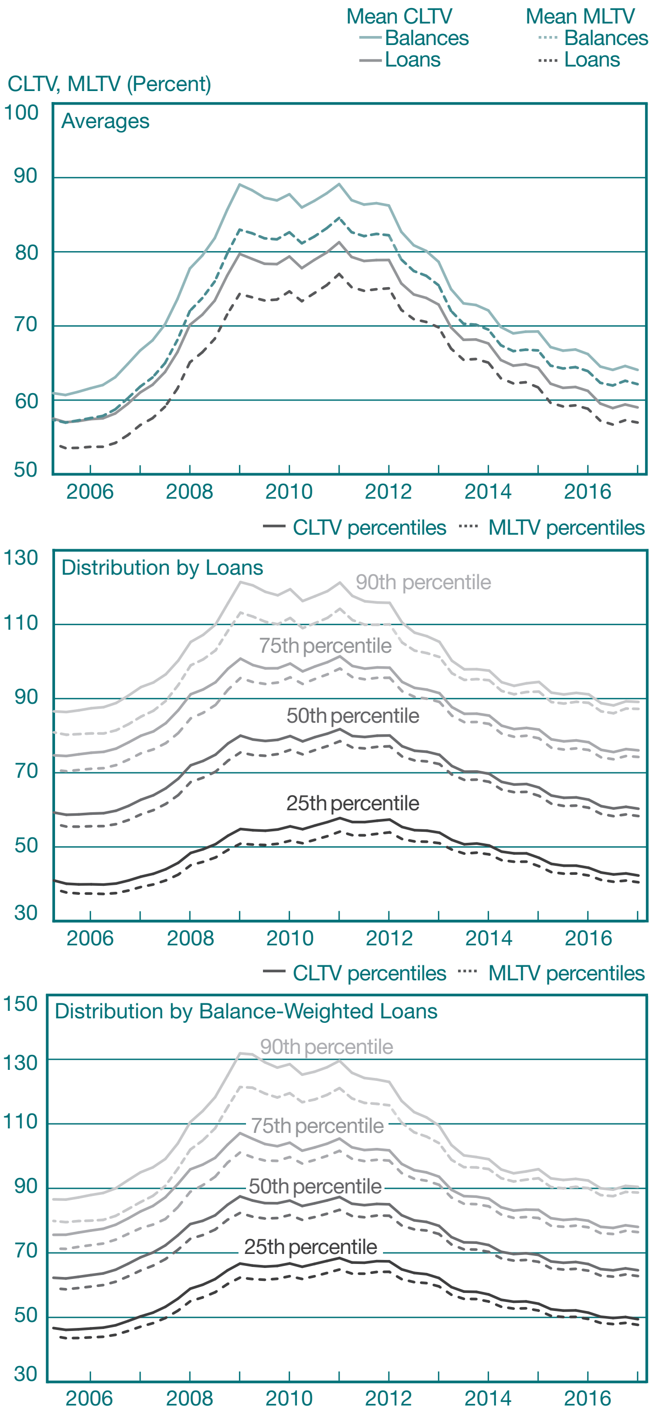
and MLTVs (dotted lines), which include only the first mortgage. The largest difference occurs in the first quarter of 2009, when second-lien balances were adding 5.1 percentage points (or 6 percent) to mean (balance-weighted) leverage.

The middle and bottom panels of Chart 3 show the 25th, 50th, 75th, and 90th percentiles 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 CLTV was around 60 percent, yet already the top decile of borrowers had CLTVs of around 90 percent. 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.

[23] Our estimates of aggregate debt balances differ slightly from those reported in the New York Fed's *Quarterly Report on Household Debt and Credit* (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 percent of total balances outstanding (according to the HHDC) over our sample period.

Chart 3

Nationwide Distribution of Leverage, 2005-17

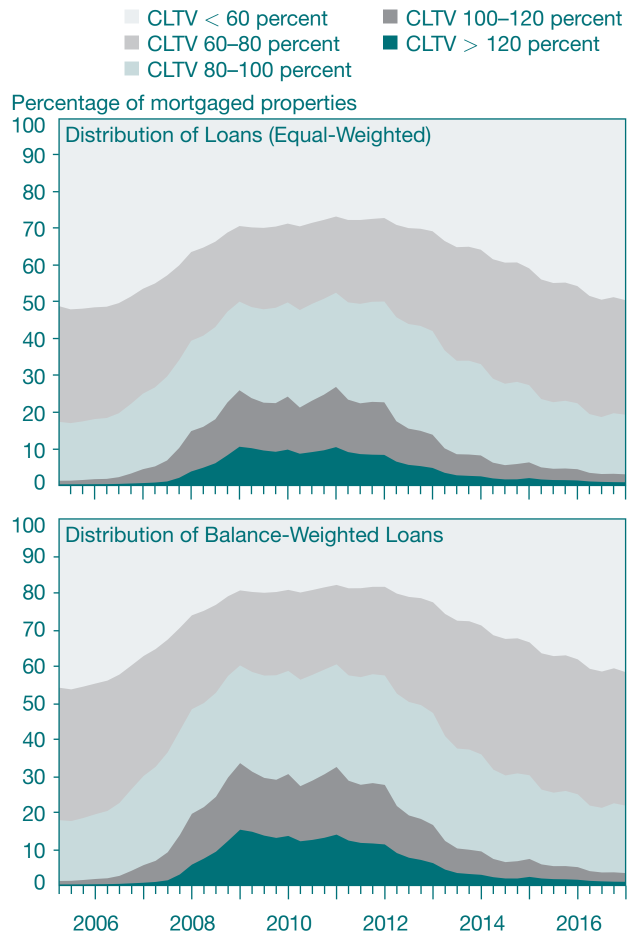


Source: Equifax Credit Risk Insight Servicing McDash (CRISM).

Notes: CLTV is combined loan-to-value ratio, as defined in Section 2.1 of this article. MLTV is mortgage loan-to-value ratio, including first-lien mortgage debt only. Solid lines reflect CLTVs at the specified percentile of the distribution. Dashed lines reflect MLTVs at the specified percentile of the distribution.

Chart 4

Nationwide Distribution of CLTVs for Properties with a First Mortgage, 2005-17



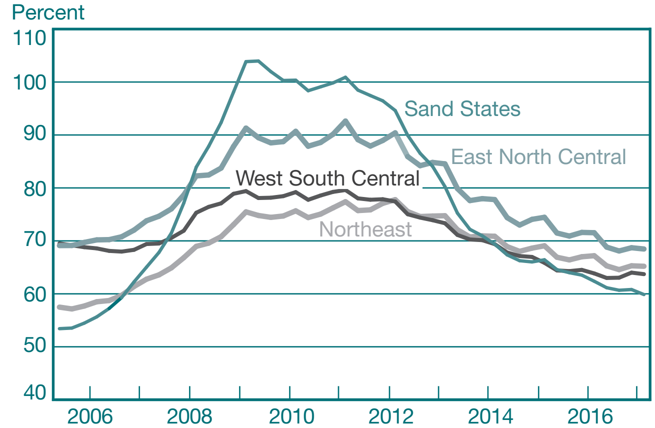
Source: Equifax Credit Risk Insight Servicing McDash (CRISM).

Note: CLTV is combined loan-to-value ratio, as defined in Section 2.1 of this article.

Chart 4 directly shows the share of loans (the top panel) or balances (the bottom panel) 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 who are in negative equity or "underwater" (in other words, CLTV above 100 percent). The chart indicates that almost no properties were in negative equity at the start of the data set in the second quarter of 2005. Toward the end of 2006, the proportions in negative equity started to increase rapidly as house prices started falling. By the second quarter of 2008, we estimate that 16 percent of loans accounting for 21 percent of balances were in negative equity—more than ten times the proportions two years earlier and triple the figure only a year before. These proportions continued to rise, peaking at 26 percent of loans and 33 percent of balances in the first quarter of 2009 before remaining stubbornly close to those levels for a couple of years, with some volatility as a result of seasonality in house prices as well as potential noise owing to relatively few transactions taking place. CLTVs started falling in the fourth quarter of 2011 as house prices started to rise. This process has continued to the latest available data from the first quarter of 2017, showing a negative equity share of 3.1 percent on an equal-weighted basis and 3.4 percent balance-weighted, levels not seen since late 2006. The proportions near negative equity have also been declining and are now near their 2006 levels; as of the first quarter of 2017, the balance-weighted shares of properties with CLTV above 90 percent and above 80 percent are at 10.4 percent and 21.8 percent, respectively.

Chart 5

Mean CLTV for Selected Regions, 2005-17



Source: Equifax Credit Risk Insight Servicing McDash (CRISM).

Note: CLTV is combined loan-to-value ratio, as defined in Section 2.1 of this article.

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 region, given the substantial heterogeneity in the evolution of house prices and borrowing observed during the boom over the first half of the 2000s and the bust that followed.

Chart 5 and Chart 6 show the evolution of average CLTVs and the balance-weighted fraction of loans with CLTV above 0.8, 1.0, or 1.2, for different groups of U.S. states:

1. "Sand states": Arizona, California, Florida, Nevada
2. "East North Central" census division: Illinois, Indiana, Michigan, Ohio, Wisconsin
3. "West South Central" census division: Arkansas, Louisiana, Oklahoma, Texas
4. "Northeast" census region: Connecticut, Massachusetts, Maine, New Hampshire, New Jersey, New York, Pennsylvania, Rhode Island, Vermont

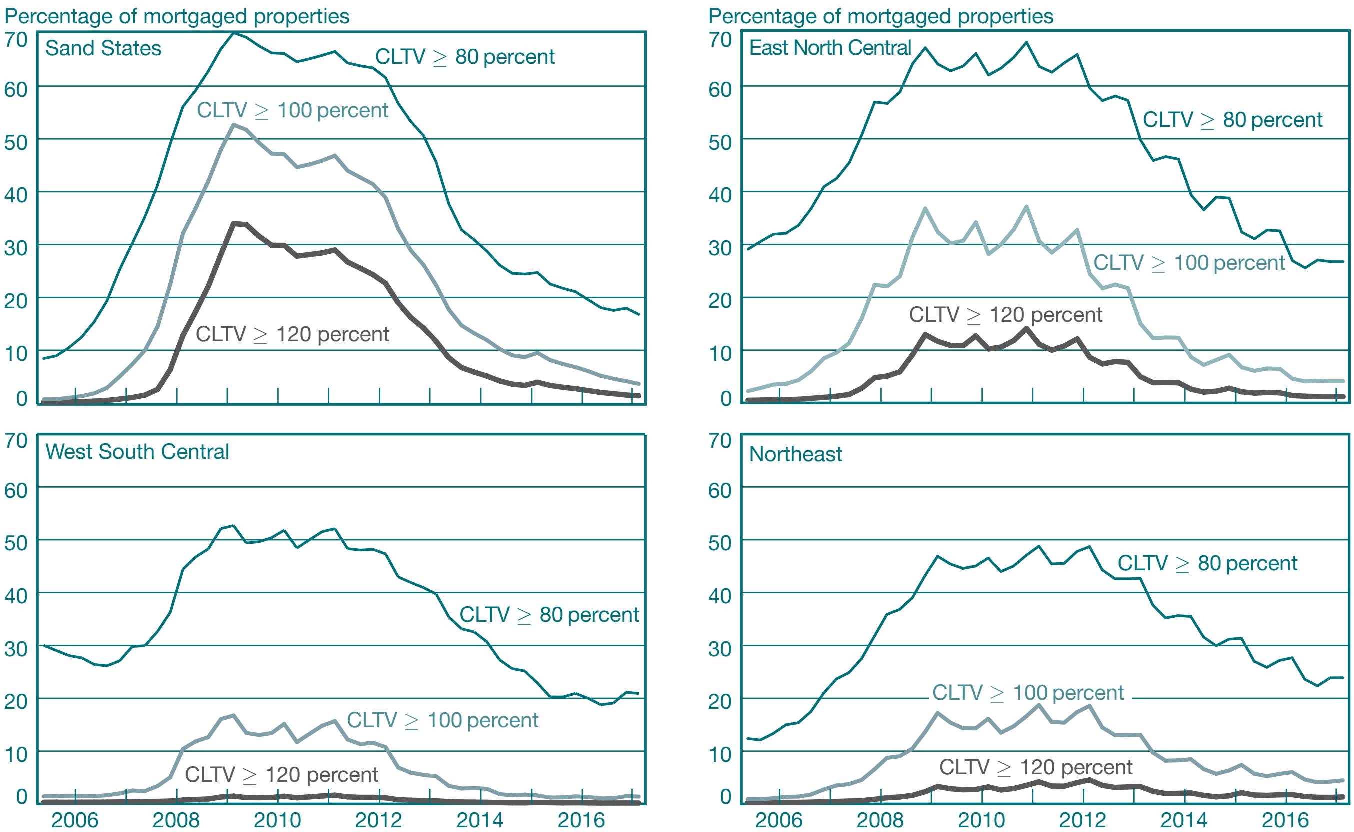
The charts illustrate that the time series patterns of leverage across these groups of states display substantial variation. Most strikingly, at the beginning of our sample period, leverage is lowest in the sand states, which had been experiencing rapid house price growth. Even though many homeowners were actively cashing out home equity, this house price growth meant that only a few of them had high CLTVs: According to our estimates, the balance-weighted share of properties with CLTV above 80 percent was only about 8 percent as of mid-2005. However, once house prices started falling, this fraction rapidly increased, peaking near 70 percent, whereas the fraction of underwater homes (CLTV above 100 percent) exceeded 50 percent at its peak in 2009.

In the East North Central 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 above 80 percent 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 of greater than 120 percent) 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 West South Central states provide a stark contrast to the previous two groups: While the fraction of loans with CLTV above 80 percent 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 percent.[24] Even more important, the fraction of underwater borrowers never rose above 17 percent, and there were essentially no severely underwater borrowers.

[24] One potential explanation as to 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 percent. See Kumar (2014) for additional discussion and evidence on the default-reducing effects of these restrictions.

Chart 6
Distribution of CLTVs for Selected Regions, 2005-17



Source: Equifax Credit Risk Insight Servicing McDash (CRISM).

Notes: All distributions are balance-weighted. CLTV is combined loan-to-value ratio, as defined in Section 2.1 of this article.

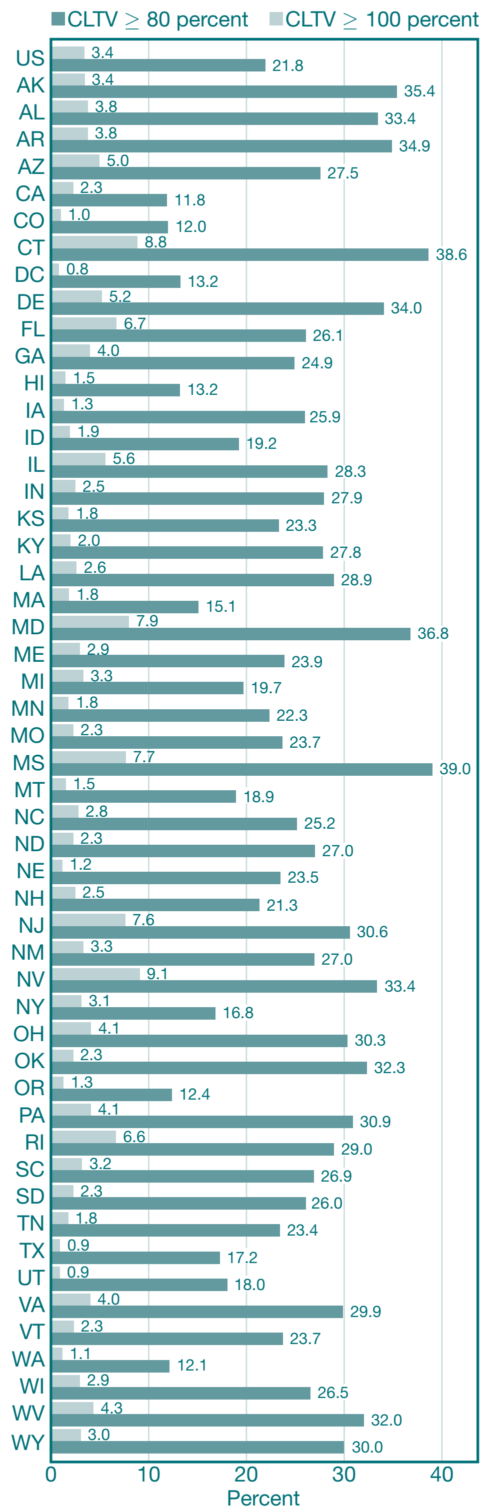
Finally, the time series pattern of CLTVs in the Northeast is in the middle compared with the other groups: Leverage never increased to levels as high as in the most cyclical areas, but the fraction of underwater borrowers nevertheless was around 15-20 percent for a substantial period and has been decreasing more gradually than elsewhere (possibly reflecting the 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 such as the ones we discuss in the next section.

As a first step to this forward-looking exercise, Chart 7 displays the proportion of households that we estimate to be in or near negative equity as of the first quarter of 2017, by state. Chart 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, perhaps surprisingly, Connecticut and Maryland. Among the states worst hit by the bust, California has made the strongest recovery owing to rapid house price increases; we estimate that as of the first quarter of 2017, only 2.3 percent of California borrowers are underwater and only 11.8 percent have a CLTV above 80 percent (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

Chart 7
Share of Mortgages with CLTV ≥ 80 Percent and CLTV ≥ 100 Percent, by State, as of 2017:Q1



Source: Equifax Credit Risk Insight Servicing McDash (CRISM).

Notes: The chart shows the estimated balance-weighted share of properties with positive first mortgage debt as of 2017:Q1 and the specified CLTV. CLTV is combined loan-to-value ratio.

heterogeneity in the extent of the recovery, as can be seen in Chart 8: The states that are farther 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.

Comparison with Other Estimates

We are able to benchmark our regional estimates against external negative equity estimates provided by CoreLogic and Zillow.[25] These firms use different data sets and empirical methodologies than we do, and therefore, we would not expect their estimates to exactly match ours. Chart 9 compares our estimated fractions of loans with a CLTV above 80 percent and a CLTV above 100 percent in the first quarter of 2016 to those published by CoreLogic and Zillow. We see that our estimated fractions of underwater loans are systematically lower than those from the other sources (especially Zillow's). However, our estimated shares of loans with CLTV of greater than 80 percent tend to be much closer, suggesting that the differences in underwater fractions may stem from relatively small differences in estimated home valuations that can put borrowers just above or below the 100 percent CLTV threshold.

Also, we note the high correlation between our estimates and those from the other sources: For the share of loans with CLTV above 80 percent, the correlations are 0.72 between our estimates and Zillow's and 0.86 between our estimates and CoreLogic's; for the share of loans with CLTV above 100 percent, the respective correlations are 0.59 and 0.90. The results of this external benchmarking are therefore encouraging as validation of our methodology.

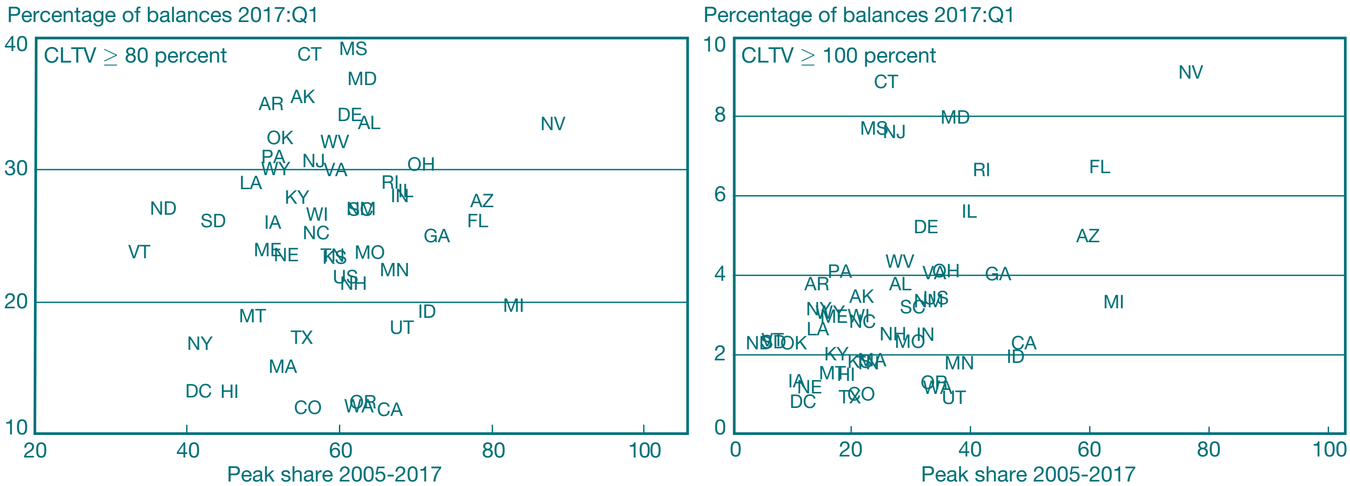
3.3 Delinquencies

One of the primary reasons it is important to track leverage is the strong correlation between a borrower's leverage and their propensity to become seriously delinquent. Chart 10 shows the fraction of loans in different CLTV bands that are seriously (ninety days or more) delinquent over the

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

Chart 8

Share of Properties with a First Mortgage and CLTV ≥ 80 Percent or ≥ 100 Percent, by State, 2017:Q1 versus Peak Share over 2005-17

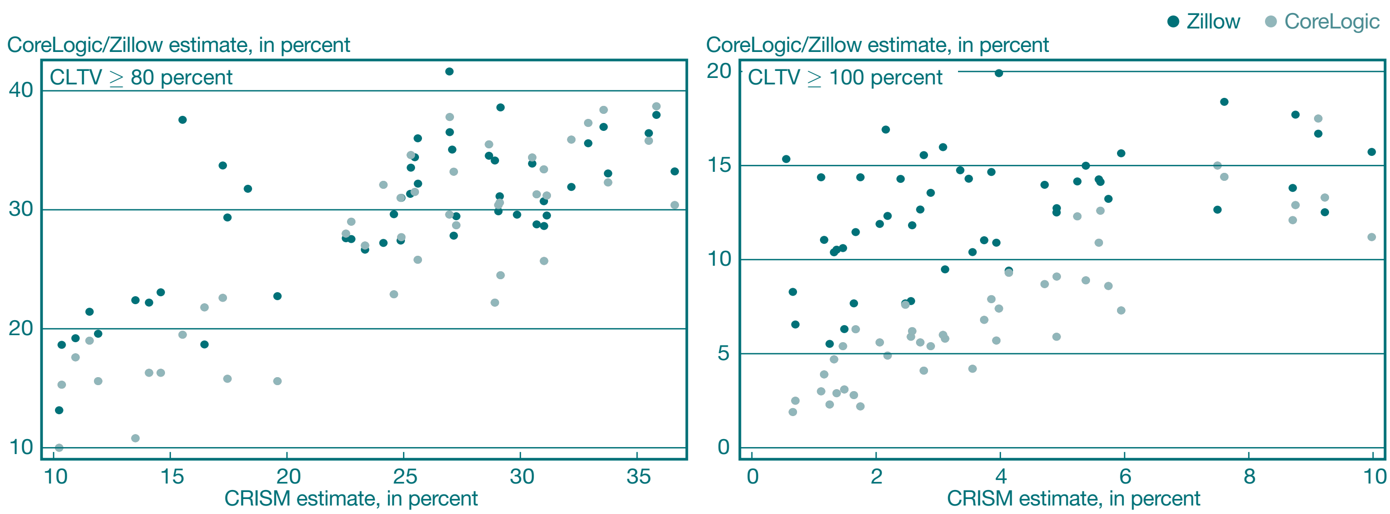


Source: Equifax Credit Risk Insight Servicing McDash (CRISM).

Notes: The chart shows the estimated balance-weighted share of properties with positive first mortgage balances. Peak share is the maximum percentage of balances with CLTV ≥ 80 (left panel) or CLTV ≥ 100 (right panel) over the period 2005:Q2–2017:Q1. CLTV is combined loan-to-value ratio, as defined in Section 2.1 of this article.

Chart 9

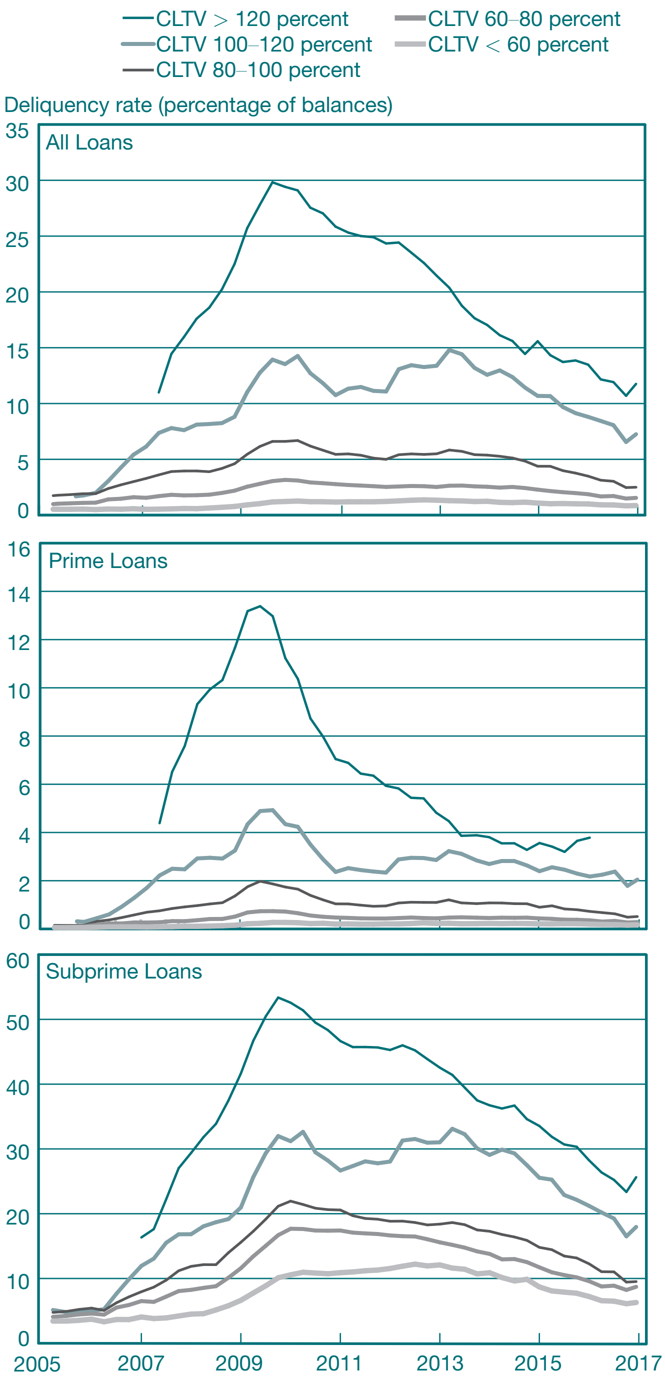
Share of Properties with a First Mortgage and CLTV ≥ 80 percent or ≥ 100 percent, Compared with CoreLogic and Zillow Estimates, by State, as of 2016:Q1



Sources: Equifax Credit Risk Insight Servicing McDash (CRISM); Zillow; CoreLogic.

Notes: Zillow and CoreLogic estimate the percentage of properties with negative equity, so we compare this estimate with our estimates of loans rather than the balance-weighted estimates we use in the rest of the article. CLTV is combined loan-to-value ratio, as defined in Section 2.1 of this article.

Chart 10
Nationwide Serious Delinquency Rates by CLTV Bucket, 2005-17



Source: Equifax Credit Risk Insight Servicing McDash (CRISM).

Notes: Serious delinquency is defined as ninety days delinquent or worse. Charts only include CLTV buckets representing at least 1 percent of total balances. Rates for all loans (top panel) are balance-weighted. Prime loans are those with twelve-month lagged FICO ≥ 660. Subprime loans are those with twelve-month lagged FICO < 660. CLTV is combined loan-to-value ratio, as defined in Section 2.1 of this article.

time period covered by our data (2005-17). We note the strong relationship between CLTV and delinquency; for instance, the delinquency rate for loans with estimated CLTVs above 120 percent peaked at 30 percent, whereas for loans with CLTVs between 80 percent and 100 percent, the rate peaked at around 7 percent. We also note that there is time series variation of delinquency within a CLTV band (especially for the highest CLTV category). This variation could occur for a number of 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 the exit of loans from the sample because of foreclosure (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 described earlier, evidence suggests that "liquidity shocks" such as job losses are an important trigger for default. Since borrowers' current 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 data set is that the FICO score is observed not just at the time of loan origination but throughout the life of the loan. In the middle and bottom panels of Chart 10, we show serious delinquency rates by CLTV band separately for "prime" and "subprime" borrowers, where we define the latter as having a twelve-month lagged FICO score of below 660. We use the lagged FICO score because using the contemporaneous FICO would mechanically lead to a correlation with delinquency (since entering delinquency leads to a drop in the borrower's FICO score). The chart 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, the CLTV remains a strong predictor of delinquency.

Given this strong relationship between CLTV, FICO score, and delinquency, it is important to track not only the distribution of leverage but also its correlation with FICO scores. In Table 1, we do so for different CLTV and FICO buckets, focusing on non-seriously-delinquent loans (meaning those that are current or less than ninety days past due). We see that the balance-weighted fraction of loans for which the borrower has a low current FICO score is much lower now than it was before and during the crisis. For instance, as of the first quarter of 2017, less than 14 percent of borrowers in nondelinquent loans have current FICO scores below 660, whereas from 2005 to 2010, this number was around 20 percent. Similarly, conditional on being underwater (CLTV above 100 percent),

Table 1

Percentage Share of Non-Seriously-Delinquent Balances by CLTV-FICO Bucket, 2005:Q3 – 2017:Q1

2006:Q1	CLTV				
FICO Score	< 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	CLTV				
FICO Score	< 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	CLTV				
FICO Score	< 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	CLTV				
FICO Score	< 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	CLTV				
FICO Score	< 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	CLTV				
FICO Score	< 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	

2017:Q1	CLTV				
FICO Score	< 80%	80-100%	100-120%	> 120%	Subtotal
< 600	4.1	1.4	0.3	0.1	5.9
600-659	5.1	2.2	0.4	0.1	7.8
660-699	7.7	3.0	0.4	0.2	11.3
700-739	10.9	3.4	0.4	0.2	14.9
≥ 740	50.8	8.1	0.8	0.3	60.0
Subtotal	78.6	18.3	2.2	0.9	

Source: Equifax Credit Risk Insight Servicing McDash (CRISM).

Notes: Non-seriously-delinquent refers to loans that are current or less than ninety days past due. FICO and CLTV are measured as of the date for each table. CLTV is combined loan-to-value ratio, as defined in Section 2.1 of this article.

the share of loans with current FICO scores below 660 is somewhat lower than it was during the crisis; as of the first quarter of 2017, it is at 28 percent, compared with 36 percent in the first quarter of 2008 and 31 percent in the first quarter of 2010 (all fractions are balance-weighted). This suggests that there is 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

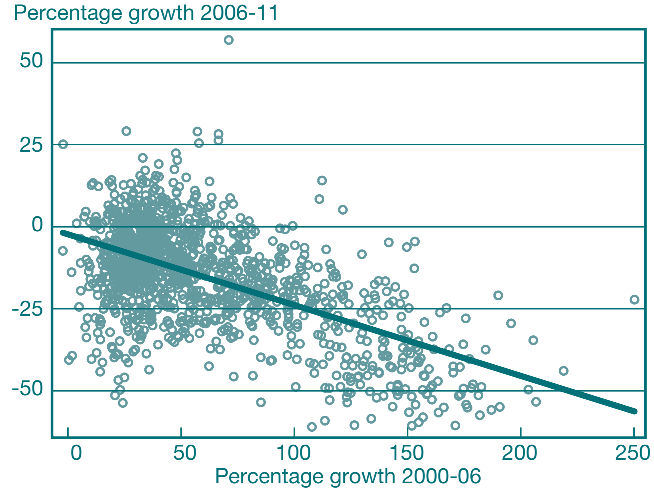
Understanding how the current stock of outstanding mortgage debt would be affected by a downturn in house prices can provide valuable insight into how the household and banking sectors, and thus the economy as a whole, would be affected by such an event. To "stress-test" the mortgage-borrowing households, we first construct simple scenarios for house prices and apply them 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 the parts of the country that 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 nonlinear, meaning that heuristic rules such as "an X percent drop in house prices would increase every borrower's CLTV by X percentage points" tend to give misleading results.[26] 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 price scenarios we consider are local, rather than uniform across the United States, reflecting the substantial heterogeneity in house price volatility across different markets. Rather than attempting to construct house price scenarios based on some measure of local fundamentals or on valuation measures such as price-to-rent ratios, we simply consider the possibility of a reversal of house prices to their level of two or four years ago. This assumption of a reversal in recent growth is based on experience during the financial crisis, where local house

Chart 11
County-Level House Price Growth, 2006-11 versus 2000-06



Source: CoreLogic.

Notes: The correlation coefficient is -0.57. The chart compares the change in house prices from June 2006 to June 2011 with the change from January 2000 to June 2006.

price changes over 2006-11 were strongly negatively correlated with the changes over 2000-06, as illustrated in Chart 11. 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, three and a half years before the peak.[27] As of the first quarter of 2017, a return of prices to their level of four years ago is a particularly 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" decline in house prices from January 2000 to today.[28] This scenario proves to be especially harsh for regions where house prices have not recovered from their troughs. However, it is arguably more realistic for areas of the country where house prices have substantially recovered

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

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

[28] This scenario is bounded such that any region that experienced only house price growth has its home values unchanged.

Table 2

Distribution of Assumed House Price Changes, in Percent, under Different Shock Scenarios, by Starting Quarter

	HPI Two Years Ago			HPI Four Years Ago		
	10th Percentile	50th Percentile	90th Percentile	10th Percentile	50th Percentile	90th Percentile
2006:Q1	-34.4	-18.4	-6.4	-51.0	-31.2	-11.6
2007:Q1	-20.7	-8.6	1.9	-43.1	-27.1	-9.7
2008:Q1	-4.9	7.1	36.5	-26.7	-11.2	5.3
2009:Q1	4.2	19.9	70.4	-8.7	10.8	52.9
2010:Q1	2.7	13.9	39.6	1.3	20.6	89.4
2011:Q1	-0.6	5.4	16.2	7.4	28.5	88.3
2012:Q1	-2.3	4.3	12.1	3.4	19.2	45.3
2013:Q1	-15.7	-6.5	1.3	-12.8	-0.4	12.4
2014:Q1	-24.7	-12.1	-3.3	-22.3	-9.0	3.0
2015:Q1	-18.7	-11.1	-3.4	-31.7	-15.6	-3.3
2016:Q1	-15.4	-8.7	-1.8	-34.4	-20.1	-6.4
2017:Q1	-15.6	-9.6	-3.3	-30.7	-19.9	-7.2

Peak to Trough		
10th Percentile	50th Percentile	90th Percentile
-51.8	-25.9	-10.5

Sources: CoreLogic; Equifax Credit Risk Insight Servicing McDash (CRISM).

or even reached new peaks.[29] Another reason why aggregate leverage and delinquency may be overstated by this scenario is that we assume the peak-to-trough 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). Table 2 displays the 10th, 50th, and 90th percentiles of assumed house price changes across scenarios and how they would have changed over time if applied to historical outstanding debt. The "harshness" of the scenarios varies substantially, both over time and in the cross section of outstanding loans at a point in time. This variation, of course, reflects the differential house price growth in different areas and time periods. Note also that these scenarios (except for peak to trough) 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.

[29] Out of 1,306 counties for which we have HPIs, 45 percent reached their (nominal) peak in 2017, and another 30 percent are within 10 percent of their peak HPI level (data as of mid-2017).

Table 3 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 (first quarter of 2017). In Panel A, the first column shows that across the United States, we estimate that 3 percent of borrowers (balance-weighted) are underwater while 78 percent have a CLTV below 80 percent. However, the following two columns illustrate that if house prices reverted to their level of two or four years ago, the share of underwater properties would increase quite dramatically, to 9 percent and 21 percent, 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 38 percent of borrowers would be underwater, many of them substantially so, and only 38 percent would have a CLTV below 80. Unsurprisingly, this outcome 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 previously 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 the first quarter of 2017), all states

Table 3

Effects of Different House Price Scenarios on CLTV Distribution, 2017:Q1

Panel A: Aggregate

	Scenario			
CLTV	HPI as of 2017:Q1	HPI Two Years Ago	HPI Four Years Ago	Peak to Trough
< 80	78	65	49	38
80-90	11	16	17	12
90-100	7	10	14	12
100-120	2	7	15	18
> 120	1	2	6	20

Panel B: State-Level Estimated Fraction of Borrowers in Negative Equity

	Base	HPI Two Years Ago	HPI Four Years Ago	Peak to Trough	Highest Level since 2005
US	3	9	21	37	33
AK	3	7	13	18	21
AL	4	9	16	34	28
AR	4	9	11	18	14
AZ	5	15	31	79	59
CA	2	7	23	44	48
CO	1	9	24	10	21
CT	9	10	11	49	25
DC	1	3	10	4	11
DE	5	10	16	48	32
FL	7	18	35	75	61
GA	4	13	32	44	44
HI	1	6	15	15	19
IA	1	7	13	8	10
ID	2	14	24	56	47
IL	6	11	25	56	39
IN	2	8	16	27	32
KS	2	6	14	17	21
KY	2	8	14	13	17
LA	3	6	13	14	14
MA	2	6	14	21	23
MD	8	13	20	56	37
ME	3	7	15	27	16
MI	3	11	32	60	63
MN	2	9	22	40	37

Table 3, Panel B, *Continued*

	Base	HPI Two Years Ago	HPI Four Years Ago	Peak to Trough	Highest Level since 2005
MO	2	8	18	30	29
MS	8	8	13	34	23
MT	2	6	14	13	16
NC	3	8	15	20	21
ND	2	4	20	4	4
NE	1	8	15	7	12
NH	2	8	15	29	26
NJ	8	9	13	45	27
NM	3	8	13	43	32
NV	9	23	49	88	76
NY	3	5	10	15	14
OH	4	11	24	35	35
OK	2	5	12	7	10
OR	1	10	28	27	33
PA	4	8	11	22	17
RI	7	16	26	59	41
SC	3	10	21	29	30
SD	2	8	19	5	6
TN	2	10	20	16	22
TX	1	7	20	11	19
UT	1	11	26	38	37
VA	4	7	14	48	33
VT	2	5	6	13	6
WA	1	10	25	25	34
WI	3	9	15	26	21
WV	4	11	17	43	27
WY	3	5	15	20	16

Source: Equifax Credit Risk Insight Servicing McDash (CRISM).

Notes: All figures are balance weighted. CLTV is combined loan-to-value ratio. HPI is home price index. The base scenario assumes that house prices stay constant at the level of the as-of date. HPI two and four years ago assume local house prices return to those levels. Peak to trough assumes local house prices experience a decline similar to their peak-to-trough drop since 2005, measured at the local (mostly county) level.

have estimated balance-weighted underwater shares below 10 percent; the regional patterns were already discussed above (in the context of Chart 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 the first quarter of 2015, we estimate that Nevada would return to a high underwater share of 23 percent, whereas in Connecticut (which has a similar current underwater fraction), the share would go to only 10 percent. If house prices were to return to their levels of four years ago, the sand states would see their underwater fractions soar again, with Nevada at 49 percent, Florida at 35 percent, Arizona at 31 percent, and California at 23 percent. Other states where underwater shares would rise substantially include Georgia and Michigan.

The fourth column in Panel B 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 Table 4 on pages 22-23, 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 the first quarter of 2006, right before (national) house prices peaked. The first column of Panel A illustrates that, as we also saw earlier, leverage at then-current house prices was generally modest and hardly any borrowers were underwater. However, the second and third columns illustrate that if one had considered a return of house prices to their levels of two or four years earlier, one could have predicted that CLTVs would become much higher and that a substantial fraction of borrowers would end up underwater: 19 percent if house prices went back to their level in the first quarter of 2004 and 40 percent if they went back to their level in the first quarter of 2002. The latter estimate is quite close to the peak nationwide negative equity share in our data of 33 percent (with the overestimate coming from the fact that house prices did not end up falling quite to the level seen in the first quarter of 2002).

Panel B repeats this analysis at the state level, looking at underwater fractions. We see that these scenarios of house price reversals would have correctly identified some states that indeed later 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 other 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 fractions during the bust is 0.61 for the "HPI two years ago" scenario and 0.48 for the "HPI four years ago" scenario. The two-year scenario understates average realized peaks during the bust, while the four-year scenario slightly overstates them; nevertheless, considering these scenarios as of the first quarter of 2006 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 them, one would have come very close, on average, to forecasting the realized underwater fractions (the correlation is 0.96).[30] This result is, of course, not surprising but is nevertheless useful in validating our methodology.

[30] States with relatively larger divergences tend to be those where house prices started falling the latest.

4.2 Stress-Testing Part II: Predicting Delinquencies

Next, we want to predict the effect that different house price scenarios would have on the delinquencies of currently outstanding loans. Doing so requires calculating delinquency transition rates to apply to our data. Significant uncertainty is associated with calculating such rates, since they are highly variable over time even for given observed loan characteristics (and macroeconomic conditions). Rather than parametrically modeling the relationship between loan characteristics and delinquency rates, for simplicity and transparency, we use a simple nonparametric approach.[31]

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

We calculate the transition rates for loans that are outstanding in 2007-08, meaning that we follow them until 2009-10.[32] The resulting transition rates are shown in Chart 12, where all fractions are balance-weighted within each cell. The matrix indicates that, for instance, a borrower with an updated FICO score below 600 at the beginning of the observation period had a 55 percent probability of transitioning into serious delinquency if his estimated updated CLTV at the end of the observation period was over 120 percent, but a much lower probability of 16 percent if his updated CLTV was below 80 percent. 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 Section 4.1. Essentially, we recalculate the distribution matrices shown in Table 1 under the three alternative house price scenarios

[31] Our approach is related to Li and Goodman's (2014) method of tracking the riskiness of originated mortgages over time.

[32] We conduct the analysis for each month from January 2007 to December 2008, and then take an equal-weighted average of transition probabilities over those twenty-four months. We purposefully choose to focus on the highest-delinquency period over the bust to make our projections conservative.

Chart 12

Transition Rates of Loans into Serious Delinquency by CLTV-FICO Bucket, in Percent

FICO \ CLTV	< 80%	80–100%	100–120%	> 120%
< 600	16.2	28.6	37.2	54.6
600–659	8.3	17.1	25.4	43.9
660–699	4.4	10.6	17.4	34.0
700–739	2.4	6.9	12.3	25.7
≥ 740	0.6	2.8	6.1	15.3

Source: Equifax Credit Risk Insight Servicing McDash (CRISM).

Notes: Rates are derived from loans that start out non-seriously-delinquent (meaning current or less than ninety days past due) over 2007-08 and are then followed for twenty-four months. Rates are balance-weighted within each cell. See text for details. CLTV is combined loan-to-value ratio.

described above (but holding current FICO scores fixed) and then multiply these matrices by the transition matrix from Chart 12 to get the predicted delinquency transition rate (obtained by taking the sum across all cells).[33]

The resulting projections at the economy-wide level, and their change over time, are shown in Chart 13. For instance, as of the first quarter of 2017, our method projects that under unchanged house prices, 4.2 percent of mortgage balances will transition over the following twenty-four months under a "baseline" scenario of unchanged home prices. (Note that this is almost certainly an overstatement; we discuss the reasons below.) If house prices were to go back to their level of two years earlier, the delinquency transition rate is predicted to be 1 percentage point (or 24 percent) higher, while house prices falling back to their levels in the first quarter of 2013 would lead to predicted delinquency transitions of 7.0 percent, or 67 percent higher than under the base scenario. Finally, a repetition of the peak-to-trough decline in home prices is predicted to lead to a 9.9 percent transition rate to serious delinquency, more than twice what it is under the baseline.

The chart illustrates that over the past five years, the portfolio of outstanding mortgages seems to have become more resilient under either constant home prices or the peak-to-trough drop (which is also held constant over time within each location). This increase in resiliency has occurred thanks to the realized home price growth, which has improved households' equity position, and also to the improvement in mortgagors' credit scores. At the same time, the vulnerability to a reversal in home prices (to their level of four years earlier) has remained relatively constant over time, as illustrated in the third column—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 Table 2).

Chart 14 shows the distribution of predicted delinquency transitions across states as of the first quarter of 2017. 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 of two or four years ago, or if they suffered another peak-to-trough drop, however, the dispersion across states would be substantial, with the

[33] 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 Table 1.

Chart 13

Serious Delinquency Forecasts by Forecast Date and House Price Scenario

	Delinquency Rate (Percentage of Balances)			
Forecast Start Date	Base	HPI Two Years Ago	HPI Four Years Ago	Peak to Trough
2012:Q1	8.8	8.0	5.7	16.0
2012:Q2	7.9	7.6	5.9	15.1
2012:Q3	7.5	7.7	6.1	14.8
2012:Q4	7.4	8.0	6.8	14.7
2013:Q1	7.1	8.3	7.3	14.7
2013:Q2	6.3	7.9	7.1	13.3
2013:Q3	5.9	7.8	7.0	12.8
2013:Q4	5.8	8.0	7.0	12.8
2014:Q1	5.7	8.0	7.2	12.6
2014:Q2	5.2	7.1	6.9	11.8
2014:Q3	5.0	6.8	7.1	11.6
2014:Q4	5.1	6.8	7.5	11.7
2015:Q1	4.9	6.5	7.8	11.4
2015:Q2	4.6	5.8	7.4	10.7
2015:Q3	4.5	5.5	7.6	10.6
2015:Q4	4.5	5.5	7.8	10.7
2016:Q1	4.4	5.3	7.8	10.4
2016:Q3	4.2	5.2	7.2	10.0
2017:Q1	4.2	5.2	7.0	9.9

Source: Equifax Credit Risk Insight Servicing McDash (CRISM).

Notes: The chart shows forecasts of transition rates into serious delinquency in the twenty-four months following the forecast date. Serious delinquency is ninety or more days past due. HPI is home price index. The base scenario assumes that house prices stay constant at the level of the as-of date. HPI two and four years ago assume that local house prices return to those levels. Peak to trough assumes that local house prices experience a drop similar to their peak-to-trough decline during the period since 2005, measured at the local (mostly county) level.

Table 4

Effects of Different House Price Scenarios on CLTV Distribution, 2006:Q1 (before House Price Decline)

Panel A: Aggregate

	Scenario			
CLTV	HPI as of 2006:Q1	HPI Two Years Ago	HPI Four Years Ago	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

Panel B: State-Level Estimated Fraction of Borrowers in Negative Equity

	Base	HPI Two Years Ago	HPI Four Years Ago	Peak to Trough	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

Table 4, Panel B, *Continued*

	Base	HPI Two Years Ago	HPI Four Years Ago	Peak to Trough	Max Crisis
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

Source: Equifax Credit Risk Insight Servicing McDash (CRISM).

Notes: All figures are balance weighted. CLTV is combined loan-to-value ratio. HPI is home price index. The base scenario assumes that house prices stay constant at the level of the as-of date. HPI two and four years ago assume local house prices return to those levels. Peak to trough assumes local house prices experience a decline similar to their peak-to-trough drop since 2005, measured at the local (mostly county) level.

sand states Arizona, Nevada, and Florida being among the most vulnerable, along with Georgia, Michigan, and West Virginia.

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, 4.2 percent of current mortgage balances will transition into serious delinquency in the next twenty-four months. This figure is above the rate of delinquency transitions shown, for example, in the New York Fed's *Quarterly Report on Household Debt and Credit*, primarily because we use transitions from the worst period of mortgage delinquency in modern history: 2007 to 2010. As described above, conditional

Chart 14

Forecasts of Serious Delinquency Transition Rates, in Percent, by State and Scenario, as of Q1:2017

	Base	HPI Two Years Ago	HPI Four Years Ago	Peak to Trough
US	4.2	5.2	7.0	9.9
AK	4.8	5.3	5.9	6.5
AL	5.6	6.6	7.6	10.1
AR	5.4	6.1	6.4	7.3
AZ	4.6	5.9	8.3	18.0
CA	3.1	4.0	6.5	10.3
CO	2.9	4.1	6.3	4.3
CT	5.5	5.7	6.0	11.3
DC	2.9	3.5	4.2	3.6
DE	5.4	6.1	6.9	11.6
FL	5.4	7.2	10.3	18.6
GA	5.2	6.7	10.0	12.2
HI	3.1	3.7	5.2	5.2
IA	3.9	4.8	5.5	4.9
ID	3.8	5.5	7.3	12.8
IL	4.7	5.7	7.6	12.6
IN	5.1	6.1	7.2	8.6
KS	4.1	4.9	6.0	6.4
KY	4.9	5.9	6.7	6.6
LA	5.7	6.4	7.4	7.5
MA	3.5	4.3	5.5	6.6
MD	5.9	6.7	7.9	13.9
ME	4.5	5.3	6.4	8.1
MI	4.3	5.6	9.0	14.5
MN	3.5	4.5	6.2	9.0
MO	4.4	5.4	6.8	8.6
MS	7.0	7.2	7.9	11.4
MT	3.5	4.2	5.3	5.3
NC	4.7	5.7	6.8	7.4
ND	3.6	3.9	5.6	3.8
NE	3.6	4.6	5.5	4.5
NH	4.1	5.1	6.1	8.2
NJ	5.0	5.3	6.0	10.9
NM	4.9	5.7	6.4	10.6
NV	5.6	7.5	12.4	21.4
NY	3.8	4.2	5.1	5.9
OH	5.1	6.3	8.0	9.8
OK	5.2	5.7	6.6	6.0
OR	2.9	4.3	6.7	6.8
PA	4.9	5.5	6.0	7.5
RI	5.1	6.5	8.1	14.4
SC	5.0	6.1	7.6	9.0
SD	3.7	4.6	5.8	4.1
TN	4.6	5.9	7.5	6.8
TX	4.4	5.3	7.6	6.0
UT	3.4	4.8	7.0	9.1
VA	4.4	4.9	5.8	11.1
VT	3.8	4.2	4.5	5.5
WA	3.0	4.5	6.8	6.8
WI	4.1	5.1	5.9	7.4
WV	6.0	7.2	8.2	12.3
WY	4.5	4.7	5.9	6.7

Source: Equifax Credit Risk Insight Servicing McDash (CRISM).

Notes: The chart shows twenty-four month balance-weighted forecasts of transition rates into serious delinquency (ninety or more days past due) as of 2017:Q1. The base scenario assumes that house prices stay constant at the level of the as-of date. HPI two and four years ago assume local house prices return to those levels. Peak to trough assumes local house prices experience a decline similar to their peak-to-trough drop since 2005, measured at the local (mostly county) level.

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 our decision to ignore the leverage-reducing effects of loan amortization and our exclusion of loans that are voluntarily prepaid. 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.

For some other sources of uncertainty in our estimates, it is more difficult to say whether they would lead to an upward or downward bias. 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 that 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 way 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:

- Government-sponsored enterprises (GSE): Loans securitized through the GSEs Fannie Mae and Freddie Mac, or held in portfolio by these firms.
- Government: Loans originated through programs run 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 category includes, in particular, many subprime, Alt-A, and jumbo mortgages.
- Portfolio: Loans held in portfolio by financial institutions.

In our (weighted) data, as of the first quarter of 2017, the GSEs have the largest share among outstanding loans, at 56 percent, followed by government (18 percent), portfolio (17 percent), and privately securitized (9 percent). The total outstanding amounts in our data for GSE, government, and privately securitized loans are roughly in line with the amounts cited in other sources (for instance, the statistics compiled by the Securities Industry and Financial Markets Association[34]).

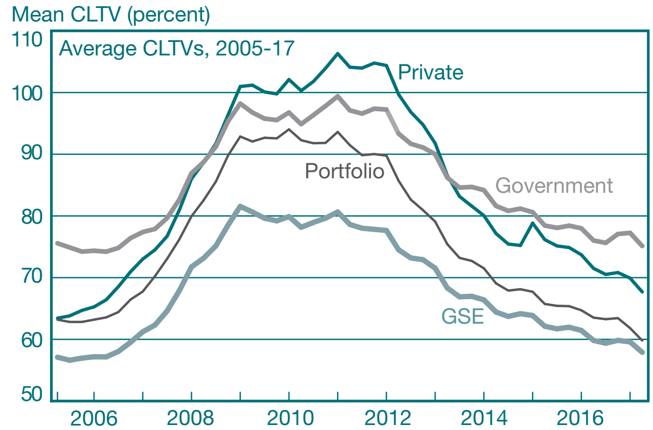
The top panel of Exhibit 1 shows the evolution of average CLTVs across the four funding sources. GSE loans are the least highly levered throughout the sample period, followed by portfolio loans. Government loans (FHA/VA) are generally originated with high LTVs (between 95 and 100 percent), and thus it is not surprising that the average updated CLTV on these loans tends to be at or above 80 percent. 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 2005-09, the average CLTV on these loans increased dramatically, eventually exceeding 100 percent. As house prices have recovered, the average CLTV on the remaining privately securitized loans has fallen quite rapidly and is now back around 70 percent.

The middle panel zooms in on the first quarter of 2017 and looks at the distribution of CLTVs across the four funding types, which reveals interesting patterns that were not reflected in the averages. Of particular note, only about half of all government loans are estimated to be backed by 20 percent equity or more, while even for privately securitized loans, more than 70 percent are now above that threshold. At the same time, however, the share of loans that are underwater (CLTV above 100 percent) is still largest for private loans, at 10 percent. In contrast, only a small share of GSE and portfolio loans are in or near negative equity (approximately 7 percent have a CLTV above 90 percent).

Finally, in the bottom panel we show the delinquency stress-test results as of the first quarter of 2017 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 result is further enhanced by the fact that FICO scores tend to be higher for these loan types than for government and privately securitized loans. Across scenarios, the projected transition into delinquency is more than twice

[34] Available at https://www.sifma.org/resources/research/us-mortgage-related-issuance-and-outstanding/.

Exhibit 1
CLTV Distribution and Delinquencies by Funding Source



CLTV Categories by Funding Source, 2017:Q1

	Funding Source			
CLTV Category	GSE	Government	Portfolio	Private
< 80 percent	85	53	87	71
80–90 percent	9	23	7	12
90–100 percent	4	20	3	8
100–120 percent	2	4	2	6
> 120 percent	1	0	1	4
Share of Total Outstanding	56	18	17	9

Delinquencies in Stress-Testing Scenarios, 2017:Q1

	Scenario			
Funding Source	Base	HPI Two Years Ago	HPI Four Years Ago	Peak to Trough
GSE	3.0	3.7	5.0	7.5
Government	7.6	9.4	12.7	16.6
Portfolio	2.9	3.7	5.3	7.9
Private	7.5	9.0	11.7	15.6

Source: Equifax Credit Risk Insight Servicing McDash (CRISM).

Notes: CLTV is combined loan-to-value ratio, as defined in Section 2.1 of this article. GSE is government-sponsored enterprise. HPI is home price index. The base scenario assumes that house prices stay constant at the level of the as-of date.HPI two and four years ago assume that local house prices return to those levels. Peak to trough assumes that local house prices experience a drop similar to their peak-to-trough decline during the period since 2005, measured at the local (mostly county) level.

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 with "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).

5. Conclusion

In this article, we describe a new methodology for tracking the housing-related leverage of U.S. households. We rely on multiple sources of data that, combined, allow us to study the distribution of leverage over time and across 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 sector's response to a variety of adverse price shocks.

After a substantial increase owing to the housing bust, as of early 2017, 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 declines in house prices, although the higher level of creditworthiness among today's borrowers serves to mitigate that effect.

Since we plan to update and potentially refine our measures going forward, we hope they will be useful to policymakers, businesses, and households alike in assessing housing-related vulnerabilities arising from excessive leverage.

Appendix: Additional Details on CRISM Data

Whereas each McDash loan is 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 New York Fed Consumer Credit Panel (CCP).

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

Since CRISM does not specify the Equifax loan to which a McDash loan is matched (with "Equifax loan" referring to the largest, second-largest, and remainder loans for FM, CES, and HELOC, as described in the preceding paragraph), we construct an algorithm to identify the likely match. 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 again no match is found, the algorithm looks for matches from other observations for the same McDash loan. The result of this algorithm is that 97 percent of the McDash loan observations are matched to an Equifax first mortgage; those that are unmatched (or that are found to closely match 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 is 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:

- the individual's Equifax credit file records a first mortgage other than the McDash mortgage; or
- prior observations for the McDash loan recorded this individual holding a first mortgage other than the current McDash loan.[35]

For observations meeting the above criteria, we would then *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;
- 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;
- 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; or
- 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 a comparison with CCP data indicates that the distribution of second liens relative to first mortgages is plausible.

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

References

Adelino, M., A. Schoar, and F. Severino. 2016. "Loan Originations and Defaults in the Mortgage Crisis: The Role of the Middle Class." Review of Financial Studies 29, no. 7 (July): 1635-70.

Agarwal, S., I. Ben-David, and V. Yao. 2015. "Collateral Valuation and Borrower Financial Constraints: Evidence from the Residential Real Estate Market." Management Science 61, no. 9 (September): 2220-40.

Anderson, G., P. Bunn, A. Pugh, and A. Uluc. 2014. "The Potential Impact of Higher Interest Rates on the Household Sector: Evidence from the 2014 NMG Consulting Survey." Bank of England Quarterly Bulletin (fourth quarter): 358-68.

Anenberg, E., and E. Kung. 2014. "Estimates of the Size and Source of Price Declines Due to Nearby Foreclosures." American Economic Review 104, no. 8 (August): 2527-51.

Beraja, M., A. Fuster, E. Hurst, and J. Vavra. 2015. "Regional Heterogeneity and Monetary Policy." Federal Reserve Bank of New York Staff Reports, no. 731, June.

Bhutta, N., and B. J. Keys. 2016. "Interest Rates and Equity Extraction during the Housing Boom." American Economic Review 106, no. 7 (July): 1742-74.

Bilston, T., R. Johnson, and M. Read. 2015. "Stress-Testing the Australian Household Sector Using the HILDA Survey." Reserve Bank of Australia Research Discussion Paper no. 2015-01, March.

Brevoort, K. P., and C. R. Cooper. 2013. "Foreclosure's Wake: The Credit Experiences of Individuals following Foreclosure." Real Estate Economics 41, no. 4 (Winter): 747-92.

Campbell, J. Y., S. Giglio, and P. Pathak. 2011. "Forced Sales and House Prices." American Economic Review 101, no. 5 (August): 2108-31.

Caplin, A., C. Freeman, and J. Tracy. 1997. "Collateral Damage: Refinancing Constraints and Regional Recessions." Journal of Money, Credit, and Banking 29, no. 4 (November): 496-516.

Claessens, S., G. Dell'Ariccia, D. Igan, and L. Laeven. 2010. "Cross-Country Experiences and Policy Implications from the Global Financial Crisis." Economic Policy 25, no. 62 (April): 267-93.

Corbae, D., and E. Quintin. 2015. "Leverage and the Foreclosure Crisis." Journal of Political Economy 123, no. 1 (February): 1-65.

Dynan, K. 2012. "Is a Household Debt Overhang Holding Back Consumption?" Brookings Papers on Economic Activity (Spring): 299-344.

Eggertsson, G., and P. Krugman. 2012. "Debt, Deleveraging, and the Liquidity Trap: A Fisher-Minsky-Koo Approach." Quarterly Journal of Economics 127, no. 3 (August): 1469-513.

Elul, R., N. S. Souleles, S. Chomsisengphet, D. Glennon, and R. Hunt. 2010. "What 'Triggers' Mortgage Default?" American Economic Review 100, no. 2 (May): 490-94.

Ferreira, F., and J. Gyourko. 2012. "Heterogeneity in Neighborhood-Level Price Growth in the United States, 1993–2009." American Economic Review 102, no. 3 (May): 134-40.

Ferreira, F., and J. Gyourko. 2015. "A New Look at the U.S. Foreclosure Crisis: Panel Data Evidence of Prime and Subprime Borrowers from 1997 to 2012." NBER Working Paper no. 21261, June.

Ferreira, F., J. Gyourko, and J. Tracy. 2010. "Housing Busts and Household Mobility." Journal of Urban Economics 68, no. 1 (July): 34-45.

Ferreira, F., J. Gyourko, and J. Tracy. 2012. "Housing Busts and Household Mobility: An Update." Federal Reserve Bank of New York Economic Policy Review 18, no. 3: 1-15.

Finansinspektionen. 2015. "The Swedish Mortgage Market 2015." Available at http://www.fi.se/en/published/reports/swedish-mortgage-reports/the-swedish-mortgage-market-2015/.

Foote, C. L., K. Gerardi, and P. S. Willen. 2008. "Negative Equity and Foreclosure: Theory and Evidence." Journal of Urban Economics 64, no. 2 (September): 234-45.

Fuster, A., and P. S. Willen. 2017. "Payment Size, Negative Equity, and Mortgage Default." American Economic Journal: Economic Policy 9, no. 4 (November): 167-91

Geanakoplos, J., and L. H. Pedersen. 2014. "Monitoring Leverage." In M. Brunnermeier and A. Krishnamurthy, eds., Risk Topography: Systemic Risk and Macro Modeling. Chicago: University of Chicago Press.

Gerardi, K., K. F. Herkenhoff, L. E. Ohanian, and P. S. Willen. Forthcoming. "Can't Pay or Won't Pay? Unemployment, Negative Equity, and Strategic Default." Review of Financial Studies.

Gerardi, K., E. Rosenblatt, P. S. Willen, and V. Yao. 2015. "Foreclosure Externalities: New Evidence." Journal of Urban Economics 87 (May): 42-56.

Glaeser, E. L., J. D. Gottlieb, and J. Gyourko. 2013. "Can Cheap Credit Explain the Housing Boom?" In E. L. Glaeser and T. Sinai, eds., Housing and the Financial Crisis. Chicago: University of Chicago Press, 301-59.

Glick, R., and K. J. Lansing. 2010. "Global Household Leverage, House Prices, and Consumption." Federal Reserve Bank of San Francisco Economic Letter 2010-01, January.

Haughwout, A., S. Sutherland, and J. Tracy. 2013. "Negative Equity and Housing Investment." Federal Reserve Bank of New York Staff Reports, no. 636, September.

Hsu, J. W., D. A. Matsa, and B. T. Melzer. 2018. "Unemployment Insurance as a Housing Market Stabilizer." American Economic Review 108, no. 1 (January): 49-81

Justiniano, A., G. Primiceri, and A. Tambalotti. 2015. "Household Leveraging and Deleveraging." Review of Economic Dynamics 18, no. 1 (January): 3-20.

Korteweg, A., and M. Sorensen. 2016. "Estimating Loan-to-Value Distributions." Real Estate Economics 44, no. 1 (Spring): 41-86.

Kumar, A. 2014. "Do Restrictions on Home Equity Extraction Contribute to Lower Mortgage Defaults? Evidence from a Policy Discontinuity at the Texas Border." Federal Reserve Bank of Dallas, Working Paper no. 1410.

Lamont, O., and J. C. Stein. 1999. "Leverage and House-Price Dynamics in U.S. Cities." RAND Journal of Economics 30, no. 3 (Autumn): 498-514.

Lee, D., C. Mayer, and J. Tracy. 2012. "A New Look at Second Liens." Federal Reserve Bank of New York Staff Reports, no. 569, August.

Lee, D., and W. van der Klaauw. 2010. "An Introduction to the FRBNY Consumer Credit Panel." Federal Reserve Bank of New York Staff Reports, no. 479, November.

Li, W., and L. Goodman. 2014. "Measuring Mortgage Credit Availability Using Ex-Ante Probability of Default." Urban Institute Research Report.

Low, D. 2015. "Mortgage Default with Positive Equity." New York University working paper.

Melzer, B. 2017. "Mortgage Debt Overhang: Reduced Investment by Homeowners at Risk of Default." Journal of Finance 72, no. 2 (April): 575-612.

Mian, A., K. Rao, and A. Sufi. 2013. "Household Balance Sheets, Consumption, and the Economic Slump." Quarterly Journal of Economics 128, no. 4 (November): 1687-1726.

Mian, A., and A. Sufi. 2010. "Household Leverage and the Recession of 2007-09." IMF Economic Review 58, no. 1: 74-117.

Stein, J. C. 1995. "Prices and Trading Volume in the Housing Market: A Model with Down-Payment Effects." Quarterly Journal of Economics 110, no. 2 (May): 379-406.

Vidangos, I. 2015. "Deleveraging and Recent Trends in Household Debt." Federal Reserve Board of Governors FEDS Notes 2015-04-06.

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