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# Stress Testing Household Debt \*

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## Abstract

We estimate a county-level model of household delinquency and use it to conduct “stress tests” of household debt. Applying house price and unemployment rate shocks from Comprehensive Capital Analysis Review (CCAR) stress tests, we find that forecasted delinquency rates for the recent stock of debt are moderately lower than for the stock of debt before the 2007-09 financial crisis, given the same set of shocks. This decline in expected delinquency rates under stress reflects an improvement in debt-to-income ratios and an increase in the share of debt held by borrowers with relatively high credit scores. Under an alternative scenario where the size of house price shocks depends on housing valuations, we forecast a much lower delinquency rate than occurred during the crisis, reflecting more reasonable housing valuations than pre-crisis. Stress tests using other scenarios for the path of house prices and unemployment also support the conclusion that household debt currently poses a lower risk to financial stability than before the financial crisis.

JEL Codes: D14, E37, G01

Keywords: loan default, stress test, household debt, delinquency

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# 1 Introduction

From 2000 to 2008, nominal debt owed by U.S. households doubled from about \$7 trillion to more than \$14 trillion, driven primarily by an increase in mortgage borrowing. This increase in household indebtedness and subsequent mortgage defaults are thought by many observers to have played an important role in creating the 2007-09 financial crisis and economic recession in the U.S. (e.g. Mian and Sufi [2010, 2014]). Indeed, past crises in the U.S. and elsewhere have often been preceded by a rapid rise in household debt [Jorda et al., 2011]. Because of the potential link between household debt and financial crises, it is important to closely monitor the current levels of risk and susceptibility to economic shocks in the outstanding stock of household debt.

In this paper, we assess risks to the financial system posed by household borrowing. Our “household stress test” is analogous to the stress testing of bank balance sheets, which, since the financial crisis, has become a useful tool for identifying potential vulnerabilities for individual financial institutions. Our stress test yields a summary measure of risk by forecasting serious delinquency rates for outstanding household debt under various economic scenarios. This exercise suggests that the outstanding stock of household debt is somewhat less vulnerable to shocks than in the past. Nonetheless, a large shock to both unemployment and house prices—similar to what occurred during the financial crisis—would still lead to significantly elevated delinquency rates.

Our stress test is based on a straightforward model where the rate of serious delinquency on household debt—defined here as 60 days or more late—is a function of shocks to liquidity and wealth (in practice, unemployment rates and house prices), and the interaction of these shocks with household credit quality and household leverage. To estimate such a model, we draw on a panel dataset of consumer credit records with quarterly observations extending back to 1999. While these data allow us to observe debt, credit scores and delinquency at the individual level, data for many of the other components of the delinquency model we

have in mind are available only at the county level. Consequently, we aggregate the credit record data, constructing county-by-quarter estimates of delinquency rates and county-by-credit-score-by-quarter estimates of outstanding debt, and then merge in county-by-quarter data on wages, unemployment, and house prices. Despite this aggregation, our county-level panel dataset provides us with a substantial amount of identifying variation.<sup>1</sup>

Similar to the suggested methodology in Sufi [2014], we focus on credit scores as a measure of credit quality, and the ratio of total county debt (disaggregated by borrower credit quality) to total county wage income (DTI) as a measure of leverage. Our model does not include another important measure of leverage, the ratio of mortgage loan balances to home values (LTV). It is well-established that having little or negative home equity (i.e. LTV close to or above 100 percent) is an important driver of mortgage default, particularly when coupled with a liquidity shock (the so-called “double-trigger” theory of mortgage default).<sup>2</sup> Although we do not directly include negative equity in our delinquency model, we do include house price changes, which determine changes in homeowner equity. Therefore, variation in the extent of negative equity across counties is likely to be captured in our model by cross-county variation in house price changes. In particular, counties that experienced the biggest house price declines during the housing bust are likely to have the highest incidence of negative-equity homeowners by 2009.<sup>3</sup>

Our estimated model indicates that delinquency rates respond more strongly to changes in house prices and unemployment when DTI ratios are higher and as more of the debt is held by lower credit score borrowers. Moreover, we find results consistent with the double trigger theory of mortgage default: delinquency rates are especially sensitive to house price

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<sup>1</sup>Hale et al. [2015] find that county-level models of consumer delinquency generate better out-of-sample predictions than individual-level models when some of the predictors, such as the unemployment rate, are measured at the county level.

<sup>2</sup>Several recent papers help establish the importance of the interaction between liquidity and negative equity, such as Bhutta et al. [2017], Bricker and Bucks [2016], Campbell and Cocco [2015], Ganong and Noel [2018], Gerardi et al. [2018], and Hsu et al. [2018].

<sup>3</sup>See Fuster et al. [2018] for descriptive evidence on the evolution of negative equity across regions from 2006 through 2017.

shocks when coupled with unemployment shocks.

Using our estimated model, we forecast delinquency rates under various stress scenarios. First, we apply the house price and unemployment rate shocks used in the Federal Reserve Comprehensive Capital Analysis Review (CCAR) stress tests.<sup>4</sup> We find that the current stock of household debt in the U.S. is somewhat less vulnerable to a given set of shocks than the stocks at various points in time prior to the 2007-09 financial crisis. That said, the “severely adverse” CCAR scenario would still be expected to sharply push up delinquency rates on household debt. Quantitatively, we estimate that the same unemployment and house price shocks that caused delinquency rates to rise to about 9 percent (from about 2.5 percent) between 2006Q4 and 2008Q4 would result in an increase to about 7.5 percent (also from about 2.5 percent) in the two years after 2017Q4. We trace this decline in risk to somewhat lower DTI ratios and a smaller share of total debt held by subprime borrowers.

Next, we consider “housing correction” scenarios where house price shocks are determined by the degree of housing overvaluation at a given point in time, defined as the deviation of the price-rent ratio from its long-term trend. By this measure, housing valuations are considerably more reasonable today than they were at the peak of the housing boom. Consequently, the housing shock in these scenarios is milder than in the severely adverse CCAR scenario and thus generates a smaller increase in delinquency rates. We find that if house prices fully corrected during the two years after 2017Q4 and unemployment rates went up as they do under the severely adverse CCAR scenario, the delinquency rate on household debt would go up to about 5 percent. This expected delinquency rate is about half the peak delinquency rate reached by the end of 2009.

Finally, we consider two alternative stress scenarios based on different ways of assigning county-level shocks. First, following Fuster et al. [2018], we consider a house price correction scenario where the house price path in each county reverts back to the level of two or four

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<sup>4</sup>We distribute the published national shocks to the county level using a simple methodology, which we describe in 6.1.1.

years earlier. Under the two-year reversion house price scenario, coupled with a severely adverse unemployment shock, we find that delinquency rates rise to about 6.25 percent — right between our forecast under the severely adverse CCAR scenario and our first price correction scenario. Second, we consider a “worst-case” scenario where the most leveraged counties receive the largest house price and unemployment shocks. In this scenario, we find the delinquency rates rise to about 8.25 percent, higher than our forecast for the severely adverse CCAR scenario, but still below the delinquency rates reached during the crisis.

Our paper makes several contributions to the literature. Conceptually, our paper resembles Mian and Sufi [2010] along a few dimensions, in particular by modeling household default as a function of household leverage, and by using county-level credit record data. However, a key difference is that we allow defaults to respond to changes in house prices and changes in unemployment, along with the interaction of these changes with leverage. Our model therefore permits us to conduct out-of-sample “stress-testing”—the aim of our paper—and project delinquency rates under various house price and unemployment scenarios, given current levels of leverage.

This stress testing component of our paper builds upon recent work by Fuster et al. [2018], who use a stress testing exercise with U.S. data and focus only on house price shocks and mortgage defaults. We add to this nascent literature by incorporating both house price and unemployment shocks, and by considering defaults on all types of household debt.<sup>5</sup>

One caveat about our model is that it does not fully capture all of the important time-varying features of consumer credit markets. For example, our analysis does not directly account for the decreased share of “exotic mortgages” or the more stringent income documentation requirements on mortgages imposed since the financial crisis. These developments have likely led to the stock of debt in recent years becoming less risky than our model would suggest. On the other hand, because of data limitations, our baseline debt and delinquency

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<sup>5</sup>Household stress testing exercises have also been evaluated using household survey and administrative data in Australia (Bilston et al. [2015]), Sweden (Finansinspektionen [2015]), Austria (Albacete and Fessler [2010]), and the U.K. (Anderson et al. [2014]), among others.

measures do not include student loans, which have more than tripled in volume since the early 2000s and could make the stock of debt somewhat more risky than our model suggests. That said, aggregate student loan balances were only about 10 percent of total household balances by the end of 2017 (Federal Reserve Bank of New York [2018]), and virtually all student loan debt is federally guaranteed, limiting the exposure of the financial system to student loan risk. We discuss the student loan data in more detail in the appendix, and provide suggestive evidence that our main results are little changed by the inclusion of the available data on student loan debt.

While our stress testing exercise helps quantify the vulnerability of household debt to major shocks, the ultimate impact of household delinquencies on the stability of the financial system depends on the extent to which financial intermediaries are exposed to the credit risk. For example, at the peak of housing boom, the largest private financial firms were heavily exposed to mortgage credit risk, including high-risk subprime mortgages [Foote et al., 2012]. Since the financial crisis, most new mortgages have been either insured by the Federal Housing Administration, guaranteed by the Department of Veterans Affairs, or purchased and guaranteed by the government-sponsored enterprises Fannie Mae and Freddie Mac.<sup>6</sup> Shifts in mortgage credit risk away from the private sector and toward the government can help shield the financial system from losses due to mortgage defaults.

The rest of the paper is organized as follows. In the next section, we discuss trends in household debt and default, and triggers of household default. After presenting some background material in section 2, we describe our data sources in section 3. We present our model in section 4 and the results of our stress-testing exercise in sections 5 and 6. Section 7 concludes the paper.

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<sup>6</sup>For example, 66 percent of mortgages originated in the first half of 2018 fell into these categories [Urban Institute, 2018]. Since 2013, some of the risk on loans owned by Fannie Mae and Freddie Mac has been transferred to private investors through their credit risk transfer programs.

## 2 Background on Household Debt and Delinquency in the U.S.

By the end of 2017, total household debt stood at just over \$13 trillion according to the Federal Reserve Bank of New York [Federal Reserve Bank of New York, 2018]. As a fraction of aggregate personal income, aggregate household debt has declined from a peak of over 1.2 in 2007 to just under one in 2017 [Ahn et al., 2018]. Just over 70 percent of household debt is housing related, including debt owed on home equity lines of credit. Student loans (\$1.4 trillion), auto loans (\$1.2 trillion) and credit cards (\$0.8 trillion) make up most of the other 30 percent of debt.<sup>7</sup>

During the recent financial crisis of 2007-09, the delinquency rate on household debt—that is, the fraction of dollars outstanding on consumer and mortgage loans that were at least 60 days past due—jumped to about 9 percent after fluctuating modestly around 2 to 3 percent from 1999 through 2005. The delinquency rate increased for all forms of household debt during the crisis, but the increase in mortgage delinquency was the most pronounced and the rate of serious delinquency for closed-end mortgage loans jumped roughly 10-fold.<sup>8</sup> While mortgages sold and packaged into nonprime securities experienced catastrophic default rates by the peak of the crisis [Mayer et al., 2009], loan performance deteriorated sharply across many types of loans and borrowers [Adelino et al., 2016].

A key trigger of household default is that debt payments can become too burdensome relative to a household’s available resources. Households who have taken on a large amount of debt relative to their income are especially vulnerable to income or expense shocks: even relatively small shocks can tip the scales towards default. Along the same lines, borrowers with lower credit scores have repayment histories that suggest they are susceptible to shocks.

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<sup>7</sup>Statistics are from Federal Reserve Bank of New York [2018], based on consumer credit record data from Equifax, which are also used in this paper.

<sup>8</sup>See Federal Reserve Bank of New York [2018] for trends in serious delinquency rates since 2003 by loan type.

Correspondingly, in our empirical work we allow for both overall indebtedness (relative to income) and the share of debt held by lower-score households to influence delinquency rates.

Mortgage borrowers facing a liquidity shock may be able to avoid default by selling their home to repay the loan.<sup>9</sup> But when borrowers have “negative home equity” (e.g. homes worth less than the current mortgage balance), selling may not be viable and default becomes the best or only option. A combination of liquidity shocks and negative equity leading to mortgage default is typically referred to in the housing literature as the “double-trigger” theory of mortgage default. Recent research suggests that most defaults during the recent crisis were likely due to the combination of liquidity shocks and negative equity (e.g. Bhutta et al. [2017]; Gerardi et al. [2018]).

Negative equity alone, if severe enough, can itself generate mortgage defaults. When house prices plummet and push home values far enough below mortgage balances, borrowers may have a financial incentive to “strategically default” even if they can afford to continue making payments [Vandell, 1995, Deng et al., 2000]. This is especially true in non-recourse states like California [Ghent and Kudlyak, 2011].

In sum, this section highlights the importance of leverage, credit scores, liquidity shocks, and house price shocks for explaining household defaults. Our discussion here emphasizes that these factors can interact with each other, amplifying their effects on default. As such, a key feature of our empirical model, which we discuss below, will be the full interaction of these variables to help better explain patterns of household default.

### 3 Data

Our analysis of household debt uses a wide array of data sources, including debt and delinquency data from the Federal Reserve Bank of New York Consumer Credit Panel/Equifax (CCP); wage data from the Bureau of Labor Statistics’ (BLS) Quarterly Census of Employ-

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<sup>9</sup>Similarly, car loan borrowers facing a shock may be able to sell their car to repay the loan.

ment and Wages (QCEW); house price data from Zillow; and unemployment data from the BLS Local Area Unemployment (LAU) Statistics. From these data sources we construct a county-quarter panel dataset from 1999 through 2017 and covering over 1,500 of the largest counties in the U.S and containing roughly 90 percent of the U.S. population. This section introduces these data sources and presents summary statistics of the key variables of our study.

### 3.1 FRBNY Consumer Credit Panel (CCP)

Our measure of household debt and delinquency rates comes from the Federal Reserve Bank of New York’s Consumer Credit Panel (CCP). The CCP draws a 5-percent random sample of U.S. consumers with valid credit histories and Social Security Numbers (about 11 million individuals in recent quarters) on a quarterly basis.<sup>10</sup> The CCP includes extensive credit history data (debt holdings and repayment history) maintained by Equifax, as well as a credit risk score and location information for each member of the panel. We aggregate this data to construct county-level aggregates of total debt holdings among borrowers of different credit quality (prime, near prime, or subprime), as measured by their current credit risk score.<sup>11</sup> Importantly, because these credit scores are calculated based on updated credit records, they represent Equifax’s estimate of borrowers’ *current* credit quality rather than an assessment of the borrower’s credit quality at the time any particular loan was originated. Our total debt measure includes mortgages, home equity loans and lines of credit, auto loans and leases, credit card and retail card debt, and other debts, but excludes student loan debt.<sup>12</sup>

We also use repayment information from the CCP to construct a measure of county-

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<sup>10</sup>The CCP sampling design generates a longitudinal dataset that is also nationally representative each quarter. See Lee and der Klaauw [2010] for more details. To make the data more manageable, we use a 10 percent sample of the CCP (i.e. a 0.5 percent sample of adults).

<sup>11</sup>The credit score available in the CCP is the Equifax 3.0 score. Similar to the FICO<sup>®</sup> Score, it ranges from 280-850 with higher scores implying lower risk. We define prime as 720 or above, near prime as 620-719, and subprime as 619 or below.

<sup>12</sup>We exclude student loan debt because complete student loan information is not available for our entire sample period, and delinquency reporting has changed over time. Please see the appendix for an analysis of student loans in our model.

level delinquency rates, defined as the share of dollar balances of our total debt measure in a county that are 60 days or more past due.<sup>13</sup> In our baseline model, we use the eight-quarter-ahead delinquency rate on all loan balances as the dependent variable. In addition, we estimate separate models for mortgage and non-mortgage debt. As shown in Table 1, the share of debt in delinquency (two years out) was 3.3 percent in the average (large) county in the early 2000s, and then increased to 9.4 percent by the middle of the sample before falling back to the levels observed in the early 2000s. Notably, Table 1 highlights significant cross-sectional variation in delinquency rates. For example, in 2007 the 10th and 90th percentile counties had delinquency rates of 4.1 percent and 17.0 percent, respectively.

### **3.2 BLS Quarterly Census of Employment and Wages (QCEW)**

While the CCP provides a measure of household debt, in order to use DTI ratios as a measure of leverage also requires data on household income. Though the CCP lacks data on consumers' income, our approach of aggregating debt balances to the county level allows us to use county-level income data to calculate DTI ratios. In particular, we merge in quarterly data on total county wage earnings from the Bureau of Labor Statistic's Quarterly Census of Employment and Wages, and measure DTI ratios at the county level as total debt to total wage income. Table 1 shows how average DTI ratio evolved over the sample period. In the 4th quarter of 2000, the average DTI ratio across counties was 1.35, then rose to about 2.2 by the end of 2007, and receded by 2014 to about 1.7. Again, the table highlights considerable cross-sectional variation. For example, in 2000 the 10th percentile DTI ratio was 0.74 and the 90th percentile was 2.18.

We note that our measure of income focuses on wage income, based on administrative state unemployment insurance program (UI) records. Thus it excludes some components of personal income such as transfer income (e.g. Social Security), interest and dividend in-

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<sup>13</sup>We account for joint balances in both our debt measurement and delinquency measurement by a standard procedure of subtracting half of the joint balance.

come, and small business income. According to data available from the Bureau of Economic Analysis, employee compensation (including pension contributions) accounted for less than two-thirds of total personal income in 2017.<sup>14</sup> However, wage income is likely the most relevant source of income for our purposes, since other forms of income are concentrated among high-wealth and older households who tend to have little debt relative to their income.<sup>15</sup>

Because differences in credit scores are expected to affect delinquency rates even among similarly leveraged borrowers, we construct separate DTI ratios for the prime, near-prime and subprime populations. Ideally, we would separately observe the income of the prime, near-prime, and subprime populations for whom we measure debt balances and would calculate a separate DTI ratio for each. In practice, however, we observe only total wages. Thus, total wages are used as the denominator for all three credit score groups' DTI ratio. For example, the subprime DTI ratio in a given county at time  $t$  would be measured as total debt at  $t$  among borrowers with a credit score at  $t$  under 620, divided by total wage income in the county at  $t$ .

### 3.3 BLS county unemployment rate

As discussed previously in section 2, our model considers two types of economic shocks: liquidity shocks and house price shocks. We measure county-level liquidity shocks as the eight-quarter-ahead change in the local unemployment rate, which the BLS estimates using a combination of household survey data and administrative UI records. We use unemployment rates to proxy for liquidity shocks rather than, for example, total income for two reasons. First, unemployment rates isolate unexpected disturbances in income, whereas, changes in total income combine expected income changes (e.g. retirement) and unexpected changes (e.g, job loss). Second, changes in total income will be dominated by those at the top of the

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<sup>14</sup>See NIPA Table 2.1 ([Bureau of Economic Analysis, 2018])

<sup>15</sup>For example, in 2016, families in the top three quartiles of the DTI distribution derived between 60 and 70 percent of their total income from wages. In contrast, families in the first quartile of the DTI distribution derived just 37 percent of their income from wages (authors' calculation based on 2016 Survey of Consumer Finances).

income distribution, and can mask changes occurring elsewhere in the distribution. This will be particularly problematic if lower-income borrowers are more vulnerable to defaulting.

Table 1 reveals considerable variation in unemployment rate changes, both across counties and over time. Unemployment rates increased modestly in the early period from 2000-2002, tended to rise sharply in the middle period, and tended to improve in the latter period. In the middle (Great Recession) period, nearly all counties saw at least a 3 percentage point increase in their unemployment rate, and some counties experienced increases of over 7 percentage points.

### **3.4 Zillow house price data**

Our measure of house price shocks relies on publicly-available data from Zillow. In particular, we use the county-level Zillow Home Value Index (ZVHI) for all single-family homes, which reflects Zillow’s estimate of the potential sales price of the median home in a given county in a given month. Zillow’s coverage has increased over time, which is why the number of counties in our dataset rises over our sample period (see Table 1).

Table 1 presents two-year-ahead growth rates in home prices. From 2000-2002, county median home prices grew by 14 percent, on average, with considerable variation between the 10th and 90th percentiles. From 2007-2009, home prices fell sharply—in excess of 40 percent for some counties. Finally, in the most recent two-year period, home prices were growing once again but, again, with considerable variation.

## **4 Model**

Our econometric model is designed to measure the expected delinquency rate after a macroeconomic shock for a given level and composition of household debt. As described above, our measures of county-level DTI ratios capture both the amount of leverage held by households and also how this borrowing is distributed among borrowers of different credit quality. The

two economic shocks considered in the model are changes in house prices and changes in the unemployment rate.

Our model is designed to be used in conjunction with the Federal Reserve Board’s Comprehensive Capital Analysis and Review (CCAR) exercise, which we describe more fully in section 6. In this exercise, shocks build and then begin to recede over approximately two years. Therefore, the outcome variable in our model is the delinquency rate eight quarters in the future, the point at which the shocks in each scenario have reached their maximum values.

The explanatory variables include measures of household borrowing that are observable today—such as delinquency rates and DTI ratios described above—and also include the realization of the two economic shocks over the next eight quarters. As noted earlier, we disaggregate DTI ratios within a county into prime, near prime, and subprime DTI ratios. Rather than make functional form assumptions about how these DTI ratios affect defaults, we compute dummy variables indicating which quartile each DTI ratio falls into within its historical distribution. For example, consider the evolution of the dummy variables describing the subprime DTI ratio. In 2007, 31 percent of counties had subprime DTI ratios in the highest quartile of the historical distribution, whereas in 2016, only 16 percent of counties did. (Over the entire sample, of course, 25 percent of counties will fall into the highest quartile.)

A second key feature of the model is interactions between the credit score-group DTI ratios and the macroeconomic shocks, which captures the additional rise in delinquency rates that occurs when the shocks occur in periods when households are more leveraged. In addition to including the income and house price shocks separately, we also include an interaction between the two shocks to capture the intuition of the “double-trigger” hypothesis, discussed earlier, that defaults may be particularly high when counties face a combination of liquidity and house price shocks.

Our full baseline model is then specified as follows:

$$\begin{aligned}
D_{c,t+8} &= \beta_0 + \beta_1 D_{c,t} + \beta_2 \Delta U_{c,t} + \beta_3 \Delta \log(HPI_{c,t}) + \beta_4 \Delta U_{c,t} \times \Delta \log(HPI_{c,t}) \\
&+ \sum_{j,k} \left( \beta_5^{j,k} + \beta_6^{j,k} \Delta U_{c,t} + \beta_7^{j,k} \Delta \log(HPI_{c,t}) + \beta_8^{j,k} \Delta U_{c,t} \times \Delta \log(HPI_{c,t}) \right) \times DTI_{c,t}^{j,k}
\end{aligned}$$

where  $c$  indexes the county,  $t$  indexes the quarter,  $D_{c,t}$  is the share of debt that is 60 or more days delinquent,  $U_{c,t}$  is the unemployment rate,  $HPI_{c,t}$  the house price index, and  $\Delta$  denotes the change in a variable over the next eight quarters (e.g.  $\Delta U_{c,t} = U_{c,t+8} - U_{c,t}$ ). Finally,  $DTI_{c,t}^{j,k}$  for  $j = subprime, near, prime$  is a dummy variable indicating that the ratio of the debt of borrowers of type  $j$  to total county wage income falls into the  $k$ th quartile of its historical distribution, where  $k = 2, 3, 4$  and  $k = 1$  is the omitted category. All regressions are weighted by the total number of borrowers observed in each county  $c$  and quarter  $t$ .

## 5 Results

### 5.1 Model fit

Table 2 presents the results of estimating equation 1 using the data described in section 3. Because our model incorporates many interaction terms, one must be careful in interpreting the coefficients. For example, the coefficient on the main house price growth term measures the expected rise in the delinquency rate from house price growth when all three DTIs are in the first quartile and the unemployment rate does not change.

For exposition, table 3 provides a more parsimonious interpretation of the coefficients. Here we estimate the change in delinquency rates under several illustrative examples, which are designed to represent the effects of relatively small and large unemployment and house price shocks on delinquency rates. The results are shown separately for counties in the lowest and highest DTI quartiles to demonstrate a key feature of the model: that delinquency rates associated with unemployment and house price shocks are larger in counties with higher DTI

ratios.

As shown in table 3, our estimates indicate that a small unemployment and house price shock—on the order of a 0.75 percentage point rise in the unemployment rate and a 5 percent decline in house prices—is associated with a 0.41 percentage point increase in delinquency rates in counties with low DTI ratios. But the same shock is associated with a 0.86 percentage point increase in delinquency rates in high debt-to-income counties—nearly double the increase in the low DTI ratio counties.<sup>16</sup>

A larger unemployment shock—on the order of a 3 percentage point increase in the rate—accompanied by the smaller 5 percent decline in house prices also leads to a somewhat larger increase in delinquency rates overall than just the two smaller shocks, and the change is larger in the high DTI ratio counties (1.80 percentage points) than in lower DTI ratio counties (1.12 percentage point increase). A similar pattern is found when a larger house prices shock—a 15 percent decline—accompanies the smaller unemployment shock, though the spread between low and high DTI county delinquency rates is even wider.

Finally, the last row of table 3 shows that delinquency rates are the highest when both the large unemployment rate shock (3 percentage points) and the large house price shock (15 percent) are applied to the model. Notably, the rise in the delinquency rate when we apply both shocks simultaneously exceeds the sum of the independent effects of each shock, reflecting the interactive effect between unemployment and house price shocks. Furthermore, the delinquency rate change resulting from the two large shocks is over one and a half percentage points higher in the highest DTI ratio counties than in the lowest DTI ratio counties. Overall, then, such shocks are expected to lead to a widening of the baseline difference in delinquency rates between high and low DTI counties.

Figure 1 displays population-weighted mean quarterly delinquency rates for the sample period 2000-2017. The blue line displays predicted delinquency rates from the estimated

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<sup>16</sup>Note that all shocks in table 3 are expressed relative to the baseline of no housing or employment shocks. As shown at the bottom of table 3, the baseline in the high DTI counties is about 0.91 percentage points higher than the low DTI county baseline.

model, and the black line displays actual delinquency rates observed in the data. The patterns in the two time series are extremely similar and display the same pattern: delinquency rates hovering around 2 percent in the early 2000s, a steep rise in delinquency rates in the 2006-2010 period, followed by a more gradual decline until the present.<sup>17</sup> The close relationship in both trends and levels in the two series provides *prima facie* evidence that our model should be able to accurately predict delinquency rates under the various stress-test scenarios discussed below.

## 5.2 Predicted delinquency rates by type of debt

To help understand how different types of debt are contributing to our estimates thus far, we disaggregate household debt and estimate two variations of equation 1. First we examine delinquency rates only for mortgage debt, and then we study delinquency rates only for non-mortgage debt.<sup>18</sup> For exposition, in lieu of presenting regression tables we again present illustrative examples, as in table 3.

The first column of table 4 shows the expected increase in delinquency rates on mortgage debt under relatively small and large shocks. These results show a similar pattern to those in table 3, whereby a larger unemployment or house price shock increases the delinquency rate on mortgages. Moving from a smaller unemployment shock (in the first row) to a larger one (in the second row) is associated with a 74 basis point larger increase the mortgage delinquency rate. The effect is similar when moving from a smaller to a larger house price shock. Again, consistent with the double trigger theory of mortgage default, the effect of simultaneously applying both of the larger shocks exceeds the sum of the two independent effects. In that scenario, mortgage delinquency rates increase by 2.46 percentage points.

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<sup>17</sup>According to the model, one reason default rates have come down so much since the crisis is the decline in the subprime DTI ratios in particular. An alternative version of the model where we don't separate out the prime, near-prime and subprime DTI ratios has trouble reproducing this large decline in delinquency rates.

<sup>18</sup>In these models, we also use separate mortgage and non-mortgage DTI ratios (and their interactions with the macroeconomic shocks) as explanatory variables.

The second column of table 4 repeats this exercise for non-mortgage delinquency rates. Like with mortgage delinquency, moving from the smaller unemployment rate shock to a larger one increases is associated with a 82 basis point larger increase the non-mortgage delinquency rate. However, unlike mortgage delinquency, moving from a smaller house price shock to a larger one has only a small effect on the non-mortgage delinquency. This difference reflects the fact that we would not expect house price changes to have a direct effect on the incentives to default on non-mortgage debt. In addition, many non-mortgage debt holders may not have mortgage debt.

## 6 Stress-testing household debt

Having established that our model is able to predict the levels and trends in observed household delinquency rates during our sample period, we next use the model to make out-of-sample predictions for household delinquency rates under various possible scenarios.

### 6.1 The scenarios

We use the Federal Reserve Board’s (FRB) 2018 Comprehensive Capital Analysis and Review (CCAR) stress scenarios as our baseline stress test for the path of house prices and unemployment rates. The CCAR stress scenarios are used for annual stress tests of the largest U.S.-based bank holding companies, and is required as part of the Federal Reserve Board’s supervisory function.<sup>19</sup> The CCAR guidelines specify three hypothetical scenarios—the baseline, adverse, and severely adverse scenarios—and are designed to assess a bank’s resilience to adverse economic conditions.<sup>20</sup>

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<sup>19</sup>See Federal Reserve Board [2018] or <https://www.federalreserve.gov/supervisionreg/files/bcreg20180201a1.pdf> for more details. The test is required by the Dodd-Frank Wall Street Reform and Consumer Protection Act and is used to help determine the required level of bank capital reserves.

<sup>20</sup>The scenarios are not forecasts of the Federal Reserve. The scenarios provide 28 measures of the forward path of economic activity and prices, of which we will use two as inputs in our model: the path of house prices and the path of unemployment rates.

The baseline scenario in 2018 is based on a moderate economic expansion of real economic activity, as projected in the *Blue Chip Economic Indicators*, a survey of professional forecasters.<sup>21</sup> In these projections, the unemployment rate remains near 4 percent through our 8 quarter scenario period and nominal house price growth averages about 2.5 percent annually.

The adverse scenario describes a moderate recession that begins in the first quarter of 2018. In this scenario, the unemployment rate increases sharply from less than 4 percent in the 4th quarter of 2017 to 7 percent by the 3rd quarter of 2019, and house prices fall 12 percent over the 8 quarters.

The severely adverse scenario describes a severe recession, along the lines of the 2007-09 recession. The unemployment rate increases to 10 percent in by the 3rd quarter of 2019 and house prices fall 30 percent by the 3rd quarter of 2019. Figure 2 displays three year trends in the forward-looking CCAR paths for house prices and unemployment. In each panel, the red line displays the severely adverse scenario, the yellow line displays the adverse scenario, and the green line displays the baseline scenario.

### 6.1.1 Construction of county-level scenarios

While the published CCAR scenarios describe economic variables at the national level, we would expect that these shocks would have heterogeneous effects in different areas of the country. This heterogeneity is important for our purposes because household borrowing poses a greater risk if there are higher degrees of leverage in counties that are likely to experience larger economic shocks. In order to capture the heterogeneous nature of these shocks, we calculate county-level scenarios for each of the three national scenarios based on historical relationships between national changes in unemployment rates or house prices and county-level changes in unemployment rates or house prices. Specifically, for each county  $c$ ,

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<sup>21</sup>Note that the details of the CCAR scenario change slightly year-to-year.

we estimate parameters  $\alpha_c$  and  $\beta_c$  from the regression

$$\Delta y_{c,t} = \alpha_c + \beta_c \Delta y_t + \varepsilon_{c,t} \tag{1}$$

where  $\Delta y_{c,t}$  is the one-quarter change in either log house prices or unemployment for county  $c$  in quarter  $t$  and  $\Delta y_t$  is the change in that variable at the national level.<sup>22</sup> We estimate these models using data for 1999Q1 to 2017Q4. Then, we use the estimated parameters to distribute the national changes in the CCAR scenarios across counties for 2018Q1 to 2019Q4. This process allows us to recover county-level estimates of the path of unemployment rates and home prices under the national CCAR scenarios, which we use as inputs in our models to estimate the path of delinquency rates.

## 6.2 Predicted delinquency rates under CCAR scenarios

In our first prediction exercise, we begin with measures of household borrowing as of the fourth quarter of 2017 and use our estimated model to predict the rise in delinquency rates under our county-level version of each of the three CCAR scenarios described above. The results of this exercise are presented in figure 3.

When we assume that unemployment and house prices evolve as in the baseline scenario, our model predicts that the fraction of household debt in delinquency would remain around 2.5 percent through the fourth quarter of 2019 (green line). If unemployment and house prices evolve as in the adverse scenario, the model predicts that delinquency rates would steadily increase and peak at about 4.5 percent in late 2019 (yellow line). Finally, if house prices and unemployment evolve as in the severely adverse scenario, our model predicts that delinquency rates would increase sharply, peaking at about 7.6 percent in late 2019 (red line).

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<sup>22</sup>Note that we use county-level Zillow median home prices, whereas the published CCAR scenarios are based on the national CoreLogic price index for owner-occupied real estate. Thus our model relates how changes in the national CoreLogic index translates into changes in each counties' Zillow median home price.

In order to assess the current risks stemming from household debt relative to previous time periods, we compare these predictions to the predictions we would have made from repeating the same exercise in previous periods. Specifically, we can apply the same eight-quarter-ahead forward paths of the 2018 CCAR scenarios, but starting with the stock of outstanding household debt from the fourth quarter of selected pre-crisis years. For brevity, we select 2002, 2004, and 2006 (figure 4). For ease of exposition, we display these results in a bar chart, where the height of the bars are the maximal 2-year ahead expected delinquency rates under each scenario.

We start with two observations based on expected delinquency rates for the pre-crisis years. First, applying the severely adverse scenario to the stock of outstanding debt in the 4th quarter of 2006 returns an expected level of delinquencies of about 9.2 percent two years later, nearly identical to the actual level of delinquencies around this time (which was 9.1 percent in the 1st quarter of 2009). This is a reassuring result from our model, as the severely adverse scenario is designed to be similar to the 2007-2009 recession. Second, this exercise suggests that the stock of debt was nearly as risky in early 2000s as it was in 2006. Expected 8-quarter out delinquency rates arising from the severely adverse CCAR shocks are around 8.3 percent in 2002, rising to 8.8 percent by 2003, 2004, and 2005, which is just slightly lower than the expected delinquency rate in the 2006 stock of debt (9.2 percent).

Moving on to our main result, we find that the delinquency rates we predicted from 2017 are lower than the predicted delinquency rates for each pre-crisis year. For example, as noted earlier the predicted delinquency rate in the adverse scenario in 2017 is about 4.5 percent, whereas it ranges from 5.2 to 5.4 percent from 2002 to 2006 (yellow bars). In the severely adverse scenario, the eight-quarters out delinquency rate in 2017 is about 7.6 percent, while it is predicted to be between 8.3 to 9.2 percent in 2002, 2004 and 2006 (red bars). Thus, although our model predicts that a severe economic shock would lead to a significant rise in household delinquency in 2017, we conclude that household borrowing is less risky than it was before the financial crisis.

Why might household debt now be more resilient to a given set of macro-economic shocks? While DTI ratios have moderated since 2010, on average they have remained near 2004 levels for much of the post-2012 period (figure 5). Thus, the post-crisis decline in aggregate debt relative to income cannot explain why household debt is less risky now than in the early 2000s. Instead, a more important reason for the decline in risk is that a larger portion of outstanding household debt is now held by higher credit score borrowers (figure 6). This pattern reflects the material shift toward borrowing by relatively low-risk households that has taken place since the Financial Crisis, in particular due to tightened credit standards for mortgages [Anenberg et al., 2017, Bhutta, 2015, Laufer and Paciorek, 2016].

### **6.3 Predicted delinquency rates under alternative house price shocks**

In the exercises discussed above, we considered how changes in the composition of household debt over time affects household default risk. However, we have not allowed for the possibility that the risk of a particular economic shock might itself change over time. For example, one important source of risk during the mid-2000s was the extreme overvaluation—by some measures—of residential real estate, which precipitated the collapse in house prices that led to the rise in mortgage defaults during the crisis.

Our next exercise attempts to capture changes over time in the risk of house price shocks by considering “housing correction” scenarios where house price shocks at each point in time are determined by the degree of housing overvaluation at that time. The degree of housing overvaluation in these scenarios is measured as the amount of deviation of the price-rent ratio from its long-term trend. Figure 7 plots the ratio of house prices (from CoreLogic) to rents (as measured by BLS) over time, together with an estimate of the long-run trend in this ratio. By this measure, house values were approximately 45 percent overvalued in 2006, whereas in the fourth quarter of 2017, they were overvalued by just five percent. To implement these “housing correction” scenarios, we consider the effects of a house price shock that

brings the price-rent ratio back to its long-run trend over the eight-quarter forecast period. Because this exercise provides no guidance for how unemployment rates should evolve, we consider paths for the unemployment rate taken from each of the three CCAR scenarios. As in the previous exercises, we distribute these national shocks across the counties using the methodology described in Section 6.1.1.

The results of our “housing correction” exercise (shown in figure 8) confirm the intuition presented above—household debt looks less risky than before the crisis because housing does not appear as overvalued at the present. For example, the red bars show the delinquency rates that would be predicted by a housing correction together with a shock to the unemployment rate taken from the severely adverse CCAR scenario. As household valuations climbed through the early 2000’s, our model predicts that a price correction at any point in time would have led to an increasingly higher rate of delinquency rates, with predicted delinquency rates rising from about 6.5 percent in 2002 to almost 10 percent in 2006. In contrast, the much lower valuations at the end of 2017 imply that the much smaller correction necessary to erase this overvaluation would only drive delinquency rate up to about 5 percent.<sup>23</sup>

### 6.3.1 House price reversion

Thus far our house price scenarios have all been derived from external national scenarios—either from CCAR or based on a model of national overvaluation. In this section, we instead consider an alternative house price scenarios based on recent house price experiences in each particular county. In particular, we consider shocks by which house prices in each county revert to their levels from either 2 or 4 years earlier.<sup>24</sup> The intuition behind this exercise uses the experience of the 2000-2012 housing boom and bust cycle, where the areas with the largest price growth from 2000 to 2006 were also those that had the largest house price declines in the 2006-2011 housing bust. As in the previous exercise, we consider paths for

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<sup>23</sup>If house price declines are positively correlated with increases in unemployment rates, this would only further reduce current period risk relative to the past.

<sup>24</sup>These scenarios are inspired by those considered in Fuster et al. [2018].

the unemployment rate from each of the three CCAR scenarios.

Under the scenario where local house prices revert to levels from two years prior and unemployment shocks follow the severely adverse CCAR scenario (the red bars in figure 9) we find that the delinquency rate rises to about 6.25 percent. For comparison, the magnitude of the expected delinquency rate under this scenario is larger than in the housing overvaluation scenario considered earlier, but smaller than the set of severely adverse CCAR shocks initially considered. Again, as in the CCAR and overvaluation exercises, the expected delinquency rates based on the current state of household debt in this scenario are substantively lower than predicted for the pre-crisis years.

In a more severe version of this exercise, we allow local house prices to revert back to the level from 4 years earlier. In 2017, for example, this scenario essentially means erasing all of the post-crisis increase in house prices. When coupled with a severe unemployment shock, the expected delinquency rate reaches nearly 8 percent (the red bars in figure 10), which is a bit higher than the severely adverse CCAR shock scenario. However, as before, the expected delinquency rate based on the current state of household debt under this scenario is still lower than predicted for the pre-crisis years.<sup>25</sup>

### **6.3.2 Worst Case Scenario: largest shocks in most highly leveraged counties**

Our final set of stress scenarios explores the risk that some adverse event may cause shocks that are particularly severe in areas where households are more indebted. For example, Mian and Sufi [2014] point out that in the recent housing crisis, areas that had amassed the largest amount of mortgage debt also suffered the largest house price declines during the bust. To explore the risks from shocks that could follow such patterns, we implement a “worst-case” scenario for unemployment rates and house prices. Rather than distributing the national scenarios to counties using historical relationships, we instead distribute the

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<sup>25</sup>Note we cannot include 2002 in the model because our data only go back to 1999 and therefore we cannot construct a four-year reversion scenario for 2002.

largest shocks to the most indebted counties. To implement these scenarios, we take the set of county-level shocks from our county-level version of the CCAR scenarios and rearrange those shocks quarterly so that the highest DTI counties in 2017Q4 receive the largest house price and unemployment shocks.<sup>26</sup>

Figure 11 shows that this “worst case” scenario would lead to slightly more elevated delinquency rates than in the original scenarios (as shown in figure 3). For example, in the severely adverse “worst case” scenario (the red line), the model predicts that the delinquency rate would peak at just over 8 percent, while in the original severely adverse scenario, the delinquency rate peaks at around 7.6 percent. This relatively small difference partially reflects the fact that more indebted counties already tended to receive larger shocks in the original scenario.<sup>27</sup>

## 7 Conclusion

Since the financial crisis, stress testing bank balances sheets has become a useful tool for identifying potential vulnerabilities in the financial sector. In this paper, we propose a similar approach to assess risks to the economy posed by household borrowing. We estimate a county-level model where household delinquency rates are a function of shocks to unemployment rates and house prices, and the interaction of these shocks with household credit quality and household leverage. We then use this model to predict the forward path of household delinquencies under the well-known CCAR stress scenarios.

Our analysis indicates that household debt is less risky than it was before the financial crisis. In particular, the decline in leverage and a shift in debt holding towards higher credit score borrowers appear to have made household borrowing notably safer over the past several years. That said, a severe economic shock—similar to the experience of the financial

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<sup>26</sup> Re-arranging the shocks in this way affects the population-weighted mean and standard deviation of the shock distribution. To allow for direct comparison with the original results in 3, we re-scale the distribution of shocks so that the population-weighted mean and standard deviation match the original scenarios.

<sup>27</sup>The correlation between the original scenario shocks and the “worst case” scenario shocks is about 0.2.

crisis—would still lead to a significant rise in household delinquency.

When using the CCAR stress scenarios, our analysis measures the expected consequences *if* a negative macroeconomic shock occurs, but says nothing about the *likelihood* of such a shock. Thus, we extend our analysis to include a time-varying house price shock based on a measure of national house price “overvaluation” at particular point in time. If house prices were to “correct” today (coupled with a severe unemployment shock), our model predicts that delinquency rates would increase to about 5 percent over the following eight quarters. In contrast, before the crisis, such a house price correction would have led to a 6.5 to 10 percentage point increase. Further extensions to our results show that our main conclusions are robust to alternate assumptions about the geographic distribution of shocks and a house price correction that erases recent growth. Overall, we conclude that the risks to financial stability from household borrowing are lower today than in the pre-crisis period.

There are several important caveats to our analysis and conclusions. First, the impact of household delinquencies on the stability of the financial system depends on the extent to which banks and other financial intermediaries are exposed to the credit risk. Recent mortgage credit trends have seemingly shifted mortgage credit risk away from the private sector towards the government, which could help shield the financial system from losses due to mortgage defaults. Second, changes in mortgage underwriting standards in recent years have led to a decline in new mortgages that lack full income documentation or contain “exotic features.” These changes have likely led to the stock of mortgage debt becoming less risky than our model would suggest.

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Table 1: Sample Summary Statistics

Table displays means and distributions of key summary variables, where the 10th and 90th percentiles of each variable is shown in brackets below the mean. Data sources are: CCP/Equifax, BLS LAU and QCEW and Zillow.

	2000 (4th Qtr)	2007 (4th Qtr)	2014 (4th Qtr)
DTI (total debt to total wages)	1.35 [0.74, 2.18]	2.20 [1.01, 3.66]	1.71 [0.83, 2.75]
House price growth, next 2 years	0.14 [0.03, 0.28]	-0.18 [-0.42, -0.02]	0.12 [0.04, 0.22]
Change in unemp rate, next 2 years	1.84 [0.85, 2.92]	4.72 [2.84, 6.88]	-1.32 [-2.27, -0.40]
Share debt 60 days late, 2 years later	0.033 [0.015, 0.054]	0.094 [0.041, 0.17]	0.031 [0.012, 0.052]
Number of counties	1421	1478	1649

Table 2: Model Estimates

Table displays the results of estimating equation 1. Standard errors in parentheses. \*  $p < .05$ , \*\*  $p < .01$ , \*\*\*  $p < .001$ . Data sources are: CCP/Equifax, BLS LAU and QCEW and Zillow.

	$\beta$	SE( $\beta$ )
Share of Borrowers 60+ DPD	0.513**	(0.049)
$\Delta$ Unemployment	0.003**	(0.000)
$\Delta \log(\text{HPI})$	-0.036**	(0.007)
$\Delta$ Unemployment $\times \Delta \log(\text{HPI})$	-0.012**	(0.002)
Subprime DTI		
DTI Quartile 2	0.005**	(0.001)
DTI Quartile 3	0.007**	(0.001)
DTI Quartile 4	0.011**	(0.001)
$\Delta$ Unemployment $\times$ Subprime DTI		
DTI Quartile 2	0.000	(0.000)
DTI Quartile 3	-0.000	(0.000)
DTI Quartile 4	-0.001	(0.001)
$\Delta \log(\text{HPI}) \times$ Subprime DTI		
DTI Quartile 2	-0.008	(0.005)
DTI Quartile 3	-0.017**	(0.007)
DTI Quartile 4	-0.035*	(0.019)
$\Delta$ Unemployment $\times \Delta \log(\text{HPI}) \times$ Subprime DTI		
DTI Quartile 2	0.002	(0.002)
DTI Quartile 3	0.008**	(0.002)
DTI Quartile 4	0.010**	(0.003)
Near Prime DTI		
DTI Quartile 2	0.001*	(0.001)
DTI Quartile 3	0.005**	(0.002)
DTI Quartile 4	0.007**	(0.003)
$\Delta$ Unemployment $\times$ Near Prime DTI		
DTI Quartile 2	0.000	(0.000)
DTI Quartile 3	0.001	(0.000)
DTI Quartile 4	0.000	(0.000)
$\Delta \log(\text{HPI}) \times$ Near Prime DTI		
DTI Quartile 2	0.008	(0.006)
DTI Quartile 3	0.001	(0.008)
DTI Quartile 4	-0.002	(0.010)
$\Delta$ Unemployment $\times \Delta \log(\text{HPI}) \times$ Near Prime DTI		
DTI Quartile 2	0.003	(0.002)
DTI Quartile 3	-0.008**	(0.002)
DTI Quartile 4	-0.012**	(0.004)
Prime DTI		
DTI Quartile 2	-0.004**	(0.001)
DTI Quartile 3	-0.005**	(0.001)
DTI Quartile 4	-0.009**	(0.002)
$\Delta$ Unemployment $\times$ Prime DTI		
DTI Quartile 2	-0.000	(0.000)
DTI Quartile 3	0.001	(0.000)
DTI Quartile 4	0.001*	(0.001)
$\Delta \log(\text{HPI}) \times$ Prime DTI		
DTI Quartile 2	-0.009	(0.006)
DTI Quartile 3	-0.031**	(0.010)
DTI Quartile 4	-0.037**	(0.007)
$\Delta$ Unemployment $\times \Delta \log(\text{HPI}) \times$ Prime DTI		
DTI Quartile 2	0.002	(0.002)
DTI Quartile 3	-0.007**	(0.003)
DTI Quartile 4	-0.004	(0.003)
Constant	0.021**	(0.002)
R-squared	0.761	
N	101399	

Table 3: Model-predicted Default Rates by DTI Quartile

Table displays predictions for the change in the delinquency rate associated with the listed change in unemployment rates and house prices, based on the results of estimating equation 1. The table shows the rise in delinquency rates compared to a baseline where there is no shock (i.e. unemployment and house prices are unchanged over the eight-quarter period). For comparison, average delinquency rates associated with no shock are displayed in the final row. Data sources are: CCP/Equifax, BLS LAU and QCEW and Zillow.

	Counties in the first quartile of subprime, near prime and prime DTI	Counties in the fourth quartile of subprime, near prime and prime DTI
Rise in county delinquency rate (pp) associated with...		
...a 0.75pp rise in unemployment and 5% decline in home values	0.41	0.86
... a 3pp rise in unemployment and 5% decline in home values	1.12	1.80
... a 0.75pp rise in unemployment and a 15% decline in home values	0.86	2.10
...a 3pp rise in unemployment and 15% decline in home values	1.83	3.45
Memo: delinquency rate associated with no shock	4.55	5.46

Table 4: Model-predicted Default Rates for Mortgage and Non-mortgage Debt

Table displays predictions for the change in the delinquency rate associated with the listed change in unemployment rates and house prices, based on the results of estimating an augmented equation 1, where defaults are mortgage-only in column (1) and non-mortgage-only in column (2). In these models, we also use separate mortgage and non-mortgage DTI ratios (and their interactions with the macroeconomic shocks) as explanatory variables. Data sources are: CCP/Equifax, BLS LAU and QCEW and Zillow.

	Mortgage delinquency rate	Nonmortgage delinquency rate
Rise in county delinquency rate (pp) associated with...		
...a 0.75pp rise in unemployment and 5% decline in home values	0.62	0.40
... a 3pp rise in unemployment and 5% decline in home values	1.36	1.22
... a 0.75pp rise in unemployment and a 15% decline in home values	1.44	0.71
...a 3pp rise in unemployment and 15% decline in home values	2.46	1.69
Mean county delinquency rate (%)	3.94	7.25

Figure 1: Model Fit

Figure displays the 60+ day delinquency rate in the black line and the model-predicted 60+ day delinquency rate in the blue line, where the blue line is based on estimating equation 1. Data sources are: CCP/Equifax, BLS LAU and QCEW and Zillow.

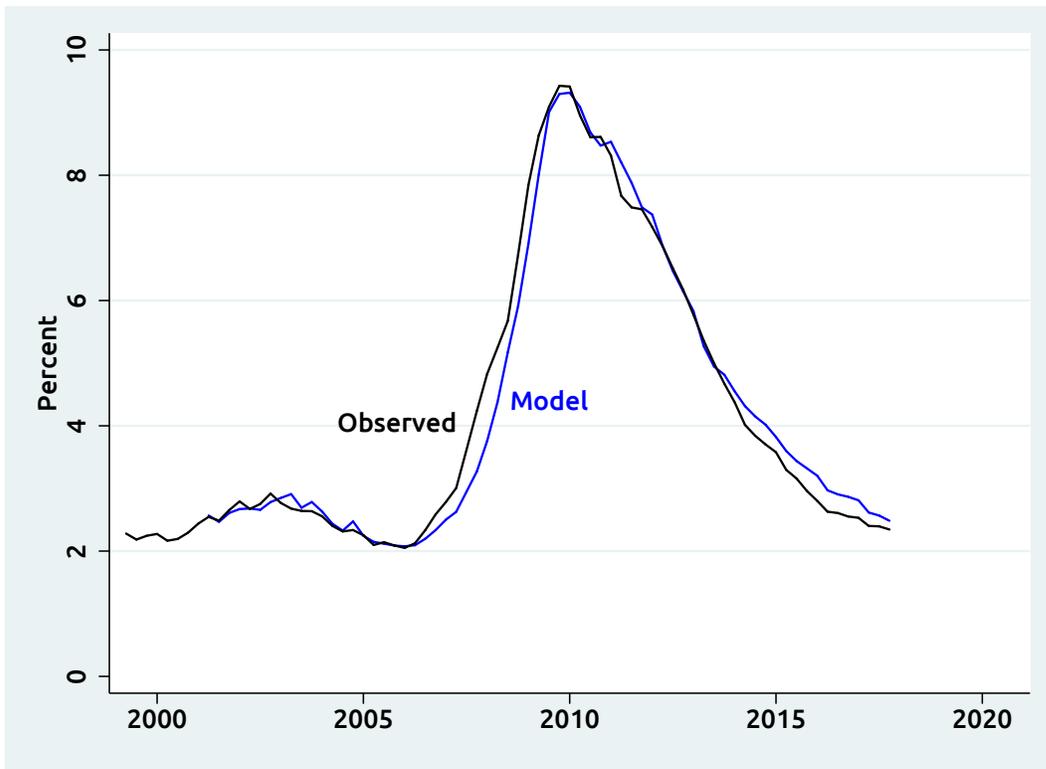
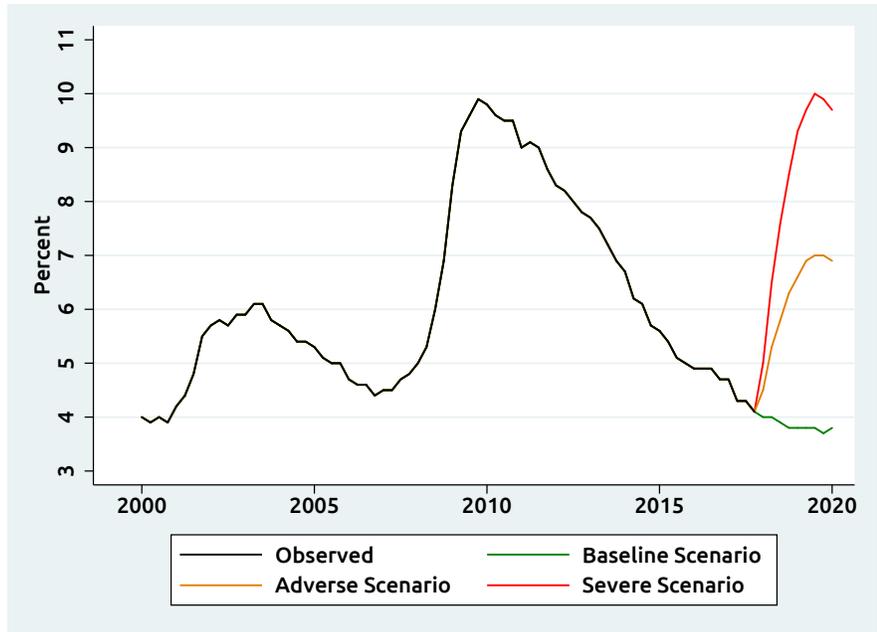
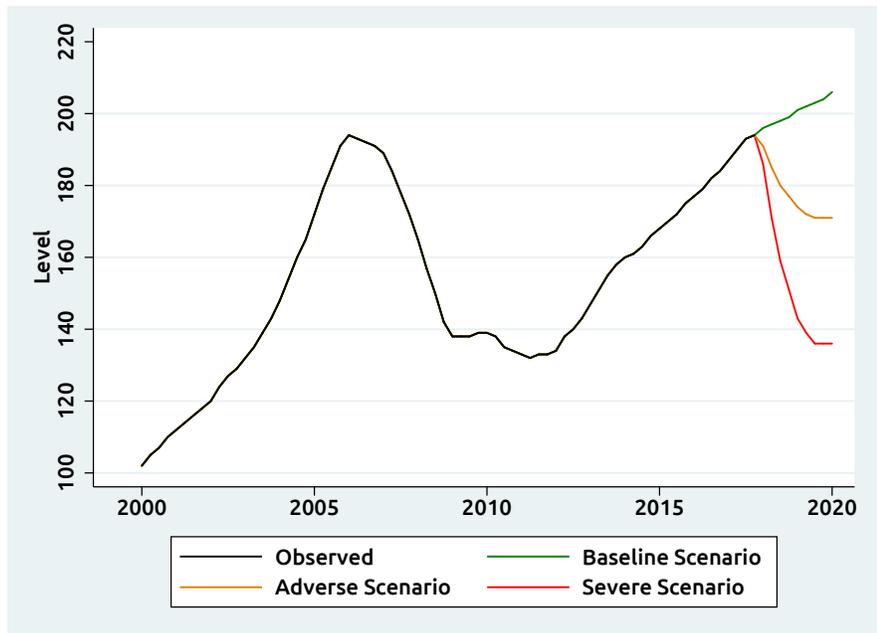


Figure 2: Unemployment and House Prices under CCAR Scenarios

The top panel displays the national unemployment rate and the right panel displays the national house price index. In each case, the black represents the data and the red, yellow and green lines represent the three indicated CCAR scenarios for 2018Q1-2019Q4. Source is Federal Reserve Board (2018).



(a) Unemployment



(b) House prices

Figure 3: Predicted Delinquency Under CCAR Scenarios

Figure displays the model-predicted 60+ day delinquency rate for 2001Q1-2017Q4 in the blue line, and the model-predicted 60+ day delinquency rate under the indicated CCAR scenario for 2018Q1-2019Q4 in the red yellow and green line, where the blue, red, yellow and green lines are based on estimating equation 1. The black line shows the observed 60+ day delinquency rate for 1999Q1-2017Q4. Data sources are: CCP/Equifax, BLS LAU and QCEW, Zillow and CCAR.

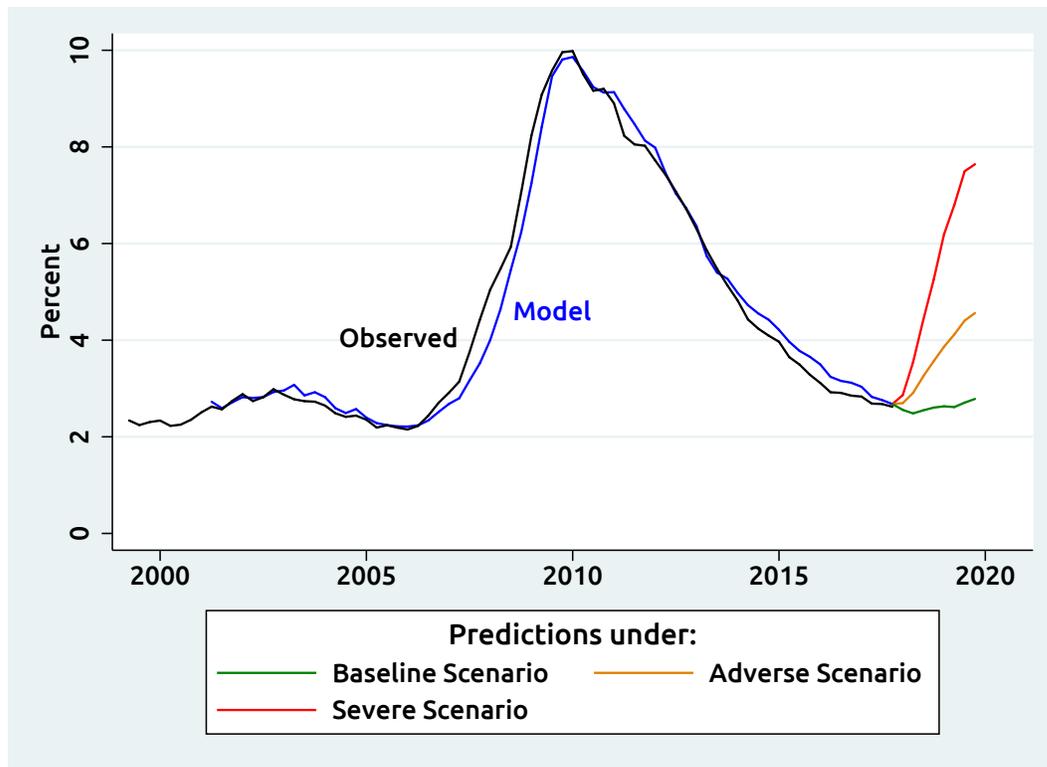


Figure 4: Comparing CCAR Stress Test Results Two Years Out Across Time

Figure displays the results of applying the eight-quarter path of the indicated CCAR scenario from the fourth quarter of the year listed, where estimates are based on estimating equation 1 for the entire sample period. Data sources are: CCP/Equifax, BLS LAU and QCEW, Zillow and CCAR.

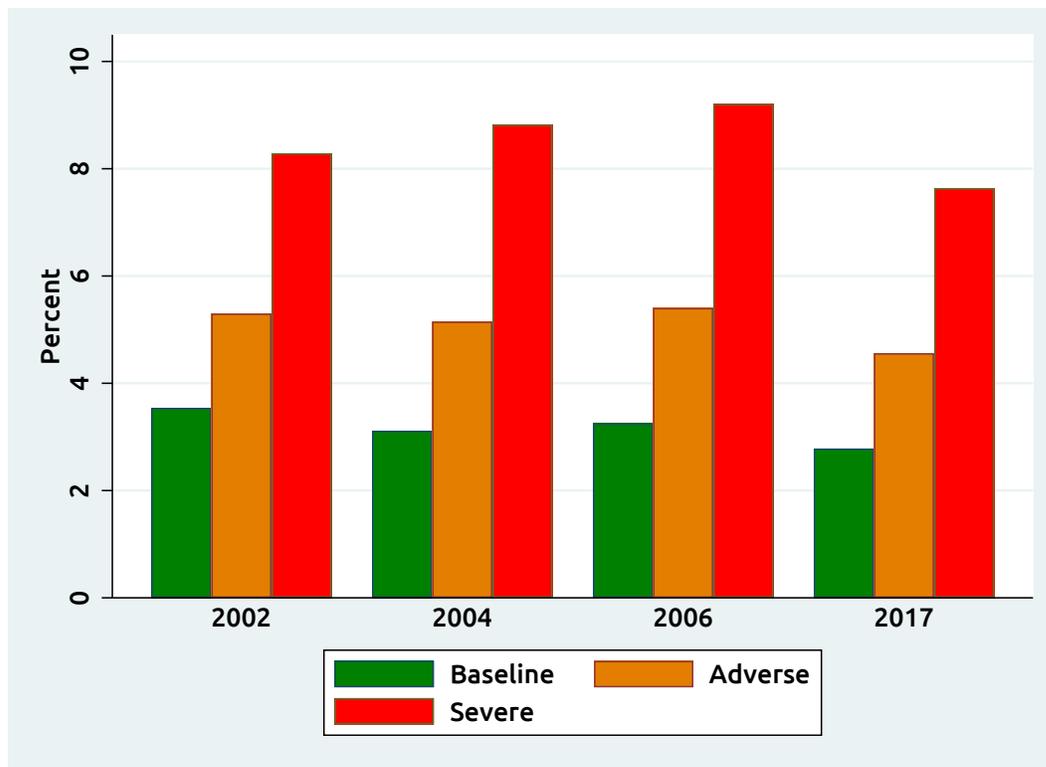


Figure 5: Mean County Debt-to-Income Ratios

Figure displays the mean of the county-level DTI ratios over time. Data sources are CCP/Equifax and BLS QCEW.

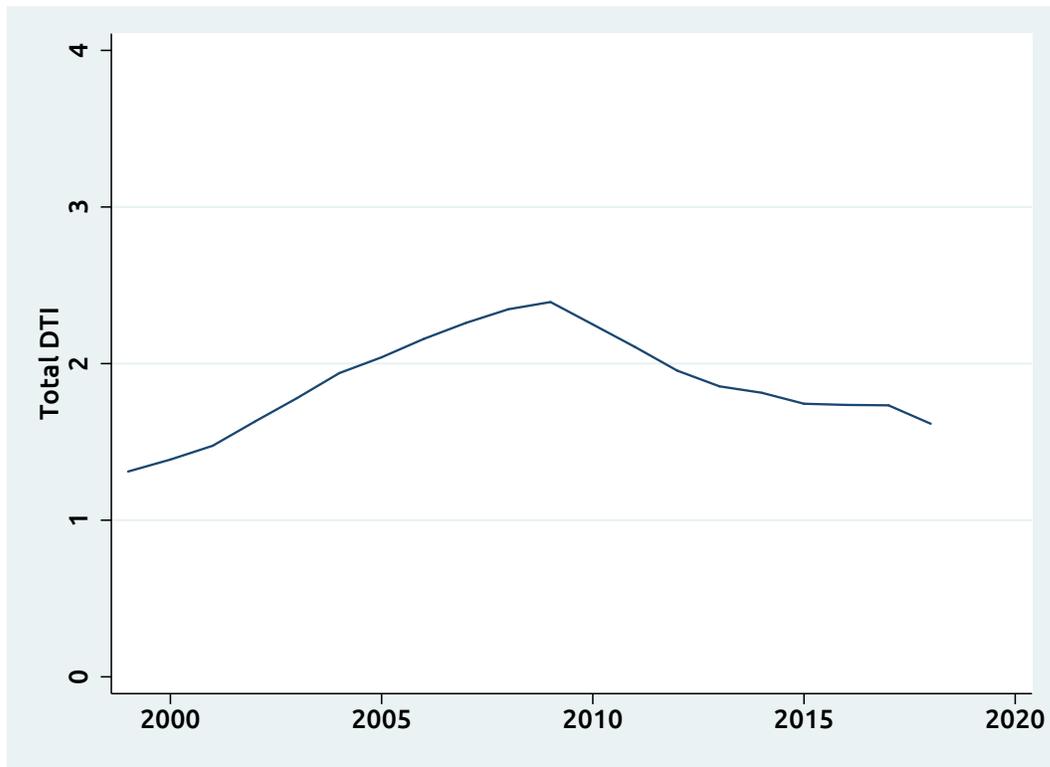


Figure 6: Share of Debt Held by Credit Score Groups

Figure displays the share of total debt held by the indicated credit score group. “Prime” is defined as 720 or above, “Near prime” as 620-719, and “subprime” as 619 or below. All scores refer to the Equifax 3.0 score. Data sources is CCP/Equifax.

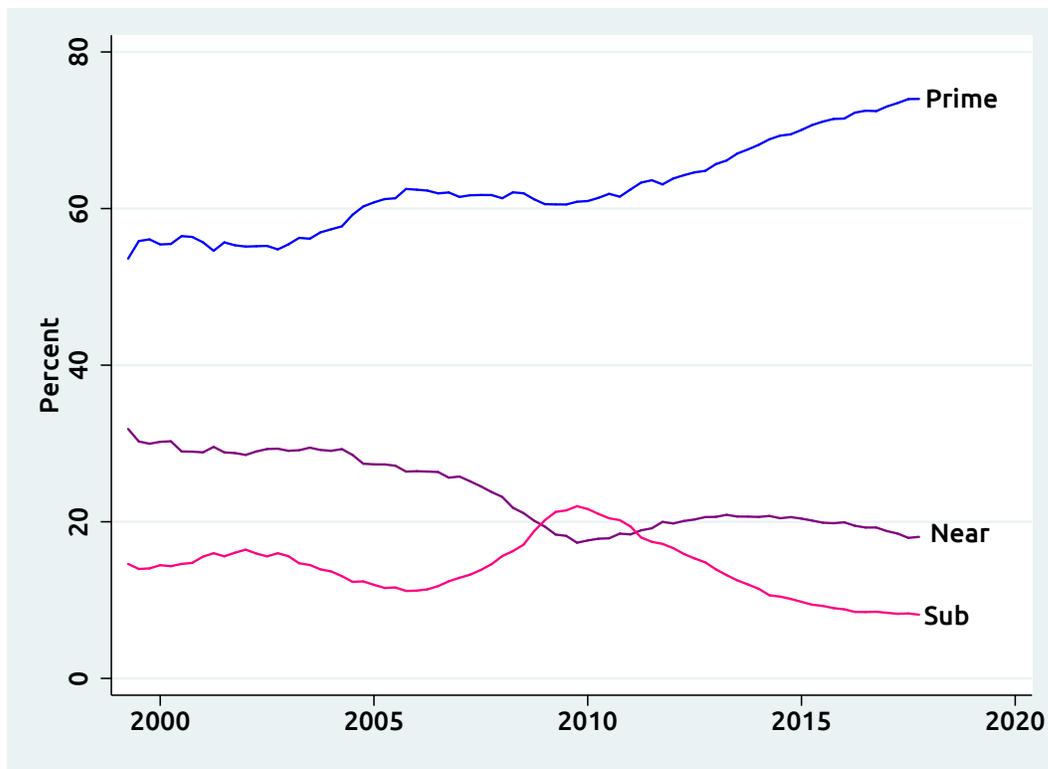


Figure 7: Price-Rent Ratio as a House Price Overvaluation Measure

Figure displays the log of the house price-to-rent ratio. The red line shows an estimate of its long-term trend, which is estimated using data from 1978-2001, and the shaded area shows a 95-percent confidence interval for this trend. Data sources are CoreLogic for prices and BLS for rents.

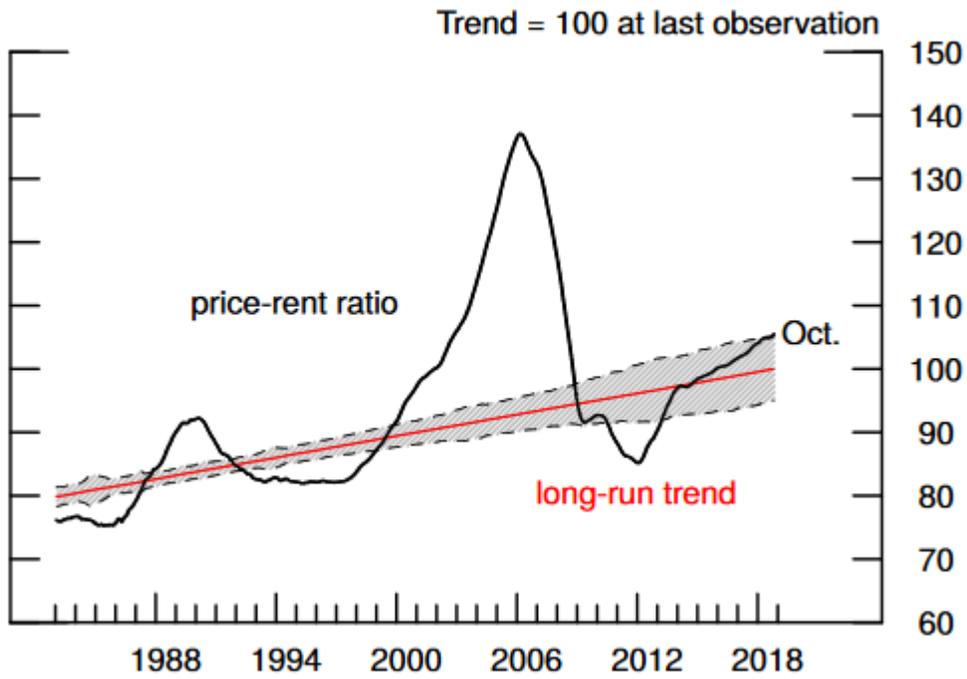


Figure 8: Delinquency Rates from a Housing Correction

Figure displays the results of applying the housing correction scenario for house prices and the indicated CCAR scenario for unemployment rates from the fourth quarter of the year listed, where estimates are based on estimating equation 1 for the entire sample period. The housing correction scenario moves the price-to-rent ratio to its long-term trend in 8 quarters. Data sources are: CCP/Equifax, BLS LAU and QCEW, Zillow, CCAR, CoreLogic and BLS.

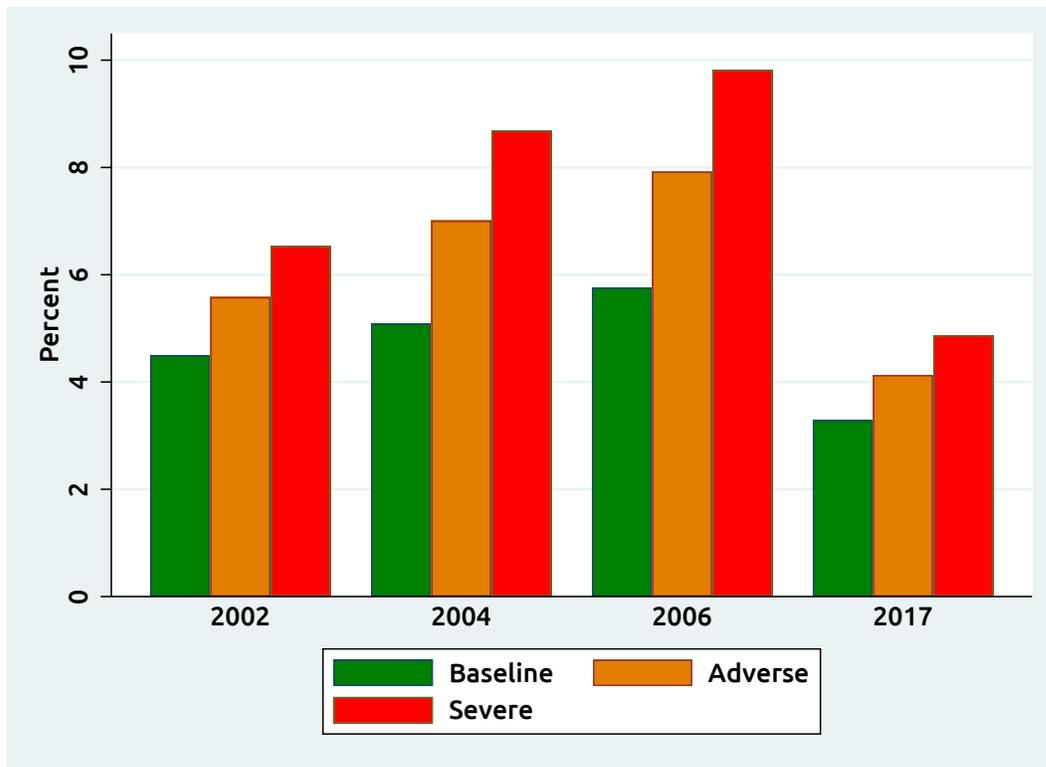


Figure 9: Delinquency Rates from Reversing Two Year House Price Growth

Figure displays the results of applying the two-year house price reversion scenario for house prices and the indicated CCAR scenario for unemployment rates from the fourth quarter of the year listed, where estimates are based on estimating equation 1 for the entire sample period. The two-year house price reversion scenario erases the past two years of local house prices gains in 8 quarters. Data sources are: CCP/Equifax, BLS LAU and QCEW, Zillow and CCAR.

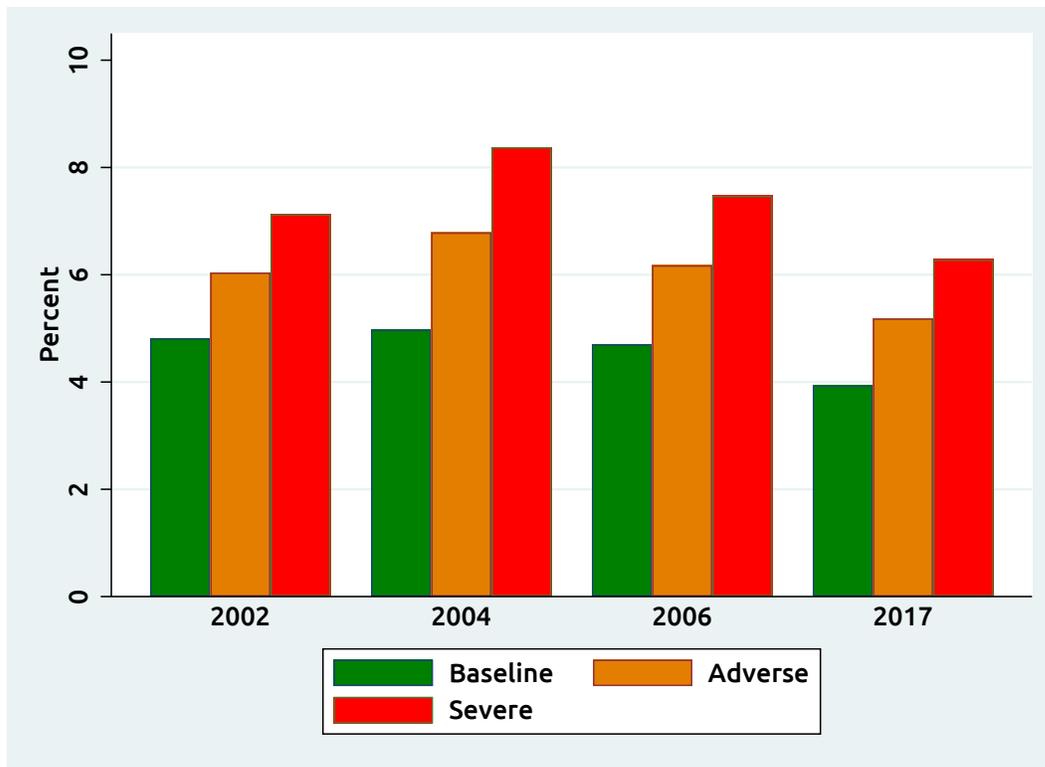


Figure 10: Delinquency Rates from Reversing Four Year House Price Growth

Figure displays the results of applying the four-year house price reversion scenario for house prices and the indicated CCAR scenario for unemployment rates from the fourth quarter of the year listed, where estimates are based on estimating equation 1 for the entire sample period. The four-year house price reversion scenario erases the past four years of local house prices gains in 8 quarters. Data sources are: CCP/Equifax, BLS LAU and QCEW, Zillow and CCAR.

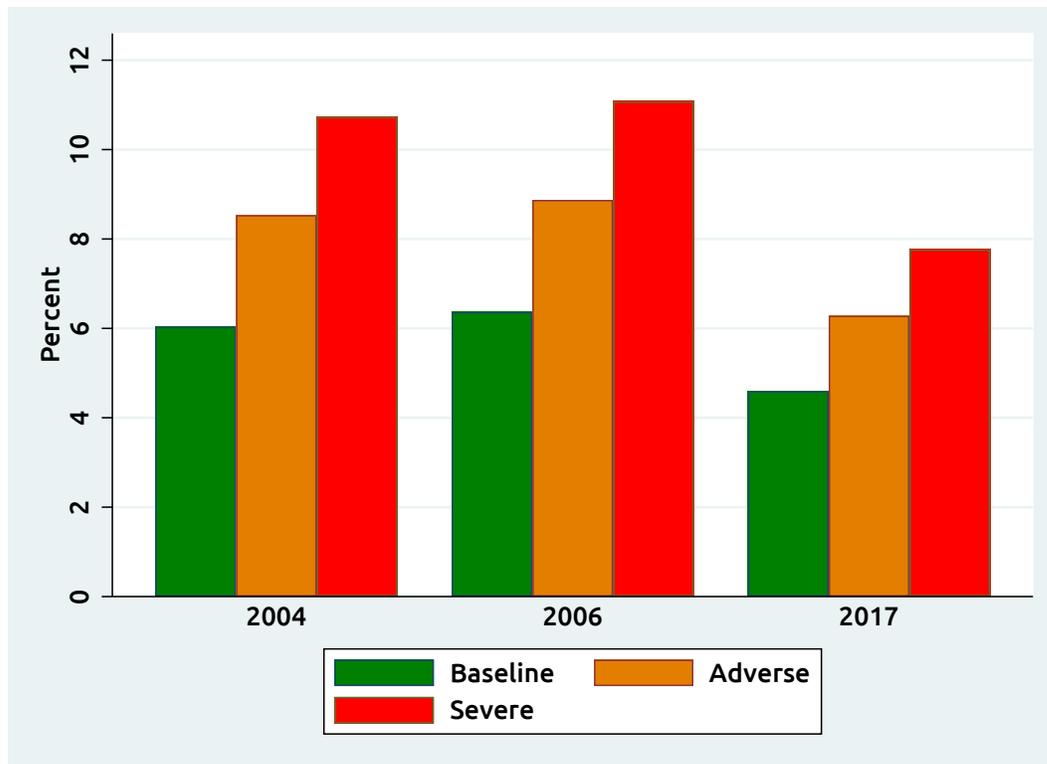
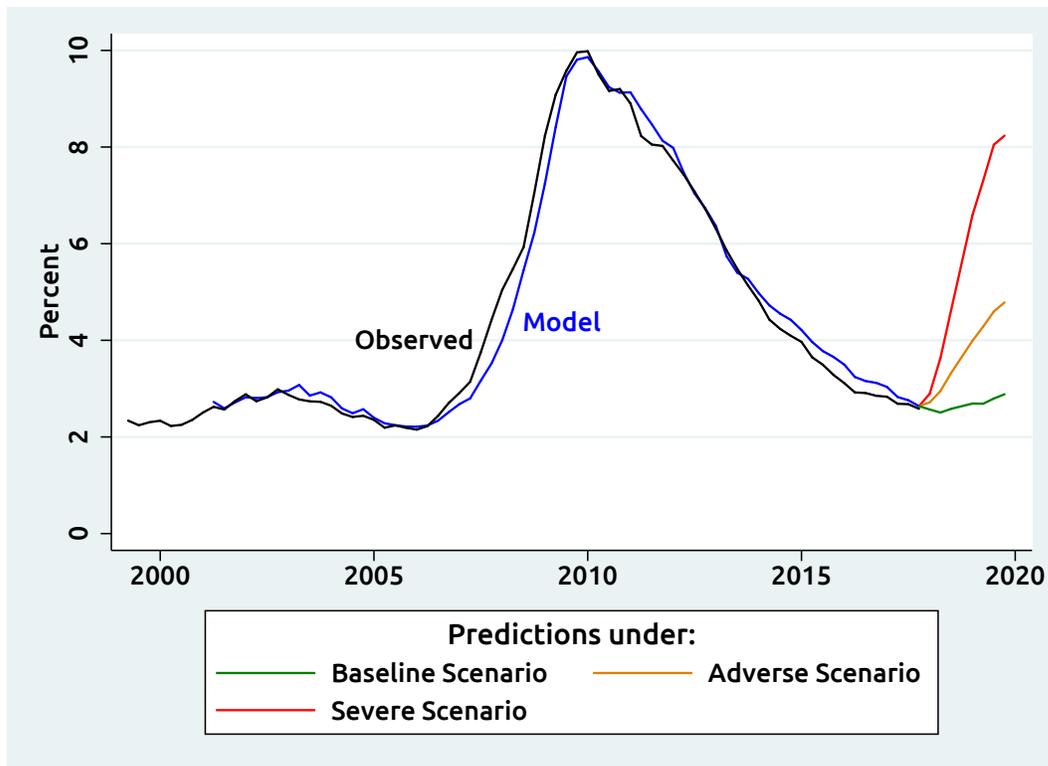


Figure 11: Delinquency Rates when the Most Leveraged Counties Receive the Largest Shocks

Figure displays the model-predicted 60+ day delinquency rate for 2001Q1-2017Q4 in the blue line, and the model-predicted 60+ day delinquency rate under the worst case scenarios for 2018Q1-2019Q4 in the red yellow and green line, where the blue, red, yellow and green lines are based on estimating equation 1. The black line shows the observed 60+ day delinquency rate for 1999Q1-2017Q4. The worst case scenarios assign the largest shocks obtained from CCAR scenario to the most leveraged counties. Data sources are: CCP/Equifax, BLS LAU and QCEW, Zillow and CCAR.



## 8 Appendix

As noted in the main text, our baseline debt and delinquency measures do not include student loan debt. Student loan debt has more than tripled since the early 2000s and could make the stock of debt more risky than our model suggests. We chose to omit student loan debt primarily because of data limitations, but the direct effect of student loan debt delinquency on the financial system may also be somewhat limited because the vast majority of student loans are guaranteed by the federal government. Still, if higher student loan debt causes borrowers to default on other types of debt, then these additional defaults would not be captured in our model predictions.<sup>28</sup>.

The measurement of student loan delinquencies is very different from other forms of debt for a number of reasons. Rather than entering delinquency after an economic shock, a borrower may choose to suspend their student debt repayment through the deferment or forbearance process, or enter into an alternative payment plan like income-based repayment. Further, the reporting of student loan delinquency to credit bureaus is different than other forms of debt. For instance, servicers typically do not report Federal student loans as in delinquency until the borrower misses more than 90 days of payments, making it hard to construct the same 60 day delinquency rate we do on other forms of debt.<sup>29</sup>. Furthermore, due to widespread changes in loan servicers' reporting, there are structural changes in the time series of loan balances in 2004, and in the time series of delinquencies in 2012. These differences make it difficult to construct measures of student loan debt and delinquency for the entire time series that are exactly comparable to the measures we use for other forms of debt.

However, as a check on the potential importance of student loan debt in our model, we include student debt in the DTI calculation (on the right hand side of the model) and also

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<sup>28</sup>However, recent evidence suggests this type of indirect exposure to risk may be limited [Feiveson et al., 2018]. And recent research indicates that, at least to some extent since the crisis, families have substituted student loans for home equity loans [Eberly et al., 2017]

<sup>29</sup>See [www.studentaid.ed.gov/repay-loans/default](http://www.studentaid.ed.gov/repay-loans/default)

include our best measure of 60-day student loan delinquency on the left hand side (figure 12). While the overall delinquency rate is higher in recent years than in the baseline figure, the change in delinquencies arising from the stress scenarios is about the same.

Figure 12: Predicted Delinquency Under CCAR Scenarios – Including Student Loans

Figure displays the model-predicted 60+ day delinquency rate for 2001Q1-2017Q4 in the blue line, and the model-predicted 60+ day delinquency rate under the indicated CCAR scenario for 2018Q1-2019Q4 in the red yellow and green line, where the blue, red, yellow and green lines are based on estimating equation 1. The black line shows the observed 60+ day delinquency rate for 1999Q1-2017Q4. This figure is similar to figure 3 but includes student loan balances in the RHS and student loan delinquency on LHS. Data sources are: CCP/Equifax, BLS LAU and QCEW, Zillow and CCAR.

