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Research Paper

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 stress tests, we find that forecasted delinquency rates for the 2017 Q4 stock of debt are moderately lower than for the stock of debt before the 2007–9 financial crisis, given the same set of shocks. We trace the decline in expected delinquency rates under stress to an improvement in debt-to-income ratios and an increase in the share of debt held by borrowers with relatively high credit scores. We also consider several alternative scenarios, including one where the size of house price shocks depends on current housing valuations. Under this scenario, we forecast a much lower delinquency rate than occurred during the crisis, as housing valuations measures were much more benign in 2017 than they were precrisis.

Keywords: loan default; stress test; household debt; delinquency; financial stability.

1 INTRODUCTION

Nominal debt owed by US households doubled from about US$7 trillion in 2000 to more than US$14 trillion in 2008, driven primarily by an increase in mortgage

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borrowing. The increases in household indebtedness and subsequent mortgage defaults are thought by many observers to have played an important role in creating the 2007–9 financial crisis and economic recession in the United States (see, for example, Mian and Sufi 2010, 2014). Indeed, past crises in the United States and elsewhere have often been preceded by a rapid rise in household debt (Jordà *et al* 2011). Because of the potential link between household debt and financial crises, it is important to closely monitor levels of risk and susceptibility to economic shocks in the outstanding stock of household debt.

In this paper, we design a "household stress test" to 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 has become a useful tool for identifying potential vulnerabilities for individual financial institutions since the financial crisis. Our stress test yields a summary measure of risk by forecasting serious delinquency rates for outstanding household debt under various economic scenarios. Although the outstanding stock of household debt as of the end of 2017 had climbed above the levels observed just before the financial crisis, our analysis suggests that this 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 sixty 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 – variables that capture households' susceptibility to shocks. To estimate such a model, we draw on a panel data set of consumer credit records with quarterly observations extending back to 1999. While this data allows 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 is 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 data set nonetheless allows us to exploit substantial cross-sectional variation in debt and economic conditions at the local level.[1]

Similar to the methodology suggested in Sufi (2014), we focus on credit scores as a measure of credit quality, and the ratio of total county debt (disaggregated

[1] 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.

by borrower credit score) to total county wage income (debt-to-income, DTI) as a measure of leverage. Due to data limitations, our model does not include another important measure of leverage: the ratio of mortgage loan balances to home values (loan-to-value, LTV). It is well established that having little or negative home equity (ie, LTV close to or above 100%) is an important driver of mortgage default, particularly when coupled with a liquidity shock (the so-called double-trigger theory of mortgage default).[2] 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 should largely 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 were likely to have the highest incidence of negative-equity homeowners by 2009.[3]

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 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.[4] We find that the 2017 Q4 stock of household debt in the United States is somewhat less vulnerable to a given set of shocks than the stocks at various points in time prior to the 2007–9 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 from about 2.5% to about 9% between 2006 Q4 and 2008 Q4 would result in an increase from about 2.5% to about 7.5% in the two years after 2017 Q4. 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

[2] Several recent papers, 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), help to establish the importance of the interaction between liquidity and negative equity.

[3] See Fuster *et al* (2018) for descriptive evidence on the evolution of negative equity across regions from 2006 through 2017.

[4] We distribute the published national shocks to the county level using a simple methodology, which we describe in Section 6.1.1.

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 2017 Q4 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%. 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 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%, 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%, 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: modeling household default as a function of household leverage and 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 work by Fuster *et al* (2018), who use a stress testing exercise with US 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.[5]

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

[5] Household stress testing exercises have also been evaluated using household survey and administrative data in, for example, Australia (Bilston *et al* 2015), Sweden (Finansinspektionen 2015), Austria (Albacete and Fessler 2010) and the United Kingdom (Anderson *et al* 2014).

more stringent income documentation requirements on mortgages imposed since the financial crisis. These developments 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 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% 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 online 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 the 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 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.[6] These 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.

In the end, trying to better understand the impact on financial institutions from potential economic shocks is crucially important for financial stability and has rightfully been a key component of the regulatory response to the financial crisis (eg, the bank stress tests that motivate this paper). Our paper complements such efforts by estimating the risks posed by household borrowing, independent of how these risks would be transmitted to the financial system.

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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[6] For example, 66% 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 UNITED STATES

By the end of 2017, total household debt stood at just over US$13 trillion according to Federal Reserve Bank of New York (2018). As a fraction of aggregate personal income, aggregate household debt declined from a peak of over 1.2 in 2007 to just under 1.0 in 2017 (Ahn *et al* 2018). Just over 70% of household debt was housing related, including debt owed on home equity lines of credit. Student loans (US$1.4 trillion), auto loans (US$1.2 trillion) and credit cards (US$0.8 trillion) made up most of the other 30% of debt.[7]

After fluctuating modestly around 2–3% from 1999 through 2005, the delinquency rate on household debt, ie, the fraction of US dollars outstanding on consumer and mortgage loans that were at least sixty days past due, jumped to about 9% during the financial crisis of 2007–9. 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 tenfold.[8] While mortgages sold and packaged into nonprime securities were experiencing 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 that 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 toward default. Along the same lines, borrowers with lower credit scores have repayment histories that suggest they are susceptible to shocks. 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.[9] But when borrowers have "negative home equity" (ie, homes worth less than the current mortgage balance), selling may not be feasible 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. Research suggests that

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

[8] See Federal Reserve Bank of New York (2018) for trends in serious delinquency rates since 2003 by loan type.

[9] Similarly, auto loan borrowers facing a shock may be able to sell their car to repay the loan.

most defaults during the recent crisis were likely due to the combination of liquidity shocks and negative equity (see, for example, 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 (Deng *et al* 2000; Vandell 1995). This is especially true in nonrecourse states such as 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. Therefore, 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 (FRBNY) Consumer Credit Panel/Equifax; wage data from the Bureau of Labor Statistics's (BLS's) quarterly census of employment 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 data set from 1999 through 2017, covering over 1500 of the largest counties in the United States and containing roughly 90% of the US population. This section introduces these data sources and presents summary statistics of the key variables of our study.

3.1 FRBNY Consumer Credit Panel

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% random sample of US consumers with valid credit histories and social security numbers (about 11 million individuals in recent quarters) on a quarterly basis.[10] 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

[10] The CCP sampling design generates a longitudinal data set 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% sample of the CCP (ie, a 0.5% sample of adults).

TABLE 1 Sample summary statistics.

	2000 (Q4)	2007 (Q4)	2014 (Q4)
Total debt/total wages (DTI)	1.35 [0.74, 2.18]	2.20 [1.01, 3.66]	1.71 [0.83, 2.75]
House price growth, next two years	0.14 [0.03, 0.28]	−0.18 [−0.42, −0.02]	0.12 [0.04, 0.22]
Change in unemployment rate, next two years	1.84 [0.85, 2.92]	4.72 [2.84, 6.88]	−1.32 [−2.27, −0.40]
Share debt sixty days late, two 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

The means and distributions of key summary variables, where the 10th and 90th percentiles of each variable are shown in brackets below the mean. *Data sources:* CCP/Equifax, BLS LAU and QCEW, and Zillow (see text).

or subprime), as measured by their current credit risk score.[11] 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.[12]

We also use repayment information from the CCP to construct a measure of county-level delinquency rates, defined as the share of US dollar balances of our total debt measure in a county that are sixty days or more past due.[13] 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 nonmortgage debt. As shown in Table 1, the share of debt in delinquency (two years out) was 3.3% in the average (large) county in the early 2000s, which then increased to 9.4% 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% and 17.0%, respectively.

[11] The credit score available in the CCP is the Equifax 3.0 score. Similar to the FICO score, it ranges from 280 to 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.

[12] 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. See the online appendix for an analysis of student loans in our model.

[13] We account for joint balances in both our debt measurement and delinquency measurement by a standard procedure of subtracting half of the joint balance.

3.2 BLS quarterly census of employment and wages

While the CCP provides a measure of household debt, constructing DTI ratios 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 BLS's QCEW, and measure DTI ratios at the county level as total debt to total wage income. Table 1 shows how the average DTI ratio evolved over the sample period. In 2000 Q4, the average DTI ratio across counties was 1.35. This rose to about 2.2 by the end of 2007, and receded to about 1.7 by 2014. 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 (UI) program records. Thus, it excludes some components of personal income, such as transfer income (eg, Social Security), interest and dividend income 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 (see Bureau of Economic Analysis 2018, Table 2.1). 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 that tend to have little debt relative to their income.[14]

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 ratios. 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.[15]

[14] For example, in 2016, families in the top three quartiles of the DTI distribution derived between 60% and 70% of their total income from wages. In contrast, families in the first quartile of the DTI distribution derived just 37% of their income from wages (authors' calculation based on the 2016 Survey of Consumer Finances; see www.federalreserve.gov/econres/scfindex.htm).

[15] The limitation of this approach is that our DTI ratios cannot account for divergences between debt growth and the income growth among the credit score groups. For example, if one credit score group had an unusually large increase in their share of total debt compared with their share of total wages, the higher risk of default among the borrowers would not be captured by our model.

3.3 BLS county unemployment rate

As discussed 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, eg, total income, for two reasons. First, unemployment rates isolate unexpected disturbances in income, whereas changes in total income combine expected income changes (eg, retirement) and unexpected changes (eg, job loss). Second, changes in total income will be dominated by those at the top of the 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 to 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 three percentage point (3pp) increase in their unemployment rate, and some counties experienced increases of over 7pp.

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 of all homes in a given county in a given month (to be sure, the ZVHI does not simply equal the median price of homes that were actually sold). Zillow's coverage has increased over time, which is why the number of counties in our data set rises over our sample period (see Table 1).

Table 1 presents two-year-ahead growth rates in home prices. From 2000 to 2002, county median home prices grew by 14% on average, with considerable variation between the 10th and 90th percentiles. From 2007 to 2009, home prices fell sharply, in excess of 40% 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 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 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 the delinquency rates and DTI ratios described above, and also 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 a total of 31% of counties had subprime DTI ratios in the highest quartile of the historical distribution, whereas in 2016 only 16% of counties did. (Over the entire sample, of course, 25% of counties will fall into the highest quartile.)

A second key feature of the model is the interaction between the credit score-group DTI ratios and the macroeconomic shocks, which captures the additional rise in delinquency rates 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, ie, 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:

$$\begin{aligned} D_{c,t+8} &= \beta_0 + \beta_1 D_{c,t} + \beta_2 \Delta U_{c,t} + \beta_3 \Delta \log(\mathrm{HPI}_{c,t}) + \beta_4 \Delta U_{c,t} \Delta \log(\mathrm{HPI}_{c,t}) \\ &\quad + \sum_{j,k} (\beta_5^{j,k} + \beta_6^{j,k} \Delta U_{c,t} + \beta_7^{j,k} \Delta \log(\mathrm{HPI}_{c,t}) + \beta_8^{j,k} \Delta U_{c,t} \Delta \log(\mathrm{HPI}_{c,t})) \\ &\qquad \times \mathrm{DTI}_{c,t}^{j,k}, \end{aligned} \tag{4.1}$$

where c indexes the county, t indexes the quarter, $D_{c,t}$ is the share of debt that is sixty or more days delinquent, $U_{c,t}$ is the unemployment rate, $\mathrm{HPI}_{c,t}$ is the house price index and Δ denotes the change in a variable over the next eight quarters (eg, $\Delta U_{c,t} = U_{c,t+8} - U_{c,t}$). Finally, $\mathrm{DTI}_{c,t}^{j,k}$ for $j = \{\text{subprime, near prime}\}$ is a dummy variable indicating that the ratio of the debt of borrowers of type j to total county wage income falls into the kth 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 (4.1) using the data described in Section 3. Because our model incorporates many interaction terms, we 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: 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 0.75pp rise in the unemployment rate and a 5% decline in house prices) is associated with a 0.41pp increase in delinquency rates in counties with low DTI ratios. But the same shock is associated with a 0.86pp increase in delinquency rates in high debt-to-income counties, nearly double the increase in the low DTI ratio counties.[16]

A larger unemployment shock (on the order of a 3pp increase in the rate) accompanied by the 5% (smaller) 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 (1.80pp) than in lower DTI ratio counties (1.12pp increase). A similar pattern is found when a larger house prices shock (a 15% 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 the delinquency rates are highest when both the large unemployment rate shock (3pp) and the large house price shock (15%) are applied to the model. Notably, relative to the first row, the rise in the delinquency rate when we apply both shocks simultaneously exceeds the sum of the independent

[16] 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 0.91pp higher than the low DTI county baseline.

effects of each shock, reflecting the interactive effect between unemployment and house price shocks. Further, the delinquency rate change resulting from the two large shocks is over 1.5pp 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 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% in the early 2000s, a steep rise in delinquency rates in the 2006–10 period, followed by a more gradual decline until 2018.[17] 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.

We also conduct an out-of-sample test of model fit, estimating the model using only data through the end of 2006. As shown in Figure 2, the resulting fit is not quite as good as the baseline model, especially around the peak of the financial crisis. This is not surprising, as the shocks in the pre-2007 sample were much smaller than the shocks during the crisis. Nevertheless, the model still delivers almost the entire jump in the delinquency rate during the crisis, which should provide additional confidence in the ability of our model to deliver credible results.[18]

5.2 Predicted delinquency rates by type of debt

To help understand how different types of debt have contributed to our estimates thus far, we disaggregate household debt and estimate two variations of (4.1). First we examine delinquency rates only for mortgage debt, and then we study delinquency rates only for nonmortgage debt.[19] 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

[17] 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 do not separate out the prime, near-prime and subprime DTI ratios has trouble reproducing this large decline in delinquency rates.

[18] In conducting this out-of-sample test, it is important to note that after 2006 we only use the out-of-sample predicted values for the lagged delinquency term on the right-hand side.

[19] In these models, we also use separate mortgage and nonmortgage DTI ratios (and their interactions with the macroeconomic shocks) as explanatory variables.

TABLE 2 Model estimates. [Table continues on next two pages.]

	β	**SE**(β)
Share of borrowers 60+ DPD	0.513**	(0.049)
Δ unemployment	0.003**	(0.000)
Δ log(HPI)	−0.036**	(0.007)
Δ unemployment $\times\Delta$log(HPI)	−0.012**	(0.002)

(a) Subprime DTI

	β	**SE**(β)
DTI quartile 2	0.005**	(0.001)
DTI quartile 3	0.007**	(0.001)
DTI quartile 4	0.011**	(0.001)

(b) Δ unemployment $\times$ subprime DTI

	β	**SE**(β)
DTI quartile 2	0.000	(0.000)
DTI quartile 3	−0.000	(0.000)
DTI quartile 4	−0.001	(0.001)

(c) Δlog(HPI) $\times$ subprime DTI

	β	**SE**(β)
DTI quartile 2	−0.008	(0.005)
DTI quartile 3	−0.017**	(0.007)
DTI quartile 4	−0.035*	(0.019)

(d) Δ unemployment $\times$ Δlog(HPI) $\times$ subprime DTI

	β	**SE**(β)
DTI quartile 2	0.002	(0.002)
DTI quartile 3	0.008**	(0.002)
DTI quartile 4	0.010**	(0.003)

TABLE 2 Continued.

(e) Near-prime DTI		
	β	**SE**(β)
DTI quartile 2	0.001*	(0.001)
DTI quartile 3	0.005**	(0.002)
DTI quartile 4	0.007**	(0.003)
(f) Δ unemployment $\times$ near-prime DTI		
	β	**SE**(β)
DTI quartile 2	0.000	(0.000)
DTI quartile 3	0.001	(0.000)
DTI quartile 4	0.000	(0.000)
(g) Δlog(HPI) $\times$ near-prime DTI		
	β	**SE**(β)
DTI quartile 2	0.008	(0.006)
DTI quartile 3	0.001	(0.008)
DTI quartile 4	−0.002	(0.010)
(h) Δ unemployment $\times$ Δlog(HPI) $\times$ near-prime DTI		
	β	**SE**(β)
DTI quartile 2	0.003	(0.002)
DTI quartile 3	−0.008**	(0.002)
DTI quartile 4	−0.012**	(0.004)
(i) Prime DTI		
	β	**SE**(β)
DTI quartile 2	−0.004**	(0.001)
DTI quartile 3	−0.005**	(0.001)
DTI quartile 4	−0.009**	(0.002)

TABLE 2 Continued.

(j) Δ unemployment $\times$ prime DTI		
	β	**SE**(β)
DTI quartile 2	−0.000	(0.000)
DTI quartile 3	0.001	(0.000)
DTI quartile 4	0.001*	(0.001)
(k) Δlog(HPI) $\times$ prime DTI		
	β	**SE**(β)
DTI quartile 2	−0.009	(0.006)
DTI quartile 3	−0.031**	(0.010)
DTI quartile 4	−0.037**	(0.007)
(l) Δ unemployment $\times$ Δlog(HPI) $\times$ prime DTI		
	β	**SE**(β)
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^2	0.761	
N	101 399	

The results of estimating (4.1). Standard errors are given in parentheses. *, ** and *** denote $p < 0.05$, $p < 0.01$ and $p < 0.001$, respectively. *Data sources:* CCP/Equifax, BLS LAU and QCEW, and Zillow (see text).

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 larger (by 74 basis points) increase in 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 2.46pp.

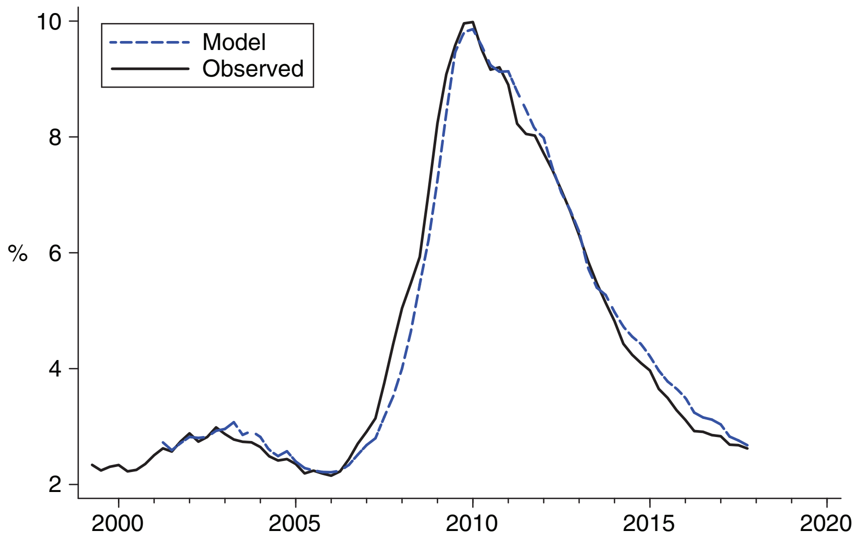
The second column of Table 4 repeats this exercise for nonmortgage delinquency rates. As with mortgage delinquency, moving from the smaller unemployment rate shock to a larger one is associated with a larger (by 82 basis points) increase in the nonmortgage delinquency rate. However, unlike mortgage delinquency, moving from

TABLE 3 Model-predicted default rates by DTI quartile.

Rise in county delinquency rate (pp) associated with...	First quartile	Fourth quartile
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 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

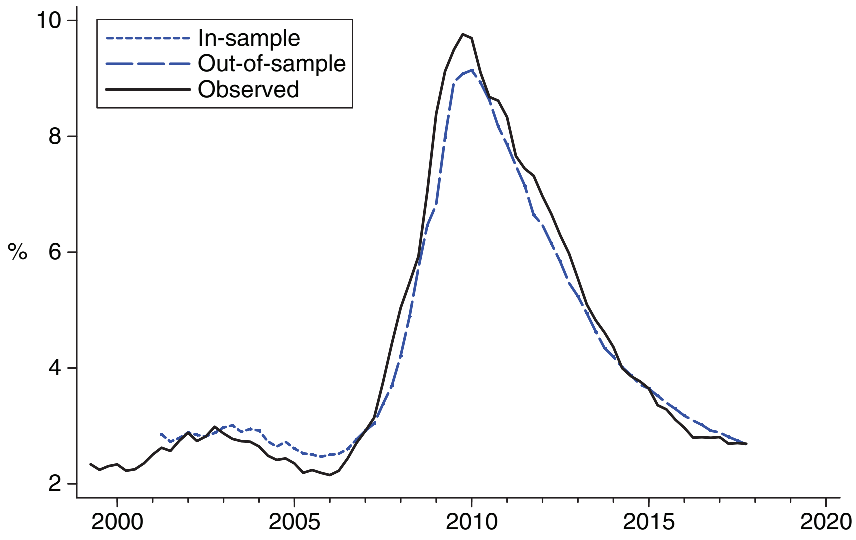
The predictions for the change in the delinquency rate associated with the listed change in unemployment rates and house prices, based on the results of estimating (4.1): counties in the first and fourth quartiles of subprime, near-prime and prime DTI. The table shows the rise in delinquency rates (in percentage points (pp)) compared with a baseline where there is no shock (ie, 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:* CCP/Equifax, BLS LAU and QCEW, and Zillow (see text).

FIGURE 1 Model fit.



The figure displays the 60+ day delinquency rate (black (solid) line) and the model-predicted 60+ day delinquency rate (blue (dashed) line), where the blue line is based on estimating (4.1). *Data sources:* CCP/Equifax, BLS LAU and QCEW, and Zillow (see text).

FIGURE 2 Out-of-sample model fit.



The figure displays the 60+ day delinquency rate (black (solid) line) and the model-predicted 60+ day delinquency rate (blue dotted line), where the dotted blue line is based on estimating (4.1) using data through 2006 Q4 (the dashed blue line reflects out-of-sample predictions). *Data sources:* CCP/Equifax, BLS LAU and QCEW, and Zillow (see text).

TABLE 4 Model-predicted default rates for mortgage and nonmortgage debt.

Rise in county delinquency rate (pp) associated with...	**Mortgage delinquency rate**	**Nonmortgage delinquency rate**
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 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 (%) in 2017 Q4	3.94	7.25

The 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 (4.1), where defaults are mortgage only in the first column and nonmortgage only in the second column. In these models, we also use separate mortgage and nonmortgage DTI ratios (and their interactions with the macroeconomic shocks) as explanatory variables. *Data sources:* CCP/Equifax, BLS LAU and QCEW, and Zillow (see text).

a smaller house price shock to a larger one has only a small effect on the nonmortgage 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 nonmortgage debt. In addition, many nonmortgage 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 2018 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 US-based bank holding companies, and are required as part of the Federal Reserve Board's supervisory function.[20] 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.[21]

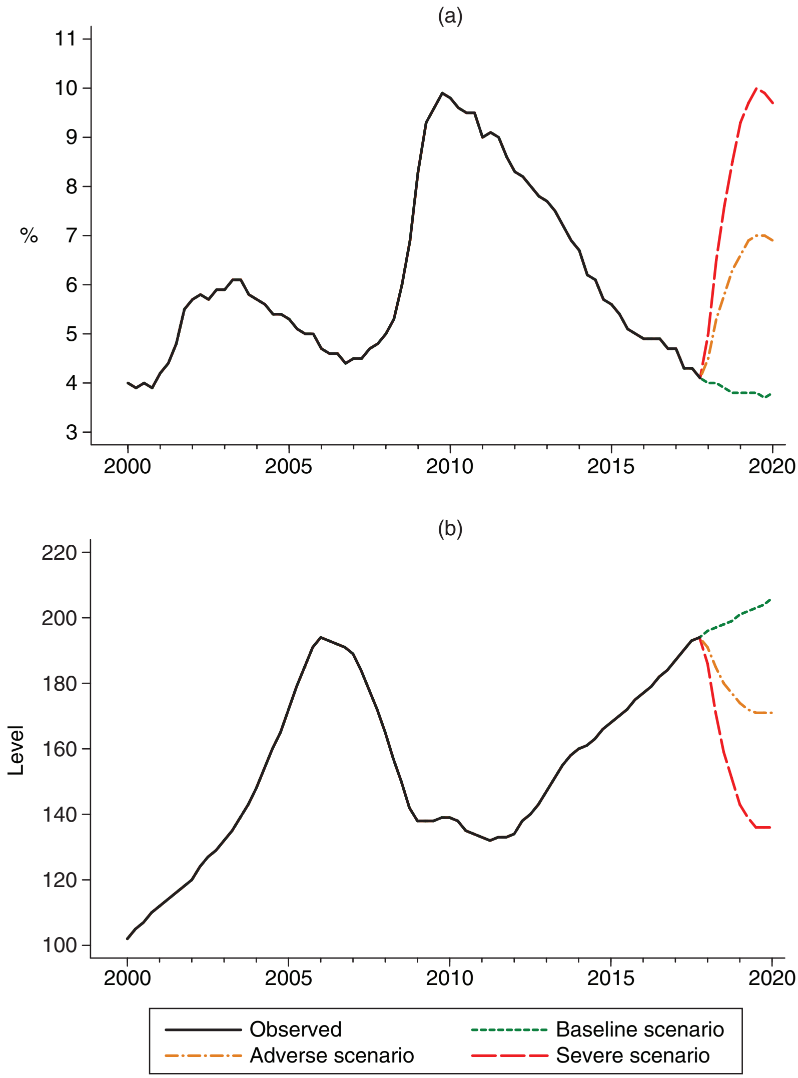
The baseline scenario in 2018 is based on a moderate economic expansion of real economic activity, as projected in the Blue Chip Economic Indicators, a survey of professional forecasters.[22] In these projections, the unemployment rate remains near 4% through our eight-quarter scenario period and nominal house price growth averages about 2.5% annually.

The adverse scenario describes a moderate recession that begins in 2018 Q1. In this scenario, the unemployment rate increases sharply from less than 4% in 2017 Q4 to 7% by 2019 Q3 and house prices fall 12% over the eight quarters.

The severely adverse scenario describes a severe recession, along the lines of the 2007–9 recession. The unemployment rate increases to 10% and house prices fall 30% by 2019 Q3. Figure 3 displays the three-year trends in the forward-looking

[20] See Federal Reserve Board (2018) or www.federalreserve.gov/supervisionreg/files/bcreg2018 0201a1.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.
[21] The scenarios are not forecasts by the Federal Reserve. The scenarios provide twenty-eight measures of the forward path of economic activity and prices, of which we use two as inputs in our model: the path of house prices and the path of unemployment rates.
[22] Note that the details of the CCAR scenario change slightly from year to year.

FIGURE 3 Unemployment and house prices under CCAR scenarios.



Panel (a) displays the national unemployment rate and panel (b) displays the national house price index. In each case, the black line represents the data and the red, yellow and green lines represent the three indicated CCAR scenarios for 2018 Q1–2019 Q4. *Source:* Federal Reserve Board (2018).

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 these shocks to 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, we estimate parameters α_c and β_c from the regression

$$\Delta y_{c,t} = \alpha_c + \beta_c \Delta y_t + \varepsilon_{c,t}, \tag{6.1}$$

where $\Delta y_{c,t}$ is the one-quarter change in either log house prices or unemployment for county c in quarter t, and Δy_t is the change in that variable at the national level.[23] We estimate these models using data for 1999 Q1 to 2017 Q4. Then, we use the estimated parameters to distribute the national changes in the CCAR scenarios across counties for 2018 Q1 to 2019 Q4. 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 2017 Q4 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 4.

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% through 2019 Q4 (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% 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% in late 2019 (red line).

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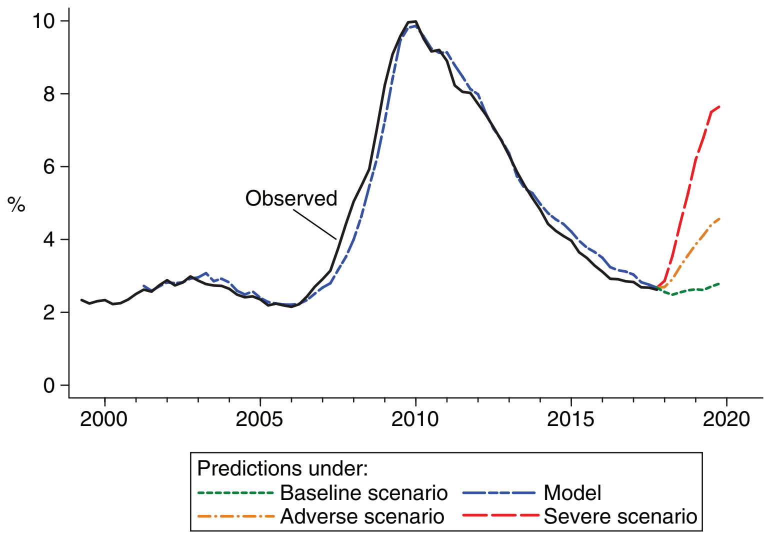
[23] Note that we use county-level Zillow median home prices, whereas the published CCAR scenarios are based on the national CoreLogic price index for owner-occupied real estate. Thus, our model relates how changes in the national CoreLogic index translate into changes in each county's Zillow median home price.

FIGURE 4 Predicted delinquency under CCAR scenarios.

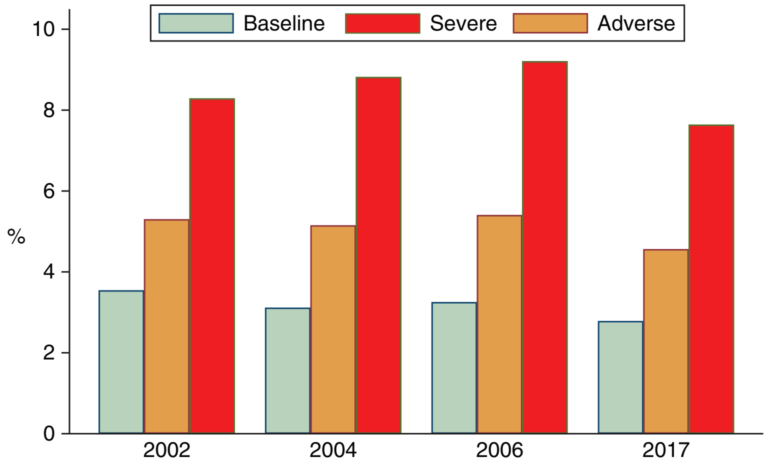


The figure displays the model-predicted 60+ day delinquency rate for 2001 Q1–2017 Q4 (blue line) and the model-predicted 60+ day delinquency rate under the indicated CCAR scenario for 2018 Q1–2019 Q4 (red, yellow and green lines, respectively), where the blue, red, yellow and green lines are based on estimating (4.1). The black line shows the observed 60+ day delinquency rate for 1999 Q1–2017 Q4. *Data sources:* CCP/Equifax, BLS LAU and QCEW, Zillow and CCAR (see text).

In order to assess the current risks stemming from household debt relative to previous time periods, we compare these predictions with those we would have made by repeating the same exercise for the previous periods. Specifically, we can apply the same eight-quarter-ahead forward paths of the 2018 CCAR scenarios, but we start with the stock of outstanding household debt from the fourth quarter of selected precrisis years. For brevity, we select 2002, 2004 and 2006 (Figure 5). For ease of exposition, we display these results in a bar chart, where the height of the bars is the maximal two-year-ahead expected delinquency rate under each scenario.

We start with two observations based on expected delinquency rates for the precrisis years. First, applying the severely adverse scenario to the stock of outstanding debt in 2006 Q4 returns an expected level of delinquencies of about 9.2% two years later, nearly identical to the actual level of delinquencies around this time (which was 9.1% in 2009 Q1). This is a reassuring result from our model, as the severely adverse scenario is designed to be similar to the 2007–9 recession. Second, this exercise suggests that the stock of debt was nearly as risky in the early 2000s as it was in 2006. Expected eight-quarter-out delinquency rates arising from the severely adverse

FIGURE 5 Comparing CCAR stress test results two years out across time.



The 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 (4.1) for the entire sample period. *Data sources:* CCP/Equifax, BLS LAU and QCEW, Zillow and CCAR (see text).

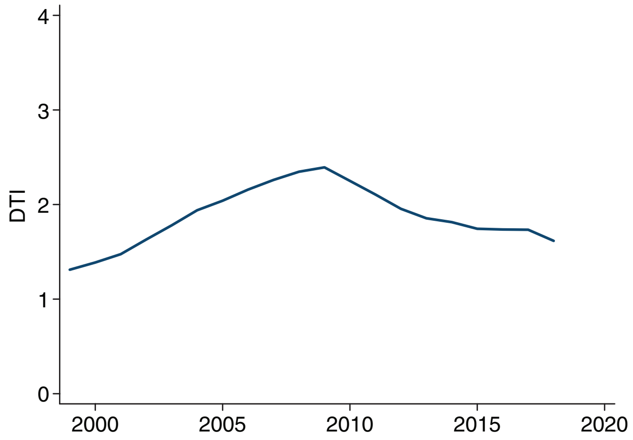
CCAR shocks are around 8.3% in 2002, rising to 8.8% in 2004, which is just slightly lower than the expected delinquency rate in the 2006 stock of debt (9.2%).

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 precrisis year. For example, as noted earlier, the predicted delinquency rate in the adverse scenario in 2017 is about 4.5%, whereas it ranges from 5.2% in 2002 to 5.4% in 2006 (yellow bars). In the severely adverse scenario, the eight-quarters-out delinquency rate in 2017 is about 7.6%, while it is predicted to be between 8.3% and 9.2% 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.[24]

Why might household debt now be more resilient to a given set of macroeconomic shocks? While DTI ratios have declined since 2010, on average they have remained

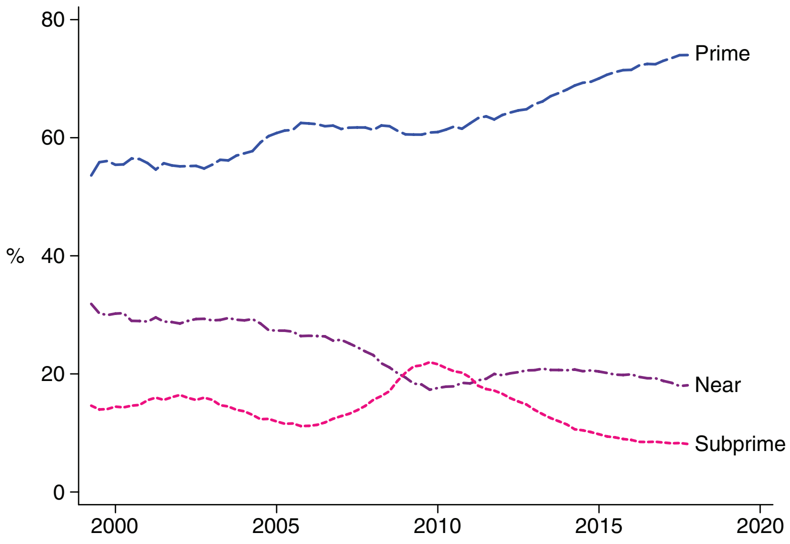
[24] The baseline model from (4.1), which is used to generate Figures 4 and 5, assumes linearity in the correlation between house price changes and delinquencies. An alternative assumption would model this correlation nonlinearly. Accordingly, we reestimate the model in (4.1) and allow house price change to enter as a set of eight dummy variables, four of which describe house price declines (by more than 20%, between 10% and 20%, between 5% and 10% or by less than 5%) and four of which describe identical house price appreciation. The predicted delinquency rates under each stress scenario are only slightly attenuated relative to those described in Figure 5.

FIGURE 6 Mean county debt-to-income ratios.



The figure displays the mean of the county-level DTI ratios over time. *Data sources:* CCP/Equifax and BLS QCEW (see text).

FIGURE 7 Share of debt held by credit score groups.



The 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:* CCP/Equifax (see text).

near 2004 levels for much of the post-2012 period (Figure 6). Thus, the postcrisis 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 7). 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).

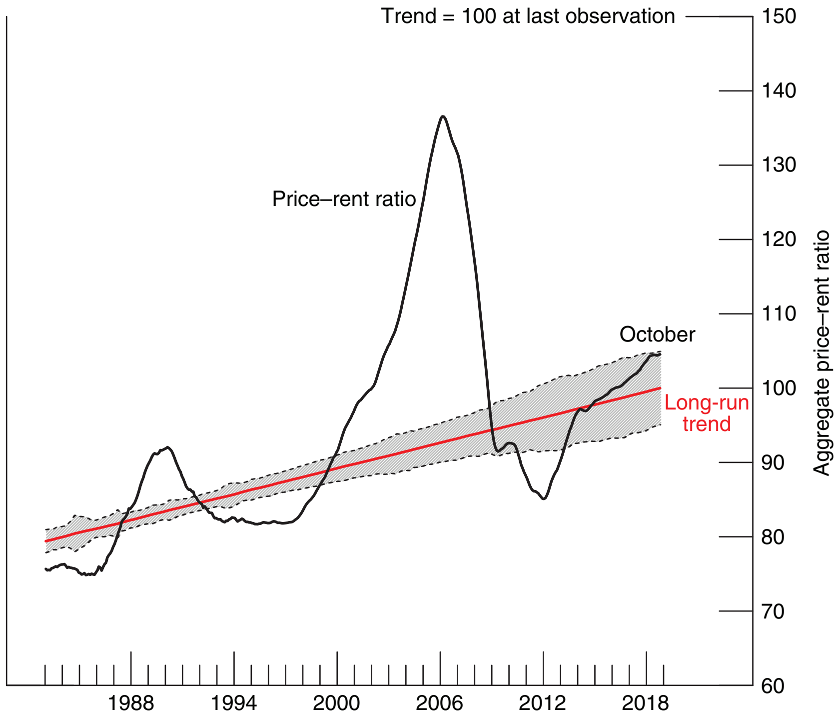
6.3 Predicted delinquency rates under alternative house price shocks

In the exercises discussed above, we considered how changes in the composition of household debt over time affect 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 national price–rent ratio from its long-term trend. Figure 8 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% overvalued in 2006, whereas they were overvalued by just 5% in 2017 Q4. To implement these “housing correction” scenarios, we consider the effects of a house price shock that brings the national 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 9) confirm the notion presented above: household debt looks less risky than before the crisis because housing does not appear as overvalued as of 2017. 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 2000s, our model predicts that a

FIGURE 8 Price-to-rent ratio as a house price overvaluation measure



The 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 to 2001, and the shaded area shows a 95% confidence interval for this trend. *Data sources:* CoreLogic for prices and BLS for rents.

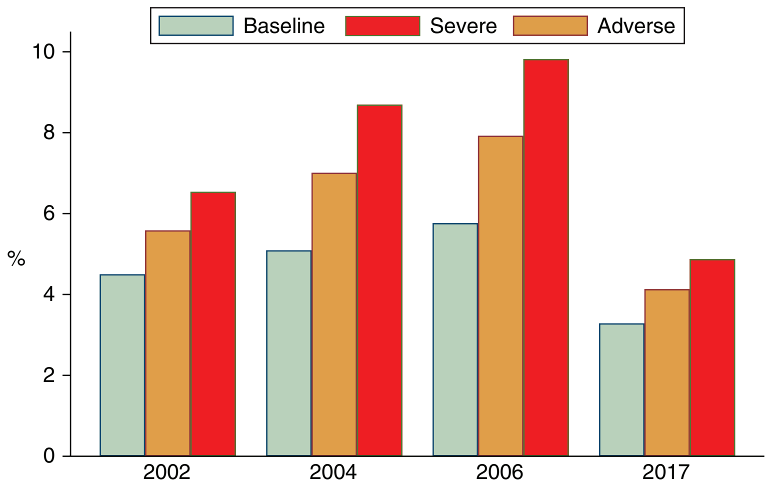
price correction at any point in time would have led to an increasingly higher rate of delinquency rates, with predicted delinquency rates rising from about 6.5% in 2002 to almost 10% in 2006. In contrast, the much lower valuations at the end of 2017 imply that the much smaller correction necessary to erase this overvaluation would only drive the delinquency rate up to about 5%.[25]

6.3.1 Local 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 alternative house price scenarios based on house price

[25] If house price declines are positively correlated with increases in unemployment rates, this would only further reduce current period risk relative to the past.

FIGURE 9 Delinquency rates from a housing correction.



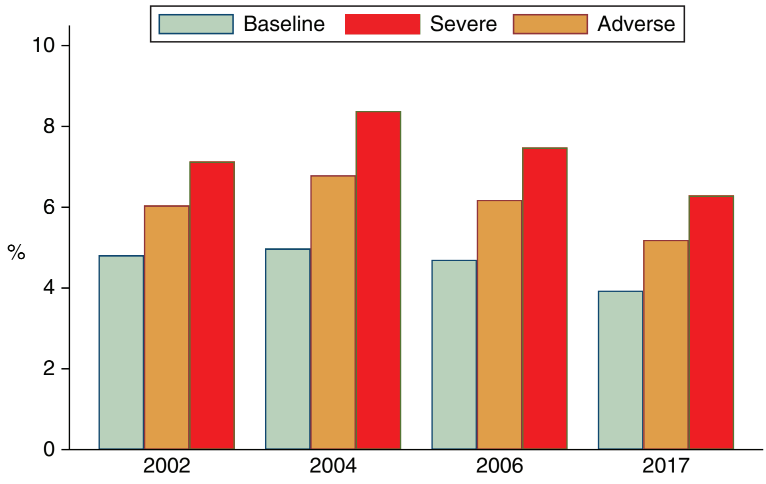
The figure displays the results of applying the housing correction scenario for house prices and the indicated CCAR scenario for unemployment rates from the fourth quarter of the year listed, where estimates are based on estimating (4.1) for the entire sample period. The housing correction scenario moves the price-to-rent ratio to its long-term trend in eight quarters. *Data sources:* CCP/Equifax, BLS LAU and QCEW, Zillow, CCAR, CoreLogic and BLS (see text).

experiences in each particular county. In particular, we consider shocks by which house prices in each county revert to their levels from either two or four years earlier.[26] 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 2006–11 housing bust. As in the previous exercise, we consider paths for 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 10), we find that the delinquency rate rises to about 6.25%. 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 end-of-2017 state of household debt in this scenario are substantively lower than predicted for the precrisis years.

[26] These scenarios are inspired by those considered in Fuster *et al* (2018).

FIGURE 10 Delinquency rates from reversing two-year house price growth.



The 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 (4.1) for the entire sample period. The two-year house price reversion scenario erases the past two years of local house prices gains in eight quarters. *Data sources:* CCP/Equifax, BLS LAU and QCEW, Zillow and CCAR (see text).

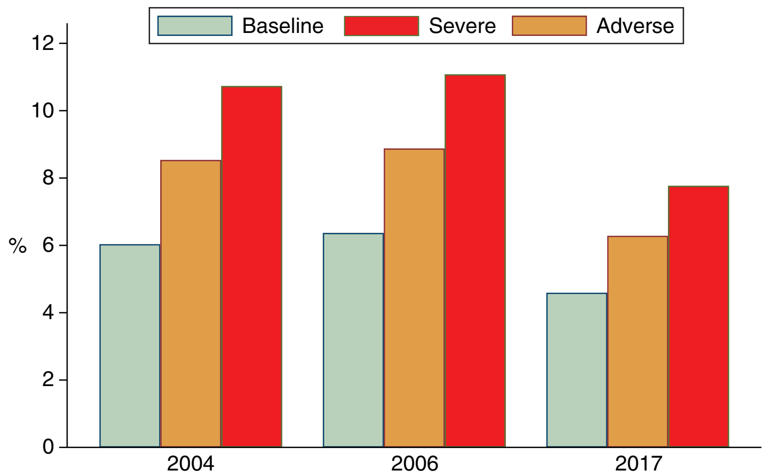
In a more severe version of this exercise, we allow local house prices to revert back to the level from four years earlier. In 2017, for example, this scenario essentially means erasing all of the postcrisis increase in house prices. When coupled with a severe unemployment shock, the expected delinquency rate reaches nearly 8% (the red bars in Figure 11), which is a bit higher than the severely adverse CCAR shock scenario. However, as before, the expected delinquency rate based on the end-of-2017 state of household debt under this scenario is still lower than predicted for the precrisis years.[27]

6.3.2 Worst-case scenario: the largest shocks in the 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 housing crisis, areas that had amassed the largest amount of mortgage debt also suffered the largest house price

[27] Note that we cannot include 2002 in the model because our data only goes back to 1999 and therefore we cannot construct a four-year reversion scenario for 2002.

FIGURE 11 Delinquency rates from reversing four-year house price growth.



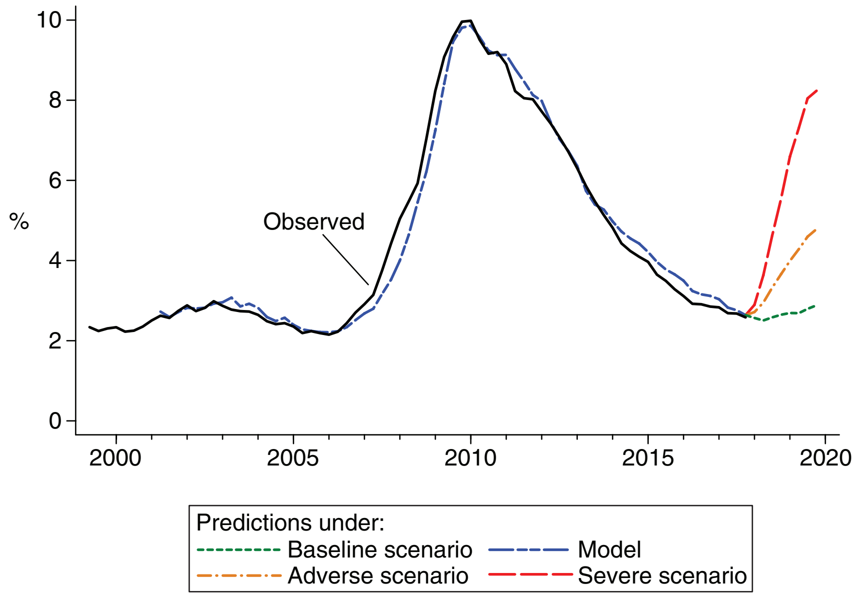
The figure displays the results of applying the four-year house price reversion scenario for house prices and the indicated CCAR scenario for unemployment rates from the fourth quarter of the year listed, where estimates are based on estimating (4.1) for the entire sample period. The four-year house price reversion scenario erases the past four years of local house prices gains in eight quarters. *Data sources:* CCP/Equifax, BLS LAU and QCEW, Zillow and CCAR (see text).

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 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 2017 Q4 receive the largest house price and unemployment shocks.[28]

Figure 12 shows that this worst-case scenario would lead to slightly more elevated delinquency rates than in the original scenarios (as shown in Figure 4). 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%, while in the original severely adverse scenario, the delinquency rate peaks at around 7.6%. This relatively small difference

[28] Rearranging 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 Figure 4, we rescale the distribution of shocks so that the population-weighted mean and standard deviation match the original scenarios.

FIGURE 12 Delinquency rates when the most leveraged counties receive the largest shocks.



The figure displays the model-predicted 60+ day delinquency rate for 2001 Q1–2017 Q4 (blue line) and the model-predicted 60+ day delinquency rate under the worst-case scenarios for 2018Q1–2019 Q4 (red, yellow and green lines, respectively), where the blue, red, yellow and green lines are based on estimating (4.1). The black line shows the observed 60+ day delinquency rate for 1999 Q1–2017 Q4. The worst-case scenarios assign the largest shocks obtained from CCAR scenario to the most leveraged counties. *Data sources:* CCP/Equifax, BLS LAU and QCEW, Zillow and CCAR (see text).

partially reflects the fact that more indebted counties already tended to receive larger shocks in the original scenario.[29]

7 CONCLUSION

Since the financial crisis, stress testing bank balance 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 we investigate the interaction of these shocks with household credit quality and household leverage. We

[29] The correlation between the original scenario shocks and the worst-case scenario shocks is about 0.2.

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 was less risky at the end of 2017 than it was before the financial crisis. In particular, the decline in leverage and a shift in debt holding toward higher credit score borrowers appear to have made household borrowing notably safer over the past few years. That said, a severe economic shock, similar to the experience of the financial 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 a particular point in time. If house prices were to "correct" during 2018 and 2019 (coupled with a severe unemployment shock), our model predicts that delinquency rates would increase to about 5%. In contrast, before the crisis, such a house price correction would have led to a 6.5pp to 10pp increase. Further extensions to our results show that our main conclusions are robust to alternative 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 were lower in 2017 Q4 than in the precrisis 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 toward 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.

DECLARATION OF INTEREST

The authors report no conflicts of interest. The authors alone are responsible for the content and writing of the paper. The analysis and conclusions set forth are those of the authors and do not indicate concurrence by the Board of Governors of the Federal Reserve System or its staff. All five authors were employees of the Federal Reserve when the analysis in this paper was completed.

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