Data Description:

Despite decades of research on the topic, economists have a limited understanding of why homeowners default on their mortgages. The issue is that there are a large number of factors that can in theory trigger default, including – but not limited to – negative equity, unemployment, divorce, medical emergencies, other expense shocks, etc. Data used for previous research typically includes information on only a small subset of these factors, leaving the roles of the others unclear. To address this problem, economists have called (so far mostly in vain) for richer datasets. In an early literature review, Vandell (1995) writes: "We need to understand empirically the role that trigger events, such as divorce or death, play in driving defaults. One way to address this issue is to develop a microbehavioral mortgage payment database. Such a database would track a panel of several thousand mortgages from origination and gather detailed information whenever termination occurs." In a much more recent literature review, Foote and Willen (2018) call for a very similar dataset.

This paper leverages uniquely rich data, almost precisely along the lines proposed by Vandell (1995). The "mortgage payment database" is the National Mortgage Database (NMDB), a sample of 5% of all closed-end first-lien mortgages in the United States. The NMDB is jointly sponsored by the CFPB and the FHFA, and it combines data from a credit bureau, Fannie Mae, Freddie Mac, the VA, the FHA, the RHS, Federal Home Loan Banks, private-label mortgage securities databases, HMDA, and McDash. The "detailed information whenever termination occurs" comes from the American Survey of Mortgage Borrowers (ASMB), which is linked to the NMDB, oversamples delinquent borrowers and is explicitly designed to study the triggers of mortgage default. The NMDB-ASMB data is far richer than any data any previous researcher has had access to, and it yields new and important insights into why borrowers default on their mortgages.

What Triggers Mortgage Default? New Evidence from Linked Administrative and Survey Data*

David Low†

Consumer Financial Protection Bureau

Preliminary. Comments welcome.

October 18, 2021

Abstract

Despite decades of research, it is still unclear why mortgage borrowers default because existing datasets are quite limited. This paper studies why borrowers default using a survey specifically designed for the purpose, with a sample drawn from (and matched to) a very rich administrative mortgage dataset. I find that other datasets with less information on adverse life events systematically understate their frequency. Adverse life events trigger nearly all defaults; many of these shocks are not unemployment or even a drop in income, and so will be missed by most existing studies. In contrast, the uniquely rich data used in this paper confirms previous empirical results that many defaults are not triggered by negative home equity, contrary to the predictions of the most popular models in the literature.

*I thank the NMDB production team for substantial help and advice with this project, and I thank Neil Bhutta, Nate Blascak, Erik Durbin, and seminar participants at the NMDB Users' Group, the Consumer Finance Round Robin, the Junior Household Finance Brownbag, and the FHFA for helpful comments. Greta Li provided outstanding research assistance. All errors are my own. The views expressed are mine and do not necessarily reflect those of the Consumer Financial Protection Bureau or the United States.

†Email address: david.low@cfpb.gov

1 Introduction

Homes and mortgages dominate U.S. households' balance sheets, so mortgage default has profound implications for both households and the broader economy. What public and private institutions should do about default obviously depends on why it occurs, but unfortunately despite decades of research this is still unclear. As a result, policies to reduce default range from suing defaulters to principal forgiveness, forbearance, and monthly payment reduction. The causes of default are so important and so unknown that Foote and Willen (2018) call it – with good reason – a "central" question in the literature. In this paper, I use extremely detailed administrative and survey data to answer this central question with unprecedented precision.

There are many theoretical models of mortgage default, which are typically divided into three categories based on (1) why a borrower does not pay her mortgage and (2) why she does not sell her home. "Strategic" models of default, dating back to Foster and Order (1984), view default as the wealth-maximizing exercise of borrowers' put option implicit in mortgage contracts. Default can only maximize wealth when a borrower has negative equity, and so in a strategic model negative equity explains both why a borrower does not pay her mortgage and why she does not sell her home. According to "double-trigger" models of default, dating at least to Riddiough (1991), one "trigger" event (e.g. unemployment) explains why a borrower does not pay her mortgage, while a second "trigger" event (e.g. a fall in house prices) drives her underwater and unable to sell her home. In "cash-flow" models, also dating back to Riddiough (1991), a liquidity shock is necessary for a borrower not to pay her mortgage, as in double-trigger models, but there is a reason besides negative equity (which varies some between models) a defaulter does not sell her home. Many modern quantitative models are hybrids and generate both strategic and double-trigger default. Models with cash-flow default are extremely rare; for example, in a recent and comprehensive literature review, Foote and Willen (2018) discuss only strategic and double-trigger models.

Distinguishing between these three broad theories requires understanding the relative contributions of liquidity shocks and negative equity to default. Unfortunately, empirical progress has been quite slow because liquidity shocks and negative equity are both difficult to measure. Recent estimates of the percent of default that is strategic range from 38% (Gerardi et al. (2018), hereafter "GHOW") to almost none (Ganong and Noel (2021), hereafter "GN"). The role of negative equity is even more muddled. The prevailing view, driven by the strategic and double-trigger theories, is that abovewater homeowners sell to avoid default and so nearly all defaulters are underwater. However, in the data abovewater default seems to be widespread.[1] But property values are measured with substantial error in most datasets, so it is possible that measurement error explains the discrepancy between the data and the strategic and double-trigger theories of

[1] See Appendix A.1 in Low (2021) or the online appendix in GN.

default. Half a century since the groundbreaking work of Herzog and Early (1970), it is still not clear why mortgage borrowers default because of major potential issues with existing datasets.

It is difficult to estimate the fraction of defaults driven by adverse life events because there are a very large number of such events, including – but not limited to – unemployment, retirement, divorce, medical shocks, mortgage payment shocks, other expense shocks, etc. These are not all observed in the loan-level datasets researchers typically have access to, so if a borrower is observed to default without a shock it is not clear if that is because the shock did not happen or because a shock did happen but was not observed. This is a significant issue. Both GHOW and GN find that more than a third of defaults occur without an income shock. GHOW call these defaults strategic, but GN argue that – after developing a new econometric methodology to account for measurement error – almost none of them are. This measurement issue has also been known for a long time; in an early literature review, Vandell (1995) writes:

"We need to understand empirically the role that trigger events, such as divorce or death, play in driving defaults. One way to address this issue is to develop a microbehavioral mortgage payment database. Such a database would track a panel of several thousand mortgages from origination and gather detailed information whenever termination occurs."[2]

This paper leverages uniquely rich data, almost precisely along the lines proposed by Vandell (1995) (but larger). The "mortgage payment database" is the National Mortgage Database (NMDB), which tracks 5% of all closed-end first-lien mortgages in the United States from origination to termination. The "detailed information whenever termination occurs" comes from the American Survey of Mortgage Borrowers (ASMB), which is linked to the NMDB, oversamples delinquent borrowers and is explicitly designed to study the triggers of mortgage default. As described in more detail below, the ASMB includes a battery of questions on the adverse shocks experienced by defaulters, including job loss, business failure, divorce, illness or death, expense shocks, etc. One central finding of this paper is simple: nearly all defaulters report at least one adverse shock contributing to their default, and so classical strategic default driven only by negative equity appears to be exceedingly rare, in line with the results from GN and contrary to those of GHOW. Moreover, there is a straightforward reason to favor the interpretation of GN over that of GHOW: roughly a third of defaults are driven by adverse life events that are not income shocks, which would not appear in the income data used in either paper.

The NMDB-ASMB data also shed new light on the role of negative equity in default. The NMDB includes the value of the property used for underwriting the mortgage, which can be updated to the

[2]In a much more recent literature review, Foote and Willen (2018) note the same issue still exists and call for a very similar dataset.

time of the time of the survey ("marked-to-market") using a house price index at the census-tract level, a very fine geographic unit that divides the U.S. into approximately 73,000 areas.[3] Since it also has administrative data on outstanding balances on primary and subordinate liens, even by itself the NMDB has data on the equity of defaulters that is among the very best in the literature. Yet this uniquely rich data produces a standard result: only 48% of foreclosed homeowners are even "effectively" underwater in the NMDB,[4] strongly suggesting that abovewater default is widespread and should be accounted for in theoretical models.

The one potentially significant downside to measuring equity in this way is that it will miss idiosyncratic property depreciation. If a property depreciates for idiosyncratic reasons (e.g. a tree fell on it), then its owner could be underwater even if she appears to be abovewater according to the MtM methodology. Indeed, many strategic and double-trigger models are calibrated to have frequent and large idiosyncratic property depreciation shocks precisely to generate enough default when negative equity would otherwise be rare. To address this issue in the NMDB, I use its link with the ASMB, which specifically asks respondents if a disaster affected a property they owned. Counting *all* defaulters who answer yes to this question as underwater increases the fraction of foreclosed homeowners with negative effective equity to just 54%.

Yet more evidence on the equity of defaulters comes directly from the ASMB. One advantage of the ASMB is that it comes from a time period during which homeowners tended to undervalue their homes (Chan et al., 2016; Anenberg, 2016; Davis and Quintin, 2017; Corradin et al., 2017); thus estimates of the prevalence of negative equity among defaulters in the ASMB should, if anything, be biased upwards. ASMB respondents who no longer have the property in question are asked several questions about why they no longer have it; only 52% of foreclosed homeowners respond that negative effective equity was a factor. This is further strong evidence that abovewater default is indeed widespread. Perhaps more importantly, it is also strong evidence that mortgage borrowers themselves do not view negative equity as a necessary condition for default, which should inform economists and policymakers interested in default.

These estimates of the percent of defaults triggered by negative equity from the NMDB and the ASMB are perhaps the highest-quality in the literature, but they are remarkably consistent with other sources. Thus for negative equity – in stark contrast to adverse shocks – measurement error does not appear to be a major concern with existing sources. This evidence is consistent with the model in Low (2021), in which mortgage borrowers default in a losing gamble to keep their homes, and it is contrary to the predictions of strategic and double-trigger theories that abovewater borrowers always sell to avoid default. Low (2021) shows that abovewater default can have major

[3] Bogin et al. (2019) find that house price indices at an even finer geographic level provides no further benefit in predicting default.

[4] An abovewater borrower is said to be "effectively" underwater if she has so little home equity that she would lose money by selling her home and repaying her mortgage, after accounting for financial moving costs.

policy implications in a quantitative model. Since theoretical and empirical work on cash-flow default is currently so limited, more research on the causes and policy implications of cash-flow default would clearly be valuable.

An important caveat is that these results are derived from the first three waves of the ASMB, which were fielded between 2016 and 2018 and reflect defaults roughly between 2014 and 2018. Unemployment and negative equity were still fairly common at the beginning of this period, but became steadily less common as the economy recovered from the Great Recession. Results from other time periods may differ; in particular, the finding of extremely low strategic default rates from 2014-2018 do not on their own imply that strategic default was as rare during the Great Recession. However the findings do largely validate the methodology of GN, who find nearly no strategic default even during the Great Recession. Moreover, the Great Recession was notable precisely because negative equity was far more common than it typically is, even compared to other recessions. The results in this paper are from a more typical time period and so are likely to be more applicable generally. Indeed, early in 2020 the U.S. economy experienced one of its sharpest downturns ever due to the COVID pandemic, and yet after years of strong house price growth virtually no one had negative equity.[5] The finding in this paper that many defaults can be triggered by liquidity shocks alone, without negative equity, suggests that foreclosure rates in 2020 and 2021 may have been much higher without the fiscal stimulus, foreclosure moratoria, and widespread forbearance offered during the time period.

2 Literature Review

What causes default has been a central question in the literature for a long time. Most empirical work on the subject has essentially regressed default on measures of equity and adverse shocks. A very large number of studies have universally found that lower levels of equity (and negative equity in particular) predict higher default rates; Foote et al. (2008) and Elul et al. (2010) are two well-known examples.

Most research on whether adverse liquidity shocks drive default has focused on the relationship between default and unemployment specifically or income drops more broadly. Some studies found that these shocks predicted default (Elul et al., 2010), while other studies found they did not (Foster and Order, 1984; Goodman et al., 2010). However, Gyourko and Tracy (2014) note that regional unemployment rates – the usual proxy for adverse shocks in early work – suffer from severe attenuation bias. More recent work measuring income shocks at the individual level has uniformly found that they are strong predictors of default (Tian et al., 2016; Gerardi et al., 2018; Hsu et al.,

[5] See https://libertystreeteconomics.newyorkfed.org/2021/09/if-prices-fall-mortgage-foreclosures-will-rise/.

2018). Work on adverse shocks besides income shocks is much rarer, but studies have shown that divorce (Low, 2015), disability (Deshpande et al., 2021), medical expenditure shocks (Gallagher et al., 2019), cancer (Gupta et al., 2018), ARM rate resets (Gupta, 2019), and even property tax increases (Wong, 2020) trigger default.

While it is now clear that adverse shocks can trigger default, research on the percent of defaults triggered by adverse shocks is quite limited. Most datasets used to study mortgage default are loan-level and have very little information on the adverse shocks experienced by borrowers. Guiso et al. (2013) employ a unique approach to overcome this issue by surveying households and asking them how many *other* households they know who defaulted strategically. In their survey data, respondents think that around a third of defaults during the Great Recession were strategic. While this methodology is intriguing, it is unclear if households know whether other households are defaulting strategically.

The more typical approach is to use loan-level data together with available proxies for adverse shocks to study the issue. Experian and Oliver-Wyman (2009), Tirupattur et al. (2010), and Keys et al. (2013) use credit bureau data and proxy for adverse shocks using the percent of defaulters that "roll straight" (go directly from current to severely delinquent without curing in between) while staying current (or almost current) on all non-mortgage debt. They label these defaulters as strategic. Bradley et al. (2015), with richer data that includes information on borrowers' incomes, employ a stricter definition of strategic default that also requires defaulters to be underwater and to have not experienced a significant drop in income. These studies argue that around 7-20% of defaults during the Great Recession were strategic. While these studies use the best data available to them at the time, credit bureau data provide only very noisy proxies for adverse shocks and so (as discussed by Foote and Willen (2018)) it is unclear how much type I and type II error they contain. For example, "rolling straight" could indicate strategic default or it could indicate a large and persistent liquidity shock; there is no way to distinguish between these possibilities without better data.

It is valuable to compare the two most recent studies on the topic, GHOW and GN, because they draw very different conclusions from nearly the same results. GHOW proxy for adverse shocks using detailed income and expenditure data from the Panel Survey of Income Dynamics (PSID). They identify a subset of defaulters that are measured to have the income to pay their mortgage and maintain an acceptable level of consumption; they call these defaults, which comprise 38% of all defaults in ther data, as strategic. GN discuss in detail the possibility of measurement error in traditional studies. In particular, if income is measured with error then some defaulters may have experienced income drops even if they are not observed. Moreover, if some adverse shocks are not income shocks, then using only income shocks to measure adverse shocks will overstate the amount

of strategic default. To overcome this issue – which also exists in their data – they compare the income of underwater defaulters (who may or may not default strategically) to that of abovewater defaulters (who should have no reason to default strategically). They find that income changes before default are nearly identical for underwater and abovewater defaulters, and they argue that this implies that only about 4% of default is strategic even though a third of defaults in their data occur with no observed adverse shock.

In contrast with the evidence on adverse shocks, evidence on the percent of defaults triggered by negative equity is fairly consistent. Appendix A in Low (2021) provides a summary, showing that in all available sources the vast majority of defaulters outside the Great Recession (and a large minority during it) appear to be abovewater; GN describe abovewater default as "ubiquitous". However, this view is controversial. The strategic and double-trigger models of default predict that abovewater homeowners should sell their homes rather than default, so negative equity should trigger most or all default. This is the general view in the literature (Foote and Willen, 2018). Still, there are some models that generate abovewater default (Riddiough, 1991; Hedlund, 2016a,b; Head et al., 2020; Garriga and Hedlund, 2019). Low (2021) develops a model explicitly to study abovewater default and shows that it has major policy implications.[6]

3 Data

This paper uses two linked datasets, the NMDB and the ASMB. Both are part of the NMDB program, which is jointly sponsored by the Federal Housing Finance Agency (FHFA) and the Consumer Financial Protection Bureau (CFPB).[7] The FHFA sponsors the NMDB program in part to meet its statutory requirements, amended in 2008,[8] requiring it to conduct a monthly survey of the mortgage market that collects data on individual mortgage loans and mortgage borrowers. The CFPB uses the NMDB program for policymaking, research, and market monitoring as required by the Dodd-Frank Wall Street Reform and Consumer Protection Act.[9]

The NMDB is a random 1-in-20 sample of all closed-end first-lien mortgages furnished to one of the three nationwide credit reporting agencies (NCRAs). An initial sample was drawn from all such mortgages outstanding at any point between January 1998 and June 2012. The sample has been updated every quarter since then to add mortgages newly reported to the NCRA. Mortgages are tracked from origination to termination, whether termination comes from prepayment, maturity,

[6]For example, relative to a nested model without abovewater default, in the full model in Low (2021) suing defaulters prevents less than one-fifth as many foreclosures after a drop in house prices, while forbearance prevents between three and seven times more foreclosures after a drop in aggregate income.

[7]For more information, see https://www.fhfa.gov/PolicyProgramsResearch/Programs/Pages/National-Mortgage-Database.aspx and https://www.fhfa.gov/PolicyProgramsResearch/Programs/Documents/NMDB-Technical-Documentation-20200310.pdf.

[8]See the Housing and Economic Recovery Act of 2008, Pub. L. 110–289, 122 Stat. 2654 (2008).

[9]See the Dodd-Frank Wall Street Reform and Consumer Protection Act, Pub. L. 111-203, 124 Stat. 1376 (2010)

or chargeoff. Mortgage borrowers are tracked from one year prior to mortgage origination until one year after its termination. NMDB data is de-identified and does not include any directly identifying information.

Data from the NCRA on the mortgage and its borrowers are then matched to administrative records from Fannie Mae and Freddie Mac (the Enterprises), the Federal Housing Administration (FHA), the Department of Veteran Affairs (VA), and the Rural Housing Service (RHS). Loans from these agencies comprise about three-quarters of the loans in the NMDB.[10] The NMDB also includes information from private-label mortgage-backed securities databases and the Federal Home Loan Banks, as well as Home Mortgage Disclosure Act (HMDA) data and McDash servicing data. Even on its own, the NMDB is one of the richest mortgage datasets ever assembled.

The ASMB is a survey specifically designed to supplement the NMDB with additional information on mortgage delinquencies. The sample for the ASMB is drawn from the NMDB. In 2016, 70% of the sample was at least 30-days delinquent on their mortgage at the beginning of the year, and the other 30% were current at that time. In 2017 and 2018, 65% were at least 30 days delinquent at the beginning of the year, 10% were both Hispanic and at least 30 days delinquent at the beginning of the year, and 25% were current. Weights are used to make the sample representative.

About 10,000 surveys were sent in each wave, yielding roughly 4,500 usable responses across the three survey years. The analysis in this paper largely focuses on the delinquent subsample of the ASMB, further restricted to loans that were current at least once within four years of the survey and that went on to become at least 90-days delinquent. This sample consists of roughly 1,400 borrowers. Throughout the rest of this paper I refer to these borrowers as "defaulters."

4 Adverse Life Events and Mortgage Default

Among defaulters, only 42% report that household income has significantly decreased in the past couple years; 11% report a significant *increase* in income. 65% report that either household income has significantly decreased in the past couple years or that the household experienced a layoff, unemployment, or reduced work hours in the past couple years. Thus in the ASMB, as in the data used by GHOW and GN, over a third of defaults occur without observed income shocks. How to interpret this result is a major outstanding question in the literature; GHOW argue that these defaults are strategic, while GN argue they are likely driven by adverse life events that are not

[10] To maximize accuracy while protecting borrowers' privacy, matches are performed by the NCRA using personally identifying information (PII) such as borrowers' names, addresses, and dates of birth under a strict third-party-blind process. None of the CFPB, FHFA, FHA, VA, or Enterprises receive PII from the NCRA, and the NCRA cannot access administrative data and borrower PII in the same place. This matching process is successful over 95% of the time.

income shocks. A significant advantage of the ASMB over the datasets used by GHOW, GN, and other researchers is that it includes information on many adverse life events besides income shocks.

4.1 Defaulters with payment concerns or difficulties

Like many surveys, the ASMB follows a skip logic so that survey respondents are not asked potentially irrelevant questions. One very important question in the survey is: "at any time during the past couple of years, did you have any concerns or face any difficulties making your mortgage payments?"[11] 92% of defaulters answered "yes" to this question, and only these respondents (hereafter, "CD" respondents for "concerns or difficulties") were asked the next series of questions regarding the sources of the payment concerns or difficulties. Specifically, CD respondents were asked if any of the following made it difficult to make their mortgage payments:[12]

1. Job loss
2. Retirement
3. Business failure
4. Separation or divorce
5. Illness, disability, or death of a household member
6. Increase in required mortgage payments[13]
7. Unexpected exponses
8. Payments for other mortgages
9. Payments for other large debts

Because these questions are the most direct way to study the triggers of mortgage default, I study them first. The first major result is straightforward: 98.6% of CD defaulters reported that at least one of these shocks contributed to their default, including 96.7% of CD defaulters without observed income shocks. This simple result demonstrates that relying on drops in income alone to identify strategic default will substantially overstate the amount of strategic default. It also validates the methodology of GN, who develop an econometric procedure to account for this measurement error that other researchers without access to the ASMB can use.[14]

To investigate this result in more detail, Figure 1 presents the percent of CD defaulters reporting

[11] In the 2016 ASMB, the phrasing was: "At any time during the past several years, did you have any concerns or face any difficulties making payments on the loan you had in January 2015?"

[12] Respondents were also asked if a disaster affecting the property made it difficult to make mortgage payments. Because this kind of shock could affect a homeowners' equity as well as her liquidity, I do not analyze it in this section.

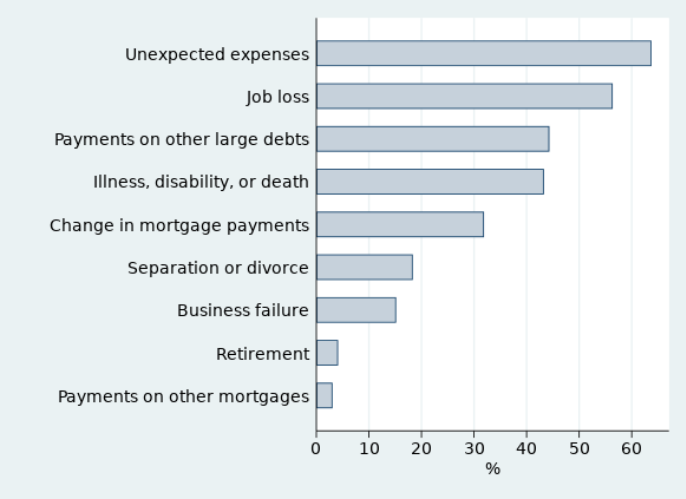
[13] Increases in mortgage payments (like several other items on this list) should in theory be predictable, so it may be surprising that they could induce default. See Jørring (2020) for evidence that many HELOC borrowers fail to adequately prepare for increases in required payments, even though these increases are predictable.

[14] GN's econometric procedure is generic and likely applicable in many contexts beyond mortgage default; thus validating it in the context of mortgage default demonstrates that it should be useful in other contexts as well. It is also notable that the methodology of GN relies heavily on abovewater default, so the fact that it produces correct results provides additional evidence that abovewater default is both real and important.

each adverse shock as a default trigger.[15] Figure 1 includes several important results. One is that expense shocks drive a very large number of defaults, which is consistent with evidence that they are a substantial source of risk for many households (Fulford, 2015). Economists often treat household expenditures as fully endogenous and not subject to shocks, but this evidently can be misleading in the context of mortgage default and likely other contexts as well.

Another important finding is that the percent of defaults triggered by these adverse shocks adds up to far more than 100%, because many CD defaulters report more than one adverse shock as a trigger; in fact, only 28% report just one.[16] Thus just as using one specific adverse shock (e.g. income shocks) to proxy for all adverse shocks will mechanically understate the frequency of adverse shocks experienced by defaulters, it will also understate the intensity of the combined adverse shocks experienced by defaulters.

Figure 1: Adverse shocks triggering default



Notes: Of the 92% of defaulters that reported payment "concerns" or "difficulties", the figure shows the percent that reported each adverse shock contributing to their difficulties. The 2016 wave of the ASMB did not ask if retirement or payments on other mortgages contributed to borrowers' payment difficulties, and so the frequency of these two shocks is somewhat underestimated.

Together these findings have important implications for quantitative mortgage default models. Such models vary widely in the adverse liquidity shocks they account for. In many models, income is a lognormal process and large drops in income are rare. Laufer (2018) explicitly allows for unemployment in his model, and notes that (at the time) doing so was unusual for the literature. Some more recent papers (e.g. Campbell et al. (2020)) allow for very realistic income processes,

[15] In 2017 and 2018, the specific survey phrasing was: "Did any of the following make it difficult to make your mortgage payments?" In 2016, the phrasing was: "Thinking about the time you had the most serious difficulties making the payments in the last few years, did any of these factors contribute to your difficulties?"

[16] Divorce, illness, a change in mortgage payments, payments on other mortgages, and payments on other large debts could all be viewed as involving "unexpected expenses." Thus for this calculation I only count unexpected expenses as a separate shock if none of these other shocks are reported.

but it is extremely rare for structural models to account for liquidity shocks that are not income shocks. However the results here suggest that doing so is likely to be very important, especially since otherwise models calibrated to match aggregate default rates are likely to compensate by generating strategic default.

The ASMB also includes valuable information on why income drops are as rare as they are among defaulters. CD respondents were asked a series of questions about what they did to address their difficulties. Possible responses include (but are not limited to) increasing work hours, starting a second job, or starting a new or better paying job. Among CD defaulters who reported no substantial drop in income, 54% chose one of these options; among defaulters who reported an increase in income, 72% did. Thus defaulters often respond to their payment difficulties specifically by increasing their income, and so studying their income alone will often understate the difficulties they face.

4.2 Defaulters without payment concerns or difficulties

About 8% of defaulters reported that they did not have concerns or difficulties paying their mortgage in the past couple years. One possibility is that this subsample (henceforth, "NCD" for "no concerns or difficulties") consists of unconstrained underwater borrowers optimally choosing to default because doing so maximizes their wealth, as in a frictionless option model of strategic default. Another possibility is that NCD respondents default because of adverse shocks, but reported no payment concerns or difficulties for some other reason. For example, NCD defaulters may include borrowers experiencing a financial shock they expected to be temporary, or borrowers who are used to financial difficulties because they frequently experience them. While NCD respondents were not directly asked about default triggers, the ASMB and NMDB still have enough information to distinguish between these two possibilities.

First I consider the evidence for strategic default in this subsample. Note that negative equity is traditionally viewed as a necessary condition for strategic default, since borrowers with positive equity have no financial incentive to default if they can easily afford their mortgage payments. 54% of NCD defaulters report either still having the mortgage and owing "significantly" or "slightly" less on the mortgage than the property is worth, or having sold the property or paid off the mortgage by the time of the survey.[17] Thus, even among NCD defaulters, at most half appear to have negative equity and so could be strategic.

Strategic default is more likely when house prices are falling and when the moral costs of defaulting are low. Among NCD defaulters, 15%, 53%, and 23% expect in the next few years

[17] See Section 5 for more information on measuring negative equity in the NMDB. Only 38% of this subsample is measured to have negative effective equity or a disaster shock according to the MtM methodology discussed in that section.

for house prices in the property's neighborhood to "increase significantly", "increase slightly", or "stay about the same". 88% disagree with the statement that "it is okay to default or stop making mortgage payments if it is in the borrower's financial interest"; Guiso et al. (2013) find that borrowers with this belief are unlikely to default strategically. These findings provide further evidence against strategic default even in this subsample.

This raises the question: did NCD borrowers experience a liquidity shock that triggered default? I do not directly observe whether specific shocks triggered NCD default, because NCD defaulters were not asked the relevant questions. But the ASMB and NMDB still have valuable information on whether respondents experienced adverse shocks. I follow the methodology developed by GN to use this information to determine whether these shocks triggered NCD defaults.

Specifically, consider a noisy measure X of an adverse shock (e.g. whether the respondent reported a "financial crisis" in the past couple years). As shown in Subsection 4.1, virtually all CD defaults are triggered by adverse liquidity shocks. Thus the percent of CD defaulters who have X is a measure of the percent of NCD defaulters that we would expect to have X, if *all* NCD defaults were triggered by adverse liquidity shocks. Moreover, the percent of all NCD respondents (including non-defaulters) who have X is a measure of the percent of NCD defaulters that we would expect to have X, if *no* NCD defaults were triggered by adverse liquidity shocks.

More formally, for each noisy measure X of an adverse shock, let $\overline{X}_i^j$ denote the mean X for borrowers in group $i \in \{CD, NCD\}$ and $j \in \{A, D\}$, where A denotes "all" and D denotes "defaulters". Then the estimate α of the percent of NCD defaults triggered by adverse liquidity shocks is given by:

$$\alpha = \frac{\overline{X}_{NCD}^D - \overline{X}_{NCD}^A}{\overline{X}_{CD}^D - \overline{X}_{NCD}^A} \tag{1}$$

The estimates of α obtained from various definitions of X are:

1. Financial crisis in the ASMB: 55%
2. Income shock reported in the ASMB: 58%
3. Adverse shock reported in the ASMB: 60%.[18]
4. Any 60-day delinquency or worse on a nonmortgage credit product in the NMDB: 95%
5. Any 60-day delinquency or worse, excluding bankruptcy, on a nonmortgage credit product in the NMDB: 77%

Broadly these estimates suggest that somewhere between 5% and 45% of the defaults in this subsample are strategic. This subsample is small (only 108 households) so it not possible to be

[18]Here an "adverse shock" is defined as reporting any of the following in the past couple years: (1) becoming separated or divorced, or that a partner left, (2) death of household member, (3) disability or serious illness of a household member, (4) disaster affecting your (or your spouse/partner's) work, (5) layoff, unemployment, or reduced hours, (6) business failure, or (7) a personal financial crisis.

more precise, but since it is also a small proportion of the sample of defaulters the results are still clear. Even assuming half of NCD defaults are strategic yields that roughly 4% of all defaults are strategic, a number very similar to that in GN and far smaller than other estimates in the literature.

5 Negative Equity and Mortgage Default

Next I investigate the role of negative equity in triggering default. There is a substantial amount of evidence on this topic already,[19] and all of it suggests that most defaulters outside the Great Recession (and a substantial minority during it) had positive equity. GN implement a unique causal methodology and estimate that only 30% of defaults are caused by negative equity. By contrast, nearly all existing models predict that abovewater homeowners sell and do not default, so nearly all defaulters have negative equity (Foote and Willen, 2018). Low (2021) demonstrates that a model in which most defaulters have positive equity has very different policy implications in which few do, so this is an important issue to study.

This section studies new, high-quality evidence on the equity of defaulters in both the NMDB and the ASMB. But since measurement error is a concern with these sources as well as all others, I first provide a brief discussion of measurement error in home values in Section 5.1.

5.1 Measurement Error and Underwater Defaulters

In this paper, we are interested in the measurement error of borrowers' LTVs. It turns out to be convenient to work in logs, so if l is a borrower's loan amount and v is her property value, note that:

$$log(\frac{l}{v}) = log(l) - log(v) \tag{2}$$

Borrowers' total outstanding mortgage debt (including 2nd liens and HELOCs) is available from the administrative data in the NMDB. Thus it is likely that v is measured with much more error than l is, so this section focuses on measurement error in $\log(v)$ (henceforth denoted "V").

Two of the most important types of measurement error are classical and Berkson. Consider the following equation:

$$\hat{V} = V + \epsilon \tag{3}$$

where V is a property's true value in logs, $\hat{V}$ is its measured value, and $E(\epsilon) = E(\epsilon|V) = 0$, i.e. the measurement error is mean-independent of the property's true value. This is classical

[19] See Appendix A.1 in Low (2021) for a review.

measurement error.

Suppose instead that:

$$V = \hat{V} + \epsilon \tag{4}$$

where $E(\epsilon) = E(\epsilon|\hat{V}) = 0$, i.e. the measurement error is mean-independent of the property's *measured* value. This is Berkson measurement error.

We are interested in estimating the fraction of defaulters who have negative equity. It is useful to study this through Bayes' rule:

$$P(Eq^-|Default) = \frac{\overbrace{P(Default|Eq^-)}^{(1)}\overbrace{P(Eq^-)}^{(2)}}{P(Default)} \tag{5}$$

where Eq^- denotes negative equity.

As is well-known, classical measurement error in V (Equation 3) will lead to attenutation bias in term (1) in Equation 5. This will lead to underestimates of the fraction of defaulters who are underwater. However, classical error introduces more variation in mismeasured variables than actually exists, i.e. $\text{Var}(\hat{V}) > \text{Var}(V)$ in Equation 3. Since negative equity is rare, this means classical measurement error will make negative equity appear more common than it really is. This will lead term (2) in Equation 5 to be too high, which will lead to overestimates of the fraction of defaulters who are underwater. Thus the effect of classical measurement error in this case is ambiguous.

The concerns with Berkson error are different. The bias introduced by Berkson error in term (1) is (literally) second-order (Schennach, 2020). Since the relationship between LTV and default risk is convex, Berkson error should still lead to attenuation bias in term (1). But in practice this bias could be quite weak or quite strong depending on how convex the relationship between LTV and default risk actually is. Another concern is that variables measured with Berkson error appear to have less variation than they actually do, i.e. $\text{Var}(\hat{V}) < \text{Var}(V)$ in Equation 4. Thus if equity is measured with Berkson error, then term (2) in Equation 5 is likely too low.

As the discussion above makes clear, measurement error could be an important concern with existing sources, but whether or not it actually is is an empirical question. This section uses some of the highest-quality data in the literature to study the issue.

5.2 Negative Equity in the NMDB

First I study the equity of defaulters in the NMDB. Suppose that, in reality, the market value V_{it} of property i at time t is given by:

$$V_{it} = V_{i0} + \Delta V_t^j + \delta_{it}^j \tag{6}$$

where V_{i0} is the market value of property i at time 0, ΔV_t^j is the average change in all property values between time 0 and t at some level of aggregation j, and δ_{it}^j is the deviation in the appreciation of property i's market value between periods 0 and t from other properties in j.

Unfortunately, V_{it} is not observed. Instead I use a common proxy for it, a property's "mark-to-market" value (henceforth denoted $\hat{V}_{it}$). This is given by:

$$\hat{V}_{it} = \hat{V}_{i0} + \hat{\Delta V_t^j} \tag{7}$$

Here, $\hat{V}_{i0}$ is the value of the property used to underwrite the mortgage (from the administrative data) and $\hat{\Delta V_t^j}$ is the change in a house price index ("HPI") between time 0 and t. Let ϵ denote measurement error in V_0, and ζ denote measurement error in the HPI. Then:

$$V_{it} = (\hat{V}_{i0} + \epsilon) + (\hat{\Delta V_t^j} + \zeta) + \delta_{it}^j \tag{8}$$

And therefore:

$$V_{it} - \hat{V}_{it} = \epsilon + \zeta + \delta_{it}^j \tag{9}$$

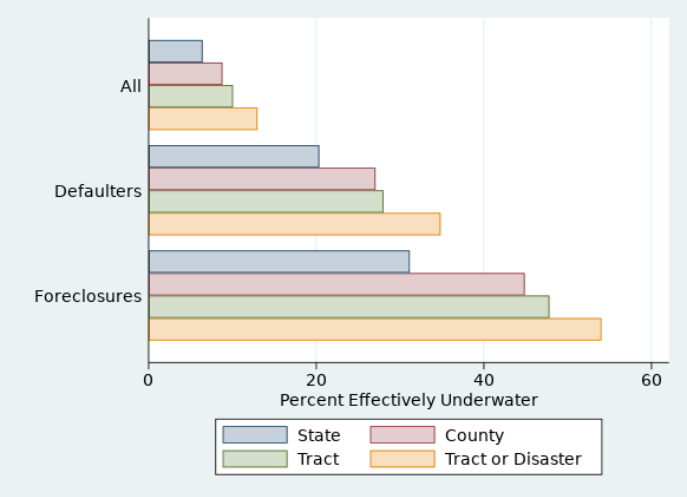
Thus there are three sources of measurement error in MtM estimates like the one I use: error in measuring a property's "initial" value (ϵ), error in the HPI used to update its value (ζ), and deviations between the appreciation in a particular property in j compared to other properties in j (δ_{it}^j).

The most common (and likely most important) concern with mark-to-market property estimates like $\hat{V}_{it}$ is that they neglect δ_{it}^j. For example, using a state-level HPI to calculate a property's MtM value neglects changes to a property's value that occurred because properties in its county appreciated at a different rate than properties in other counties in the state. Assuming $E(\delta_{it}^j | \hat{V}_{it}) = 0$, this introduces Berkson measurement error into MtM estimates like the one used here. This Berkson error from δ_{it}^j can be reduced by using HPIs at finer levels of aggregation, but as emphasized by Bogin et al. (2019) this comes at the cost of more error in the HPI ζ since HPIs at finer levels of aggregation will use data from fewer properties and will therefore be less reliable. Thus it is not necessarily true that MtM estimates from finer levels of aggregation are preferable.

Geography in the NMDB is available at the census-tract level. This is a very fine geographic unit; there are over 73,000 census tracts in the U.S. I compute MtM estimates using HPIs from the FHFA at the state, county, and census-tract level. All of these estimates will miss depreciation

that occurs at the level of an individual property. This could be an important issue; indeed, many traditional quantitative models generate enough default, even when negative MtM equity is rare, by introducing frequent and large idiosyncratic property depreciation shocks. To address this concern, I use a question from the ASMB: "in the last couple of years, have any of the following happened to you?" with a possible answer being "disaster affecting a property you own." There is no way to tell from this question how much the disaster affected the property's value (or whether the disaster affected the property securing the mortgage), so to be conservative, I count all affirmative responses to this question as indicating negative effective equity.[20] Results are in Figure 2.

Figure 2: Percent Effectively Underwater



Notes: Figure shows the percent of respondents, defaulters, and foreclosed homeowners in the ASMB who have a MtM LTV greater than 90 at the time the survey sample is drawn. MtM LTVs are calculated using HPIs at the state, county, and census-tract level from the FHFA. Foreclosures are identified in the ASMB.

First note it is not surprising that MtM estimates at finer levels of aggregation yield more homeowners estimated to be effectively underwater. Moving to finer levels of aggregation reduces Berkson error in δ_{it}^{j} while increasing classical error in ζ. As discussed in Subsection 5.1, reducing Berkson error and increasing classical error should both increase the number of homeowners estimated to have negative effective equity.

Still the results do indicate that measurement error is a concern. For example, moving from a state-level to a tract-level HPI increases the percent of defaulters with negative effective MtM equity from about 20% to 28%. Still, 28% is very far below the 100% predicted by the strategic and double-trigger theories.

[20] This measure of property depreciation is likely to pick up depreciation the respondent views as exogenous (a "disaster"), but may not pick up depreciation the respondent views as endogenous (e.g. inadequate property maintenance triggered by the respondent's awareness that foreclosure is likely). The question of interest in this paper is whether negative equity triggers default, not whether default triggers negative equity, so this is an advantage of the question. See Appendix A.2 in Low (2021) for a formal discussion.

More importantly, Figure 2 indicates that "defaulters" (as defined in Section 3) have more equity than foreclosed homeowners do, but also that even many foreclosed homeowners have positive effective equity. Using the census-tract MtM estimates, while only 28% of defaulters have negative effective equity, 48% of foreclosures do. These numbers rise slightly to 35% and 54%, counting all homeowners who report a disaster in the ASMB as underwater. These results suggests that some delinquent abovewater homeowners escape foreclosure through selling their homes or refinancing their mortgages, but also that many do not.[21] This in turn suggests that theoretical models should allow for some imperfect selection on equity between delinquency and foreclosure, as in Low (2021).

Of course, these estimates are still imperfect. But given the quality of the data, the scope for remaining measurement error to affect the results seems limited. Classical measurement error in the HPIs at the census-tract level will lead to attenuation bias in the relationship between equity and default, but it will also inflate the number of estimated underwater homeowners. The MtM estimates will also miss HPI movements that occur below the level of the census tract and and above the level of individual properties, but it is not clear there is much variation at this level; Giacoletti (2021) finds that appreciation at the zip-code level (which in general is a much coarser level than census-tract) explains nearly all the spatial correlation in appreciation between properties. The numbers in Figure 2 may even be conservative, because (1) it counts all respondents who report a disaster affecting a property as effectively underwater, and (2) it controls for idiosyncratic property depreciation but not appreciation.

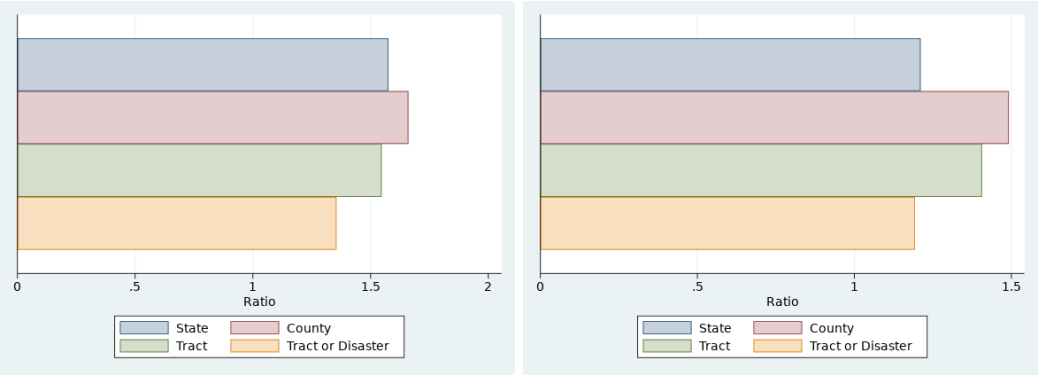
To understand these results in more detail, Figure 3a shows the foreclosure rate of underwater homeowners as computed from these MtM estimates. Removing a substantial amount of Berkson error in the MtM estimates by using county-level HPIs, rather than state-level, increases the estimated underwater foreclosure rate only very slightly, from 1.58% to 1.66%. However, as noted by Bogin et al. (2019), using HPIs at finer levels of geography increases measurement error in the HPIs (ζ in Equation 9) which could explain why the increase in the underwater foreclosure rate is so small. Thus as recommended by Bogin et al. (2019) to deal with this issue, Figure 3b shows estimated foreclosure rates for urban mortgage borrowers. Here the increase is somewhat larger, from 1.21% to 1.49%, but still not nearly large enough to explain observed abovewater default.

Overall, this evidence suggests that measurement error is a concern and that higher-quality LTV estimates lead to a stronger estimated relationship between negative equity and default. However, it is also suggests there is a significant limit on what measurement error can explain. Using county-level rather than state-level HPIs increases the estimated underwater foreclosure rate only slightly. The fact that the estimated underwater foreclosure rate goes *down* when moving from county-level to

[21] Foreclosure starts are around half as likely to result in involuntary liquidation for homeowners with CLTVs below 60 than for those with CLTVs above 100; see https://cdn.blackknightinc.com/wp-content/uploads/2021/10/BKI_MM_Aug2021_Report.pdf.

Figure 3: Estimated Underwater Foreclosure Rate

(a) All Borrowers **(b)** Urban Borrowers



NOTES: Figures show, out of all effectively underwater borrowers in the ASMB, the percent that are foreclosures. "Effectively underwater" is defined as a MtM LTV greater than 90 at the time the survey sample is drawn. MtM LTVs are calculated using HPIs at the state, county, and census-tract level from the FHFA. "Urban" denotes counties in metropolitan areas (as defined by the USDA) with at least 250,000 inhabitants.

tract-level HPIs is likely only because the increase in ζ outweighs the decrease in δ_{it}^{j} in Equation 9; nevertheless, the fact that it does so even for urban borrowers suggests that the attenuation bias from Berkson error in county-level MtM estimates is limited.

5.3 Negative Equity in the ASMB

Finally I study negative equity in the ASMB. ASMB respondents are asked the value of their property, but a quarter of respondents report that they do not know or refuse to answer the question. The ASMB also asks more direct questions about negative equity, which perhaps because they are simpler have much higher response rates. Because self-reported property values are unlikely to be missing at random, I use the more direct questions.

Respondents who still have the mortgage from the NMDB by the time of the survey (80% of the sample) are asked "Is the amount you owe on this mortgage today…", with possible responses being "significantly less than", "slightly less than", "about the same as", "slightly more than", and "significantly more than" the property value. I label respondents who chose any of the latter three responses as effectively underwater. Respondents who no longer have the mortgage from the NMDB by the time of the survey (20% of the sample) were asked "Were any of the following a reason you no longer have this mortgage?" with one possible response being "owed more on the loan than the property was worth or could sell it for." I also label respondents who chose this response as being effectively underwater.

Among all respondents (including non-defaulters), 14% of the sample reports being effectively underwater. Thus negative equity is more common in the ASMB than in the MtM estimates from

the NMDB. This is consistent with other studies that argue that homeowners update their beliefs only gradually to reflect market conditions, and so during the recovery in house prices following the Great Recession (i.e. the period studied in this paper) homeowners generally undervalued their homes (Chan et al., 2016; Anenberg, 2016; Davis and Quintin, 2017; Corradin et al., 2017).[22] This force will lead to overestimates of the number of defaults triggered by negative equity in the ASMB.

Among the sample of defaulters, 38% report being effectively underwater; among the sample of foreclosures, 52% do. An advantage of these survey responses over the MtM estimates from Subsection 5.2 is that they should account for all depreciation and appreciation that occurs at the individual-property level. When this depreciation is exogenous to the borrower and triggers the default, then it would be appropriate to account for it in this paper. However, if instead the depreciation is triggered by the default (i.e. the borrower stops maintaining the home because she expects to lose it), or triggered by the adverse shock that triggered the default (i.e. the borrower stops maintaining the home because she can no longer afford to), then it is not itself a default trigger and so for the purposes of distinguishing between different theories of default ideally would not be counted.[23] There is substantial evidence that reduced property maintenance during default often reduces property values (Lambie-Hanson, 2015; Melzer, 2017), which will also lead to overestimates of the number of defaults triggered by negative equity in the ASMB.

Thus the ASMB provides yet more evidence that abovewater default is widespread. While the effects of bias introduced by the remaining (likely limited) measurement error in the NMDB are ambiguous, it seems likely that the evidence from the ASMB is if anything conservative.

6 Conclusion

What policymakers should do about default depends on why it occurs. Researchers have studied this question for decades but have been hampered by a lack of good data. This paper leverages uniquely rich data, which includes information on a large number of adverse shocks missing from most datasets, to show that adverse liquidity shocks trigger nearly all defaults. In line with previous empirical research, but counter to most previous theoretical research, I also find that many defaulters have positive effective equity (even though negative equity makes default more likely).

Together these findings call for much more research on cash-flow default, i.e. default that is triggered by liquidity shocks but not negative equity. There are exceptionally few cash-flow models in the very large literature on mortgage default. Given that cash-flow default is about as common

[22] The bias in homeowner-reported values changes over time. Benítez-Silva et al. (2015) find that homeowners overvalued their homes during the Great Recession (i.e. during and immediately after a large decline in home values), while Molloy and Nielsen (2018) use data from early in the recovery (2014) and find that homeowners only very slightly overvalue their home.

[23] See Appendix A.2 in Low (2021), which formally makes this point.

as double-trigger default and an order of magnitude more common than strategic default during the time period studied in this paper (and likely much more common than either kind of default during more typical time periods), a firmer understanding of the causes and policy implications of cash-flow default would be quite valuable.

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