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

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December 31, 2021

Abstract

Why do homeowners default on mortgages? The answer is still unclear because researchers typically observe only a limited subset of the shocks that might trigger default. This paper addresses the question using a survey specifically designed for the purpose, with a sample drawn from (and matched to) a very rich administrative dataset. I find that a wide variety of typically-unobserved liquidity shocks – including not only job loss but also health shocks, divorce, increases in required mortgage payments, other expense shocks, etc. – together trigger nearly all defaults. Thus "strategic" default with no liquidity trigger is much less common than it usually appears. Conversely, even in this uniquely rich data, the percent of defaults triggered by negative equity is close to previous estimates and much lower than researchers seem to have expected. Thus many defaults are not triggered by negative home equity, contrary to the predictions of the most popular models in the literature.

*I thank Bob Avery, Tim Critchfield, Saty Patrabansh, and the rest of the NMDB production team for their invaluable help and advice with this project. I thank Robert Argento, Neil Bhutta, Nate Blascak, Erik Durbin, Peter Ganong, Pascal Noel, and seminar participants at the NBER Conference on Innovative Data in Household Finance, the FHFA, the Junior Household Finance Brownbag, the Consumer Finance Round Robin, and the NMDB Users' Group for helpful comments that greatly improved this paper. 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.

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1 Introduction

Mortgage borrowers routinely spend more than a third of their income on mortgage payments; home equity constitutes more than half of the median homeowner's wealth.[1] In aggregate, the mortgage market is more than twice as large as all other personal credit markets combined.[2] Mortgages' sheer size naturally leads them to play a critical role in borrowers' financial lives, so when borrowers default the implications can be profound. Infamously, foreclosures played a central role in the Great Recession. They were also a major factor in the Great Depression (Bernanke, 1983) and other business cycles. Foreclosures can also have major consequences for individual homeowners (Diamond et al., 2020) and for society, with important implications for subjects ranging from crime (Ellen et al., 2013) to education (Been et al., 2021) and the racial wealth gap (Kermani and Wong, 2021). Yet despite widespread agreement that mortgage default matters, surprisingly little is known about why it occurs. As a result, policies to reduce default rates range from suing defaulters to principal forgiveness and forbearance. Why borrowers default is so important and so unknown that Foote and Willen (2018) call it – with good reason – a "central" question in the mortgage default literature. This paper answers this central question using data of unprecedented quality.

There are many economic models to explain why borrowers might default, which are typically placed into one of three categories based on (1) why a borrower does not pay her mortgage and (2) why she does not sell her home instead of defaulting. In "strategic" models of default, borrowers *can* pay their mortgage but "strategically" *choose* to walk away instead because they have negative equity. Thus in strategic models negative equity explains both why a borrower does not pay her mortgage and why she does not sell her home. In "double-trigger" models, one liquidity "trigger" (e.g. unemployment) explains why a borrower does not pay her mortgage, while a second equity "trigger" (e.g. a fall in house prices) drives her underwater and unable to sell her home. In "cash-flow" models, a liquidity trigger also explains why a borrower does not pay her mortgage, 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 of classical strategic and double-trigger models and generate both kinds of default. But models with cash-flow default are quite rare. For example, in a recent and comprehensive literature review, Foote and Willen (2018) discuss only strategic and double-trigger models.

Empirically distinguishing between these three classes of models requires understanding the number of defaults triggered by liquidity shocks, by negative equity, or both. This is conceptually simple but practically quite difficult because liquidity shocks and negative equity are both hard to observe.

[1] See Greenwald (2018) and https://www.census.gov/library/stories/2020/11/gaps-in-wealth-of-americans-by-household-type-in-2017.html.

[2] See https://www.newyorkfed.org/medialibrary/interactives/householdcredit/data/pdf/HHDC_2020Q4.pdf.

It is difficult to estimate the fraction of defaults driven by liquidity shocks because there are a very large number of such shocks, including – but not limited to – unemployment, business failure, divorce, illness and death, mortgage payment shocks, other expense shocks, etc. These are not all observed in the 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 a shock did not happen or because a shock did happen but was not observed. This is a significant issue. Gerardi et al. (2018) (hereafter "GHOW") and Ganong and Noel (2021) (hereafter "GN") both find that more than a third of defaults occur without an observed liquidity 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."[3]

This paper leverages uniquely rich data, almost precisely along the lines proposed by Vandell (1995) (but larger), to study the role of a wide variety of different liquidity shocks in triggering default. 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 liquidity shocks triggering default, 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 liquidity trigger 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 liquidity shocks that are not income shocks, which are unlikely to be observed in the income data used in either paper.

The role of negative equity is also currently muddled. The prevailing view, driven by the strategic and double-trigger theories, is that abovewater homeowners sell to avoid default and so nearly all

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

defaulters are underwater (Foote and Willen, 2018). But as with liquidity shocks, equity shocks are often not observed among defaulters. Indeed, abovewater default seems widespread.[4] Again the question is whether the shocks are not observed because they did not happen (and many defaulters are indeed abovewater) or because they did happen but were not observed (and so defaulters are actually underwater).

The NMDB-ASMB data have unusually rich information on borrowers' equity and so can shed valuable light on this question. The NMDB includes the value of the property used for underwriting the mortgage, which can be updated to the time of the survey ("marked-to-market" or "MtM") 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.[5] 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 rich data produces a standard result: from 2015 to 2017, only 52% of foreclosed homeowners are even "effectively" underwater in the NMDB.[6]

The most significant downside to measuring equity in this way is that it will miss idiosyncratic or highly-localized 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, such disaster shocks are perhaps the leading explanation in modern structural models for default with positive MtM equity. To address this issue in the NMDB, I use its link with the ASMB, which 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 57%.

Yet more evidence on the equity of defaulters comes directly from the ASMB. For the purposes of this paper, one advantage of the ASMB is that it comes from a time period during which homeowners tended to undervalue their homes (Chan et al., 2016a; 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 strongly suggests that remaining measurement error in the MtM estimates, e.g. non-disaster depreciation below the census-tract level, is not a significant concern and abovewater default is indeed widespread.

One major contribution of this paper is to document the liquidity shocks that trigger defaults.

[4] I provide a brief discussion of existing evidence in Section 2.2. See also appendix A.1 in Low (2021) or the online appendix in GN.

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

[6] 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 selling costs such as brokers' fees.

This fills a long-standing and well-known gap in the literature,[7] while providing novel and important insights to guide future research. For example, one important insight is that expense shocks matter. They help trigger as many foreclosures as negative equity, which has been a central focus of the literature for decades. But without data like the ASMB, researchers have tended to implicitly assume that all defaults not driven by income shocks are strategic. GHOW's methodology labels defaulters who have the income to pay for their predefault expenditure levels as strategic, which by construction seems likely to mislabel defaults driven by expense shocks. Analogously, many structural models of mortgage default generate as many liquidity-driven defaults as they can with income shocks, and generate the other defaults they need to match aggregate default rates through strategic default.[8] By quantifying the percent of defaults driven by various liquidity shocks, this paper reconciles the empirical findings of GN and GHOW, while providing actionable information future structural models can use to account for liquidity shocks besides income shocks. More broadly, this paper joins a very thin empirical literature documenting the importance of expense shocks for households (e.g. French and Jones, 2004; Fulford, 2015, 2018; Fulford and Rush, 2020; Miranda-Pinto et al., 2020). While the focus of this paper is mortgage default, its results may be useful more generally. Expense shocks are in general poorly understood but have significant implications for many areas in household finance (e.g. Dynan et al., 2002; De Nardi et al., 2010; Ameriks et al., 2020) and macroeconomics (e.g. Miranda-Pinto et al. (2021)).

Another major contribution of this paper is to document the prevalence of abovewater default. As discussed in Section 2.2, all available evidence already suggests that many defaulters have positive equity. However, most existing datasets have limited information on property values and so raise potentially serious concerns about measurement error. Thus a particularly important contribution of this paper is to show that, even in the unusually rich NMDB-ASMB data, abovewater default is still widespread. This finding complements GN, who use the prices of homes that sold to discipline measurement error in house values and also find that cash-flow default is common. This finding also complements Low (2021); in that paper, I compare a quantitative structural model that matches the empirical relationship between equity and default (allowing for measurement error) with a more standard model, and find that the richer model comes much closer to matching many moments from the data, such as the foreclosure start rate, the mortgage chargeoff rate, etc.[9] Together with these

[7]For example, previous researchers write "there are no nationally representative data sets that include both loan-level mortgage characteristics and information on shocks to a borrower's liquidity" (Anderson and Dokko, 2016), "due in large part to data limitations, there is surprisingly little empirical evidence on the importance of strategic considerations versus ability-to-pay issues" (Cunningham et al., 2020) and "a lack of data has been an enduring challenge for the literature" (Ganong and Noel, 2021).

[8]More formally, structural models are usually calibrated in two stages. In the first, the size and frequency of income shocks (but not other liquidity shocks) are estimated from income data. In the second stage, the model is fit to moments which typically include the aggregate default rate. Roughly speaking, models calibrated in this way will generate as many liquidity-driven defaults as the income process (calibrated in the first stage) provides, and then will generate as much strategic default as necessary to match aggregate default rates (targeted in the second stage.) Of course, the calibration of a structural model is a complex process, and this intuition is approximate.

[9]See Table 5 in Low (2021).

papers, this paper shows that measurement error can no longer be viewed as a plausible explanation for why abovewater default appears so common.

The results in this paper suggest that cash-flow default is roughly as common as double-trigger default and an order of magnitude more common than strategic default. These findings, with very different data and a very different empirical approach, are very similar to those of GN. But they contrast sharply with the rest of the literature, which places roughly equal weight on strategic and double-trigger default and nearly no weight on cash-flow default (Foote and Willen, 2018). These findings lend empirical support to the very few models with cash-flow default (Riddiough, 1991; Hedlund, 2016a,b; Garriga and Hedlund, 2019; Head et al., 2020). In Low (2021) I show that abovewater default has many significant policy implications in a theoretical model.[10] Thus, while strategic default is much less common than previous studies suggest, abovewater default is quantitatively important and should be accounted for in future empirical and theoretical research.

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.[11] 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.

[10] One example is that matching the relationship between equity and default leads the model to predict a much smaller increase in foreclosures after a drop in house prices, e.g. after the 2007 financial crisis, than a typical model would predict if there is no accompanying increase in financial distress. Another example is that when financial distress is common but negative equity is rare (as during the COVID pandemic), forbearance is much more effective at preventing foreclosures than a typical model would predict, because it helps financially distressed abovewater homeowners avoid foreclosure.

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

2 Literature Review

2.1 Liquidity Shocks and Mortgage Default

What causes default has been a central question in the literature for a long time. Most research on whether liquidity shocks drive default has focused on the relationship between default and unemployment specifically or income shocks 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 income 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), GHOW, Hsu et al. (2018)). Work on liquidity shocks besides income shocks is less common, but studies have shown that divorce (Low, 2015), medical expenditure shocks (Gallagher et al., 2019), cancer (Gupta et al., 2018), disability (Deshpande et al., 2021), ARM rate resets (Gupta, 2019), property tax increases (Wong, 2020), and even regularly scheduled tax payments (Anderson and Dokko, 2016) trigger default.

While it is now clear that liquidity shocks can trigger default, research on the percent of defaults triggered by liquidity shocks is quite limited. Most datasets used to study mortgage default are loan-level and have very little information on the liquidity shocks experienced by borrowers. Thus until fairly recently rigorous evidence that liquidity shocks cause *any* defaults was a major contribution (Anderson and Dokko, 2016). Limited evidence that a variety of liquidity shocks drive many defaults is available from previous surveys,[12] foreshadowing important results in this paper. But these surveys typically allowed respondents to choose only one default trigger, leaving it unclear whether various reported liquidity shocks are just different kinds of income shocks. Moreover these surveys asked about fewer liquidity shocks than the ASMB, leaving a large unexplained "other" category of defaults. Surveys may also be subject to concerns about "social desirability bias", i.e. defaulters may report liquidity shocks they did not actually experience to avoid being seen as strategically defaulting. In Section 4.3, I investigate this possibility in the ASMB using its link with the NMDB.

Guiso et al. (2013) employ a unique approach to avoiding social desirability bias in a survey by asking households 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.

[12] See Gardner and Mills (1989), Fannie Mae's National Housing Survey at `https://www.fanniemae.com/research-and-insights/surveys/national-housing-survey/national-housing-survey-archive` and the FHFA's quarterly Foreclosure Prevention Reports (e.g. `https://www.fhfa.gov/AboutUs/Reports/Pages/Foreclosure-Prevention-Refinance-and-FPM-Report-Fourth-Quarter-2019.aspx`).

The more typical approach is to use loan-level data together with available proxies for liquidity 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 liquidity 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 liquidity 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 use detailed income and expenditure data from the Panel Survey of Income Dynamics (PSID) and find that 38% of defaulters appear to have the income to pay their mortgage and still maintain their level of consumption from the previous year. They call these defaulters strategic.

GN discuss in detail the possibility of measurement error in GHOW and other studies. First, if income is measured with error then some defaulters may have experienced income shocks even if they are not observed. Second, if some liquidity shocks are not income shocks, then using only income shocks to measure liquidity shocks will overstate the amount of strategic default. To overcome these issues – which also exist in their data from borrowers' checking accounts – 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 income shock.

Thus, if anything, the dispersion in researchers' estimates of the prevalence of strategic default is going up over time. As the gap between GHOW and GN demonstrates, this dispersion can be quite large even when the empirical results are nearly identical, because the shortcomings of existing datasets mean that empirical results can reasonably be interpreted in different ways. To make progress on this important issue, the literature needs richer data on liquidity shocks than researchers have previously had access to. This is one major gap in the literature that is filled by this paper.

2.2 Negative Equity and Mortgage Default

A very large number of studies dating at least to Herzog and Early (1970) have universally found that underwater borrowers are more likely to default. This evidence is usually interpreted as supporting a key prediction from the strategic and double-trigger theories of default, which is that most or all defaulters are underwater (Foote and Willen, 2018). In this section I revisit this evidence to place the contributions of this paper into context. For concreteness, I focus on estimates of the relationship between equity and default from one particularly well-known paper, Foote et al. (2008) (hereafter, "FGW"). But quantitatively similar results can be found in many other papers (e.g. Elul et al., 2010; Fuster and Willen, 2017; Fuster et al., 2018; Laufer, 2018; An et al., 2021).

Estimates of foreclosure hazard as a function of LTV, normalized by foreclosure hazard at an LTV of 80, from FGW are in Figure 1a. Qualitatively, Figure 1a is consistent with strategic and double-trigger models, since foreclosure risk decreases with equity. But quantitatively the empirical relationship between foreclosure risk and equity in Figure 1a is much weaker than it is in strategic and double-trigger models. These models predict that abovewater homeowners sell their homes and do not default, and so (for example) the foreclosure risk at an LTV of 120 relative to 80 should be infinite. FGW estimate it is around five.[13]

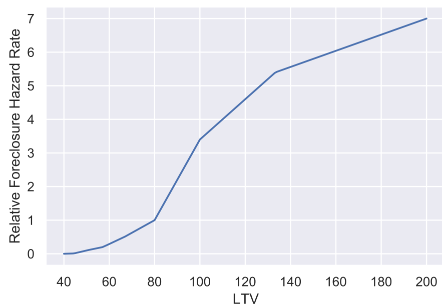
An important but rarely-made point is that the fraction of foreclosures triggered by negative equity depends not only on how much negative equity increases foreclosure risk, but also on how common negative equity is. For intuition, an analogy is that even though lightning strikes are often deadly when they occur, few people die from lightning strikes because few people are struck by lightning. Figure 1b plots the PDF of county-level MtM LTVs in the NMDB in January 2016 (roughly the midpoint of the date ranges studied in this paper). The figure shows that negative equity is rare. For example, in January 2016, a MtM LTV of 80 was around 18 times more common than a MtM LTV of 120.

If the foreclosure hazards from FGW were correct for NMDB loans in January 2016, how many foreclosures would we expect to be abovewater? The mass of properties at each LTV can be combined with the foreclosure hazard at that LTV to estimate the PDF of LTVs for foreclosures that we would expect from the estimates in FGW. Figure 1c performs this calculation. The figure shows that significant mass is still to the left of 90, i.e. for effectively abovewater borrowers. But the figure is shifted noticeably to the right from Figure 1b, since negative equity makes foreclosure more likely. Thus according to the results from FGW, in January 2016 we would expect foreclosures at an LTV of 80 to outnumber those at an LTV of 120 by roughly four to one.

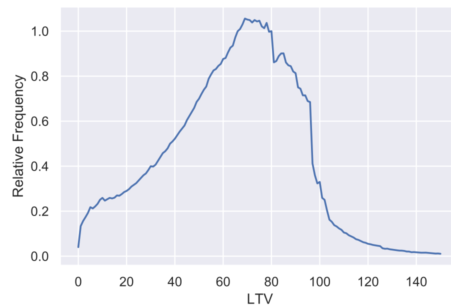
[13] This relatively low estimate arises in part because underwater default rates are much lower than typical models predict, which is already a widely-noted puzzle in the literature (FGW, Foote and Willen (2018)).

Figure 1: Interpreting Estimates from FGW

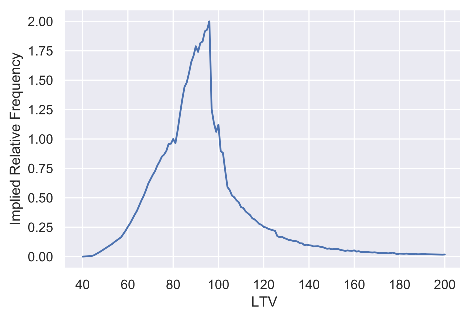
(a) Foreclosure Risk by LTV from FGW



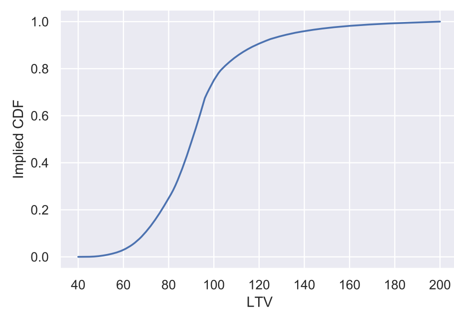
(b) Normalized PDF for Mortgagors



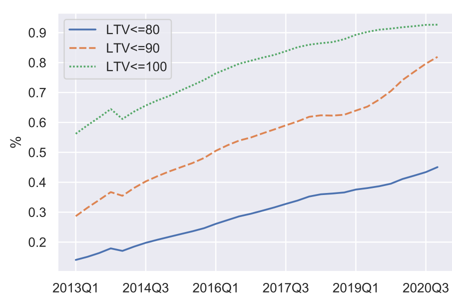
(c) Normalized PDF for FGW Foreclosures



(d) CDF for FGW Foreclosures



(e) % FGW Foreclosures Abovewater



Notes: Figure 1a shows foreclosure hazard rates as a function of LTV, relative to an LTV of 80, from the lower right figure in Table 3 in FGW. Foreclosure rates are taken for values of E_{it} in FGW between -50 and 150 at intervals of 25; intermediate values are interpolated. Because of the data FGW had, their x-axis is equity as a % of the original mortgage. I have converted these numbers to LTVs to simplify the discussion, assuming as FGW do that mortgage balances do not change over time. Figure 1b plots the PDF of county-level MtM LTVs among mortgage borrowers in the NMDB in January 2016 using the FHFA HPI; see Section 5 for how MtM LTVs are calculated. Figure 1c plots the PDF of MtM LTVs among foreclosures that would result if foreclosure hazards from FGW applied to the MtM LTVs in the NMDB in January 2016. Both PDFs have been normalized to be 1 at an LTV of 80. Figure 1d plots the resulting CDF of MtM LTVs among foreclosures. Figure 1e repeats this exercise over time and plots the percent of foreclosures with MtM LTVs below 80, 90, and 100. 2013Q1 is the first quarter for which data on balances on subordinate liens are available.

Figure 1d plots the implied CDF of LTVs for foreclosures from this exercise. This provides a useful quantitative interpretation of the estimates from FGW. Assuming that the FGW estimates are roughly applicable to the NMDB in January 2016 and that LTVs are not measured with too much error, the figure shows that in January 2016 we should expect that around 51% of foreclosures would be effectively abovewater (i.e. LTV<90).

Finally, Figure 1e repeats this exercise for different quarters and plots the percent of foreclosures we would expect to have LTVs below 80, 90, and 100 over time. The figure suggests that – according to the estimates from FGW – even during the Great Recession cash-flow default was roughly as common as previous estimates suggested strategic default was (see Section 2.1), and several times more common than strategic default actually was (see Section 4 or GN.) As house prices recovered, the estimates from FGW imply that cash-flow default became several times more common than strategic and double-trigger default combined.

This is a simple exercise. But it provides a new and useful interpretation of existing evidence, using just one well-known example from the literature. A comprehensive review of evidence from the literature on the equity of defaulters is given by Low (2021); all sources are comparable to FGW and so all existing evidence suggests that abovewater default is widespread. However, the consensus view in the literature is that the strategic and double-trigger models are correct and few or no defaulters are abovewater (Foote and Willen, 2018). Thus the prevailing view in the literature is at odds with the data.

There are still two reasons the prevailing view could be at least approximately correct. First, abovewater default rates, although positive, could be low enough to be ignore. Second, many defaulters who are technically effectively abovewater still have little equity, so the equity they have could be small enough to ignore. Both of these points are especially plausible given that LTVs are almost certainly measured with substantial error both by FGW and in the county-level MtM estimates in the NMDB. Measurement error would likely lead to attenuation bias in the estimates from FGW; it could also lead to artificially low estimates of the number of underwater homeowners in the NMDB. Addressing these points requires comparing results from (1) a quantitative structural model that reproduces the estimated relationship between equity and default allowing for measurement error and (2) a more standard quantitative model that predicts no abovewater default.

Low (2021) performs such a comparison. That paper finds that a model that matches the relationship between equity and default estimated by FGW (allowing for measurement error roughly as documented by Molloy and Nielsen (2018)) has very different implications from a standard model without abovewater default in two policy experiments. First, if house prices drop then matching the relatively weak relationship between equity and default leads the model to predict just one-quarter of the increase in foreclosures.[14] This suggests that standard models will substantially overstate the relationship between equity and default, which is a concern since the relationship between equity and default is a common topic in the literature. In a second policy experiment, house prices do not change but financial distress becomes more common. In this experiment, matching abovewater default rates leads the model to predict that forbearance prevents between three and seven times more foreclosures relative to a more standard model because it helps distressed abovewater homeowners avoid foreclosure. This experiment has important implications for the recession induced by the COVID pandemic, when negative equity was rare but financial distress was common and forbearance was readily available.

Thus standard measurement error, of a magnitude suggested by the literature on measurement error in house prices, cannot reconcile the strategic and double-trigger models with the data. A final important possibility is that defaulters may be subject to unusually severe, localized depreciation shocks. Highly-localized shocks would likely not show up in county-level MtM estimates or in the results from FGW. If such shocks are frequent and often induce default, perhaps because they are correlated with liquidity shocks, then they could explain why so many borrowers who appear to be abovewater default on their mortgages anyway. Indeed, such depreciation shocks are a popular explanation in the literature for apparently-abovewater default; they play a major role in many structural models, yet it is unclear whether or not they should. Addressing this gap in the literature is a goal of this paper.

3 Data

3.1 NMDB-ASMB

This paper primarily 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).[15] The FHFA sponsors the NMDB program in part to meet its statutory requirements to conduct a monthly survey of the mortgage market that collects data on individual mortgage loans and mortgage borrowers.[16] 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.[17]

[14] The magnitude of this effect is not necessarily obvious from Figure 1. It arises because the model without abovewater default, like most such models, is calibrated to match aggregate default rates. The way it does so, without abovewater default, is by exaggerating the underwater default rate significantly above the low rate documented by FGW and many others.

[15] 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.

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

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

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, or chargeoff. Mortgage borrowers are tracked from one year prior to mortgage origination through one year after termination. NMDB data are de-identified and do 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).[18] Loans from these agencies comprise about three-quarters of the loans in the NMDB. 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 delinquent mortgage borrowers. This paper uses the 2016, 2017, and 2018 waves of the ASMB.[19] The sample for the ASMB is drawn from the NMDB. For the 2016 survey, 70% of the sample was at least 30-days delinquent on their mortgage at the beginning of 2015, 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 before the survey, 10% were both Hispanic and at least 30-days delinquent at the beginning of the year before the survey, and 25% were current at the beginning of the year before the survey. The 2016, 2017, and 2018 surveys were mailed in August, July, and June of their respective years. Each survey was in the field for roughly three months. About 10,000 surveys were sent in each wave, yielding roughly 4,500 usable responses across the three survey years. Weights are used to make the sample representative of all mortgage borrowers.

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 some time between two years before the survey was first sent (since the surveys generally ask about delinquencies in the previous couple years) and the last date

[18]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, RHS, 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.

[19]The survey instruments are available at https://drive.google.com/file/d/1qadkj_FwHEhSffp0aYhC-76Zio5T_71w/view?usp=sharing. There was no ASMB in 2019 or 2021. The 2020 ASMB is valuable for other topics but not for this paper because during the COVID pandemic mortgage forbearance was readily available and so mortgage default was extremely rare.

the survey was in the field. This sample consists of roughly 1,400 borrowers. Throughout the rest of this paper I refer to these borrowers as "defaulters."

Though this is one common definition of mortgage "default", the term is vague and in both the academic literature and in the mortgage market it has other definitions ranging from 60-day delinquency to foreclosure. Using 90-day delinquency to define "default" has two important advantages. First, it is comparable to the definition of default used in previous research, including GHOW and GN. Second, while it restricts the analysis to borrowers who became seriously delinquent on their loans, it still maintains a fairly large sample size. However, foreclosure is also an important outcome to study, since it likely has more significant implications for both borrowers and lenders than 90-day delinquency does. Moreover, testing the prediction from strategic and double-trigger models that abovewater borrowers always sell to avoid foreclosure naturally requires analyzing foreclosed homeowners, not just seriously delinquent ones. Therefore, I also analyze the roughly 150 defaulters who reported losing their home to foreclosure; I refer to these borrowers as "foreclosures" or "foreclosed homeowners."

3.2 House price data

This paper also uses two sets of house price indices (HPIs). The first, from the FHFA, are free and publicly available.[20] I use FHFA HPIs at the state, county, and census-tract level.

I also use commercial HPI data from Black Knight. Unlike the FHFA data, Black Knight data are not available at the census-tract level, but they do have two other advantages. First, Black Knight data are available at the county level for five different property price tiers, separately for single-family homes and for condos. Later this allows me to investigate whether house price appreciation in different non-geographic segments of the market explains my results. Second, Black Knight data are in general available further back in time than FHFA data.

4 Liquidity Shocks and Mortgage Default

In this section I study the role of liquidity shocks in triggering default. Note that income shocks are one kind of liquidity shock, but so are expense shocks and wealth shocks. Some specific shocks, such as divorce or a death in the household, may affect a household's income, expenses, and wealth simultaneously; they may also affect a household's ability to allocate the resources it has efficiently.

Before this paper, the richest datasets used to study the role of liquidity shocks in triggering default included information mostly or entirely on income shocks. A common finding is that many defaults occur without income shocks, a finding which I replicate. Among defaulters in the ASMB,

[20]See https://www.fhfa.gov/DataTools/Downloads/Pages/House-Price-Index.aspx.

only 42% report that household income has significantly decreased in the past couple years; 11% report a significant *increase* in income. 65% either report that 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.[21] Thus in the ASMB, as in the data used by GHOW and GN, roughly a third of defaults occur without observed income shocks. As discussed above, how to interpret this result is a major outstanding question in the literature; GHOW argue these are strategic defaults while GN argue they are driven by unobserved liquidity shocks. A significant advantage of the ASMB over the datasets used by GHOW, GN, and other researchers is that it includes information on many liquidity shocks besides income shocks.

4.1 Defaulters with payment concerns or difficulties

Like many surveys, the ASMB follows a skip logic so that 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?"[22] 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.[23] Specifically, CD respondents were asked if any of the following made it difficult to make their mortgage payments:[24]

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[25]
7. Unexpected expenses

[21] One possible explanation for this low number is that defaulters' incomes recovered after delinquency was measured for the ASMB sample selection, but before the survey was sent. However, this explanation does not appear to be promising. Even focusing on defaulters who are still delinquent by the time of the survey, this number is 66%.

[22] 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?"

[23] Besides being important for skip logic, CD status also appears to be a good proxy for financial distress. Among borrowers in the current sample of the ASMB, 18% reported CD. Among borrowers in the delinquent sample who only became 30-59 or 60-89 days past due, 76% and 85% (respectively) reported CD.

[24] 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?" 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.

[25] Increases in mortgage payments (like several other items on this list) could 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. Similarly, see Anderson and Dokko (2016) for evidence that regularly-scheduled property tax payments trigger some defaults.

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.[26]

Figure 2a presents the percent of CD defaulters reporting each liquidity shock as a default trigger, and includes several important results. One is that a very wide variety of liquidity shocks beyond job loss are important. Previous researchers have shown that many different kinds of liquidity shocks each trigger some defaults, including divorce (Low, 2015), cancer (Gupta et al., 2018), medical expenditure shocks (Gallagher et al., 2019), disability (Deshpande et al., 2021), ARM rate resets (Gupta, 2019), property tax payments (Anderson and Dokko, 2016), and property tax increases (Wong, 2020). One contribution of Figure 2a is to show that, in aggregate, these kinds of shocks help trigger most defaults.

Perhaps most notably, unexpected expenses help trigger nearly two-thirds of CD defaults.[27] This is consistent with evidence that ex-ante many households are more concerned about expense shocks than income shocks (Fulford, 2015) and that, ex-post, households are more likely to report expense shocks as a source of financial difficulties than income shocks (Fulford and Rush, 2020). Indeed, expense shocks may be particularly important for defaulters, who tend to have lower income than most mortgage borrowers and so may be more susceptible to expense shocks than higher-income households (Fulford, 2018). 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.

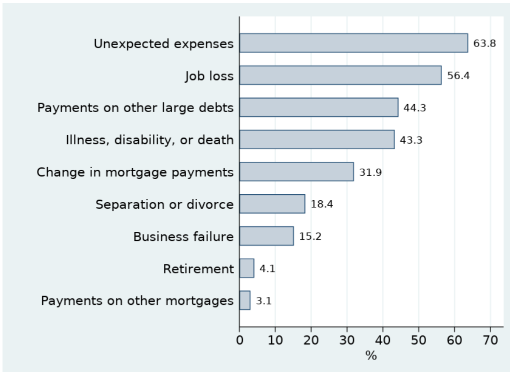
Why does strategic default appear so much less common in the ASMB than in GHOW? One likely explanation is GHOW's approach to identifying a household's expenditure needs by using, as a proxy, the household's expenditure levels in the year before default is measured. As GHOW state, they identify strategic defaulters as those with "the ability to pay their mortgage without reducing

[26] 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.

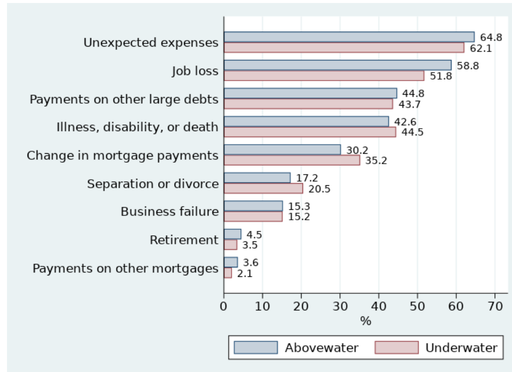
[27] While the ASMB does not break down expense shocks into more detail, another CFPB-run survey – the Making Ends Meet ("MEM") survey – does. The most important expense shocks reported by MEM respondents include medical expenses, auto repair, helping a friend or family member, and home repair, but the category is broad and also includes legal expenses, appliance repair, etc. (Fulford and Rush, 2020).

Figure 2: Liquidity shocks triggering default

(a) Unconditional



(b) By equity status



Notes: Of the 92% of defaulters that reported payment "concerns" or "difficulties", the figure on the left shows the percent that reported each liquidity shock contributing to their difficulties. The figure on the right shows the percent that reported each liquidity shock contributing to their difficulties by equity status. "Abovewater" refers to a MtM LTV ≤ 90 as computed using the FHFA HPIs at the census-tract level, while "underwater" refers to a MtM LTV > 90; see Section 5.2 for details. The 2016 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.

consumption from its predefault levels." Unfortunately, this means their methodology likely misses expenditure shocks that increase a household's consumpion needs beyond its predefault levels. Since unexpected expenses help trigger nearly two-thirds of defaults in the ASMB, this seems to be a significant issue. This helps to explain why so many abovewater defaulters (who should not strategically default) are labeled by GHOW as strategic. Similarly, it helps explain why GN appear correct to argue that abovewater defaults are triggered by liquidity shocks, even if they are not observed in income data.

Another important finding from Figure 2a is that adding the percent of defaults triggered by each liquidity shock yields a number much greater than 100%. Indeed, 72% of CD defaulters report at least two liquidity shocks contributing to their default.[28] Thus just as using one specific liquidity shock (e.g. income shocks) to proxy for all liquidity shocks will understate the number of defaults triggered by liquidity shocks, it will also understate the intensity of the combined liquidity shocks triggering default.

While strategic default is evidently quite rare, it is possible that because of their greater financial incentive to default underwater defaulters in general experience different or fewer liquidity shocks than abovewater borrowers. 91.7% of abovewater defaulters are CD, while 91.6% of underwater defaulters are CD, which is not encouraging for this idea. But to investigate it further, Figure 2b shows default triggers by equity status. It finds little support for this hypothesis.

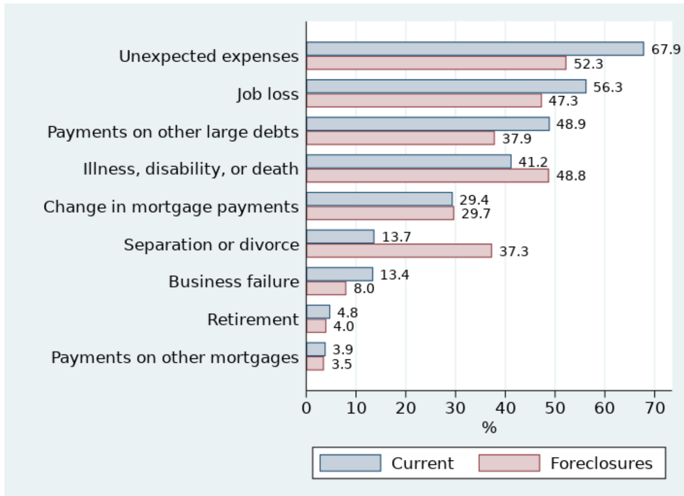
[28]Divorce, illness, a change in mortgage payments, payments on other mortgages, and payments on other large debts could all be viewed as involving "unexpected expenses." Thus for this calculation I only count unexpected expenses as a separate shock if none of these other shocks are reported.

Together these findings have important implications for quantitative models. Models of mortgage default vary widely in the liquidity shocks they account for. In many models, income is a lognormal process and large drops in income are rare. Laufer (2018) 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)) make substantial contributions to the literature by allowing for very realistic income processes, but it is extremely rare for structural models to account for liquidity shocks that are not income shocks. This paper shows 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. Perhaps more importantly, this paper provides specific actionable information that can be used in structural models of default to account for liquidity shocks beyond income shocks, for example as implemented in Low (2021). Even more broadly, Figure 2 suggests that expense shocks should be included in many more consumption-savings models intended to study risk or precautionary wealth; Miranda-Pinto et al. (2020) make important progress on this issue.

But why are income drops as rare as they are among defaulters? CD respondents were asked a series of questions about what they did to address their payment 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 CD defaulters who reported an increase in income, 72% did. Thus just as it can be misleading to view consumption as fully endogenous, it can also be misleading to view income as fully exogenous. 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.

How do the liquidity shocks documented in Figure 2 differ by duration and severity? How do they differ in their implications for defaulters? Figure 3 begins to address these questions by comparing reported shocks for defaulters who became current by the time of the survey (and therefore likely experienced relatively mild liquidity shocks) to shocks for foreclosed homeowners (who likely experienced severe liquidity shocks). The figure shows that different kinds of liquidity shocks may have different implications for mortgage borrowers. Unexpected expenses, job loss, and other debt payments – the top three reasons listed for default – are notably *less* common among foreclosures than among defaulters who became current, suggesting that these shocks could often be comparatively mild. But health shocks and especially divorce are much more common among foreclosures, suggesting that these shocks may be particularly severe. Indeed, health shocks appear to drive slightly more foreclosures than job loss does. Understanding in more detail how these shocks differ in their implications for borrowers seems to be a promising direction for future research.

Figure 3: Liquidity shocks triggering default, by payment status



Notes: Among "CD" defaulters (those who reported payment concerns or difficulties) that (1) became current by the time of the survey or (2) lost their homes to foreclosure, the figure shows the percent that reported each liquidity shock contributing to their payment concerns or difficulties. 91% of defaulters who became current were CD; 96% of foreclosures were. The 2016 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.

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 liquidity 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 whose financial situation has already recovered, 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 partially 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. Only 44% of NCD defaulters had negative effective equity or a disaster shock affect the property according to the MtM methodology discussed in Section 5. 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. Thus, even among NCD defaulters, at most half appear to have had negative effective 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, 73% experienced property appreciation between the time delinquency was measured for the ASMB and the time the survey was sent, according to the FHFA census-tract HPI. In the ASMB, 15%, 53%, and 23% of NCD defaulters expect in the next few years for house prices in the property's neighborhood to "increase significantly", "increase slightly", or "stay about the same", respectively. 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 in this subsample.

This raises the question: are NCD defaults triggered by liquidity shocks? 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 liquidity shocks. I follow the methodology developed by GN to use this information to determine whether these shocks triggered NCD defaults.

Specifically, consider a noisy binary measure X of a liquidity 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 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 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 liquidity shocks.

More formally, for each noisy measure X of a liquidity 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 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. Liquidity shock reported in the ASMB:[29] 60%
4. Any 60-day delinquency or worse on a nonmortgage credit product within two years of the survey in the NMDB: 95%
5. Any 60-day delinquency or worse, excluding bankruptcy, on a nonmortgage credit product within two years of the survey in the NMDB: 77%

Intuitively, I obtain the estimates above because NCD defaulters appear to have experienced more liquidity shocks than NCD borrowers, but fewer liquidity shocks than CD defaulters. Quantitatively, the estimates above indicate that half or more, but not all, of NCD defaults are triggered by liquidity shocks. This is consistent with the evidence discussed above that half or more, but not all, of NCD defaults do not satisfy classic requirements for strategic default (negative equity, falling house prices, etc.)

There are several potential explanations for these results. One plausible explanation is that CD status is itself an imperfect proxy for liquidity shocks, and that borrowers who experienced severe liquidity shocks are more likely to be CD than those who experienced mild liquidity shocks.[30] Another is that borrowers who frequently experience financial distress (or who manage their money poorly) may have a higher bar for reporting CD and specific liquidity shocks, which could explain why the credit bureau proxies for liquidity shocks from the NMDB indicate more liquidity triggers for NCD defaulters than the ASMB proxies. Yet another potential explanation is that some of these borrowers may have been defaulting after mild liquidity shocks to obtain a favorable loan modification (Mayer et al., 2014).[31] Finally, these results are also consistent with some strategic default among NCD borrowers.

The subsample of NCD defaulters is small (only 108 households) so it not possible to disentangle the various explanations above. But since few defaulters are NCD, the results are still clear. Even conservatively 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.

[29] Here a "liquidity 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.

[30] See footnote 23.

[31] Confusingly, this kind of default is also frequently referred to as "strategic", even though it can be very different than strategic default driven by negative equity. After a moderate liquidity shock, a borrower with multiple payment obligations may be able to make some of them but not all, and so faces a complicated financial management problem (e.g. Chan et al., 2016b). The possibility of a favorable mortgage modifiation may naturally induce such a borrower to prioritize her other payment obligations over her mortgage payment. This kind of default is particularly likely after a liquidity shock and does not require a negative equity trigger. As in GHOW and GN, this paper studies wealth-maximizing strategic default, which is driven by negative equity and not a liquidity shock.

4.3 Liquidity Shocks in the ASMB and Social Desirability Bias

As discussed in Section 4.1 and Section 4.2, ASMB responses indicate that virtually all defaults are triggered in part by liquidity shocks. But in surveys like the ASMB, respondents may avoid reporting events or conditions that are socially undesirable, thus introducing "social desirability bias" to the results. Strategic default is viewed by many as morally wrong (Guiso et al., 2013), so an important possibility is that some ASMB respondents reported liquidity shocks that they did not actually experience to avoid being seen as strategically defaulting.

If this were the case, it seems likely that ASMB respondents would report more income shocks than they actually experience, and so income shocks should appear more common among defaulters in the ASMB than in other datasets. Since this is not the case (see the beginning of Section 4), this does not appear to be a major concern. But to investigate it further, I use 60-day delinquency or worse on any nonmortgage credit product within two years of the survey (hereafter, "60D"). Note that this proxy for liquidity shocks comes from the administrative data in the NMDB and so it raises no concerns about social desirability bias. Following the logic in GN, if some default were strategic we would expect 60D to be less common among underwater borrowers (who might have an incentive to strategically default) than for abovewater borrowers (who have no incentive to default strategically). 88% and 86% of effectively abovewater and effectively underwater defaulters, respectively, have 60D.[32] Thus social desirability bias does not appear to be a concern among ASMB respondents.

A related concern is that strategic defaulters may have been less likely to respond to the ASMB at all, perhaps because of social desirability bias. Among NMDB borrowers that were selected for the delinquent subsample of the ASMB and responded, 85% have 60D. Including those that were sent the survey but did not respond, 88% have 60D. Thus in the administrative data, delinquent ASMB non-respondents do not appear to be in any less financial difficulty than delinquent ASMB respondents. But this average could mask important heterogeneity, if for example abovewater borrowers were less likely to respond to the ASMB if they were in more financial difficulty, and underwater borrowers were less likely to respond to the ASMB if they were strategically defaulting. Splitting the results out by equity status, 88% of effectively abovewater borrowers chosen for the delinquent subsample have 60D; 88% of effectively underwater borrowers chosen for the delinquent subsample do. This is evidence against the idea that strategic default rates appear low in the ASMB only because strategic defaulters were less likely to respond to the survey.

[32] Here, effectively abovewater denotes a MtM LTV$<$ 90, as calculated using the FHFA census tract HPI, while effectively underwater denotes a MtM LTV $\geq$ 90. See Section 5 for more details. Even 83% of defaulters with a MtM LTV $\geq$ 120 have 60D.

5 Negative Equity and Mortgage Default

Next I investigate the role of negative equity in triggering default. As discussed in Section 2.2, there is a substantial amount of evidence on this topic already, 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 that matches existing evidence has very different policy implications from a more standard model, so this is a critical issue to study.

Property values are typically measured with substantial error (e.g. Molloy and Nielsen, 2018). But recall from Section 2.2 that measurement error of the magnitude already documented in the literature cannot reconcile the strategic and double-trigger theories with the data. Therefore this section is primarily intended to investigate whether severe, highly-localized depreciation shocks can. This section uses unusually high-quality evidence in both the NMDB and the ASMB to study this issue. 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 Negative Equity

In this paper, we are interested in the measurement error of borrowers' LTVs. It is 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 second 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 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 attenuation 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 some 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 MtM[33] 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_{i0}, 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 MtM 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 classical 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.

Computing MtM estimates requires choosing a time t at which to measure borrowers' equity. One possibility is to try to measure a borrowers' equity when they first become delinquent. However many defaulters enter and exit delinquency frequently, and just because a delinquent borrower has become current does not mean her financial situation has recovered. Thus clearly defining the start of a delinquency is often difficult. Another possibility, which may be more appropriate for

[33]Recall that "MtM" stands for "mark-to-market."

testing the strategic and double-trigger theories, is to measure equity as late as possible in the foreclosure process. When house prices are rising – as they generally were during the time period studied in this paper – some defaulters who were underwater when they first became delinquent may become abovewater, and so according to the strategic and double-trigger theories should likely still sell before foreclosure occurs. However delinquency that is initially triggered by negative equity could itself further reduce a borrower's equity (e.g. through foreclosure fees or reduced property maintenance), which could offset this property appreciation and would not be observed in MtM estimates. Thus instead I choose t to reflect the timing of "delinquency" that was used to select the delinquent subsample of the ASMB. This means that for borrowers in the 2016, 2017, and 2018 waves of the ASMB, I compute MtM estimates in January of 2015, 2016, and 2017, respectively.

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. I also compute MtM estimates using HPIs from Black Knight at the state, "coarse county" (i.e. aggregating all properties in a county), and "fine county" (i.e. separately for single family vs. condo, for each of five price tiers). FHFA data at the census-tract level are not available for roughly 10% of the sample, which consists of properties in census tracts with housing markets that are too thin for the FHFA to estimate an HPI. I use county-level FHFA HPI data for these properties. FHFA data at the county level are not available for roughly 1% of the sample; nearly all mortages in this category were originated before FHFA data at the county level became available (generally in the 90s). I use Black Knight data at the coarse county level for these properties.

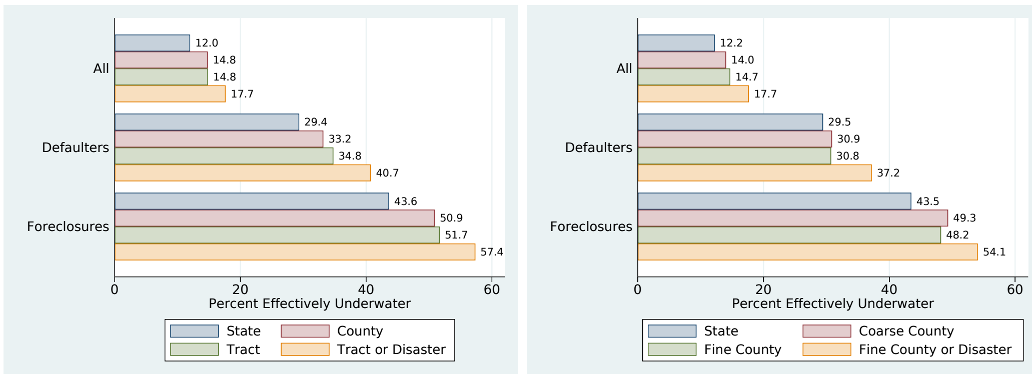
Even census-tract MtM estimates will miss depreciation that occurs below the census-tract level, such as at the level of an individual property. This kind of depreciation is arguably the leading explanation in the literature for why abovewater default appears to be so common. Indeed, many quantitative models generate default when negative MtM equity is rare through 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). For example, if the homeowner repaired the property after the disaster, it would likely be a liquidity shock and not an equity shock. If insurance paid for the repairs, it might not be a shock at all. Still, to be conservative, I count all affirmative responses to this question as indicating negative effective equity.[34]

[34] 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

Results using the FHFA HPIs are in Figure 4a; results using the Black Knight HPIs are in Figure 4b.

Figure 4: Percent Effectively Underwater

(a) FHFA **(b)** Black Knight



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 delinquency is measured for the ASMB. MtM LTVs are calculated using HPIs at the state, county, and census-tract level from the FHFA and HPIs at the state, coarse-county, and fine-county level from Black Knight. Disasters affecting the property and foreclosures are identified in the ASMB.

The results indicate that measurement error is a moderate concern when measuring the equity of defaulters. For example, moving from a state-level to a county-level FHFA HPI increases the percent of defaulters with negative effective MtM equity from about 29% to 33%. But a state-level HPI is very coarse and almost all existing studies use better data. A contribution of this paper is to move from county-level to census-tract level. Doing so gives very little indication that measurement error at a finer level than county is a serious concern; it increases the percent of defaulters with negative effective MtM equity from 33% to just 35%.

A greater concern is simply how "default" is measured. Figure 4 indicates that foreclosed homeowners are substantially more likely to be underwater than defaulters. Using the FHFA county-level MtM estimates, while only 33% of defaulters have negative effective equity, 51% of foreclosures do. But this is not a particularly new result. Many existing studies use data at the county or even zip-code level,[35] and the 51% estimate I obtain at the county level is very close to the 49% we would have expected naively applying the foreclosure hazard estimates from FGW to the distribution of county-level MtM LTVs in the NMDB, as discussed in Section 2.2. The more novel result is that moving to the census-tract level increases this estimate to just 52%.

Perhaps the last remaining plausible explanation for these results that is consistent with the strategic and double-trigger theories is idiosyncratic disasters affecting individual properties or very

the question. See Appendix A.2 in Low (2021) for a formal discussion.

[35] See Fuster et al. (2018) for previous research documenting the distribution of MtM LTVs at the zip-code level.

local areas. But the estimates for defaulters and foreclosures rise only slightly to 41% and 57%, respectively, counting all homeowners who report a disaster in the ASMB as underwater. Thus it appears that some delinquent abovewater homeowners escape foreclosure through selling their homes or refinancing their mortgages, but also that many do not and go on to experience foreclosure despite having equity in their homes.[36] This in turn suggests that theoretical models should allow for only limited 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. For example, classical measurement error in the FHFA 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 FHFA MtM estimates will also miss HPI movements that occur below the level of the census tract and that ASMB respondents do not view as "disasters", but the attenuation bias this Berkson error introduces is second-order and in any case 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, and Bogin et al. (2019) find that measuring MtM equity at the census-block rather than census-tract level provides nearly no improvement in predicting default. The numbers in Figure 4 may even be conservative, because (1) Figure 4 ignores the general house price increases that occured after delinquency was measured for the ASMB, (2) it counts all respondents who report a disaster affecting a property as effectively underwater, and (3) it controls for some idiosyncratic property depreciation but not appreciation.

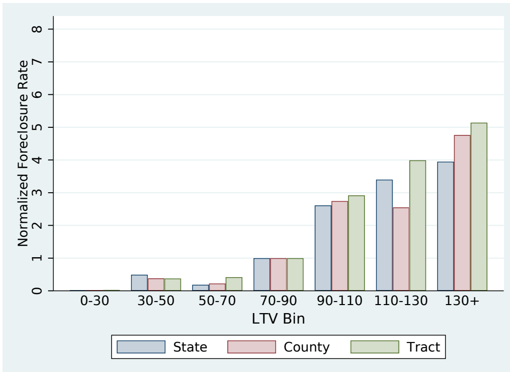
To understand these results in more detail, Figure 5a plots foreclosure rates by state, county, and census-tract MtM LTV bins (using HPIs from the FHFA). The figure again shows that measurement error is a concern; the estimated relationship between foreclosure risk and LTV is stronger when LTV is measured with less error, i.e. at the census-tract rather than state level. Yet using census-tract rather than state-level HPIs strengthens this relationship only modestly. For example, at the census-tract level foreclosure rates for borrowers with LTVs between 110 and 130 are roughly four times higher than for borrowers with LTVs between 70 and 90, rather than about three and a half times higher at the state level.

As emphasized by Bogin et al. (2019), HPIs at finer levels of geography are measured with more error (greater variance in ζ in Equation 9) because they are constructed from fewer observations. In theory, this greater variance in ζ could counteract the decreased variance in δ_{it}^{j} that comes from using finer HPIs, which might in turn explain why using census-tract HPIs strengthens the

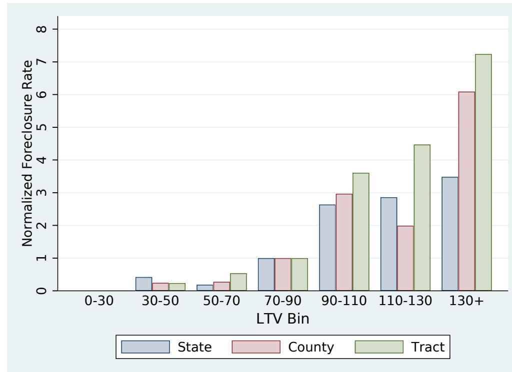
[36]This is consistent with evidence that foreclosure starts are e.g. around half as likely to result in involuntary liquidation for homeowners with CLTVs below 60 than for those with CLTVs above 100; see https://cdn.blackknightinc.com/wp-content/uploads/2021/10/BKI_MM_Aug2021_Report.pdf.

Figure 5: Normalized Foreclosure Rates by LTV Bin

(a) All Borrowers



(b) Urban Borrowers



NOTES: Figures shows the average probability by LTV bin, normalized by the probability for the 70-90 bin, that an ASMB respondent reports no longer owning the property in question because of foreclosure. Foreclosures that are not in the sample of "defaulters" (e.g. because they have not been current at least once within four years of the survey) are not counted; see Section 3.1 for sample selection criteria. The x-axis is the MtM LTV bin, as computed using the FHFA HPIs either at the state, county, or census-tract level. "Urban" denotes counties in metropolitan areas as defined by the USDA with at least 250,000 inhabitants.

relationship between equity and foreclosure risk so modestly. Thus as recommended by Bogin et al. (2019), Figure 5b repeats the analysis only for urban mortgage borrowers, since urban areas likely have housing markets thick enough for measurement error in HPIs to be small. For MtM LTVs below 130, the effect of focusing on urban areas is small. The effect is larger for MtM LTVs above 130, where focusing on urban areas increases the relative foreclosure rate from roughly five to roughly seven. But according to standard models this number should be infinite. Measuring property values in urban areas at the census-tract level, and using administrative contemporaneous data on balances on primary and subordinate liens, the relationship between equity and default shown in Figure 5b is remarkably similar to that estimated by FGW (see Figure 1a) and far weaker than that predicted by standard models in which abovewater borrowers do not default.

Figure 5 shows that removing a very large amount of Berkson error in LTVs only modestly strengthens the estimated relationship between equity and default. As discussed in Section 5.1, attenuation bias from Berkson error is second-order, and so in this context its actual importance depends on how convex the relationship between equity and default actually is. The small effect of substantial Berkson error on the estimates in Figure 5 suggests that the relationship between actual equity (measured without error) and default is not strongly convex and likely not much stronger than the relationship between MtM equity and default. This in turn helps explain why estimates of the relationship between equity and default in the literature are so consistent, despite the wide variation in data and methodology used in other papers.[37]

[37]For example, Elul et al. (2010) and Fuster and Willen (2017) both find that homeowners with a combined LTV

5.3 Negative Equity in the ASMB

As discussed above, remaining measurement error in the MtM estimates from Section 5.2 is likely limited. Morever, although remaining measurement error likely still biases the estimates in Section 5.2, it seems unlikely that even higher-quality estimates would produce significantly different results. Still, there remains a possibility that either measurement error in the HPIs or non-disaster property depreciation below the census-tract level could meaningfully affect the results in Section 5.1. To address this possibility, in this section I study negative equity as reported by ASMB respondents.

ASMB respondents are asked the value of their property, but valuing properties is difficult for homeowners as well as for economists. It is particularly unclear how respondents who no longer own the property are supposed to interpret this question. Thus 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 have much higher response rates, perhaps because they are simpler and more targeted. Because self-reported property values are unlikely to be missing at random, I use the more direct questions.

An advantage of survey responses over the MtM estimates from Section 5.2 is that they should account for all depreciation and appreciation that occurs at any geographic level. When this depreciation is exogenous to the borrower and triggers the default, it should be accounted for 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 liquidity 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.[38] There is substantial evidence that reduced property maintenance during default often reduces property values (Lambie-Hanson, 2015; Melzer, 2017). This force will lead to overestimates of the number of defaults triggered by negative equity in the ASMB.

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

("CLTV") above 120 are less than four times more likely to default than those with a CLTV between 70 and 80. Fuster et al. (2018) find that delinquency rates for properties with CLTVs between 60-80 are roughly one-tenth of those with CLTVs above 120. Laufer (2018) finds that default rates for homeowners with LTVs between 75 and 100 are a quarter of those with LTVs between 100 and 125. FGW estimate that homeowners with an LTV of 120 are roughly five times more likely to experience foreclosure than those with an LTV of 80. An et al. (2021) examine the relationship between equity and default over time; they find that it was quite weak immediately before the 2007 foreclosure crisis, but close to these other estimates during it.

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

responses as effectively underwater.

Among all respondents (including non-defaulters) who still have the mortgage by the time of the ASMB, 16% report being effectively underwater. But using census-tract MtM estimates at the time of the survey, only 8% are effectively underwater. Thus negative equity is more common according to ASMB respondents than it is in 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., 2016a; Anenberg, 2016; Davis and Quintin, 2017; Corradin et al., 2017).[39] This force will also lead to overestimates of the number of defaults triggered by negative equity in the ASMB.

Because ASMB respondents who still had the mortgage by the time of the survey were asked about their equity at the time of the survey, here I focus on (1) equity at the time of the survey for (2) the roughly 510 defaulters who still have the mortgage, and are still delinquent on it, at the time of the ASMB. Among these defaulters, 46% report being effectively underwater. This is much higher than the 23% that are measured to be effectively underwater by the time of the ASMB, according to the census-tract MtM estimates. There are several potential explanations for this result. First, as noted above, at the time of the ASMB borrowers tended to undervalue their homes. Second, this bias could be especially strong for defaulters, who may be less numerate than borrowers in general (Gerardi et al., 2013). Third, the same amount of bias could have a larger effect for defaulters, who tend to have less equity than borrowers in general and so even if abovewater require less measurement error to be misclassified as underwater. Fourth, as discussed above, it could reflect negative equity endogenous to the default, which ideally would not be counted. Finally, it could reflect negative equity exogenous to the default that could have helped trigger the default and yet was missed by the MtM estimates.

A potential issue with the survey question about equity for borrowers who still have the mortgage is that it asks only about the amount owed on "this mortgage." This phrasing was intentionally chosen to maximize respondent understanding, and its intent to ask about borrowers' equity is arguably clear, but still it is possible that respondents ignored balances on subordinate liens in their responses, which could bias the percent of defaulters estimated to have negative effective equity downwards. To investigate this concern, I focus on the roughly 470 defaulters described in the paragraph above who did not have a second mortgage at the time of the survey. Among these defaulters, 47% report being effectively underwater and 21% have negative effective MtM equity,

[39]Consistent with the argument that homeowners update their beliefs only gradually, 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.

suggesting that this issue is minor.

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.

For foreclosures, the discrepancy between ASMB responses and the MtM estimates is small. Recall from Section 5.2 that 51.7% of foreclosures have negative effective MtM equity at the census-tract level. This is remarkably close to the 52.2% of foreclosed homeowners that, in the ASMB, report that negative effective equity was a contributing factor to their foreclosure. This could indicate that, although delinquent borrowers may not be aware of the equity they have in their home because they hope to keep it, homeowners who experienced foreclosure learned through that process how much equity they had. Another potential explanation is that the upward bias in the ASMB estimates is counteracted by the fact that, for foreclosures, respondents were essentially asked if negative equity helped *cause* the foreclosure. As emphasized by GN a foreclosure could occur with negative equity but not be caused by it; indeed there is evidence that a substantial portion of the correlation between negative equity and default risk is not causal (Gupta and Hansman, 2021). Some foreclosed homeowners may have viewed themselves as underwater, but viewed the negative equity as immaterial to (or caused by, rather than causing) the foreclosure. Since ideally this paper aims to identify the percent of defaults triggered by – not just concurrent with – negative equity, this is an advantage of the question.

Again, a potential concern with this question is that it asks about the amount owed on "the loan". Again, this phrasing was intentionally chosen to maximize respondent understanding, and its intent to ask about borrowers' equity is arguably clear, but still it is possible that respondents ignored balances on subordinate liens in their responses, which could bias the percent of foreclosures estimated to have negative effective equity downwards. To investigate this concern, I focus on the roughly 130 ASMB foreclosures who did not have a second mortgage at the time delinquency was measured. 50% had negative effective MtM equity and 49% reported that negative effective equity contributed to their foreclosure. Thus again this issue seems minor.

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.

5.4 Discussion

As discussed above, the NMDB-ASMB data have major advantages over existing datasets. Yet they only validate results on the relationship between equity and default that have been widely documented before. The relationship between equity and default risk is statistically and economically significant, but it is much weaker than most existing models predict. The surprisingly low underwater default rate is a widely-noted puzzle in the literature (Foote et al., 2008; Foote and Willen, 2018). An arguably even more important puzzle is abovewater default rates that are substantially above zero. So why is the relationship between equity and default so weak?

Research on this question is only beginning. Hembre (2018) and Laufer (2018) argue that homeowners' non-financial moving costs may explain why underwater borrowers default so rarely. Empirically, homeowners' non-financial moving costs are often at least an order of magnitude larger than their financial incentives to sell or default (Koşar et al., 2021). Low (2021) develops a quantitative model in which homeowners have non-financial moving costs consistent with this evidence. In that model, agents are aware of and account for the financial incentives they have to default, but their non-financial reasons to avoid moving are generally much more important and so drive their decisions. After liquidity shocks, abovewater homeowners sometimes default rather than sell in an ex-ante optimal gamble to avoid moving, which explains abovewater default. Meanwhile underwater homeowners do not strategically default nearly as often as they "should", also to avoid moving. Thus non-financial moving costs may explain why the relationship between equity and default risk is as weak as it is.

Obviously, non-financial moving costs are just one possible theoretical mechanism to explain the empirical results in this section. But Low (2021) also demonstrates that the relationship between equity and default risk has many important policy implications, so the relationship is important to understand whatever its underlying mechanisms. Establishing whether non-financial moving costs indeed help explain the weak relationship between equity and default, and whether there are other mechanisms at play, should likely be a priority for future research.

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 high-quality data on homeowners' equity and on many liquidity shocks. This paper leverages uniquely rich data, which includes information on a large number of liquidity shocks missing from most datasets, to show that a wide variety of liquidity shocks together trigger nearly all defaults. Thus strategic default with no liquidity trigger is very rare. Furthermore, in line with previous empirical research but counter to the predictions of most existing models, I also find that many defaulters have positive effective equity (even though negative equity makes default more likely).

In the data used in this paper, defaulters experience many more observable liquidity shocks than in more typical datasets. This is because many households experience liquidity shocks that are severe enough to induce default, but are not income shocks. Indeed, many defaulters respond to the shocks they experience specifically by increasing their income. In general economists have made far more progress in studying the size, frequency, and effects of income shocks on households than of other kinds of liquidity shocks, so this paper makes an important contribution by documenting the liquidity shocks besides income shocks triggering mortgage default. Further work quantifying the size and duration of these shocks and incorporating them into quantitative models, both on mortgage default and on other topics, would clearly be valuable.

The findings in this paper call for much more research on cash-flow default, i.e. default that is triggered by liquidity shocks but not negative equity. The mortgage default literature is quite large, but there are exceptionally few cash-flow models and there is nearly no empirical research on why abovewater defaulters do not refinance or sell their homes to avoid foreclosure as existing theories predict they should.[40] Cash-flow default is about as common as double-trigger default and an order of magnitude more common than strategic default during the time period studied in this paper. Together with previous research, these results imply that even during the depths of the Great Recession – when negative equity was far deeper and more common than it typically is – cash-flow default was still about five times more common than strategic default and accounted for around a quarter of all defaults. When negative equity is rare – as it usually is – cash-flow default is several times more common than double-trigger and strategic default combined. Clearly, a promising direction for future research is to provide a firmer understanding of the causes and policy implications of cash-flow default.

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[40] Defusco and Mondragon (2020) is an important exception; they show that documentation requirements and out-of-pocket closing costs prevent many liquidity-constrained borrowers from refinancing.

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