Borrower Misreporting and Loan Performance

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Abstract

Borrower misreporting is associated with seriously adverse loan outcomes. Significantly more residential mortgage borrowers reported personal assets just above round number thresholds rather than just below. Borrowers who reported above-threshold assets were almost 25 percentage points more likely to experience subsequent delinquency (mean delinquency was 20%). For applicants with unverified assets, the increase in delinquency was above 40 percentage points. Misreporting was most frequent in areas with low financial literacy and social capital. Incorporating behavioral cues such as threshold effects into a risk assessment model meaningfully improves its ability to uncover potential delinquencies, though at a cost of mischaracterizing some safe loans.

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Risk assessment and control are core functions of financial institutions. In transactions with retail clients, one strategy for loss mitigation is to identify behavioral patterns or cues associated with worse outcomes that can be incorporated into risk models. The importance of better delinquency models in sectors such as the residential mortgage market has been brought into stark relief by the events of the recent financial crisis. The use of new behavioral-based risk measurement tools may lead to more successful lending results and help support the long-run stability and performance of financial institutions.

In this paper I offer an empirical description of a behavioral pattern in personal asset misreporting by a bank's mortgage borrowers during the 2004-2008 period that was associated with seriously adverse consequences for loan outcomes. Specifically, using regression discontinuity techniques, I show that many more borrowers reported assets just above a round number threshold (e.g., \$203,000), rather than just below it (e.g., \$198,000). This pattern is apparent in the reports of borrowers with unverified personal assets, but not in the reports of those with verified assets. This is consistent with the hypothesis that there is systematic misreporting by a certain subset of borrowers with unverified assets. Moreover, I find that borrowers who claimed a personal asset level just above a round number threshold were almost 25 percentage points more likely to experience subsequent delinquency than those who claimed personal assets just below the threshold. This more than doubled their delinquency risk relative to the mean and suggests that misreporting is associated with a very negative unobserved borrower risk characteristic. The discontinuity in delinquency is magnified to above 40 percentage points for those with unverified assets, but is insignificant for those with verified assets. These results highlight the importance of borrower misreporting in predicting the success of mortgage lending.

The data in this study are from a U.S. bank that originated and retained residential mortgages to high quality borrowers. As part of the loan application, the bank required that borrowers detail their net personal assets (excluding the house to be financed). While I find both that the density of unverified assets exhibits a sharp discontinuity at round number thresholds that are multiples of \$100,000, and that there is a large discontinuous increase in delinquency risk specifically at these points, loan terms and observed borrower risk characteristics, by contrast, do not change significantly at the thresholds. This has two implications. First, the bank was clearly unaware of this specific asset reporting practice, and did not even partially adjust upwards the price of loans to reflect the risk of misreporting borrowers. Second, these borrowers did not benefit from stating above-threshold assets. (Very few borrowers reported asset levels at round numbers precisely as the bank requested that the actual asset level be supplied, and round number estimates would likely not appear credible.)

Which borrowers misreported their assets and why did these borrowers experience such poor loan outcomes? To provide some insight into these questions, I consider behavioral studies that suggest that when asked to estimate a value, individuals tend to provide a round number, particularly if they lack specific knowledge or documentation (Kaufman 1949, Rosch 1975 and Kleven and Waseem 2013). While a round number report would thus be attractive to a borrower without information, in the empirical context of this paper it would be inappropriate due to the request for actual assets, not a rounded estimate. These borrowers would therefore likely be drawn to above round number values, which have been shown to generate more satisfaction than those below (Medvec and Savitsky 1997 and Pope and Simonsohn 2011). On this argument, borrowers who do not know their asset levels should be expected to disproportionately report assets above round numbers. Financially ill-informed borrowers typically experience poor loan outcomes (Hirad and Zorn 2001 and Gerardi, Goette and Stephan Meier 2010). Together, these behavioral insights suggest that borrowers who report above round number asset values are more likely to be financially ill-informed, and, as a result of their lack of knowledge, they may be expected to subsequently enter delinquency more frequently.

To explore this hypothesis, I examine where misreporting was most common. I find that misreporting was significantly less frequent in areas with high financial literacy (as measured by the extent of local household English usage or the fraction of adults with at least some college education). Regions with high social capital (as proxied by the fraction of families with a married couple present or the percentage of residents who are citizens) also exhibit less misreporting. Overall, there does appear to be more misreporting in areas in which borrowers might be expected to know less about their finances (or to be less driven to supply an accurate report on their loan application). The cross-sectional evidence on the association between misreporting and delinquency is more mixed. The link is stronger in neighborhoods with less English usage and more non-citizens, but it does not differ significantly with the level of education or the ratio of married families. The connection between misreporting and delinquency is also stronger for borrowers who potentially experienced negative home equity than for those who did not. Although they are subject to concerns about omitted factors (e.g., borrower optimism), the findings do suggest that misreporting is associated with a very negative unobserved borrower risk characteristic that may be correlated with low financial literacy or social capital.

To quantify the benefits of identifying misreporting, I contrast the forecasting accuracy of a basic delinquency model including common risk factors such as the loan rate spread, borrower credit score and loan-to-value ratio with an enhanced model that accounts for above-threshold asset reporting. An in-sample comparison shows that the enhanced model outperforms the base model in correctly identifying loans that later became delinquent, at the cost of correctly classifying fewer of the loans that later had good outcomes. To provide a cleaner comparison between the two models and to minimize issues of over-fitting, I consider simulations that split the data into a training sample on which the models are estimated and a test sample on which their forecasting ability is assessed. These out-of-sample simulations show that the enhanced model identifies significantly more of the truly delinquent loans (12.7% versus 8.8% for the base model), but classifies significantly fewer of the truly safe loans correctly (95.6% versus 97.6% for the base model). The enhanced model that captures the risks of above-threshold asset reporters thus improves the bank's ability to identify delinquent loans (an apparently difficult task), while somewhat impairing its success in correctly characterizing safe loans. Given the large losses banks experience in foreclosure, compared to the small gains from a successful loan, the trade off provided by the enhanced model is likely to be attractive to a bank. Nonetheless, its adoption would lead to the denial of credit to some good borrowers who correctly report their true above-threshold assets.

A competing risks discrete time hazard model helps to clarify the mechanisms driving the basic binary outcome results of the paper. Borrowers with above-threshold assets have a higher delinquency hazard each month and are also less likely to fully repay their loans. Given that all the loans in the study are floating rate, slower prepayment is not as attractive to the bank as it might be for fixed rate mortgages. Instead, the higher on-going delinquency hazard and the lower propensity to fully repay both lead to worse eventual outcomes for above-threshold borrowers.

The analysis in this paper complements other work that has emphasized different features of the financial crisis.[1] The focus in this study is on borrowers, rather than on the other central actors in the mortgage origination process. Moreover, these loans were made to high credit score applicants and were retained by the bank, so issues with subprime lending and securitization do not apply here. The emphasis in this paper, by contrast, is on a behavioral cue of borrowers and its striking power to predict future loan outcomes.

Information collection and risk mitigation by banks have been the themes of a broad stream of research. Some of this work has focused on a bank's sourcing of soft information (Stein 2002, Petersen and Rajan 2002, Berger et al. 2005 and Agarwal and Hauswald 2010), the study of bank organization (Liberti and Mian 2009 and Hertzberg, Liberti and Mian 2010) and the importance of bank screening (Ruckes 2004, Dell'Ariccia and Marquez 2006, Norden and Weber 2010 and Maddaloni and Peydró 2011).

As part of this effort, the role of misreporting in residential real estate mortgages has be-

[1]Previous research has highlighted the role of lenders (Ivashina and Scharfstein 2010, Fahlenbrach and Stulz 2011 and Cornett et al. 2011), securitization (Keys, Mukherjee, Seru and Vig 2010), mortgage contract features (Piskorski and Tchistyi 2011 and Barlevy Fisher 2011), regulations and regulatory arbitrage (Acharya and Richarson 2009 and Beltratti and Stulz 2012), servicers (Gan and Mayer 2007) and the special problems in the subprime market (Mian and Sufi 2009 and Demyanyk and Van Hemert 2011).

gun to attract more attention, and it has been documented in transaction prices and appraisals (Agarawal, Ben-David and Yao, 2012, Ben-David 2011 and Carrillo 2010) and personal income (Jiang, Nelson and Vytlacil 2009). Misreporting thus plays an important role in this setting, as it does in many other financial environments (Fich and Shivdansani 2007, Povel, Singh and Winton 2007, Graham, Li and Qiu 2008 and Bollen and Pool 2009 and 2012). The importance of thresholds and misreporting has also been a focus of the earnings management literature (Burgstahler and Dichev 1997, Degeorge, Patel and Zeckhauser 1999 and Peasnell, Pope and Young 2005)

While the above-threshold asset reporting I analyze is a strong predictor of delinquency, there are certain limitations to the behavioral-based empirical model presented in this paper. First, while I do find evidence of misreporting not only around multiples of $100,000, but also at multiples of $50,000 and $25,000, there does not appear to be misreporting at multiples of $20,000 or $10,000. Second, the association between misreporting and subsequent delinquency is clearly strongest around multiples of $100,000. Third, borrowers were asked to supply their actual current assets, and the strategy of identifying misreporting relies on the fact that very few borrowers reported a round number. By contrast, borrowers were requested to report their typical monthly income, and many responded by providing a rounded estimate. There may have been borrowers who misreported their income as well, but they are hidden in the mass of good borrowers with round number income reports. As a result, there is no increase in delinquency at round numbers of income. The widespread use of a rounding heuristic (Goldreich 2004) in the income data thus make it less suitable for detecting misreporting. These limitations suggest that models making use of behavioral cues must be carefully calibrated.

The findings in this paper, however, do indicate that behavioral biases such as round number targeting may play an especially important role in interactions between consumers and financial institutions. A closer study of the form and frequency of these biases may therefore be quite helpful in mitigating the risks of incomplete or incorrect disclosures, a key aspect of the broader problem of asymmetric information in finance.

The rest of the paper is organized as follows. Section 1 details the residential mortgage data that I use to analyze misreporting. Section 2 relates round number thresholds to behavioral theories. In Section 3 I outline my econometric approach, and I describe the empirical findings in Section 4. Finally, Section 5 concludes.

1 Data

The data in this paper describe 8,287 residential single-family mortgage loans originated by a U.S. financial institution in the period January 2004- October 2008.[2] Loans made to insiders are excluded, as are loans for which the personal asset or income information of the borrower is not provided. These loans were retained by the bank and not securitized. As described in Table I, the data include pricing information and details on borrower and property attributes. This bank offers floating rate mortgages, and the mean spread between the loan interest rate and the underlying index is 3.36 percentage points (various indices are used, including the prime rate, the Treasury bill rate and LIBOR). Many of the loans allow borrowers to make payments less than the current interest rate, thereby causing negative amortization. The mean loan-to-value (LTV) ratio is 72%, the mean monthly borrower income is $16,086 and the mean borrower FICO credit score is 719.4. This relatively high mean FICO score and income reflect the fact that the bank made almost no subprime loans (e.g., only 0.3% of borrowers had FICO credit scores below 620). Data is also provided on the purpose of the loan (home purchase, cash out refinance or rate/term refinance).

In common with broader market trends, the bank experienced significant delinquencies in its residential lending. Specifically, 20% of the loans in the data are delinquent (30 or more days past due).

[2]During the sample period this bank made 23,590 mortgage loans. Reported asset or income data are provided for 8,287 loans.

1.1 Origination Process

Essentially all the residential loans made by the bank are presented to them by mortgage brokers. A loan officer employee of the bank works with the broker and prepares a mortgage file. The base interest rate charged is determined by a fixed set of loan characteristics (LTV, FICO score, etc.), but the bank may also adjust the pricing to reflect other perceived risks. The mean of this exception pricing is 15.2 basis points.

As part of the application, borrowers state their level of personal net assets (excluding the property to be purchased) and income. Borrowers were asked to supply their actual current assets. For reported income, however, applicants were asked for their typical or stable monthly income. Mortgages differ in their level of documentation: a borrower chooses how much documentation to supply and receives a rate that depends on this choice. Borrowers may provide documentation verifying both personal assets and income, verifying assets but not income, or neither. Low-documentation mortgages were designed for borrowers whose assets or income were difficult to substantiate (e.g. owners of small private businesses); the house serving as the loan collateral was, in any case, regarded to be the main security for the mortgage. Some borrowers may misreport their personal information.

The bank made use of asset and income information in its approval process in a manner that is not completely transparent to borrowers. Internal bank protocols required that assets exceed a multiple of the monthly principal and interest payments plus insurance and property taxes (PITI) due from the borrower. The bank did not, however, compare the stated asset levels to round number thresholds. Borrower income was also considered in the mortgage evaluation process.

2 Round Number Thresholds and Behavioral Theories

This study focuses on patterns in the reporting of personal assets by borrowers, and connections between these asset reports and subsequent loan outcomes. What types of asset reports should be expected? To help answer this question, I consider the predictions of several behavioral theories.

The first insight is that round numbers are reference points (Rosch 1975) and they are the numbers that are most cognitively accessible (Schindler and Kirby 1997). As a result, when asked to estimate a value, people display a pronounced tendency to provide a round number (Kaufman 1949, Krueger 1982 and Lipton and Spelke 2005). Those without specific knowledge or documentation are more likely to offer round number estimates (Ormerod and Ritchie 2007 and Kleven and Waseem 2013), and there is evidence consistent with the argument that round numbers are used when people feel it is difficult to acquire exact information (Whynes et al. 2007). These theories and empirical studies suggest that borrowers who simply do not know their assets, or who are unwilling to undertake the effort necessary to find their precise asset level, are more likely to be drawn to round number asset reports.

Which numbers are considered round? In societies using a decimal number system, powers of ten and integer multiples of these powers are considered most prominent (Dehaene and Mehler 1992 and Jansen and Pollmann 2001). The attraction to round numbers of this type has been documented in finance settings (Goldreich 2004, Kandel, Sarig and Wohl 2001 and Bhattacharya, Holden and Jacobsen 2012).

In the empirical analysis in this paper, however, I study borrowers who were asked to report their actual current asset levels, not an estimate. In this context, a round number asset report would likely not appear credible. If borrowers without precise asset level information (or who are unwilling to seek this information) are attracted to round number estimates but think it unwise to provide an actual round number, what sorts of reports should they be likely to make?

There are two types of theories that suggest that these borrowers should be more likely to make asset reports that are just above round numbers. The first theory emphasizes that just exceeding a cutoff significantly increases satisfaction (Medvec and Savitsky 1997), perhaps because it generates a favorable comparison between the outcome and the round number just below it (Markman et al. 1993). In fact, individuals work hard to exceed round number thresholds in baseball batting averages and SAT scores (Pope and Simonsohn 2011). In the setting of this study, borrowers without precise information can exceed an asset level threshold (in the perception of the bank and, perhaps, in their own self-perception), simply by reporting a number that is just above their round number estimate of their assets. In support of this idea, Bopp and Faeh (2008) find that men are more likely to self-report heights that are above round numbers than are women. The social importance of height is more pronounced for men (Jackson and Ervin 1992 and Nettle 2002), so men would likely achieve greater satisfaction from reporting an above threshold height, and they are indeed more likely to do so. For the case of assets, it seems likely that borrowers would prefer to have higher assets and an above round number report should create greater satisfaction.

The second theory points to the fact that people place more emphasis on the left-most digit of a number and tend to truncate the digits to the right (Hinrichs, Berie and Mosdell 1981, Poltrock and Schwartz 1984, Thomas and Morwitz 2005 and Olsen 2013). Consequently, an asset report slightly above a round number will be viewed by borrowers as very similar to a report of the round number itself. For borrowers without exact knowledge of their asset levels, a just above round number estimate allows them to thus essentially report the round number to which they are drawn, without raising questions about their credibility. That is, in the absence of information, an above-threshold response may be more often supplied than a below-threshold response, since the former will be perceived to be closer to the round number estimate that is attractive. In a study of mid-20th century census data from developing countries, Nagi, Stockwell and Snavley (1973) find that older (and, typically, less-educated) individuals are more likely to not know their ages and therefore to supply above round number reports of their ages, rather than below (round numbers themselves are the most popular).

Taken together, these behavioral findings suggest a first prediction that borrowers without detailed asset information (either due to financial illiteracy or a lack of concern for submitting a meticulous loan application) should be more likely to report assets above round number thresholds. Mortgage borrowers who are financially ill-informed have poor loan outcomes (Hirad and Zorn 2001 and Gerardi, Goette and Stephan Meier 2010). This suggests the second prediction that borrowers who make above round number asset reports should be more likely to subsequently experience delinquency.

3 Empirical Specification

The empirical analysis is focused on these two predictions. First, I consider whether there is evidence that some borrowers (especially those without information) engage in systematic misreporting of their personal assets on mortgage applications. Second, I analyze to what extent this misreporting is correlated with poor subsequent loan outcomes.

I explore the general hypothesis that borrowers who misreport their personal asset holdings are more likely to state asset levels above, rather than below, round number thresholds. In other words, a borrower who is misreporting his assets is more likely claim an asset level of $102,000 rather than $97,000.

I take asset multiples of $100,000 to be the round number thresholds and define $round(x, y)$ to be the value of x rounded to the nearest positive multiple of y. I define normalized assets A as

$$A = assets - round(assets, 100000). \tag{1}$$

The indicator variable I_A denotes mortgages with reported assets above the threshold:

$$I_A = \begin{cases} 1 & \text{if } A \geq 0 \\ 0 & \text{otherwise} \end{cases} \tag{2}$$

My first set of tests analyzes whether there is indeed an observed pattern of above-threshold asset reporting. To examine this question I employ McCrary's (2008) test for a discontinuity in a density function. McCrary also proposes a test to evaluate the log difference in the density heights on either side of the threshold point. If this log difference is significant, it indicates that the density is discontinuous at the threshold.

Other methods for assessing discontinuities are considered in Burgstahler and Dichev (1997), Garrod, Pirkovic and Valentincic (2006) and Bollen and Pool (2009). McCrary's methodology is useful for this study, as it allows for distinct kernel density estimates on both sides of the threshold, while correcting for boundary bias. Rather than comparing the empirical distribution to a kernel estimate of a single smoothed distribution that is fit using data on both sides of the potential discontinuity, the McCrary test generates separate below- and above-threshold density estimates. These estimates enable me to quantify the magnitude of over-reporting relative to under-reporting.

The second set of tests examine the impact of above-threshold borrower-reported assets on the eventual delinquency of mortgages. To analyze the hypothesis of a discontinuity in delinquency probabilities at the thresholds, I estimate the following formal model:

$$Delinquent_{i,t} = \alpha + \beta I_{Ai,t} + \sum_{j=1}^{6} \omega_j^A A_{i,t}^j + \sum_{j=1}^{6} \xi_j^A I_{Ai,t} A_{i,t}^j + \gamma * controls_{i,t} + \lambda_t + \epsilon_{i,t}, \tag{3}$$

where $Delinquent_{i,t}$ is an indicator for whether loan i provided in month t subsequently became delinquent, $A_{i,t}$ is the personal asset level claimed by the borrower, $I_{Ai,t}$ is an indicator for whether this asset level is above a round number threshold, $controls_{i,t}$ is a vector of loan and property controls, λ_t is a month fixed effect and $\epsilon_{i,t}$ is an error term. Other controls include zip code fixed effects.

The coefficient of central interest is β, which measures discontinuities in the delinquency probability at round number personal asset thresholds. Under the null hypothesis of no asset misreporting (or no systematic misreporting around round number thresholds), we should expect to find $\beta = 0$. Under the alternative hypothesis that some borrowers misreport their asset levels to be just above round number thresholds and that these borrowers are more likely to become delinquent, we should find that $\beta > 0$: there should be a discrete jump in delinquency probabilities just above the thresholds.

I estimate (3) using OLS, despite the binary nature of the *Delinquent* variable, due to the large number of fixed effects along several dimensions and the resulting incidental parameters problem in non-linear maximum likelihood estimation (Abrevaya, 1997). OLS coefficients are estimated consistently even with multiple fixed effects. This approach is similar to the one used in the models of Card, Dobkin, and Maestas (2004) and Matsudaira (2008). The specification allows the delinquency probability to be continuous in personal assets, with the shape of the probability function permitted to be different on either side of round number threshold. For robustness, I also discuss results from a local linear kernel regression (Lee and Lemieux 2010). The OLS specification with polynomials is the main specification presented because it accommodates the inclusion of month-of-origination and zip code fixed effects and loan level controls that are likely to be important in this setting.

For some tests I study cross-sectional variation in the impact of above-threshold assets on delinquency probabilities by estimating (3) in subsamples that differ, for example, by characteristics of the neighborhood. Significant differences in the estimates of β in distinct subsamples provide evidence that the magnitude of the misreporting-delinquency correlation may have varied in different areas.

In estimating (3) to detect jumps in delinquency above round number asset reporting thresholds, I make use of the tools of regression discontinuity analysis (Hahn, Todd and Van der Klaauw 2001). The motivation and empirical setting in this study, however, differ from those in a typical regression discontinuity design. In a standard regression discontinuity approach, a policy or treatment is applied in a manner that varies discontinuously with some underlying variable, and the goal of the analysis is to determine the causal impact of that policy, under the assumption that unobservable characteristics do not vary discontinuously at the policy threshold. In this paper, I examine the hypothesis that a behavioral cue leads certain borrowers with negative unobservable risk characteristics to report assets above round numbers. If this is the case, then above- and below-threshold asset reporters will have quite different risk profiles. Even though there is no causal effect or policy change implemented at round number thresholds, an analysis of jumps in delinquency risk at these thresholds can illuminate the effects of the behavioral cue. The techniques of regression discontinuity analysis are designed to describe any such jumps, so they are well-suited for this study, but I note that the context and interpretation differ from those in a standard regression discontinuity design.

4 Results

4.1 Distribution of Reported Assets

I begin by testing the hypothesis that some borrowers systematically misreport asset levels just above round number thresholds. If there is misreporting, then it should be exhibited in the sample of loans for which the borrower stated his assets without supplying verification. Loans for which verifiable asset documentation was provided should presumably reflect the true asset levels and should not be subject (or should be much less subject) to any behavioral misreporting bias. I therefore divide the loans into two samples, one for which asset documentation was not supplied (consisting of 3,280 loans) and one for which it was (composed of 5,007 loans) and contrast the distribution of reported assets across the two samples.

4.1.1 Round Number Heuristic

As described in Section 2, there is a tendency in financial markets for participants to make use of round number heuristics. To what extent do borrowers make use of this heuristic in reporting assets? Applicants were requested to provide their actual current asset levels, not rounded estimates.

As a result, out of 8,287 data points, only 23 loans (fewer than 0.3%) have normalized assets of zero. That is, very few of the borrowers submitted round number values for their reported assets.

4.1.2 Prevalence of Above and Below Threshold Reported Assets

Given the inappropriateness of submitting a round number asset value, the first prediction in Section 2 is that borrowers who do not know the correct level of their assets will be more likely to supply numbers just above round numbers. Systematic borrower misreporting would thus generate a distribution of unverified reported assets that exhibits a discontinuity at round number thresholds. Misreporting borrowers should be unusually likely to display normalized unverified asset levels of just above zero, in analogy to the patterns found in the reporting of corporate earnings (Burgstahler and Dichev 1997 and Degeorge, Patel and Zeckhauser 1999) and hedge fund returns (Bollen and Pool 2009 and 2012).

I examine this hypothesis using McCrary's (2008) test for a discontinuity in a density function. The estimated kernel density of reported unverified assets is described in Figure 1. The thick line represented the density estimate and the surrounding thin lines depict the 95% confidence interval. The circles describe scaled frequencies (i.e., they are analogous to histograms). The bin size of 1,342.8 and bandwidth of 14,638.3 are selected using McCrary's automatic algorithm.

As the figure makes clear, there is a sharp discontinuity at normalized assets of zero, with significantly more reported assets above the threshold than below. The estimated log difference in kernel heights is 0.81 (t-statistic= 3.49). This discontinuity is not driven only by borrowers with normalized assets of zero (i.e., reported assets equal to a round number); excluding those borrowers for a pure test of over versus under-reporting yields an estimated log difference in kernel heights of 0.49 (t-statistic=2.11).

By contrast, the estimated kernel density of reported verified assets is described in Figure 2. Verified assets should be less subject to misreporting, and this suggests that there should not be a discontinuity in the density of reported assets for the verified sample. Figure 2 is consistent with this hypothesis. The estimated log difference in kernel heights is -0.09 (t-statistic= -0.65). In the sample excluding reported assets equal to a round number the log difference in heights is -0.20 (t-statistic=-1.32).

The statistical significance of the difference in the density discontinuities in the unverified and verified asset samples can be assessed using a bootstrapping technique. The discontinuity is significantly greater (at the 1% level) in the unverified sample, both if round number reported assets are included or excluded.

4.1.3 Where is Misreporting Most Prevalent?

Figure 1 makes clear that some borrowers are systematically reporting above-threshold unverified assets. This may be driven by a borrower strategy or it may simply reflect some unobserved borrower characteristics. The behavioral studies described in Section 2 suggest that ill-informed borrowers are most likely to report above-threshold assets. In this section, I consider whether the prevalence of misreporting varies across neighborhoods. These neighborhood characteristics may clearly be associated with other, unobserved risk characteristics. Nonetheless, while these results may be not be interpreted in a causal sense, they do provide some evidence on the types of regions in which misreporting was most common.

A. Financial Literacy

Borrowers with a lower level of financial literacy may be more likely to exhibit a behavioral bias that leads them to report above-threshold assets as they may simply not know their asset level.[3] To assess this, I construct two zip code level measures of financial literacy using data from the 2000 census (matched to borrower zip codes using zip code tabulation areas). The first measure describes for each zip code the fraction of households in which the language is English. The bank's

[3] Lusardi and Mitchell (2007), Agarwal et al. (2009) and Cole, Sampson and Zia (2011) examine the impact of financial literacy on decision-making.

mortgage application and instructions were in English, so English literacy would presumably be important for understanding the documents and requirements. I split the sample into zip codes in which the fraction of households speaking English is above and below the sample median (62%). The McCrary tests of over-reporting of unverified assets give an estimated log difference in kernel heights of 0.12 (t-statistic= 0.44) in the high English usage zip codes, and an estimated log difference in kernel heights of 1.20 (t-statistic= 2.89) in the low English usage zip codes. This difference is significant at the 5% level.

As a second measure of financial literacy, I consider for each zip code the fraction of the population 25 years and older that has attended at least some college. Formal education should be linked to financial literacy. I split the sample into zip codes in which the fraction of the population above 25 who have attended at least some college is above and below the sample median (55%). The McCrary tests of over-reporting provide an estimated log difference in kernel heights of 0.03 (t-statistic= 0.10) in the more highly educated zip codes, and an estimated log difference in kernel heights of 1.51 (t-statistic= 3.18) in the less highly educated zip codes. This difference is also significant at the 5% level. Figures A.1-A.4 illustrating the results in this section are provided in the Appendix.

Taken together, these results suggest that borrowers from areas with lower levels of financial literacy are significantly more likely to engage in misreporting.

B. Social Capital

Misreporting may also be more prevalent in areas with lower levels of social capital, as borrowers in these regions may not attach special importance to presenting a loan application with correct asset information.[4] As measures of social capital, I propose the proportion of families containing married couples and the fraction of residents who are citizens. I use the census data to split the sample into zip codes in which the fraction of families in which there is a married couple

[4]Putnam (2001) provides an overview of the role of social capital and Agarwal, Chomsisengphet and Liu (2011) examine its effect on default.

present is above and below the sample median (76%). McCrary tests of over-reporting provide an estimated log difference in kernel heights of 0.02 (t-statistic= 0.07) in the zip codes with a higher marriage ratio, and an estimated log difference in kernel heights of 1.25 (t-statistic= 3.03) in the lower marriage ratio zip codes. This difference is significant at the 5% level. As a second test, I split the sample into zip codes in which the fraction of residents who are citizens is above and below the sample median (86%). The tests of over-reporting yield an estimated log difference in kernel heights of -0.01 (t-statistic= -0.02) in the zip codes with a higher citizen proportion, and an estimated log difference in kernel heights of 1.62 (t-statistic= 3.25) in the lower citizen proportion zip codes. This difference is significant at the 5% level as well. Figures A.5-A.8 illustrating the results in this section are provided in the Appendix.

Overall, there is compelling evidence that misreporting is more likely in areas in which there are low levels of financial literacy and social capital. Low financial literacy and low social capital are both likely to be characteristics of borrowers who do not know the exact level of their assets, either out of a lack of information or a limited desire to provide an accurate report.

4.1.4 Other Thresholds

The results described above provide clear evidence of systematic over-reporting of unverified assets relative to thresholds set as positive multiples of \$100,000. Is there evidence of over-reporting at other thresholds?

To analyze this question, I conduct McCrary tests of over-reporting for multiples of various other round numbers. For these tests, I redefine normalized assets in equation (1) using each of \$50,000, \$25,000, \$20,000 and \$10,000 in turn, in the sample of unverified assets. For multiples of \$50,000, the McCrary test yields an estimated log difference in kernel heights of 0.47 (t-statistic= 2.69). For multiples of \$25,000, the McCrary test yields an estimated log difference in kernel heights of 0.24 (t-statistic= 1.72). For multiples of \$20,000, the McCrary test yields an estimated log difference in kernel heights of 0.16 (t-statistic= 1.25), and for multiples of \$10,000 the estimated log difference is -0.01 (t-statistic= -0.10).

There is thus strong evidence of over-reporting at multiples of $100,000 and $50,000, weaker evidence at multiples of $25,000, and apparently no systematic over-reporting at other round number multiples. This is consistent with the argument that the attractiveness of a number will depend on its salience (DellaVigna 2009) and that numbers differ in their salience.[5] Evidence from newspaper and word databases (Dehaene and Mehler 1992 and Jansen and Pollmann 2001), contingent valuation responses (Whynes et al. 2007) and age reporting (Nagi, Stockwell and Snavly 1973) shows that in societies using a decimal number system, the most common and salient numbers are powers of ten. Between powers of ten, the most frequently reported numbers are integer multiples of the lower power of ten, with the multiple of five often being especially popular. In the setting of this study, in which the mean asset value is $246,477 and the mean loan amount is $502,195, the salience research thus suggests that asset reports of $100,000 and multiples of $100,000 should be most common, followed by multiples of $50,000. Multiples of $10,000 such as $180,000 etc., would not be expected to be especially popular, nor would multiples of $25,000 and $20,000. In general, the frequencies of above round number asset reporting documented above therefore fit reasonably well with the findings from the salience literature.

4.2 Misreporting of Assets and Delinquency

Section 4.1 documents a pattern of above-threshold asset misreporting by some borrowers. In this section, I consider the loan outcomes for misreporting borrowers. These tests are motivated by the argument in Section 2 that the financially ill-informed borrowers who misreport their personal assets may have personal characteristics that make them more likely to become subsequently delinquent. I estimate the discontinuity model exploring the link between delinquency and reported assets described in equation (3).

[5]Salience has been shown to be important for understanding the response of individuals to mutual fund expenses (Barber, Odean and Zheng 2005), shipping costs (Hossain and Morgan 2006) and taxes (Chetty, Looney and Kroft 2009).

In the first test, I regress an indicator variable for delinquency on a dummy for whether the borrower reported assets above a round number threshold, a sixth degree polynomial in reported assets and the interaction between the above-threshold dummy and the sixth degree polynomial. I begin by considering thresholds set at multiples of $100,000; results for other thresholds are discussed below. The estimation is via OLS, with robust t-statistics clustered by the month of mortgage origination.

As described in the first column of Table II, I find a positive and significant (t-statistic=3.47) coefficient on the above-threshold dummy. The coefficient estimate is 0.25, which indicates that borrowers who reported assets just above round number thresholds experienced delinquency rates 25 percentage points above those who reported assets just below the thresholds. The coefficient is large in absolute terms, and is also large compared to the mean delinquency rate of 0.20 observed in the data. This finding of dramatically higher delinquency rates for above-threshold asset reporters is consistent with the second prediction in Section 2 that ill-informed borrowers are both more likely to report assets above round numbers and are more likely to become delinquent.

The results in Section 4.1 suggest that misreporting is only an issue for borrowers with unverified assets. I therefore confine the sample to these borrowers, and then regress delinquency on the above-threshold dummy, the sixth degree polynomial in assets, the interaction of the above-threshold and the polynomial. The second column of Table II details the results: an estimated coefficient of 0.41 (t-statistic=3.38) coefficient on the above-threshold dummy, indicating that the link between above-threshold reporting and delinquency is much stronger in the sample of borrowers with unverified assets. The regression results are graphically depicted in Figure 3. The curved lines represent the fitted polynomials and the connected points describe the average delinquency rates for each of the buckets of $4,000 in normalized assets. (Each bucket contains an average of 88.6 observations.) As the figure makes clear, there is a large jump in the delinquency risk at the round number thresholds (asset multiples of $100,000) where the normalized assets are equal to zero.

In the sample of mortgages with verified assets, however, the results displayed in the third column of Table II show that the coefficient on the above-threshold variable is both very small (0.027) and statistically insignificant (t-statistic=0.38). Figure 4 shows clearly that there is no meaningful jump at zero normalized assets in this sample. Combining both the verified and unverified samples, a test for the equality of the coefficients on above-threshold assets in the two samples is rejected at the 1%-level. A related regression in the combined sample of delinquency on above-threshold assets, an indicator for unverified assets, the interaction of these two variables and the usual set of controls yields a positive and significant (at the 1%-level) coefficient on the interaction. Taken together, these findings provide strong evidence that misreporting of assets is tied to loan performance: there is a very large jump in delinquency at round number asset thresholds, but this jump only exists for the set of mortgages for which asset verification was not provided.

These results are not driven by data points that are far from the threshold. Reducing the sample to just those data points with normalized assets within $10,000 of the threshold yields a jump estimate of 0.48 (t-statistic=2.53) in the unverified assets sample and an estimate of -0.12 (t-statistic=-0.87) in the verified assets sample. (There are 770 loans with normalized assets within $10,000 of the threshold, representing 9.3% of the sample.) Excluding the 23 loans with reported assets precisely at the threshold yields discontinuity effects that vary little from the base case: the coefficient estimate is 0.49 in the unverified asset sample (t-statistic=3.01) and 0.07 in the verified asset sample (t-statistic=0.84).

I now introduce additional controls into the analysis. The controls include the interest rate charged, the loan to value ratio of the mortgage, the credit score of the borrower and fixed effects for the month of origination and property zip code. In addition, housing returns were clearly an important determinant of delinquency during the sample period. For each loan, I use zip code level pricing indices to calculate the minimum housing return experienced by the associated property, as measured from the origination date until the sample close. (I do not take into account subsequent loan payoff or default dates, as these are clearly endogenous.)

The regression is estimated via OLS with robust standard errors clustered by month of origination. As detailed in the fourth column of Table II, in the sample of mortgages submitted with unverified assets, the coefficient on the above-threshold indicator is 0.45 and significant (t-statistic=3.05). The inclusion of the controls has only a minor impact on the main finding.

As Figure 3 suggests, the central result of a large and significant jump in delinquency probability at the round number threshold for the unverified asset mortgages is robust to a variety of specifications. Table A.I in the Appendix describes the estimated effect for asset polynomial specifications varying from a degree of three to a degree of seven: the estimated coefficients lie in the range of 0.34 to 0.52, and are highly significant in all tests (t-statistics range from 3.05 to 4.80). There is some curvature in the underlying data, so higher order polynomials offer a more stable fit, though the particular choice of polynomial length does not have a material effect. A triangle kernel local linear regression model without any controls yields an estimated coefficient of 0.44 (t-statistic=4.22), and a uniform kernel gives an estimated coefficient of 0.48 (t-statistic=4.43) (bandwidths of 2.30 and 1.81, respectively, were selected using the Imbens and Kalyanaraman 2012 method). The results for the triangle kernel are illustrated in Figure A.9 in the Appendix.

To give a sense of the relative magnitude of the 0.45 effect of misreporting on delinquency, I compare it to the impact of an increase in rate spread from the first to the ninety-ninth percentiles (2.25% to 4.275%). The coefficient estimate in column four of Table II shows that this rate spread increase is associated with a 0.09 increase in delinquency risk. As a second point of contrast, I consider housing returns. Although housing returns enter insignificantly in the fourth column of Table II, that is due to the inclusion of zip code fixed effects. In the unreported specification without zip code fixed effects, the coefficient on housing returns is -0.40 (t-statistic=-9.88). An increase from the first to the ninety-ninth percentiles (-71% to 0%) in subsequent minimum housing returns is associated with 0.28 decrease in delinquency risk. By any measure, the impact of misreporting is of first-order magnitude relative to other factors influencing delinquency.

In Section 4.1.4 I showed that there is evidence of misreporting around thresholds defined as multiples of \$50,000. Column five of Table II displays the results from a regression of delinquency on above-threshold assets using this new threshold definition: the estimated coefficient is 0.19 (t-statistic=2.23). The jump in delinquency for above-threshold asset reports is significant, but it is less than half the estimated effect around multiples of \$100,000.

It is also of course the case that half the multiples of \$50,000 are also multiples of \$100,000. Is it perhaps only the latter thresholds that are generating the connection between delinquency and above-threshold reporting? To test this hypothesis, I define new thresholds at \$50,000, \$150,000, \$250,000, etc. and regress an indicator for delinquency on above-threshold assets using this modified threshold definition. As reported in the sixth column of Table II, the estimated coefficient on above-threshold assets is 0.13 (t-statistic=1.36). That is, thresholds defined relative to multiples of \$50,000 that are not multiples of \$100,000 do not appear to add much explanatory power to the delinquency model.

In unreported results, I find no significant link between delinquency and above-threshold asset reporting around multiples of \$25,000, \$20,000 or \$10,000. It is clear that the main effect is around multiples of \$100,000. What is distinctive about these multiples? As described in Section 4.1.4, in the data range of this sample (in which nearly all asset levels are below \$1 million), \$100,000 and its multiples would be expected to be most salient for borrowers. Given these results, my subsequent analysis will focus on above-threshold asset reporting around multiples of \$100,000 in the sample of loans with unverified asset documentation.

4.3 Asset Discontinuity and Loan and Borrower Characteristics

The results in Table II column four showing that there is a very large jump in delinquency above round number asset thresholds control for the rate spread charged by the bank, so they make clear that the bank did not properly assess the risk of these loans. In fact, the increase in delinquency risk is so pronounced, that it is clear that if the bank had been fully aware of it, these loans would not have been made at all. Still, one may ask if the bank was aware of this risk in any respect. Do the loan terms exhibit any discontinuities at the asset thresholds?

To evaluate this question, I regress the rate spread on the above-threshold indicator, a sixth degree polynomial in assets and all the previous controls (excluding the rate spread). The result, described in the first column of Table III shows that the coefficient on the above-threshold dummy is insignificant (t-statistic=-0.09, with standard errors clustered by month of origination). Not only is the coefficient estimate insignificant, it is also very small: the asset threshold discontinuity is associated with less than a 1 basis point increase in the rate spread. The bank is not pricing up the above-threshold loans in any systematic way, and it is certainly not pricing them up in a manner reflective of their dramatically higher risk.

I also regress the exception pricing, the loan-to-value (LTV) ratio, the cumulative loan-to-value (CumLTV) ratio (including any other persisting mortgage), the log of the loan size, the log of the loan maturity, the maximum permitted negative amortization and the borrower credit (FICO) score on the above-threshold indicator, the sixth degree polynomial in assets and the standard controls (omitting LTV as a control in the LTV, CumLTV and loan size regressions). The results, displayed in Table III columns 2-8 are uniformly insignificant and small in magnitude. For example, LTVs are 10 basis points smaller (t-statistic=-0.03) above the threshold and borrower credit scores are 1.4 points lower (t-statistic=-0.10), relative a sample standard deviation of 45.4. There is no apparent distinction between the observable characteristics of above- and under-threshold asset applications at the time the loan is extended. The bank was not aware of this specific practice of asset misreporting and did adjust loan features to reflect it.

These findings also make clear that borrowers did not receive any benefits from reporting just above-threshold assets: loan size, loan price and all other contract terms are unaffected by misreporting.

4.4 Misreporting and Delinquency- Where is the Effect Greatest?

4.4.1 Financial Literacy and Social Capital

The analysis in Section 4.1.3 showed that misreporting was more frequent in zip codes with lower levels of financial literacy and social capital. Was the correlation between misreporting and delinquency also higher in these areas?

To examine this question, I estimate equation (3) separately in subsamples with varying levels of financial literacy and social capital and compare the coefficient estimates across the two samples. I include the full set of standard controls (including month of origination and zip code fixed effects) and, given that the subsamples are defined by zip code, I cluster by zip code. (Clustering by month of origination yields very similar results in all the tests described below.)

In the first two columns of Panel A of Table IV, I report the results in the high and low English usage zip codes (the usual loan-level controls such as rate spread, etc., are included but not reported to make the table easier to read). The coefficient on above-threshold assets is 0.29 (t-statistic=1.47) in the high English usage areas, and 0.67 (t-statistic=3.42) in the low English usage areas. These coefficients are statistically different at the 10% level. In columns three and four of Table IV, Panel A, I detail the results from splitting the sample into more and less highly educated zip codes. These coefficients are both positive and significant and are not statistically different.

The first two columns of Panel B of Table IV detailed the results from splitting the sample into properties from zip codes with higher and lower married ratios. The two coefficients on above-threshold assets are both positive and significant (at least at the 10% level), and do not differ in a statistical sense. In the third and fourth columns of Table IV, Panel B I describe the results from splitting sample based on the proportion of citizens. The above-threshold coefficient is 0.25 (t-statistic=1.33) in the high citizen proportion areas, and 0.71 (t-statistic=3.30) in the low citizen proportion zip codes. These coefficients are different at the 10% level.

Overall, the results are somewhat mixed on whether there is a pattern of a tighter connection between misreporting and delinquency in areas with lower financial literacy and social capital. There does appear to be some evidence that misreporting is more associated with delinquency in areas with low English usage and low citizen proportions.

4.4.2 Housing Returns- Underwater Mortgages

It seems reasonable to hypothesize that misreporting may be more highly correlated with delinquency when subsequent housing returns are low. Default is more attractive when home values fall below the debt balance on the mortgage (i.e., for underwater mortgages) and these properties may also have been purchased by borrowers who were unrealistically optimistic or who had poor information. To test this hypothesis, I calculate for each mortgage the maximum potential indebtedness, which is the product of the initial LTV and the maximum possible negative amortization. Using the housing return indices described earlier, I then classify a loan as potentially underwater if the minimum subsequent estimated housing value falls below the maximum potential indebtedness. In the first column of Table IV, Panel C I report that in the sample of potentially underwater mortgages, the coefficient on above-threshold assets is 0.72 (t-statistic=4.02). As shown in the second column of Table IV, Panel C, this coefficient is 0.01 (t-statistic=0.02) in the sample of mortgages that are not potentially underwater. The difference in coefficients is significant at the 10% level. The association between misreporting and delinquency is stronger for mortgages that subsequently potentially experienced negative equity.

4.4.3 Misreporting and Borrower Risk Characteristics

Tables II and III show that misreporting is correlated with some borrower risk characteristic that leads to very poor loan outcomes and that is unobserved by the bank. What is the nature of this characteristic? The cross-sectional results described in Table IV show that the link between misreporting and delinquency is stronger in areas with low English usage and with a low proportion of citizens, and is also more pronounced for borrowers who faced the prospect of negative home equity. A number of hypotheses are consistent with these results. It could be argued, consistent with the theories detailed in Section 2, that borrowers with low financial literacy or low social capital are more likely to misreport personal assets due to a lack of information about their financial condition, and that this dearth of financial knowledge also makes it more likely they will enter delinquency. A second, potentially related, possibility is that misreporting may be a signal of an optimistic, inattentive or overconfident borrower who is more likely to undertake a mortgage s/he cannot afford (de Meza and Southey 1996, Hirshleifer and Teoh 2003 and Malmendier and Tate 2005). Third, misreporting may be undertaken willfully by borrowers hoping to deceive, which may explain why these borrowers are more likely to engage in strategic default when they experience negative equity. The data do not allow for an unambiguous description of the borrower risk characteristic associated with misreporting, but it is clear that a financial institution would benefit from being able to identify borrowers with this negative attribute.

4.5 Improving Risk Assessment

The results in Table II demonstrate that above-threshold asset reporting by the borrower is a powerful predictor of subsequent delinquency. The findings detailed in Table III show that the bank did not make use of this predictor in setting interest rates or other contract terms. In this section, I examine to what extent including above-threshold asset reporting can improve a risk assessment model.

Historically, risk assessment was conducted by an individual loan officer, but the emphasis in the last thirty years has shifted to formal credit scoring models (Altman and Saunders 1998 and Avery et al. 1996 and 2000). Standard techniques for classifying applicant risk such as logistic regressions and linear discriminant analyses have recently been complemented by data intensive approaches using neural networks, genetic programming and support vector machines (Desai, Crook and Oversteet 1996 and Abdou and Pointon 2011). This bank, in common with others

(Haughwout, Peach and Tracy 2008), made use of data on credit scores, level of documentation, LTV and borrower asset and income levels in evaluating loan applications. In general, credit scoring models make use of financial information (e.g., credit score, LTV, income and number of accounts), demographic data (e.g., age, marital status and number of dependents) and applicant history with the financial institution (e.g., previous payment performance, maximum days past due and maximum balance), as described in Hand and Henley (1997), Yu, Wang and Lai (2009), Marshall, Tang and Milne (2010), Banasik and Crook (2010) and Abdou and Pointon (2011). The analysis below explores the impact of incorporating the behavioral cue of above threshold asset reporting into a risk model.

I consider a basic version of the delinquency equation (3) that includes as explanatory variables the rate spread on the mortgage, the credit score of the borrower and the loan-to-value ratio on the mortgage. I exclude the month of origination and zip code fixed effects, as these would not be available to the bank in real time. Given this simple formulation, equation (3) can be estimated using a logistic regression. I contrast the base model with an enhanced model that includes the basic controls as well an indicator for above-threshold assets and a sixth degree polynomial in assets, to identify threshold effects.

To evaluate the performance of each model, I classify a mortgage as "identified as delinquent" if the model-predicted probability of delinquency is 0.5 or above. Mortgages with model-predicted delinquencies of less than 0.5 are classified as "identified as safe." There are two natural metrics against which a model should be assessed. First, conditional on the loan actually becoming subsequently delinquent, what is the probability that the model correctly identified the loan as delinquent? This may be labeled the sensitivity of the model or the probability of not experiencing a type I error (assuming that the null hypothesis is that the loan is delinquent). Second, conditional on the loan actually not becoming subsequently delinquent, what is the probability that the model correctly identified the loan as safe? This may be labeled the specificity of the model or the probability of not experiencing a type II error.

I first use the full data sample to estimate both the base and enhanced models. These models are then used to classify all the loans: this is a form of in-sample estimation. Panel A of Table V displays the results from both models. The base model correctly identifies only 7.96% of the delinquent mortgages, but is successful in identifying 98.09% of the safe mortgages. The enhanced model correctly identifies 10.96% of the delinquent mortgages, and identifies 97.06% of the safe mortgages. The in-sample analysis makes clear that the base model is very good at identifying safe mortgages but is quite unsuccessful at identifying delinquent mortgages. The enhanced model is able to identify more of the delinquent mortgages, but at the cost of mislabeling a small number of safe mortgages.

In addition to the fact that it appears much easier for these models to identify safe mortgages, it is worth emphasizing that the costs to the bank of these two types of errors are highly asymmetric. A misidentified safe mortgage would cause the bank to reject a safe application. The bank likely makes a small profit on each safe mortgage, and this profit would be lost. By contrast, a misidentified delinquent mortgage would be funded by the bank and would subsequently lead to a great loss, as average foreclosure losses are very high (White 2008). In other words, the enhanced model would appear to help the bank save greatly by avoiding bad mortgages at the small cost of reducing the bank's quite high success rate in identifying good mortgages.

The in-sample test, however, is subject to concerns of over-fitting. To get a better sense of the actual effectiveness of the two models, I randomly divide the sample into two equal subsamples. The first, labeled the training sample, is used to estimate both the base and enhanced models. The estimated parameters are then applied to the data for each loan in the test sample, to generate predicted outcomes. The model predictions are then compared to the actual outcomes for the test sample. This process is repeated 10,000 times and the results are displayed in Table V, Panel B.

As shown in Panel B, on average the enhanced model successfully identifies 12.7% of the delinquent loans in the test sample, while the base model successfully identifies 8.8%. The 3.9 percentage point difference between the two is statistically significant (t-statistic=2.46, estimated via bootstrapping). The enhanced model does a worse job of identifying safe loans, correctly identifying 95.6%, while the base model correctly labels 97.6% of these loans. The -2.0 percentage point difference is also statistically significant (t-statistic=-2.31).

The enhanced model is most effective in identifying near-threshold applications that are delinquent. It is unlikely to have much additional predictive power for applications with assets far from the thresholds. In Panel C of Table V, I display the results from classifying only the loans in the test sample that have assets within $25,000 of a threshold. The enhanced model is very effective in identifying 21.2% of the delinquent loans in this sample, versus 9.3% for the base model (the difference of 11.9 percentage points has a t-statistic of 1.97). The enhanced model's performance in identifying safe loans is somewhat degraded in the restricted sample (90.6% versus 97.0% for the base model and the difference of -6.3 percentage points has a t-statistic of 1.91). Nonetheless, it is clear that the enhanced model is quite successful in labeling as delinquent poor quality borrowers with assets close to the thresholds.

The enhanced model incorporating above-threshold reporting is better at identifying very poor risks. To what extent are behavioral cues of this type currently being used in credit scoring models? As described above, borrower risk models typically make use of financial, demographic and relationship history variables, and standard references do not describe behavioral cues being used in practice to any meaningful extent. There have been recent proposals to make use of Benford's Law[6] to review mortgage applications for potential fraud (Watrin, Struffert and Ullmann 2008) and to incorporate psychometric evaluations of managers into corporate credit assessments (Shoham 2004), but these are preliminary suggestions that have not been empirically validated using loan data. Individual lending officers do use behavioral cues such as politeness and appropriate eye contact to evaluate applicants (Moulton 2007), but that is quite different from the model-based behavioral risk assessment approach that is described in this study.

[6]Benford's Law describes the distribution of the first digits of the numbers in many data sets, and fraudulent data often deviates significantly from this distribution (Nigrini and Mittermaier 1997).

From a social welfare standpoint, the adoption of the enhanced risk assessment model would lead to both fewer good and fewer bad mortgages being financed. Given the asymmetry discussed above between the costs of these kinds of errors, it is likely that using the enhanced model would benefit the bank. From the perspective of an average borrower, it may also arguably be claimed that the enhanced model is welfare enhancing, given that the personal costs of foreclosure are likely to be high for homeowners (Li 2009). On the other hand, it must be acknowledged that adopting risk assessment models that make use of behavioral cues may lead some perfectly good borrowers to be denied credit. For example, in this setting there are almost certainly some good borrowers with actual assets just above round number thresholds who would be turned down for a mortgage if they correctly reported their assets. These borrowers would be disadvantaged by the adoption of the enhanced model.

4.6 Competing Risks Hazard Model

The analysis in the previous sections has focused on the binary outcome for a loan, either delinquent or not. To complement these findings, I now consider a hazard model for each loan. In any given month, a loan may continue normal payment, enter delinquency or be fully repaid. Given the discrete timing and the three possible outcomes, this competing risks model may be estimated via a multinomial logit model (Calhoun and Deng 2002).

In this model, each loan-month is treated as an observation, and the loan outcomes are regressed on an above-threshold reported asset indicator, a sixth degree polynomial in assets, and controls for the rate spread, the borrower credit score, the LTV ratio, a time varying indicator for an underwater loan (calculated using the zip code price index and the maximum possible indebtedness) and a measure of the loan life (i.e., duration). Results from the first model, which includes the log of duration as a control, are detailed in the first two columns of Table VI (under the heading Model 1). The omitted category is continued loan payment. These results indicate that mortgages with above-threshold assets are significantly less likely each month to be fully repaid (t-statistic=-2.86) and are significantly more likely to enter delinquency (t-statistic=2.73). Both of these features lead to the higher overall probability of subsequent delinquency described in Table II. (Given that these are floating rate loans, a reduced propensity to fully repay does not benefit the bank in the way that it might for fixed rate loans.) The results also show, as expected, that underwater loans are far more likely to enter delinquency.

Model 2, depicted in columns 3-4 of Table VI includes duration itself as the control, and Model 3, detailed in columns 5-6 of Table VI includes duration squared. All the specifications yield a consistent finding that above-threshold mortgages are less likely each month to be fully repaid and are more likely to enter delinquency. The hazard model thus confirms the main finding of the previous binary outcome analysis and also elucidates an additional channel through which above-threshold asset reporting loans are associated with eventual delinquency; not only is their delinquency hazard higher, but their repayment hazard is lower.

4.7 Reported Income

Was misreporting confined to asset levels or was there also systematic misreporting of reported income? As discussed in Section 4.1.1, applicants were asked to provide their actual current asset levels. For reported income, by contrast, applicants were requested to supply their typical or stable monthly income. To assess misreporting of income, I compare the reported monthly income to rounded multiples of \$1,000. The bank, like other mortgage providers, wished to exclude unusual income in a given month from the underwriting decision, so it did not request the borrower's monthly income precisely at the time of application. Many borrowers apparently regarded this instruction as an invitation to supply a rounded estimate of their monthly income. Consequently, 979 (11.7%) of the borrowers in the full sample have normalized reported income of zero. For the sample of 6,017 loans with unverified income reported by the borrower, 15.5% of the borrowers reported income as a round number. When asked to provide their typical monthly income, borrowers made far greater use of the round number heuristic described in Section 2.

To examine the relationship between misreported income and delinquency, I estimate the equivalent of equation (3), substituting the reported monthly income for assets, and comparing it to thresholds that are multiples of \$1,000. I regress the delinquency indicator on the income threshold, a sixth degree polynomial in income, the interaction between the above-threshold income dummy and the polynomial and the full set of controls. In an unreported regression, I find that there is no significant discontinuity (the coefficient is -0.03 and the t-statistic=-0.30) in delinquency rates around round number income thresholds. I also conduct the analogous test for annual reported income and thresholds of \$10,000 and again find an insignificant effect.

There is not a significant jump in delinquency at a normalized income of zero, as those borrowers who are possibly misreporting are likely grouped together with the large number of other borrowers who simply rounded and also reported at-threshold income. A round number threshold approach for identifying misreporting requires that borrowers make precise data reports and that not many borrowers utilize the round number heuristic. In other words, the income data, given the evidently common use of the round number heuristic, are not suitable for detecting the relatively small number of borrowers who may have misreported their income as well.

5 Conclusion

Personal asset misreporting by borrowers was associated with very poor outcomes for a bank making loans in the residential mortgage market during the 2004-2008 period. Many more borrowers reported personal assets just above round number thresholds rather than just below. Borrowers who reported above-threshold assets were almost 25 percentage points more likely to experience subsequent delinquency, more than doubling their delinquency risk relative to the mean. This effect was present only for loans with undocumented assets. Consistent with behavioral theories linking above threshold reporting to a lack of precise information, I find that misreporting was more frequent and may have had a greater impact in areas with low financial literacy and social capital. Misreporting was also more tightly associated with delinquency for borrowers who faced the prospect of negative equity. A hazard model shows that each month misreporting borrowers were more likely to enter delinquency and less likely to repay their loans; both characteristics contributed to their dramatically worse overall loan performance.

The findings in this paper illustrate the prominent role that a behavioral pattern, in this case the tendency of some borrowers to state above threshold assets, can play in explaining financial outcomes. I show that including threshold effects in delinquency models can aid in the difficult task of detecting potentially unattractive borrowers, though it does also lead to the mischaracterization of some high quality applicants. If this technique is widely adopted in credit scoring models and becomes commonly known, is it likely to continue to have predictive power in the long-run? Evidence on debiasing indicates that individuals can be trained to moderate behavioral tendencies such as overconfidence (Koriat, Lichtenstein and Fischhoff 1980 and Tetlock and Kim 1987) and hindsight bias (Arkes et al. 1988). Simple instructions to avoid a bias can be quite effective (Arkes 1991 and Larrick 2004). This suggests that over time borrowers could probably adjust and come to avoid reporting above-threshold values in order to improve their loan application prospects. The use of this particular behavioral cue is therefore likely to be most effective in the short-medium term.

From a broader perspective, however, financial institutions may well benefit from research aimed at uncovering new behavioral cues on an on-going basis. This approach may enable them to regularly develop new models identifying lending hazards that are not yet widely known and that are therefore not yet susceptible to debiasing. It is also likely the case that some behavioral cues are relatively resistant to debiasing. The results in this paper suggest that the power of behavioral cues in predicting default will make such research worthwhile for lenders.

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Figure 1: Density of Normalized Assets- Unverified Assets

This figure depicts the estimated kernel densities of normalized reported assets on both sides of zero for the sample of borrowers with unverified assets. The 95% confidence bands are portrayed in thin lines. The circles describe scaled frequencies analogous to histograms. Estimation is via the McCrary (2008) method.

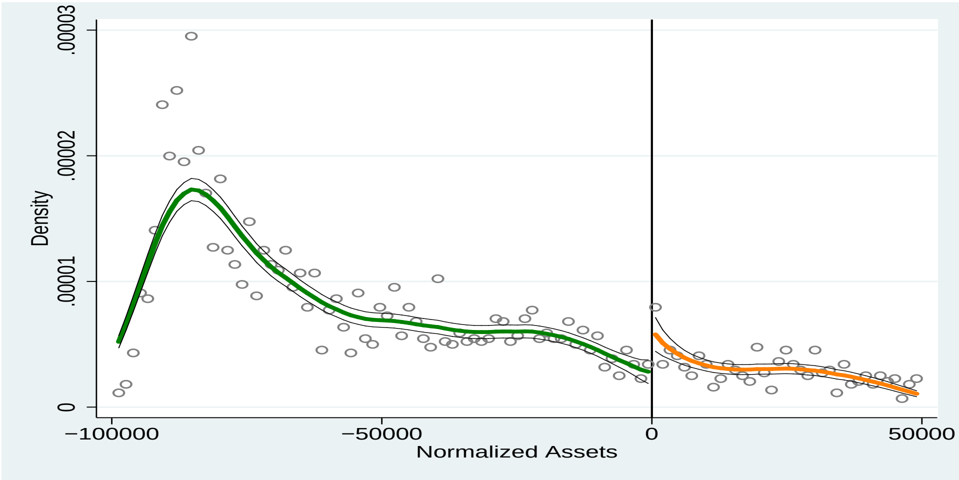

Figure 2: Density of Normalized Assets- Verified Assets

This figure depicts the estimated kernel densities of normalized reported assets on both sides of zero for the sample of borrowers with verified assets. The 95% confidence bands are portrayed in thin lines. The circles describe scaled frequencies analogous to histograms. Estimation is via the McCrary (2008) method.

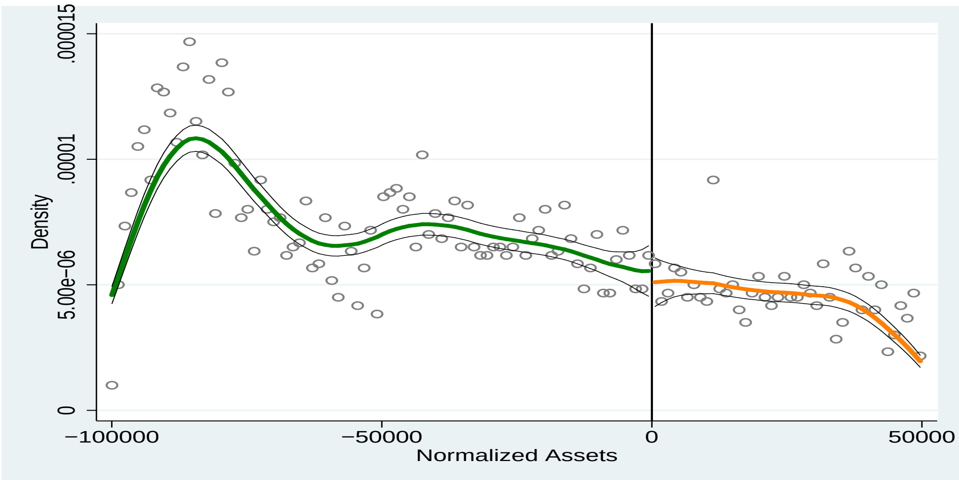

Figure 3: Delinquency and Reported Personal Assets- Unverified Assets

This figure depicts the estimated delinquency probability for each level of normalized reported assets for the sample of borrowers with unverified assets. The thick curved lines represent the predicted delinquency from an OLS regression of delinquency on a sixth degree polynomial of normalized assets. The 95% confidence interval is portrayed in thin lines, and the connected points describe the average delinquency rates for each of the buckets of $4,000 in normalized assets.

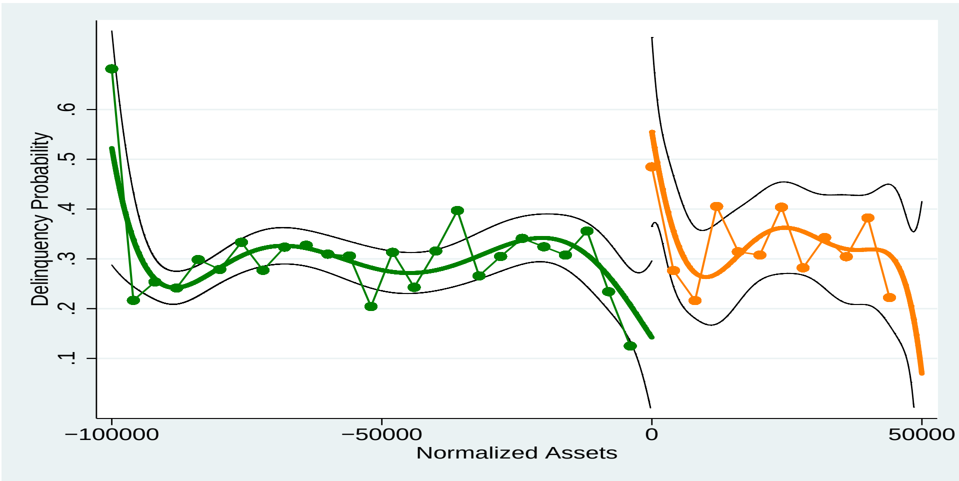

Figure 4: Delinquency and Reported Personal Assets- Verified Assets

This figure depicts the estimated delinquency probability for each level of normalized reported assets for the sample of borrowers with verified assets. The thick curved lines represent the predicted delinquency from an OLS regression of delinquency on a sixth degree polynomial of normalized assets. The 95% confidence interval is portrayed in thin lines, and the connected points describe the average delinquency rates for each of the buckets of $4,000 in normalized assets.

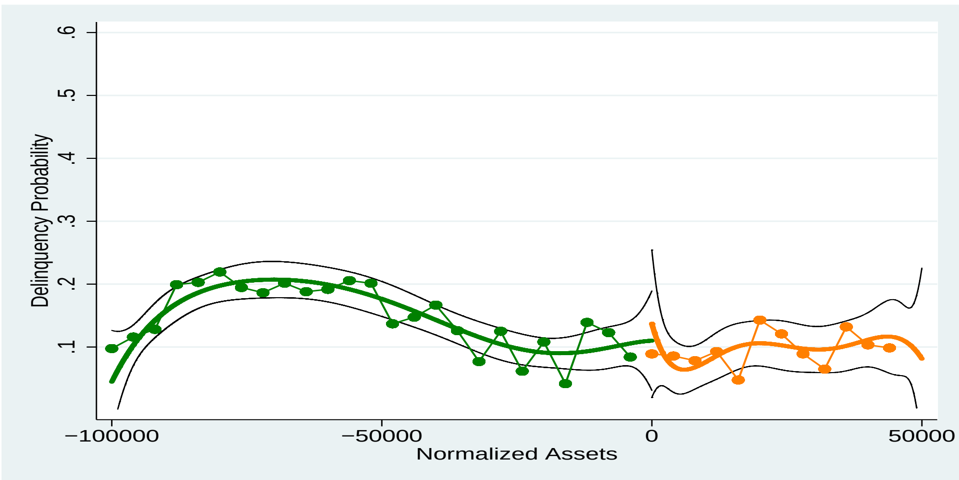

Table I: Summary Statistics

Observations are at the loan level. Assets describes the personal assets of the borrower, excluding the property used as collateral. Assets above threshold is an indicator for whether the normalized assets of the borrower (as defined in (1)) exceed zero. Income is the monthly income of the borrower. Rate spread is the interest premium paid by the borrower relative to an index. Credit score is the borrower's FICO score, the loan amount is given in dollars, LTV is the loan-to-value ratio and CumLTV is the cumulative LTV including any existing mortgage on the property. Broker compensation consists of a rebate paid to the broker by the bank and may also include a direct payment from the borrower. In cash out refinances, the borrower withdraws equity from the property, while rate/term refinances only involve a change in the interest rate or maturity. Assets and income verified are indicators for whether the borrower provided documentation supporting his asset and income claims, respectively. Delinquency is an indicator for whether a loan was 30 or more days past due.

	Mean	Median	Standard Deviation	1^{st}%	99^{th}%
Assets	246477.18	53392.00	1243156.60	2798.00	3666909.00
Assets Above Threshold	0.68	1.00	0.47	0.00	1.00
Income	16086.35	10319.00	34334.46	2920.00	132100.00
Rate Spread	3.36	3.50	0.60	2.25	4.55
Credit Score	719.45	716.00	45.40	628.00	808.00
Loan Amount	502195.00	412500.00	388161.25	122500.00	2000000.00
LTV	0.72	0.77	0.14	0.27	0.95
CumLTV	0.73	0.78	0.15	0.27	0.95
Broker Compensation	10446.55	9215.00	6604.49	1130.00	34111.91
Cash out Refinance	0.65	1.00	0.48	0.00	1.00
Rate/Term Refinance	0.17	0.00	0.38	0.00	1.00
Assets Verified	0.60	1.00	0.49	0.00	1.00
Income Verified	0.28	0.00	0.45	0.00	1.00
Delinquent	0.20	0.00	0.40	0.00	1.00

Table II: Misreporting of Assets and Delinquency

Results from the regressions of an indicator for delinquency on borrower and transaction characteristics. The regressors with reported coefficients are a dummy for whether the normalized assets of the borrower exceed zero, the rate spread on the mortgage (columns 3-6), the credit score of the borrower (columns 3-6), the loan-to-value ratio on the mortgage (columns 3-6) and the minimum housing return in the property zip code in the period subsequent to the financing (columns 3-6). The regressions also include as controls a sixth degree polynomial in assets, monthly fixed effects (columns 3-6) and zip code fixed effects (columns 3-6). The threshold for the calculation of normalized assets is the nearest positive multiple of 100,000 (columns 1-4), nearest positive multiple of 50,000 (column 5) and nearest of 50,000, 150,000, 250,000 etc. (column 6). Reported t-statistics are heteroskedasticity-robust and clustered by month of origination.

	Delinq?	Delinq?	Delinq?	Delinq?	Delinq?	Delinq?
Assets Above Threshold	0.246**	0.413**	0.0268	0.454**	0.187**	0.126
	(3.47)	(3.38)	(0.38)	(3.05)	(2.23)	(1.36)
Rate Spread				0.0465**	0.0467**	0.0468**
				(2.38)	(2.33)	(2.26)
Credit Score				-0.640	-0.663	-0.650
				(-0.76)	(-0.78)	(-0.76)
LTV				0.229*	0.257*	0.221
				(1.72)	(1.77)	(1.66)
Housing Return				-0.0475	-0.0827	-0.0524
				(-0.22)	(-0.35)	(-0.23)
6th-degree polyn. in Assets	Yes	Yes	Yes	Yes	Yes	Yes
Monthly F.E.	No	No	No	Yes	Yes	Yes
Zip Code F.E.	No	No	No	Yes	Yes	Yes
Sample	Full	Unver. Assets	Ver. Assets	Unver. Assets	Unver. Assets	Unver. Assets
Threshold	Multiples of 100K	Multiples of 100K	Multiples of 100K	Multiples of 100K	Multiples of 50K	50K, 150K, 250K, ...
Observations	8287	3280	5007	3275	3275	3275
Adjusted R^2	0.008	0.006	0.014	0.125	0.125	0.129

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$

Table III: Asset Discontinuity and Loan and Borrower Characteristics

Results from the regressions of loan and borrower and transaction characteristics on reported asset discontinuities. The dependent variables are the rate spread on the loan (column 1), the exception pricing on the loan (column 2), the loan-to-value ratio (column 3), the cumulative loan-to-value including any existing mortgage (column 4), the log of the loan amount in dollars (column 5), the log of the loan maturity in months (column 6), the maximum permitted negative amortization (column 7) and the borrower credit score (column 8) The regressors with reported coefficients are a dummy for whether the normalized assets of the borrower exceed zero, the credit score of the borrower (columns 1-7) and the loan-to-value ratio on the mortgage (columns 1,2 and 6-8). The regressions also include as controls a sixth degree polynomial in assets, monthly fixed effects and zip code fixed effects. Reported t-statistics are heteroskedasticity-robust and clustered by month of origination.

	Rate Spr.	Exc. Pr.	LTV	CumLTV	Ln(Size)	Mat.	NegAm	Cred. Sc.
Assets Abv. Thresh.	-0.00779	0.0970	-0.000951	-0.00248	0.00983	0.0269	0.0169	-0.00140
	(-0.09)	(1.37)	(-0.03)	(-0.06)	(0.10)	(1.00)	(0.47)	(-0.10)
Credit Score	0.0427	-0.770**	-0.971**	-1.153**	-3.371**	0.0833	0.202	
	(0.05)	(-2.13)	(-4.13)	(-4.34)	(-6.95)	(0.39)	(0.45)	
LTV	-0.0506	0.125				0.0209	0.0191	-0.0838**
	(-0.27)	(0.84)				(0.55)	(0.29)	(-4.47)
6th-deg. polyn. Assets	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Monthly F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Zip Code F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3276	3276	3276	3276	3276	3276	3182	3276
Adjusted R^2	0.081	0.072	0.240	0.235	0.602	0.049	0.012	0.082

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$

Table IV: Misreporting and Delinquency - Where is the Effect Greatest?

Results from the regressions of an indicator for delinquency on reported asset discontinuities in subsamples varying by zip code characteristics. The regressor with reported coefficients is a dummy for whether the normalized assets of the borrower exceed zero. The regressions also include as controls the rate spread on the mortgage, the credit score of the borrower, the loan-to-value ratio on the mortgage, the minimum housing return in the property zip code in the period subsequent to the financing, a sixth degree polynomial in assets, monthly fixed effects and zip code fixed effects. All zip code data is drawn from the 2000 Census. Columns 1 and 2 of Panel A split the sample into zip codes in which the fraction of households speaking English is above and below the sample median (62%). Columns 3 and 4 of Panel A split the sample into zip codes in which the fraction of the population above 25 who have attended at least some college is above and below the sample median (55%). Columns 1 and 2 of Panel B split the sample into zip codes in which the fraction of families in which there is a married couple present is above and below the sample median (76%). Columns 3 and 4 of Panel B split the sample into zip codes in which the fraction of residents who are citizens is above and below the sample median (86%). Columns 1 and 2 of Panel C split the sample into loans that could potentially have become underwater during the sample period and those that could not. Reported t-statistics are heteroskedasticity-robust and clustered by zip code.

Panel A: Financial Literacy	Delinq?	Delinq?	Delinq?	Delinq?
Assets Above Threshold	0.285	0.669**	0.489**	0.565**
	(1.47)	(3.42)	(2.80)	(2.30)
6th-degree polyn. in Assets	Yes	Yes	Yes	Yes
Standard Controls	Yes	Yes	Yes	Yes
Monthly F.E.	Yes	Yes	Yes	Yes
Zip Code F.E.	Yes	Yes	Yes	Yes
Sample	High English	Low English	High Educat.	Low Educat.
Observations	1627	1648	1631	1644
Adjusted R^2	0.102	0.146	0.101	0.156

Panel B: Social Capital	Delinq?	Delinq?	Delinq?	Delinq?
Assets Above Threshold	0.352*	0.578**	0.254	0.709**
	(1.80)	(2.98)	(1.33)	(3.30)
6th-degree polyn. in Assets	Yes	Yes	Yes	Yes
Standard Controls	Yes	Yes	Yes	Yes
Monthly F.E.	Yes	Yes	Yes	Yes
Zip Code F.E.	Yes	Yes	Yes	Yes
Sample	High Married	Low Married	High Citizen	Low Citizen
Observations	1631	1644	1629	1646
Adjusted R^2	0.074	0.168	0.095	0.142

Panel C: Housing Returns	Delinq?	Delinq?
Assets Above Threshold	0.722**	0.00953
	(4.02)	(0.02)
6th-degree polyn. in Assets	Yes	Yes
Standard Controls	Yes	Yes
Monthly F.E.	Yes	Yes
Zip Code F.E.	Yes	Yes
Sample	Potentially Underwater	Not Potentially Underwater
Observations	2514	667
Adjusted R^2	0.133	0.142

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$

Table V: Improving Risk Assessment

Results assessing the forecasting accuracy of various logistic delinquency models. The base model includes as explanatory variables the rate spread on the mortgage, the credit score of the borrower and the loan-to-value ratio on the mortgage. The enhanced model includes these variables and a dummy for whether the normalized assets of the borrower exceed zero and a sixth degree polynomial in assets. Observations with an estimated probability of delinquency of 0.5 and above are identified as delinquent. Panel A reports classification results estimated from models using the full data and classifying all observations in-sample. Panel B reports results from models estimated using a randomly selected half of the observations as a training sample, and applying the forecast model to the other half of the data (labeled the test sample). Panel C reports results from models estimated using a randomly selected half of the observations as a training sample, and applying the forecast model to only those observations in the test sample that have normalized assets within $25,000 of a threshold. In Panels B and C, the reported coefficients are averages over 10,000 draws, and the t-statistics detailed in parentheses are estimated using bootstrapping.

Panel A: In-Sample

Performance Measure	Base Model (no threshold effect)	Enhanced Model (incl. threshold effect)
P(identified as delinquent | delinquent)	7.96%	10.96%
P(identified as safe | safe)	98.09%	97.06%
Classify	full sample	full sample
Classified Observations	3276	3276

Panel B: Out-of-Sample

Performance Measure	Base Model (no threshold effect)	Enhanced Model (incl. threshold effect)	Difference
P(identified as delinquent | delinquent)	8.83%	12.68%	3.85%**
			(2.46)
P(identified as safe | safe)	97.60%	95.55%	-2.04%**
			(-2.31)
Classify	full test sample	full test sample	
Avg. Classified Observations	1638	1638	

Panel C: Out-of-Sample

Performance Measure	Base Model (no threshold effect)	Enhanced Model (incl. threshold effect)	Difference
P(identified as delinquent | delinquent)	9.33%	21.17 %	11.85%**
			(1.97)
P(identified as safe | safe)	96.96%	90.62 %	-6.33%*
			(-1.91)
Classify	test sample normal. assets $\in [-25K, +25K]$	test sample normal. assets $\in [-25K, +25K]$	
Avg. Classified Observations	341.30	341.30	

Table VI: Competing Risks Hazard Model

Results from the competing risks multinomial logit regressions of indicators for repayment and delinquency on borrower and transaction characteristics. The omitted category is continued loan payment. The regressors with reported coefficients are a dummy for whether the normalized assets of the borrower exceed zero, the rate spread on the mortgage, the credit score of the borrower, the loan-to-value ratio on the mortgage, an indicator for an underwater mortgage, the log of the number of months since origination (columns 1-2), the number of months since origination (columns 3-4) and the square of the number of months since origination (columns 5-6). The regressions also include as controls a sixth degree polynomial in assets. Reported t-statistics are heteroskedasticity-robust and clustered by loan.

	Model 1		Model 2		Model 3	
	Repay.	Delinq.	Repay.	Delinq.	Repay.	Delinq.
Assets Above Threshold	-0.986**	1.353**	-0.819**	1.413**	-0.789**	1.422**
	(-2.86)	(2.73)	(-2.64)	(2.90)	(-2.61)	(2.94)
Rate Spread	0.659**	0.390**	0.478**	0.335**	0.394**	0.293**
	(12.21)	(5.70)	(9.48)	(4.87)	(7.52)	(4.24)
Credit Score	0.00130	-0.00634**	0.00113	-0.00675**	0.000894	-0.00714**
	(0.86)	(-2.14)	(0.84)	(-2.30)	(0.68)	(-2.44)
LTV	-0.0694	2.802**	-0.402	2.712*	-0.601**	2.616*
	(-0.25)	(1.99)	(-1.60)	(1.93)	(-2.51)	(1.88)
Underwater	0.141	2.520**	0.396**	2.600**	0.463**	2.629**
	(1.27)	(33.62)	(3.53)	(34.16)	(4.07)	(35.08)
Log(Durat.)	-2.260**	-1.084**				
	(-66.16)	(-14.39)				
Durat.			-0.151**	-0.0636**		
			(-64.47)	(-16.63)		
Durat. Sqrd.					-0.00406**	-0.00149**
					(-47.00)	(-18.26)
Observations	80953		80953		80953	

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$

Appendix

Table A.I: Misreporting of Assets and Delinquency- Robustness

Results from the OLS (columns 1-5), triangle kernel (column 6) and uniform kernel (column 7) regressions of an indicator for delinquency on borrower and transaction characteristics. The regressors with reported coefficients are a dummy for whether the normalized assets of the borrower exceed zero, the rate spread on the mortgage (columns 1-5), the credit score of the borrower (columns 1-5), the loan-to-value ratio on the mortgage (columns 1-5) and the minimum housing return in the property zip code in the period subsequent to the financing (columns 1-5). The regressions also include as controls polynomials in assets of the indicated degree (columns 1-5), monthly fixed effects (columns 1-5) and zip code fixed effects (columns 1-5). The threshold for the calculation of normalized assets is the nearest positive multiple of 100,000. Reported t-statistics are heteroskedasticity-robust and clustered by month of origination (columns 1-5). Kernel regression results for scaled assets are presented for bandwidths of 2.30 (column 6) and 1.81 (column 7), the default bandwidths from Imbens and Kalyanaraman (2012).

	Delinq?	Delinq?	Delinq?	Delinq?	Delinq?	Delinq?	Delinq?
Assets Above Threshold	0.335**	0.419**	0.509**	0.454**	0.521**	0.437**	0.478**
	(4.49)	(4.55)	(4.80)	(3.05)	(3.85)	(4.22)	(4.43)
Rate Spread	0.0455**	0.0460**	0.0460**	0.0465**	0.0464**		
	(2.30)	(2.32)	(2.37)	(2.38)	(2.41)		
Credit Score	-0.686	-0.677	-0.638	-0.640	-0.628		
	(-0.81)	(-0.81)	(-0.76)	(-0.76)	(-0.74)		
LTV	0.227	0.210	0.221	0.229*	0.231*		
	(1.62)	(1.50)	(1.63)	(1.72)	(1.75)		
Housing Return	-0.0852	-0.0731	-0.0490	-0.0475	-0.0471		
	(-0.39)	(-0.34)	(-0.23)	(-0.22)	(-0.21)		
Polyn. in Assets of degree	3	4	5	6	7	NA	NA
Monthly F.E.	Yes	Yes	Yes	Yes	Yes	No	No
Zip Code F.E.	Yes	Yes	Yes	Yes	Yes	No	No
Sample	Unver. Assets	Unver. Assets	Unver. Assets	Unver. Assets	Unver. Assets	Unver. Assets	Unver. Assets
Threshold	Mult. of 100K	Mult. of 100K	Mult. of 100K	Mult. of 100K	Mult. of 100K	Mult. of 100K	Mult. of 100K
Estimation Method	OLS	OLS	OLS	OLS	OLS	Triang. Kernel Regress.	Unif. Kernel Regress.
Observations	3275	3275	3275	3275	3275	3280	3280
Adjusted R^2	0.125	0.125	0.126	0.125	0.125		

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$

Figure A.1: Density of Normalized Unverified Assets- High English Usage

This figure depicts the estimated kernel densities of normalized reported assets on both sides of zero for the sample of borrowers with unverified assets residing in zip codes with in which the fraction of households speaking English is above the sample median (62%). The 95% confidence bands are portrayed in thin lines, and the circles describe scaled frequencies analogous to histograms. Estimation is via the McCrary (2008) method.

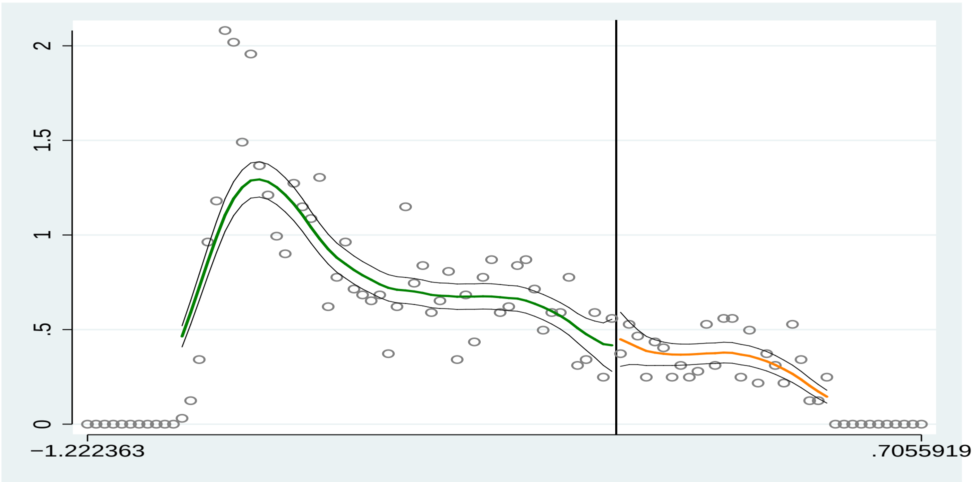

Figure A.2: Density of Normalized Unverified Assets- Low English Usage

This figure depicts the estimated kernel densities of normalized reported assets on both sides of zero for the sample of borrowers with unverified assets residing in zip codes with in which the fraction of households speaking English is at or below the sample median (62%). The 95% confidence bands are portrayed in thin lines, and the circles describe scaled frequencies analogous to histograms. Estimation is via the McCrary (2008) method.

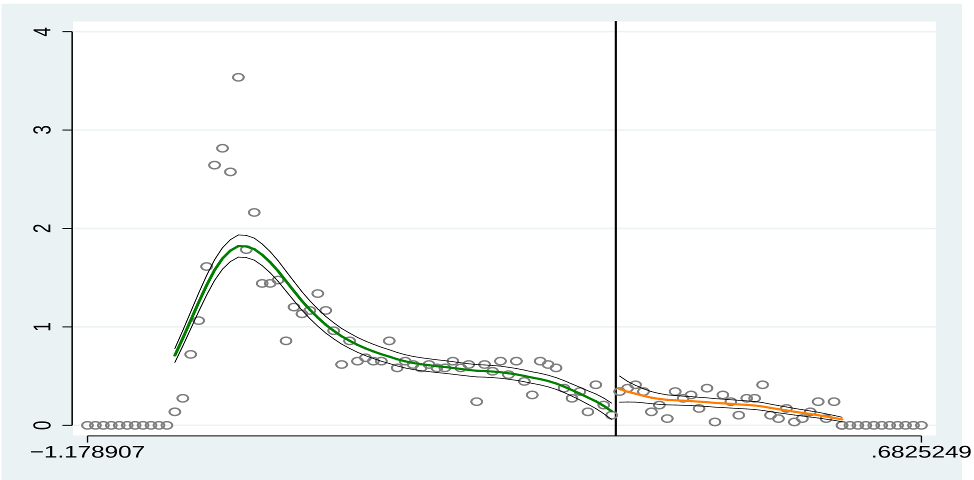

Figure A.3: Density of Normalized Unverified Assets- High Education

This figure depicts the estimated kernel densities of normalized reported assets on both sides of zero for the sample of borrowers with unverified assets residing in zip codes in which the fraction of the population above 25 who have attended at least some college is above the sample median (55%). The 95% confidence bands are portrayed in thin lines, and the circles describe scaled frequencies analogous to histograms. Estimation is via the McCrary (2008) method.

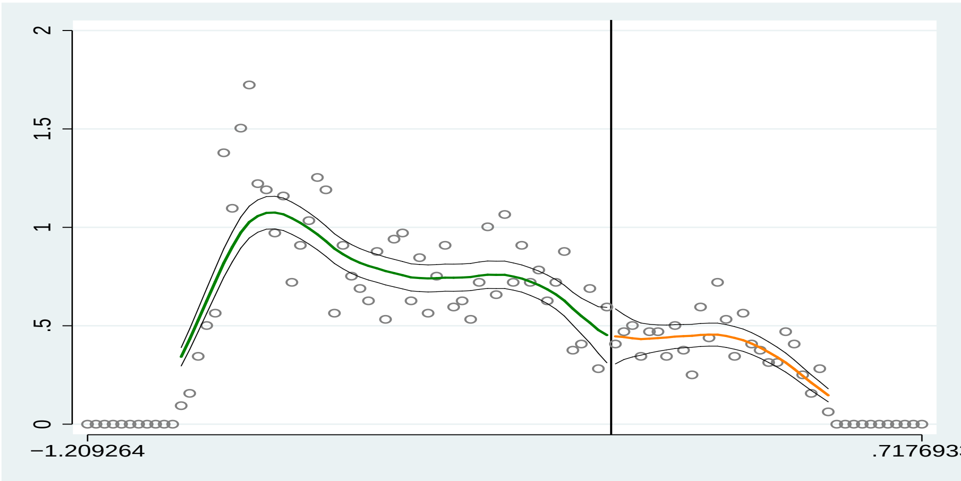

Figure A.4: Density of Normalized Unverified Assets- Low Education

This figure depicts the estimated kernel densities of normalized reported assets on both sides of zero for the sample of borrowers with unverified assets residing in zip codes in which the fraction of the population above 25 who have attended at least some college is at or below the sample median (55%). The 95% confidence bands are portrayed in thin lines, and the circles describe scaled frequencies analogous to histograms. Estimation is via the McCrary (2008) method.

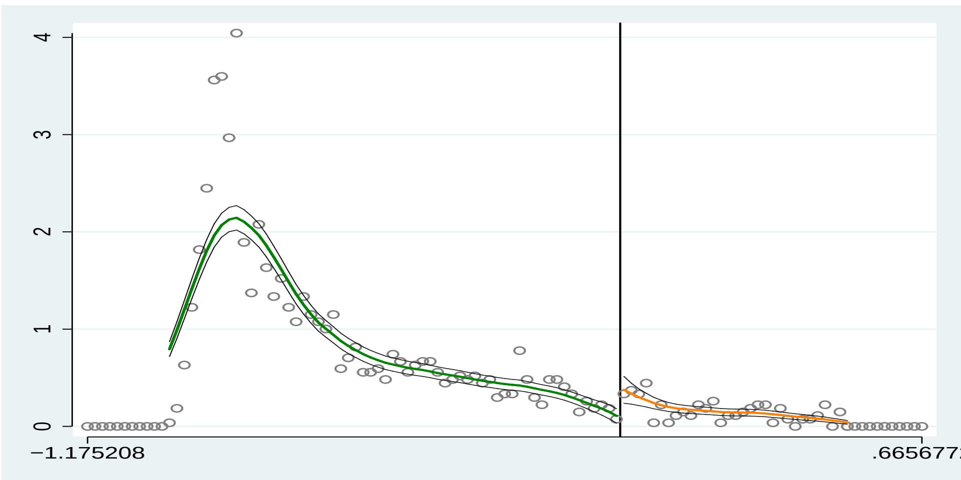

Figure A.5: Density of Normalized Unverified Assets- High Married Ratio

This figure depicts the estimated kernel densities of normalized reported assets on both sides of zero for the sample of borrowers with unverified assets residing in zip codes in which the fraction of families in which there is a married couple present is above the sample median (76%). The 95% confidence bands are portrayed in thin lines, and the circles describe scaled frequencies analogous to histograms. Estimation is via the McCrary (2008) method.

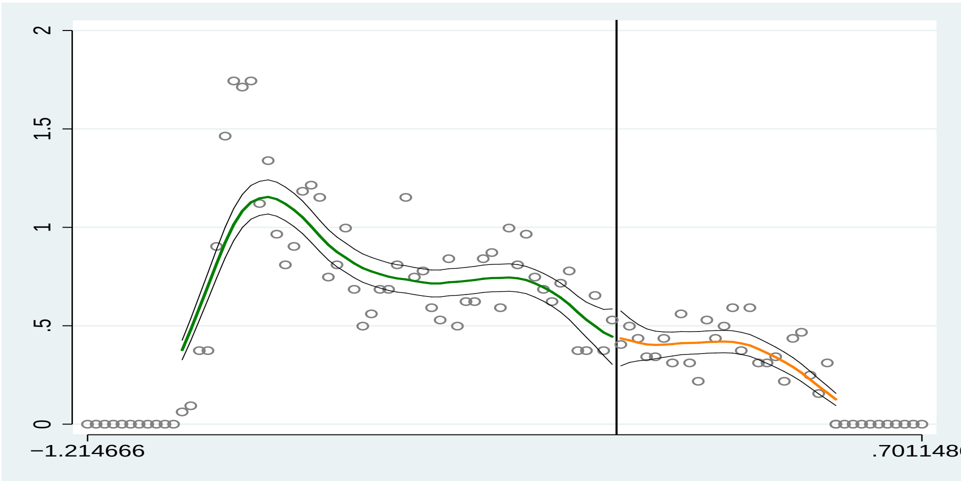

Figure A.6: Density of Normalized Unverified Assets- Low Married Ratio

This figure depicts the estimated kernel densities of normalized reported assets on both sides of zero for the sample of borrowers with unverified assets residing in zip codes in which the fraction of families in which there is a married couple present is at or below the sample median (76%). The 95% confidence bands are portrayed in thin lines, and the circles describe scaled frequencies analogous to histograms. Estimation is via the McCrary (2008) method.

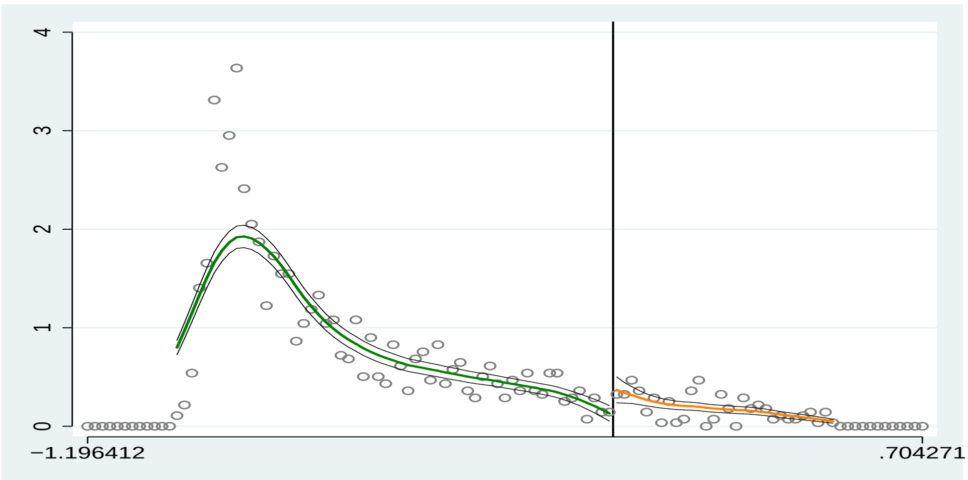

Figure A.7: Density of Normalized Unverified Assets- High Citizen Proportion

This figure depicts the estimated kernel densities of normalized reported assets on both sides of zero for the sample of borrowers with unverified assets residing in zip codes in which the fraction of residents who are citizens is above the sample median (86%). The 95% confidence bands are portrayed in thin lines, and the circles describe scaled frequencies analogous to histograms. Estimation is via the McCrary (2008) method.

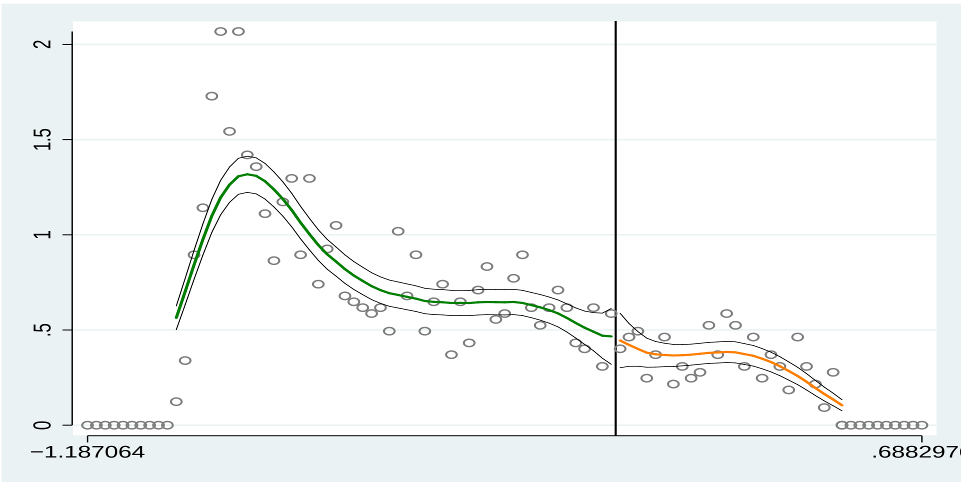

Figure A.8: Density of Normalized Unverified Assets- Low Citizen Proportion

This figure depicts the estimated kernel densities of normalized reported assets on both sides of zero for the sample of borrowers with unverified assets residing in zip codes in which the fraction of residents who are citizens is at or below the sample median (86%). The 95% confidence bands are portrayed in thin lines, and the circles describe scaled frequencies analogous to histograms. Estimation is via the McCrary (2008) method.

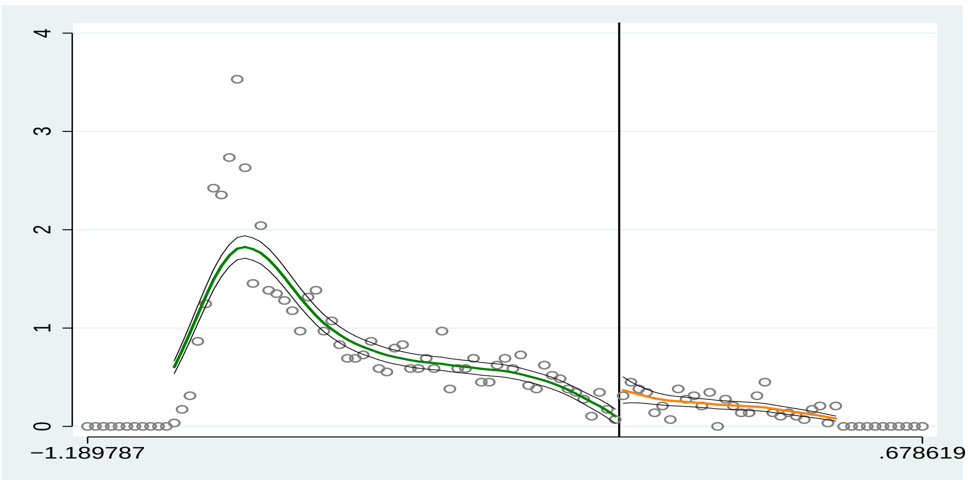

Figure A.9: Delinquency and Reported Personal Assets- Unverified Assets (Kernel Regression)

This figure depicts the estimated delinquency probability for each level of normalized reported scaled assets for the sample of borrowers with unverified assets. The thick curved lines represent the predicted delinquency from a triangle kernel regression of delinquency on normalized assets. The 95% confidence interval is portrayed in thin lines. Results are presented for a bandwidth of 2.30, the default bandwidth from Imbens and Kalyanaraman (2012).