

Borrower Misrepresentation and Loan Performance

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Abstract

Misrepresentations by borrowers are associated with grave loan outcomes. I document a specific form of personal asset misrepresentation by loan applicants in the mortgage market from 2004-2008 that led to very high delinquency rates. The problem was undiscovered by the bank, but its severity varied significantly with the loan form and the review process, suggesting that it can be mitigated by both appropriate loan contract design and organizational policies. Loans that granted borrowers immediate cash payments or high leverage were more subject to misrepresentation. The problem was also more severe for loans originated later in a loan officer's tenure and for loans generated by brokers working in large offices.

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Risk assessment and control are core functions of financial institutions. In any setting with asymmetric information, one central concern is misrepresentation risk, the risk that other parties will provide false or misleading information. In this paper I offer an empirical description of personal asset misrepresentation by a bank's mortgage borrowers and show that it had grave consequences for loan outcomes. The bank was unaware of the problem during the sample period, and its impact varied substantially with both a loan's terms and the manner in which it was evaluated. First, misrepresentation risk was lower for loan contracts designed to discourage applications from borrowers who needed immediate cash payments or high leverage. Second, the severity of misrepresentation risk increased over the course of a loan officer's tenure, even though observable risk did not. Third, misrepresentation was substantially more severe for loans originated by brokers in large offices. These findings suggest that contract design and organizational policies can be effective in shielding financial institutions from misrepresentation risk.

The links between loan contract terms, the internal organization of a bank and the success of its lending policies have been the theme of a broad stream of research. Some of this work has focused on the bank's sourcing of soft information and its incorporation into loan provisions (Stein 2002, Petersen and Rajan 2002 and Berger et al. 2005). Recent intra-bank studies have analyzed the role of hierarchy in discouraging information collection (Liberti and Mian 2009), the impact of moral hazard on within-firm communication (Hertzberg, Liberti and Mian 2010) and the importance of influence in internal capital allocation (Cremers et al. 2011). In this paper, I present mortgage data from a bank along with detailed organizational data on the loan officer who evaluates the mortgage. These data allow me to consider the question of how a bank's product offerings and review processes can be best be structured to minimize the damage caused by misrepresentation risk. Reducing this risk will help improve bank screening and thereby raise lending standards (Ruckes 2004, Dell'Araccia and Marquez 2006, Norden and Weber 2010 and Maddaloni and Peydró 2011), a policy goal that has received much greater attention lately in light of the events of the last several years.

The context of the data is a U.S. bank that originates and retains residential mortgages. In their loan applications some of its borrowers were misrepresenting their personal assets, and I show that these borrowers were much more likely subsequently to become delinquent in their mortgages. Using a regression discontinuity approach, I show that borrowers who claimed a personal asset level just above a round number threshold (e.g., \$203,000) were three times as likely to experience subsequent delinquency as those who claimed personal assets just below the threshold (e.g., \$198,000). This jump in delinquency at round number thresholds is observed only for borrowers whose asset claims are not documented; borrowers with verified assets experience no discontinuity at thresholds. This is consistent with the idea that some borrowers misreported their unverified assets to be above round number thresholds and that these borrowers were much more likely to subsequently become delinquent. (Very few borrowers reported asset levels at round numbers precisely; the delinquency results are not driven by the use of a rounding heuristic by a class of applicants.)

The distribution of reported assets offers additional support for the hypothesis of misrepresentation. The density of unverified assets exhibits a sharp discontinuity at round number thresholds, with significantly more borrowers reporting assets just above the thresholds than just below. The density of verified assets displays no discontinuity at thresholds. This is precisely the pattern that would be generated by systematic claims of above-threshold assets by misrepresenting borrowers, and it indicates that misreporting plays an important role in this setting, as does in many other financial environments (Fich and Shivdarsani 2007, Povel, Singh and Winton 2007, Graham, Li and Qiu 2008 and Bollen and Pool 2009).

Borrowers had two incentives to report high asset levels. First, assets were required to exceed a certain multiple of the monthly payment for loan acceptance (these were not, however, round number thresholds). Second, assets were used in determining loan terms and applicants with higher reported assets received larger loans and loans with lower interest rates. These reasons provide a general motive for misrepresentation.

Why did misrepresenting borrowers choose to state assets just above a round number threshold? There is substantial evidence that numbers above these thresholds are perceived to be significantly larger than numbers just below them (this is related to the phenomenon that retail prices generally end in 99 cents: Kalyanam and Shively 1998, Anderson and Simester 2003 and Thomas and Morwitz 2005). Once a borrower has elected to misrepresent assets, the cost to choosing an above threshold number relative to a below threshold number is likely trivial, and the potential benefits from reporting a considerably higher perceived asset level could have been material.

Loan terms and borrower risk characteristics, however, do not significantly differ between above- and below-threshold mortgages. 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 misrepresentation risk. Second, misreporting borrowers may have over-estimated the positive effects of stating above-threshold assets. Nonetheless, given the likely minor cost of misreporting above-threshold rather than below-threshold assets, and the insignificant effect on loan terms, it is unlikely that they were harmed by this strategy.

The severity of the misrepresentation problem varies significantly with several cross-sectional aspects of the data. Loan contract design has a first-order effect. Misrepresentation is most severe in cash out refinancings and has no measurable impact in rate or term refinancings undertaken without a cash payment to the borrower. Controlling for rate, loan size and maturity, cash out and rate/term refinancings both leave the bank with an identical security that is originated in a similar way. If anything, the loan review process should be more stringent for cash out refinancings. The finding that misrepresentation risk is only present for cash out refinancings suggests that these contracts induce much worse borrower selection. These borrower are often desperate to extract cash from their home equity and are apparently much more prone to misrepresentation. The effect on home purchase loans is intermediate between the impact on the two type of refinancings and is harder to compare because of possible differences in the origination

procedures.

Loan terms can also induce borrower selection. The delinquency jump associated with above-threshold assets is stronger for high loan-to-value (LTV) mortgages and for mortgages with higher overall interest rates. Finding financing may be more difficult for borrowers in these high risk deals, so the gains from misrepresentation may be greater. Alternatively, different types of borrowers may be willing to accept these loans. High risk loans should receive additional scrutiny from the bank, so it seems unlikely that they exhibit greater misrepresentation risk due to slack screening. The link between high LTV mortgages and increased misrepresentation risk is likely due to borrower selection, and the appropriate design of loan contracts can help financial institutions attract fewer applicants with a predisposition to misrepresent assets. On the other hand, not all observable borrower characteristics are linked to the severity of misrepresentation; low credit score borrowers, for example, are not significantly more likely to engage in misreporting. This suggests that selection based on observable borrower characteristics must be used judiciously to reduce misrepresentation risk.

Misrepresentation risk has a more severe effect later in a loan officer's tenure with the bank. Though loan officers were not aware of this specific risk, they may have had other means of screening out loans with misrepresented assets. These loans may have had omissions or suspicious features in other portions of their applications that may have been uncovered in the course of careful scrutiny. The fact that misrepresentation risk increases with loan officer experience is consistent with the hypothesis that over time loan officers adopt certain efficient routines in processing loans that may reduce their ability to detect unusual factors. It does not appear to be the case that loan officers receive more challenging applications over time: observable risk characteristics, including those correlated with misrepresentation, do not worsen with experience. The main change is apparently in the mortgage evaluation process of the loan officer himself.

This finding suggests that an organizational policy that rotates financial institution employees through different roles may reduce misrepresentation risk. This will help

keep risk assessment from becoming excessively routinized. Alternatively, a second level of review may make sense for employees with long tenures in a specific job function. Previous research has indicated that loan officer rotation may lead to reduced moral hazard (Holmstrom 1982, Hertzberg, Liberti and Paravisini 2010), perhaps at the cost of a loss of information (Scott 2006). In our context the issue is not a concern with loan officer honesty (they have no greater incentive to approve unattractive loans later in their tenure) but with the development of a process that appears to neglect misrepresentation risk.

Large broker offices are a source of disproportionately many loans with misrepresented assets. Contrary to the conventional wisdom that small offices are unreliable and more prone to fraud, brokers from smaller establishments appear to have submitted loans with lower misrepresentation risk. Oversight may be better in smaller offices, and the effects of competition in larger offices may be pernicious.

Borrower misreporting has also been documented in residential real estate mortgages for transaction prices (Ben David 2008 and Carrillo 2010) and personal income (Jiang, Nelson and Vytlačil 2009). In general, there are not many broad prescriptions for managing misrepresentation risk other than the retention of excess capital. The results in this paper analyze the ways in which appropriate contract design and organizational policies can help mitigate this risk.

The rest of the paper is organized as follows. Section 1 details the residential mortgage data that I use to analyze misrepresentation risk. In Section 2 I outline my econometric approach, and I describe the empirical findings in Section 3. Finally, Section 4 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. Loans made to insiders are excluded, as are loans for which the personal asset information of the borrower is not provided. These loans were retained by the bank and not securitized. As described in Table 1, 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).

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. There are 155 loan officers observed in the data. 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 a relatively small 15.2 basis points.

As part of the application, borrowers state their level of personal assets (excluding the property to be purchased) and 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 misrepresent their personal information. While misrepresentation may be costly in general (and these costs may vary with the level of documentation required), misrepresenting borrowers can likely make claims for their asset/income data that are plausible in some range.

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. Borrower income was also considered in the mortgage evaluation process.

2 Empirical Specification

The focus of my empirical analysis is on the impact of borrower-reported assets on the eventual delinquency of mortgages. I explore the hypothesis that borrowers who misrepresent 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 misrepresenting his assets is more likely claim an asset level of \$102,000 rather than \$97,000. If this is the case, and if misrepresenting borrowers are more likely to eventually become delinquent, then we should expect to see a positive discontinuity in delinquency probabilities at round number asset thresholds. Under the null hypothesis of no misrepresentation,

or no threshold-gaming, there should be no discontinuity in delinquency probabilities at round number thresholds.

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

$$A = assets - round(assets, 100000). \quad (1)$$

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

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

To analyze the hypothesis of a discontinuity in delinquency probabilities at the thresholds, I estimate the following formal model:

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

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, $I_{A_{i,t}}$ 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. The controls may include fixed effects for the loan officer, depending on the specification.

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 misrepresentation (or no systematic misrepresentation around round number thresholds), we should expect to find $\beta = 0$. Under the alternative hypothesis that some

borrowers misrepresent 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 some tests I study cross-sectional variation in the impact of above-threshold assets on delinquency probabilities. For example, it may be that this impact differs across borrowers who presented varying amounts of documentation to the bank. For tests of this kind, I estimate the following model:

$$\begin{aligned}
 \text{Delinquent}_{i,t} = & \alpha + \beta I_{Ai,t} + \sum_{j=1}^6 \omega_j^A A_{i,t}^j + \sum_{j=1}^6 \xi_j^A I_{Ai,t} A_{i,t}^j & (4) \\
 & + \eta I_{Ai,t} V_{i,t} + \sum_{j=1}^6 \omega_j^{AV} A_{i,t}^j V_{i,t} + \sum_{j=1}^6 \xi_j^{AV} I_{Ai,t} A_{i,t}^j V_{i,t} \\
 & + \pi V_{i,t} + \gamma * \text{controls}_{i,t} + \lambda_t + \epsilon_{i,t},
 \end{aligned}$$

where $V_{i,t}$ is a mortgage characteristic. In this specification the main coefficient of interest is η , which measures variation in the impact of above-threshold assets on delinquency for differing values of V . The inclusion of interactions of V with the asset polynomials implies that η measures the extent to which the delinquency discontinuity effect varies

with V . A significant estimated coefficient for η indicates that the discontinuity in delinquency for just above-threshold stated assets is different for borrowers with different values of V , controlling for changes in the composition of borrower characteristics over time.

2.1 Bank Policy

As described in Section 1.1, the bank requested personal asset levels from borrowers for use in determining loan eligibility. The bank did not, however, compare the stated asset levels to round number thresholds. Instead, the assets were required to exceed a multiple of the monthly PITI due from the borrower. This bank requirement was therefore unrelated to the round number thresholds I study.

3 Results

3.1 Misrepresentation of Assets

I begin by testing the hypothesis that borrowers that stated asset levels just above round number thresholds experienced higher subsequent delinquency rates. This test is motivated by the idea that borrowers who misrepresented their personal assets were likely to state assets above, rather than below, round numbers, and that misrepresenting borrowers were more likely to become delinquent. I estimate the discontinuity model exploring the link between delinquency and reported assets described in equation (3). 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. The estimation is via OLS, with robust t -statistics clustered by the month of mortgage origination.

As described in the first column of Table 2, 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. The regression results are graphically depicted in Figure 1. 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. 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. This finding of dramatically higher delinquency rates for above-threshold asset reporters is consistent with the hypothesis that misrepresenting borrowers are both more likely to report assets above round numbers and are more likely to become delinquent. The higher delinquency rates of misrepresenting borrowers are probably not simply attributable to the fact that they have lower assets than they report; misrepresentation is likely a signal of wider dishonesty and perhaps a greater willingness to engage in strategic default.

Figure 1 extends from -\$100,000 to +\$50,000 because borrowers with less than \$50,000 in assets have normalized assets of below -\$50,000. All other borrowers are within \$50,000 of a threshold. Excluding the borrowers with assets below \$50,000 has little effect, as they are quite distant from the normalized asset threshold of zero and have little impact on the discontinuity estimate. In the specification without these low asset borrowers, the estimated coefficient on the above-threshold dummy is 0.256 with a *t*-statistic of 3.20.

I next consider a second implication of the misrepresentation hypothesis, namely that it should be more severe for loans for which misrepresentation was more feasible. Specifically, misrepresentation should be expected to be a more serious problem for loans in which the borrower stated his assets without supplying verification. I divide the loans into two samples, one for which asset documentation was not supplied (consisting of 3,276

loans) and one for which it was (composed of 4,994 loans). I then regress delinquency on the above-threshold dummy, the sixth degree polynomial in assets, the interaction of the above-threshold and the polynomial and the full set of controls. 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. These regressions are estimated via OLS with robust standard errors clustered by month of origination. As detailed in the second column of Table 2, in the sample of mortgages submitted with unverified assets, the coefficient on the above-threshold indicator is 0.405 and significant (t -statistic=3.42). This result is described visually in Figure 2. The general shape of the delinquency curve resembles that in Figure 1, but the magnitude of the jump at zero is much bigger in the unverified assets sample: the asset misrepresentation problem is indeed more severe when supporting documents were not required.

In the sample of mortgages with verified assets, however, the results displayed in the third column of Table 2 show that the coefficient on the above-threshold variable is both very small (-0.023) and statistically insignificant (t -statistic=-0.29). Figure 3 shows clearly that there is no meaningful jump at zero normalized assets in this sample. Taken together, these findings provide strong evidence of misrepresentation of assets: 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.

As the figures make clear, the central finding of a large significant jump in delinquency probability at the round number threshold for the unverified asset mortgages and no significant jump in the verified asset sample is robust to a variety of specifications. In the basic sixth-degree polynomial specification described above the jump coefficients are 0.41 and -0.02 in the unverified and verified asset samples, respectively. In the fifth-degree polynomial specification, the estimates are 0.48 and -0.03, and in the seventh-degree polynomial specification the estimates are 0.48 and 0.04. 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. The

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 0.57 in the unverified assets sample and an estimate of -0.04 in the verified assets sample. All the above estimates are statistically significant in the unverified sample and insignificant in the verified sample.

Was misrepresentation confined to asset levels or was there also systematic misrepresentation of income? To consider this question, 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. For the sample of 6,017 loans with unverified income reported by the borrower, 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. As documented in the fifth column of Table 2, there is no significant discontinuity (t -statistic=-0.19) in delinquency rates around round number income thresholds. In unreported results, I conduct the analogous test for annual reported income and thresholds of \$10,000 and again find an insignificant effect.

It may be that, due to the nature of the thresholds, the benefits from misrepresenting income around round number thresholds were perceived to be smaller than those from misrepresenting assets. An asset level of \$103,000 may appear to be significantly higher than an asset level of \$98,000 because the first exceeds \$100,000 while the second does not. Income was reported as a monthly value, and the difference between monthly income levels of \$13,800 and \$14,300 may seem less important because the intervening threshold is less notable. Borrower income misrepresentation may therefore have been more likely to take place in ways other than the threshold manipulation that I find for reported assets.

Alternatively, borrowers may have been less likely to manipulate income. Income is required to support regular mortgage payments on a property. Misrepresenting income may therefore not be a good strategy for a prospective borrower. Of course, some

borrowers may have hoped to quickly sell the property for a profit (“flippers”), in which case their income may not have been needed to make payments for very long, but this sample does not appear to include many borrowers of that kind. The average time between origination and the final observed payment is 633 days, and 55% of the loans are still outstanding at the close of the sample period. This suggests that the average turnaround period on the loans is not very short. In contrast to income, borrowers may have thought that their personal assets would only be called upon in the event of what they thought to be a very unlikely job loss. These borrowers may have felt comfortable over-stating assets because they assumed that their assets were irrelevant to their ability to make their mortgage payments. Borrowers may also have imagined that they could always simply sell their houses rather than have recourse to their personal assets in the shadow of a looming foreclosure.

Given the evidence in Table 2, our subsequent analysis will focus on asset misrepresentation in the sample of loans with unverified asset documentation.

3.1.1 Round Number Heuristic

There is a tendency in financial markets for participants to make use of round number heuristics. Goldreich (2005), for example, shows that dealers in U.S. Treasury auctions frequently submit bids with a final digit of zero. He attributes this to boundedly rational investors making use of a heuristic. One might ask if the discontinuity in delinquency at round number asset thresholds described in Table 2 is driven by the use of this heuristic by a subset of borrowers.

Applicants were requested to provide their actual 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, almost none of the borrowers submitted round number values for their reported assets. Excluding these 23 loans yields discontinuity effects that vary little from the base case: the coefficient estimate is 0.46 in the unverified asset

sample (significant at the 1% level) and 0.01 in the verified asset sample (insignificant). The results are not determined by data points precisely at the threshold.

3.2 Distribution of Reported Assets

Borrowers with unverified assets just above round number thresholds are much more likely to become delinquent in their loans. If, as I have argued, this is driven by borrower misrepresentation, then the distribution of unverified reported assets should exhibit a discontinuity at the threshold. Specifically, there should be relatively few borrowers with reported assets just below the threshold and relatively many borrowers with assets just above the threshold. Misrepresenting borrowers should cluster around normalized unverified asset levels of just above zero.

To examine this hypothesis I employ McCrary's (2008) test for a discontinuity in a density function. McCrary's methodology is well-suited for this setting, as it allows for distinct kernel density estimates on both sides of the threshold, while correcting for boundary bias.¹ 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.

The estimated kernel density of reported unverified assets is described in Figure 4. 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).

¹Other methods for assessing discontinuities are considered in Burgstahler and Dichev (1997) and Bollen and Pool (2009).

By contrast, the estimated kernel density of reported verified assets is described in Figure 5. Verified assets should be difficult to manipulate, and in Table 2 I find no significant discontinuity in delinquency at normalized verified assets of zero. This suggests that there should not be a discontinuity in the density of reported assets for the verified sample, and Figure 5 is consistent with this hypothesis. The estimated log difference in kernel heights is -0.09 (t -statistic= -0.65).

3.2.1 Benefits of Misreporting Assets

The discontinuity described in Figure 4 in the distribution of reported assets and the results in Table 2 linking above-threshold assets to much higher delinquency rates together provide strong evidence of misrepresentation of unverified assets by some borrowers. What incentives were there for borrowers to engage in this misrepresentation?

The first point is that borrower assets were required to be above a specific multiple of the monthly PITI for an application to be accepted. Second, borrowers were informed that their assets would be used in the underwriting decision to determine loan terms. I find in untabulated tests that borrowers with greater reported assets received larger loans and loans with lower rate spreads. For both these reasons, borrowers had a general incentive to report high asset levels.

Why did misrepresenting borrowers report assets just above round number thresholds? There is extensive empirical and experimental evidence in the marketing literature that numbers just below round number thresholds are perceived to be significantly lower than those at the threshold or above (Kalyanam and Shively 1998, Anderson and Simester 2003 and Thomas and Morwitz 2005). This fact is used to explain the ubiquitous odd pricing phenomenon (i.e., that retail prices generally end in 99 cents). Reported asset levels above round number thresholds were therefore likely perceived by borrowers to appear significantly larger than those just below. Once a borrower has elected to misrepresent his assets, there is likely little cost in choosing to report \$101,000 rather

than \$98,000. The first number, however, appears significantly larger. (As discussed in Section 3.1.1, borrowers were asked to report actual asset levels, so reporting a round number would likely have appeared unusual, and very few borrowers did so.) Given the general benefits accruing from reporting higher assets, the perceived larger magnitudes of above-threshold assets and the minor cost associated with misreporting above-threshold rather than below-threshold assets, misreporting borrowers choose to state asset levels just above round numbers.

In the following section we discuss the impact of this misreporting on the actual terms received by borrowers.

3.3 Asset Discontinuity and Loan and Borrower Characteristics

The results in Table 2 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 3 shows that the coefficient on the above-threshold dummy is insignificant (t -statistic=0.48, with standard errors cluster by month of origination). Not only is the coefficient estimate insignificant, it is also very small: the asset threshold discontinuity is associated with a 6 basis point increase in the rate spread. That is, the effect is measured quite precisely and it is clearly very close to zero. 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 loan-to-value (LTV) ratio, the log of the loan size and the log of the loan maturity on the above-threshold indicator, the sixth degree polynomial in assets and the standard controls (omitting LTV as a control in the LTV and loan size regressions). The results, displayed in Table 3 columns 2-4 are uniformly insignificant and small in magnitude. For example, LTVs are 34 basis points smaller (t -statistic=-0.12) above the threshold and loan maturities are 1.5 percent shorter (t -statistic=-0.82). Borrower characteristics also show no apparent discontinuities at asset jumps. The borrower credit score is 1.1 points lower (t -statistic=-0.08) above the threshold, which is very small compared to 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 misrepresentation.

The evidence in Table 3 makes clear that reporting above-threshold assets did not lead to significantly better contract terms for borrowers. In other words, misreporting borrowers may have over-estimated the positive effects of stating above-threshold assets. Nonetheless, given the likely trivial cost of misreporting above-threshold rather than below-threshold assets and the insignificant effect on loan terms, it is unlikely that they were harmed by this strategy.

3.4 Misrepresentation across Deal Types

The evidence in Table 2 established that there were significant discontinuities in delinquency at round number reported asset thresholds. I now consider whether certain deal types exhibited larger threshold effects. Evidence that some deals had larger discontinuities than others could suggest that the prevalence and depth of misrepresentation varied with the characteristics of the mortgage or it might indicate that the bank had

varying skill in mitigating misrepresentation risk across different mortgage types. In the analysis below, I will attempt to distinguish these two possible explanations of the cross-sectional findings.

First, I turn to the classification of the purpose of the loan as either cash out refinancing, rate/term refinancing or home purchase. I estimate the discontinuity regression of delinquency on assets described in (3), with the previous full set of controls, in the restricted sample of cash out refinancings. I also include loan officer fixed effects in this regression and cluster by loan officer. (All subsequent standard errors are clustered by loan officer.) As reported in the first column of Table 4, the coefficient on the above-threshold coefficient is large in this specification: 0.46, with a t -statistic of 4.51. This is consistent with the hypothesis that asset misrepresentation was common and severe for cash out refinancings.

In a rate/term refinancing, the borrower withdraws no equity from his home and uses the refinancing only to reduce the interest rate he pays or change the loan maturity. In the second column of Table 4, I detail the results from the discontinuity regression of delinquency on reported assets in the sample of rate refinancings. The estimated coefficient of -0.08 on the above-threshold dummy is insignificant (t -statistic=-0.25). There is little evidence for misrepresentation in the set of rate/term refinancings.

Cash out and rate/term refinancings are in most ways very similar from the bank's perspective. The bank is purchasing a debt stake on the borrower's existing asset. There is usually no current purchase price, so the appraisal is an important source of information on the home value. Controlling for the loan terms, the bank's mortgage security has essentially the same features after the origination for both types of refinancing. Nonetheless, our analysis above, incorporating loan officer fixed effects, finds a large asset misrepresentation effect for cash out refinancings and none for rate/term refinancings. It seems implausible that the bank was more careful in evaluating rate/term refinancings- the contrary is more likely the case.

The key distinguishing feature between cash out and rate/term refinancings, however, is the type of borrower who selects each. Borrowers who undertook cash out refinancings in which they increased their mortgage balances and received money from the bank may have been the most eager to have their loan applications approved. In some cases, these borrowers may even have been desperate to raise cash by borrowing against their homes. While a rate/term refinancing does generate value for a borrower, those who undertake these refinancings are likely in less dire need of cash than borrowers who negotiated cash out refinancings. As a consequence, we should expect to see less frequent asset misrepresentation amongst borrowers engaged in rate/term refinancings: these are marginally beneficial transactions for the applicants, and are unlikely to save them from an immediate cash crisis, in contrast to a cash out refinancing. The weight of this argument suggests that borrower selection drives the differences between the cash out and rate/term refinancing results. Cash out refinancings were more likely to attract misrepresenting borrowers.

Some loans were used to support purchases of houses. As shown in the third column of Table 4, the coefficient on above-threshold assets is large (0.36) and but not significant (t -statistic=1.16) in the sample of home purchase mortgages. This finding on home purchase loans is harder to compare with the refinancing results. The purchase loans may have been handled differently by the bank due to the availability of sales price information or potential timing pressures driven by the need to close the transaction.

The cross-sectional findings in Table 4 support the argument that asset misrepresentation had its greatest impact when the immediate cash flow need of the borrowers was large, and that the bank could have reduced its exposure to this risk through selection against borrowers who explicitly exhibited this characteristic. More broadly, this suggests that financial institutions can reduce their exposure to misrepresentation risk by designing contracts that do not offer an immediate cash payout.

3.5 Misrepresentation by Loan Characteristics

Misrepresentation may vary for reasons unrelated to the pressing liquidity needs of borrowers. Borrowers deemed more risky, or borrowers willing to accept loans at higher interest rates, may exhibit different predispositions to misrepresentation from other borrowers. To test this hypothesis, I regress delinquency on the above-threshold indicator, the rate spread, the indicator interacted with the rate spread, and the full set of controls described in (4) (including the interaction between the rate spread and asset polynomials). Fixed effects for the month, lending officer and deal type (e.g., cash out refinancing) are included, and standard errors are clustered by loan officer. This specification tests whether the jump in delinquency is more severe for borrowers who accept loans with higher spread rates.

The result, detailed in the first column of Table 5, shows that high spread rate borrowers are marginally more likely to exhibit jumps in delinquency at asset thresholds (t -statistic=1.65). Overall risk therefore has a weak association with misrepresentation risk.

In high loan-to-value (LTV) transactions, the borrower has little equity invested and may view the financing as an opportunity to invest in a lottery with little downside risk. Finding financing may also be more difficult in high LTV deals. For both these reasons, the mortgage is quite valuable to a high LTV borrower, and these borrowers may be more willing to misrepresent their assets. As I show in the second column of Table 5, the coefficient on the interaction between the above threshold asset indicator and LTV is positive and significant (t -statistic=2.06). A 10 percentage point increase in the LTV increases the estimated delinquency jump at an asset threshold by 9.9 percentage points.

Is misrepresentation risk higher for borrowers with lower credit scores? To consider this question, I regress delinquency on the above threshold indicator, the borrower credit score, the interaction between the indicator and the credit score and the full set of controls. The third column of Table 5 displays the result: the delinquency jump is

slightly greater, though not significantly different for borrowers with high credit scores (t -statistic=0.37). A shorter or less pristine credit history is not associated with greater misrepresentation risk. This suggests that selection based on observable borrower characteristics must be used judiciously to reduce asset misrepresentation. Borrowers who need cash quickly should be excluded, but low credit score borrowers need not be turned away.

In column four of Table 5, I describe the result from including the interaction of the above threshold indicator with rate spread, LTV and credit score simultaneously. This regression confirms the previous findings: the delinquency jump is stronger for high LTV loans (t -statistic=2.11), marginally stronger for high rate spread loans (t -statistic=1.87) and not affected by borrower credit score (t -statistic=0.37).

These findings control for the direct impacts of LTV and rate spread on delinquency risk and for any loan-officer-specific effects. Any general differences in the way the bank handles high risk loans will therefore not affect these estimates of the delinquency jump at zero normalized assets. Might it be that the bank is less thorough or skilled in assessing misrepresentation risk for high LTV or high rate spread loans? This cannot be ruled out, though more careful review should be expected for these mortgages. Overall, the evidence is supportive of the hypothesis that by restricting its contract offerings to lower LTV loans, the bank could have significantly reduced its losses due to borrower asset misrepresentation.

3.6 Loan Officer Experience

The discussion in the previous sections emphasized the importance of borrower selection and the role that can be played by appropriate loan contract design. I now consider the effects of loan officers in mitigating asset misrepresentation risk. The bank did not uncover this risk during the sample period. Loan officers who approved mortgages that subsequently became delinquent placed their employment in jeopardy. No loan officer

would wish to approve a loan that had a 40.5 percent higher than average likelihood of delinquency, as exhibited by loans just above asset thresholds. Though loan officers were not aware of this specific form of misrepresentation, they may have other means of screening out these loans.

Borrowers who misrepresented their assets may have also had omissions or oddities in other portions of their applications. These negative indicators may have taken the form of soft information uncovered by a loan officer during the underwriting process. If loan officers detected these other unusual features, they may have declined credit to borrowers who misrepresented their assets, even though the bank was unaware of that particular concern. In this case, we should observe a reduced jump in delinquency at round number asset thresholds.

What role did loan officer experience play in determining the depth and quality of the scrutiny applied to the evaluation of applications? Were more experienced loan officers more successful in determining which applications had unusual features? Or were loan officers more careful in assessing applications earlier in their tenure? I now turn to these questions.

To analyze the effect of loan officer experience, I regress delinquency on the above-threshold indicator, the interaction of the above-threshold dummy and the total experience of the loan officer (measured as the total number of transactions), and the full set of controls described in (4), including loan officer fixed effects and MSA fixed effects to control for any potential changes in property locations over time. (The direct effect of experience is subsumed in the loan officer fixed effects.) The coefficient on the interaction is likely to be biased downwards due to both selection and lending officer heterogeneity. Selection describes the fact that loan officers that experienced misrepresentation-driven delinquencies early on through bad luck are more likely to be terminated, and as a result loan officers with longer experience will exhibit fewer such delinquencies on average, even if there is no causal effect of relationships on delinquency. Heterogeneity in loan officer handling of misrepresentation will lead worse loan officers to be terminated earlier, so

the pool of loan officers with longer experience should be superior, again generating a negative effect of experience on delinquencies caused by misrepresentation.

Despite these two sources of downward bias, I find, as I report in the first column of Table 6, a positive and significant (t -statistic=2.38) coefficient on the interaction. This is a conservative estimate that likely somewhat understates the true effect, because of the impact of selection and loan officer heterogeneity. Loan officer experience exacerbates the impact of the asset misrepresentation risk.

As an additional test, I consider whether the effect worsens over time for a given loan officer. I regress delinquency on the above-threshold indicator, the deal # (the count of this transaction in the time-ordered sequence of deals undertaken by the loan officer), the product of the above-threshold dummy and deal # , and the full set of controls excluding loan officer fixed effects. I omit the loan officer fixed effects due to concerns about regression to the mean: a bank policy of terminating unsuccessful loan officers will lead to upward bias in the coefficient on the product in the presence of loan officer fixed effects, as only loan officers that enjoy early successes will provide data on the impact of additional deals. Any randomness in delinquency outcomes will thus artificially make it appear that loan officers experience worse outcomes over time.

In this specification the coefficient on the product of the above threshold dummy and the deal # is therefore identified only from the differential impact of asset misrepresentation occurring in early and late deals. Under the null hypothesis that the number of previous deals undertaken has no impact on the loan officer's effectiveness in avoiding misrepresentation risks, the unconditional probability that asset misrepresentation will lead to delinquency will be the same for any deal, and the coefficient on the product should be zero. (Including loan officer fixed effects causes the coefficient to be identified from within-loan-officer differences in outcomes and regression to the mean would cause an upward bias, as described above.)

As detailed in the second column of Table 6, the coefficient on the product is

positive and significant (coefficient of 0.000344 and t -statistic=2.46). Later deals are associated with a more severe impact of asset misrepresentation. This estimate is also conservative, as it ignores loan officer heterogeneity, which generates an improving pool of loan officers in later interactions.

Including loan officer fixed effects can help control for heterogeneity, through it leads to the issues with regression to the mean discussed earlier. In the third column of Table 6 I display the results from including these additional fixed effects and find very similar results (coefficient of 0.000353 and t -statistic=2.58). As expected, the coefficient estimate rose relative to column 2, but the effect is slight. This indicates that selection issues are likely not severe in these data. Overall, given the conservative and significant estimates in the first and second columns, the results provide evidence that the misrepresentation effect is made worse by experience.

One explanation for these findings is that loan officers are allocated more difficult applications as time passes. To assess this explanation, I analyze how the observable risk of applications changes over the course of a loan officer's tenure. In untabulated regressions I find that loan officer exposure to the risk factors rate spread, LTV and (lower) credit score do not increase over time. This implies that observable risk does not increase over time, and I have shown that several of these risk factors are correlated with misrepresentation risk. It therefore seems unlikely that the bank increased loan officer exposure to misrepresentation risk (a risk of which the bank was unaware) with experience. Moreover, any general change in the quality of applications directed to a given loan officer should be controlled for the direct impact of the deal # on delinquency.

These findings suggest that financial institutions interested in mitigating misrepresentation risk should consider rotating employees through roles. As loan officers evaluate more mortgage applications they appear to become less adept at detecting features associated with borrower misrepresentation. Another strategy would be subject mortgages evaluated by a loan officer with a long tenure to a second level of scrutiny. Misrepresentation risk by its nature is hard to quantify *ex ante*, and organizations that are

averse to exposure to potentially large tail events may be advised to undertake ongoing reorganizations or additional reviews to ensure that employee evaluation skills do not become too stale.

3.7 Large and Small Broker Offices

It is commonly argued that reputation effects should encourage larger firms to conduct operations in a more forthright manner, with a focus on maintaining long-term relationships. In the mortgage crisis, small “fly-by-night” brokerage firms were often blamed for terrible lending outcomes. To test this hypothesis, I estimate the base delinquency regression in two samples, one for transactions originated by brokers working in offices with ten (the sample median) or fewer brokers and a second for transactions originated by brokers working in offices with eleven or more brokers.

The regression results are detailed in Table 7. As I show there, brokers from small offices exhibit an insignificant jump in delinquency at normalized assets of zero, while brokers from large offices display a large and significant discontinuity (coefficient= 0.59 and t -stat=5.25). This difference is significant at the 5%-level. This provides clear evidence that misrepresentation was substantially more severe at larger offices. Screening and oversight of brokers may be more carefully performed in small offices. It is also possible that brokers in large offices are pushed by competition to originate marginal loans from potentially unattractive borrowers.

Banks considering expanding their geographic or product reach may be tempted to use large broker offices as a first distribution channel, due to their scale advantages. The findings in Table 7 suggest that this may not be an optimal strategy, as it may expose the bank to unexpected misrepresentation risk. Larger broker offices should also be subject to more careful review by bank officials.

4 Conclusion

The experience of the last several years has led financial institutions to think more carefully about misrepresentation risk. I show that personal asset misrepresentation by borrowers was a significant risk for a bank making loans in the residential mortgage market during the 2004-2008 sample period. This risk was present only for loans with undocumented assets, and I show that its severity was affected by both the form of the loan and the way in which it was evaluated by the bank. Loans that granted borrowers immediate cash payments or high leverage were more subject to misrepresentation. The problem was also more severe for loans originated later in a loan officer's tenure and for loans generated by large broker offices.

The specific form of asset misrepresentation that I describe was not known to the bank during the sample period. In that sense, it is an example of an unknown risk - a risk that a financial institution does not anticipate or cannot quantify *ex ante*. As I show in this paper, the magnitude of an unknown risk can be very large. Moreover, it is a risk that is particularly unappealing to banks and regulators because it is so difficult to assess.

Successful risk management certainly requires the careful measurement and estimation of well-understood hazards. Expanding the range of risks that can be quantified will also help improve the performance of financial models and the accuracy of forecasts. Nonetheless, there will always be unanticipated and undiscovered risks. Creative contract design and risk evaluation processes can help preserve the resilience of financial institutions even in the presence of previously unknown risks.

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Figure 1: Delinquency and Reported Personal Assets- Full Sample

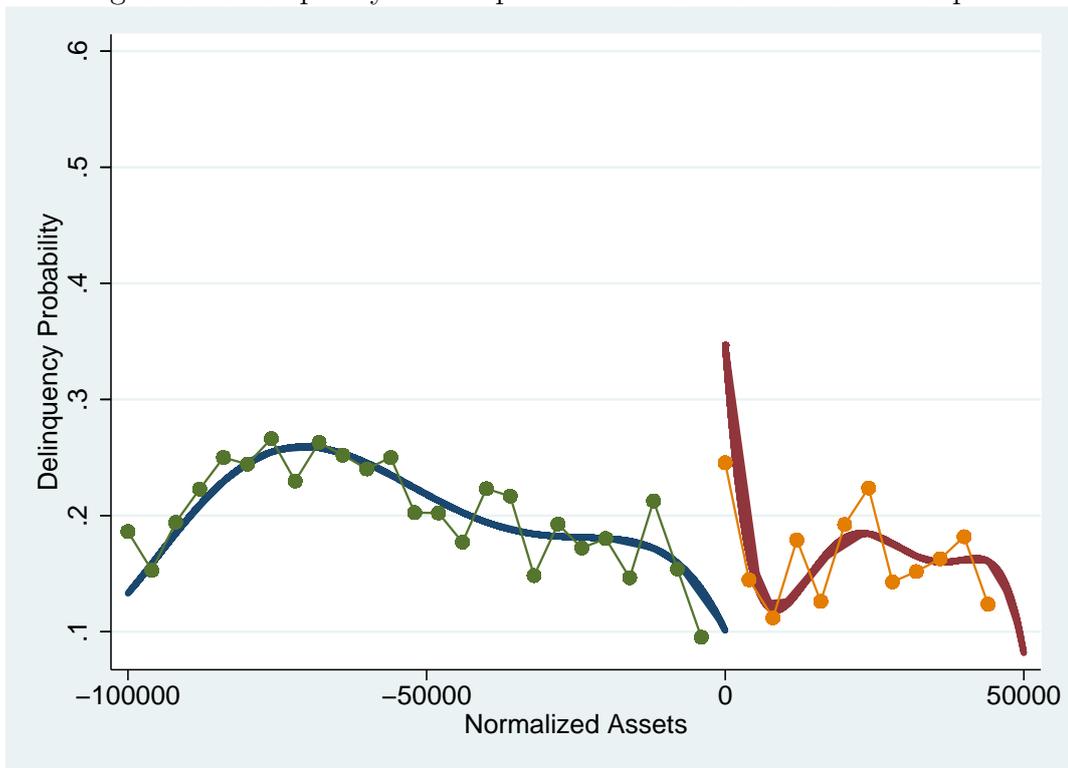


Figure 2: Delinquency and Reported Personal Assets- Unverified Assets

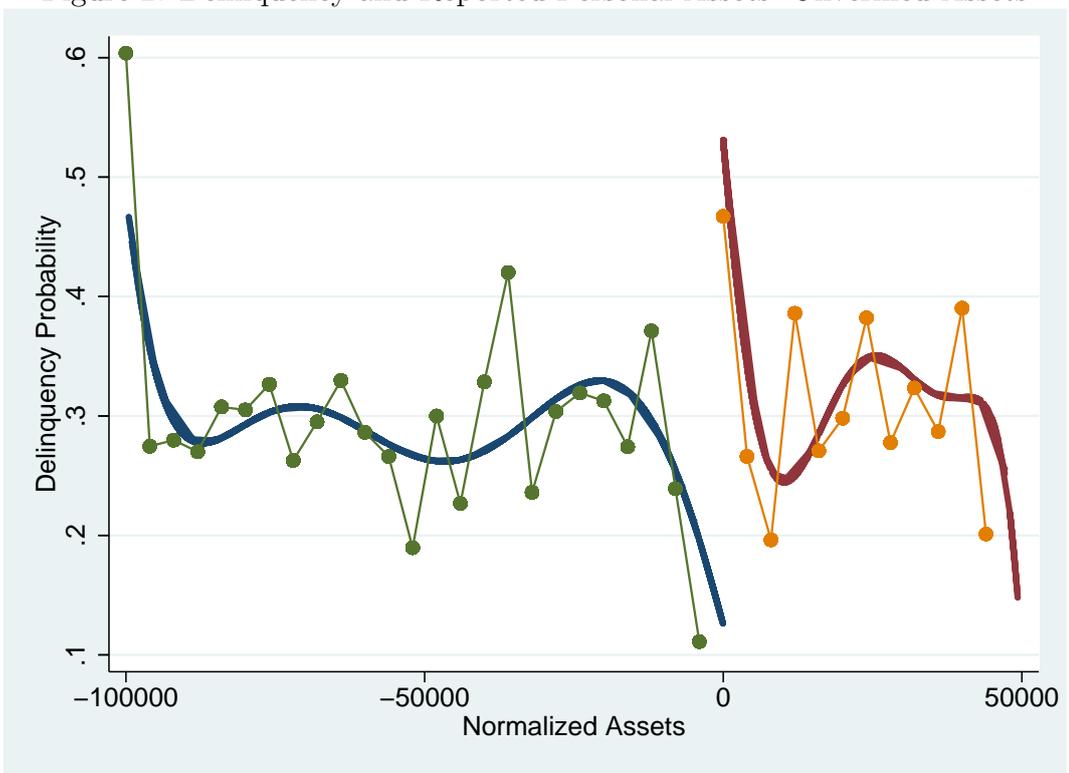


Figure 3: Delinquency and Reported Personal Assets- Verified Assets

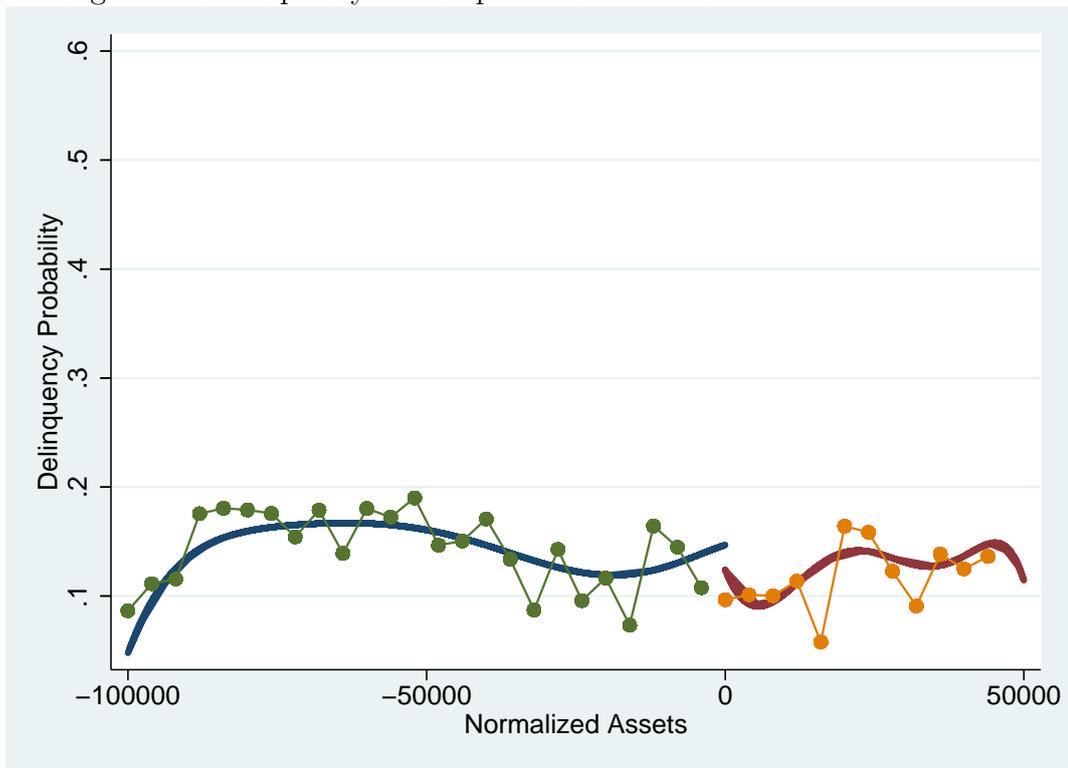


Figure 4: Density of Normalized Assets- Unverified Assets

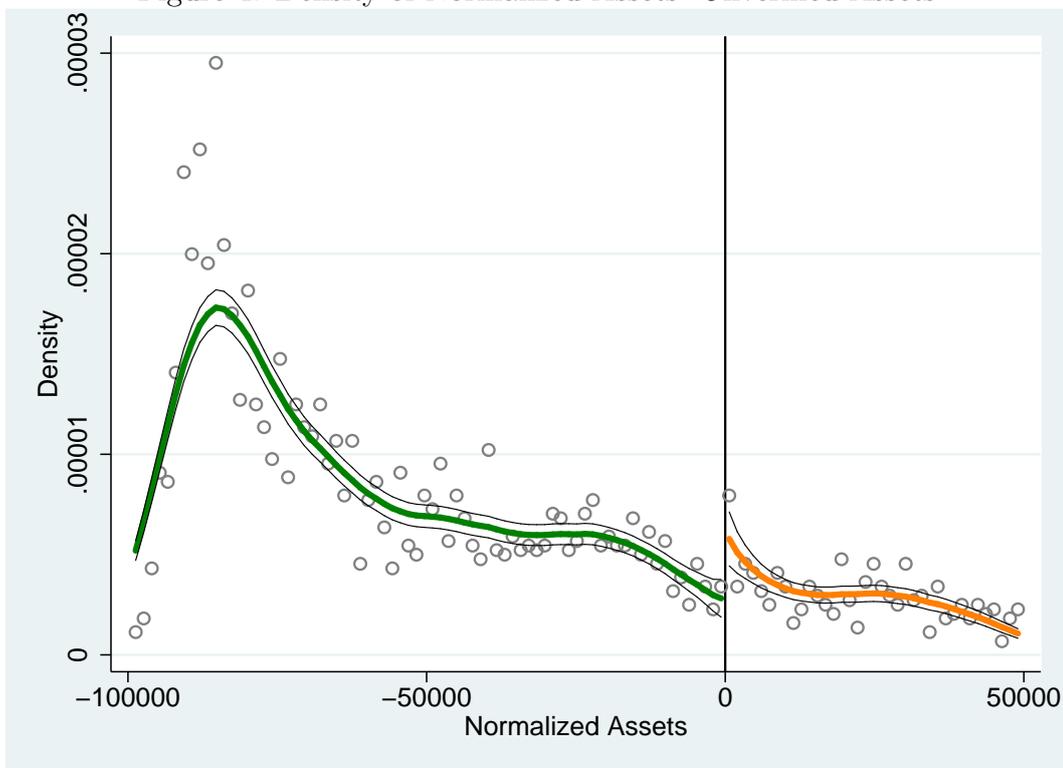


Figure 5: Density of Normalized Assets- Verified Assets

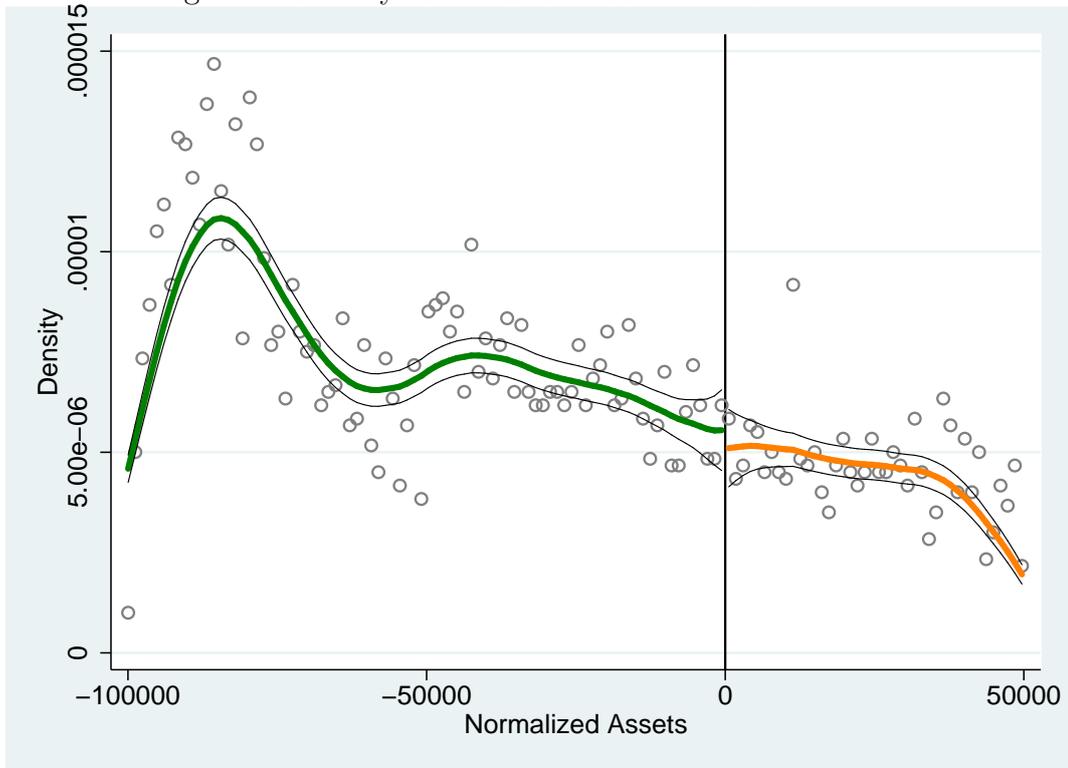


Table 1: Summary Statistics

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 and LTV is the loan-to-value ratio. 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
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 2: Misrepresentation of Assets

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 (in columns 1-3), the rate spread on the mortgage (columns 2-4), the credit score of the borrower (columns 2-4), the loan-to-value ratio on the mortgage (columns 2-4) and a dummy for whether the normalized income of the borrower exceeds zero (column 4). The regressions also include as controls a sixth degree polynomial in assets (columns 1-3), a sixth degree polynomial in income (column 4) and monthly fixed effects (columns 2-4). Reported t -statistics are heteroskedasticity-robust and clustered by month of origination.

	Delinquent?	Delinquent?	Delinquent?	Delinquent?
Assets Above Threshold	0.246** (3.47)	0.405** (3.42)	-0.0230 (-0.29)	
Rate Spread		0.0368* (1.85)	0.0455** (3.86)	0.0462** (2.57)
Credit Score		-0.000740 (-1.03)	-0.000814** (-3.00)	-0.00128** (-2.67)
LTV		0.241** (3.34)	0.0717 (1.47)	0.247** (4.49)
Income Above Threshold				-0.0154 (-0.19)
6th-degree polyn. in Assets	Yes	Yes	Yes	No
6th-degree polyn. in Income	No	No	No	Yes
Monthly F.E.	No	Yes	Yes	Yes
Sample	Full	Unver. Assets	Ver. Assets	Unver. Income
Observations	8287	3276	4994	6017
Adjusted R^2	0.008	0.102	0.124	0.103

t statistics in parentheses

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

Table 3: 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 loan-to-value ratio (column 2), the log of the loan size in dollars (column 3), the log of the loan maturity in months (column 4) and the borrower credit score (column 5). 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 1-4) and the loan-to-value ratio on the mortgage (columns 1,4 and 5). The regressions also include as controls a sixth degree polynomial in assets and monthly fixed effects. Reported t -statistics are heteroskedasticity-robust and clustered by month of origination.

	Rate Spread	LTV	Loan Size	Maturity	Credit Score
Assets Above Threshold	0.000569 (0.48)	-0.00359 (-0.12)	-0.0643 (-0.48)	-0.0148 (-0.82)	-1.133 (-0.08)
Credit Score	0.000000353 (0.05)	-0.00104** (-4.92)	-0.00339** (-7.14)	0.0000618 (0.34)	
LTV	-0.00142 (-0.81)			0.0371 (0.97)	-75.40** (-5.09)
6th-degree polyn. in Assets	Yes	Yes	Yes	Yes	Yes
Monthly F.E.	Yes	Yes	Yes	Yes	Yes
Observations	3276	3276	3276	3276	3276
Adjusted R^2	0.052	0.111	0.349	0.048	0.064

t statistics in parentheses

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

Table 4: Misrepresentation by Deal Type

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, the credit score of the borrower and the loan-to-value ratio on the mortgage. The regressions also include as controls a sixth degree polynomial in assets, loan officer fixed effects and monthly fixed effects. Reported t -statistics are heteroskedasticity-robust and clustered by loan officer.

	Delinquent?	Delinquent?	Delinquent?
Assets Above Threshold	0.457** (4.51)	-0.0766 (-0.25)	0.358 (1.16)
Rate Spread	0.0218 (1.19)	0.0671 (1.06)	0.204** (3.47)
Credit Score	-0.000745 (-0.86)	0.00244 (1.11)	-0.00120 (-0.54)
LTV	0.272** (2.52)	-0.279 (-0.71)	-0.959 (-0.98)
6th-degree polyn. in Assets	Yes	Yes	Yes
Monthly F.E.	Yes	Yes	Yes
Lending Officer F.E.	Yes	Yes	Yes
Sample	Cash out refi	Rate/term refi	Purchase
Observations	2376	438	390
Adjusted R^2	0.112	0.115	0.156

t statistics in parentheses

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

Table 5: Misrepresentation by Loan Characteristics

Results from the regressions of an indicator for delinquency on loan characteristics. The regressors with reported coefficients are the rate spread on the mortgage, the interaction between the rate spread and a dummy for whether the normalized assets of the borrower exceed zero (columns 1 and 4), the loan-to-value ratio on the mortgage, the interaction between the loan-to-value ratio and a dummy for whether the normalized assets of the borrower exceed zero (columns 2 and 4), the borrower credit score and the interaction between the credit score and a dummy for whether the normalized assets of the borrower exceed zero (columns 3 and 4). The regressions also include as controls a sixth degree polynomial in assets, interactions between this polynomial and the rate spread, the loan-to-value ratio and the credit score, loan officer, deal type and monthly fixed effects. Reported t -statistics are heteroskedasticity-robust and clustered by loan officer.

	Delinquent?	Delinquent?	Delinquent?	Delinquent?
Assets Above Threshold	-1.192 (-1.17)	-0.344 (-1.11)	-0.355 (-0.17)	-2.937 (-0.93)
Rate Spread	-0.179 (-1.15)	0.0489** (2.94)	0.0463** (2.87)	-0.193 (-1.26)
Rate Spread \times As. $>$ Thresh.	0.459 (1.65)			0.489* (1.87)
LTV	0.250** (2.65)	-0.312 (-0.94)	0.267** (2.83)	-0.312 (-0.94)
LTV \times As. $>$ Thresh.		0.989** (2.06)		1.100** (2.11)
Credit Score	-0.000443 (-0.58)	-0.000475 (-0.63)	-0.00197 (-1.39)	-0.00209 (-1.44)
Credit Score \times As. $>$ Thresh.			0.00104 (0.37)	0.00117 (0.37)
6th-degree polyn. in Assets	Yes	Yes	Yes	Yes
Monthly F.E.	Yes	Yes	Yes	Yes
Lending Officer F.E.	Yes	Yes	Yes	Yes
Deal Type F.E.	Yes	Yes	Yes	Yes
Observations	3204	3204	3204	3204
Adjusted R^2	0.119	0.117	0.118	0.116

t statistics in parentheses

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

Table 6: Loan Officer Experience

Results from the regressions of an indicator for delinquency on loan officer characteristics. The regressors with reported coefficients are a dummy for whether the normalized assets of the borrower exceed zero, an interaction between the total number of transactions observed over the entire sample that are originated by the loan officer and a dummy for whether the normalized assets of the borrower exceed zero (column 1), the count of this transaction in the sequence of deals undertaken by the loan officer (columns 2-3), and the product of this count and a dummy for whether the normalized assets of the borrower exceed zero (columns 2 and 3). Regressors with coefficients unreported for brevity include loan to value ratio, rate spread and borrower credit score. The regressions also include as controls a sixth degree polynomial in assets, monthly, deal type and MSA fixed effects and loan officer fixed effects (columns 1 and 3). Reported t -statistics are heteroskedasticity-robust and clustered by loan officer.

	Delinquent?	Delinquent?	Delinquent?
Assets Above Threshold	0.0700 (0.35)	0.0978 (0.51)	0.0771 (0.41)
Total Experience # \times As. > Thresh.	0.000281** (2.38)		
Deal #		-0.000370** (-2.98)	-0.000557** (-3.52)
Deal # \times As. > Thresh.		0.000344** (2.46)	0.000353** (2.58)
Observations	3204	3204	3204
Adjusted R^2	0.154	0.149	0.155
6th-degree polyn. in Assets	Yes	Yes	Yes
Monthly F.E.	Yes	Yes	Yes
Loan Officer F.E.	Yes	No	Yes
Deal Type F.E.	Yes	Yes	Yes

t statistics in parentheses

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

Table 7: Large and Small Broker Offices

Results from the regressions of an indicator for delinquency on loan characteristics in samples from large and small broker offices. 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 loan-to-value ratio on the mortgage and the borrower credit score. Regressors with coefficients unreported for brevity a sixth degree polynomial in assets, monthly, deal type and MSA fixed effects. The sample is split into transactions originating from small broker offices (ten or fewer brokers) and large broker offices (more than ten brokers). Reported t -statistics are heteroskedasticity-robust and clustered by broker.

	Delinquent?	Delinquent?
Assets Above Threshold	0.126 (0.70)	0.594** (5.25)
Rate Spread	0.0474* (1.79)	0.0643** (2.12)
Credit Score	-0.00146 (-1.40)	0.000191 (0.20)
LTV	0.237 (1.51)	0.398** (2.83)
6th-degree polyn. in Assets	Yes	Yes
Monthly F.E.	Yes	Yes
Sample	Small Broker Offices	Large Broker Offices
Observations	1592	1607
Adjusted R^2	0.18	0.18

t statistics in parentheses

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