

Liar's Loan?

Effects of Origination Channel and Information Falsification on Mortgage Delinquency¹

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ABSTRACT

This paper presents a comprehensive predictive model of mortgage delinquency using a unique dataset from a major national mortgage bank containing all of its loan origination information from 2004 to 2008. Our analysis highlights two major agency problems underlying the mortgage crisis: an agency problem between the bank and mortgage brokers that results in lower quality broker-originated loans, and an agency problem between banks and borrowers that results in information falsification by borrowers of low-documentation loans--known in the industry as "liars' loans"--especially when originated through a broker. We also document significant differences in loan performance by race/ethnicity that cannot be explained by observable risk factors or loan pricing.

The recent crisis in the housing and mortgage debt market has drawn considerable attention from regulators and market participants. A decade-long boom in the housing market and related financial sectors was followed in 2007 by a market bust with falling house prices and a rapid increase in mortgage defaults and foreclosures. The nationwide delinquency rate on subprime loans reached 39% by early 2009, more than seven times the level in 2005.⁵ Those caught in the crisis included large financial institutions that experienced sharp expansion in, and profited from, their exposure to mortgage loans. The crisis that started from the mortgage market quickly spread to other financial markets and throughout the economy.

We use the experience of a major national mortgage bank to uncover the determinants of the mortgage crisis and the evolution of the crisis at a micro level. The particular bank provides an ideal context for the study by presenting a representative and yet amplified version of the boom-and-bust cycle experienced by the national mortgage sector in the last decade. First, the bank was among the nation's top ten mortgage banks in 2006 and was one of the fastest growing players in the mortgage market, specializing in low- and no-documentation loans (nicknamed "liars' loans," which constitute a large portion of the Alt-A loans) while also providing full-documentation loans (about 30% of their total loan originations). Second, the bank suffered one of the largest losses in the industry since the 2007 crisis.

⁵ Source of information: LPS Applied Analytics website: <http://www.lpsvcs.com/NewsRoom/IndustryData/Pages/default.aspx>. Delinquency is commonly defined as payment delinquency of 60 days or more, including foreclosure.

Loans issued by the bank since the beginning of 2004 reached a cumulative delinquency rate of 28% by early 2009; approximately half of these delinquent loans were in the state of short sale or foreclosure. Finally, the borrowers and properties underlying the bank's loans during our sample period have fair representations in all 50 states. Therefore, lessons from this particular bank have general implications for the national mortgage market.

The proprietary data set represents the most detailed and disaggregated data sets so far in the mortgage loan literature. Our data set consists of all 721,767 loans that the bank originated between January 2004 and February 2008. We have all of the information that the bank collected at the time of loan origination, as well as monthly performance data for each loan through January 2009. Our data set includes not only information about the loan (pricing, loan product, and other contractual terms) and the property (address, appraisal value, owner occupancy status, etc.), but also about the borrowers demographic characteristics (race, age, gender, etc.) and economic conditions (income, cash reserves, employment status, etc.). Finally, we are able to use the property address information to match about three-quarters of the loans to community attributes such as demographics and business opportunities in narrow localities.

Our sample is divided into four distinct subsamples by a two-way sorting. The first sorting variable is the loan origination channel: whether a loan is originated directly by the bank or through a third party originator (such as a mortgage broker or a correspondent; henceforth, we simply call this category brokered loans). The second sorting variable is the loan documentation level: whether a loan is originated with full documentation of borrowers' economic conditions or with various reduced levels of documentation (including no documentation). Throughout the paper we refer to the four subsamples (with the initial letters capitalized) as: Bank/Full-Doc; Bank/Low-Doc; Broker/Full-Doc; Broker/Low-Doc. The Bank (Broker) subsamples include both Bank/Full-Doc and Bank/Low-Doc (Broker/Full-Doc and Broker/Low-Doc) subsamples, and the Full-Doc (Low-Doc) subsamples are defined analogously.

Our empirical analysis uncovers two types of agency problems in mortgage lending which constitute the fundamental causes of high loan delinquency rates, and by extension, the mortgage crisis. The first agency problem lies between the bank and its mortgage brokers. We find that loans in the Broker subsamples have delinquency probabilities that are 10-14 percentage points (or more than 50%) higher than the Bank subsamples, a manifestation of the misalignment of incentives for brokers who issue loans on the bank's behalf for commissions but do not bear the long-term consequences of low-quality loans. A binary decomposition attributes three-quarters of the Bank-Broker delinquency gap to differences in observable borrower characteristics, and the remaining quarter to differences due to unobserved heterogeneity. Hence, the higher delinquency rates among brokered loans are explained

largely by broker penetration of borrower pools that were of observably worse quality (according to credit score, loan-to-value ratio, income, etc.) than the borrower pools penetrated by the bank.

Within each origination channel, the Low-Doc subsample exhibits worse performance than the Full-Doc subsample, and the difference in delinquency is 5-8 percentage points. The same decomposition method reveals that unobserved heterogeneity explains nearly 100% of this difference. In contrast to the Broker channel, the Low-Doc channel does not necessarily compromise lending standards along the observable metrics, but suffers from less careful verification of some reported information (such as income and owner occupancy status) or less diligent screening of borrowers along hard-to-quantify measures (such as other major expenditures). This relation highlights the second agency problem that lies between the lender and the borrower, where the latter could hide or even falsify unfavorable information, especially in the context of lax screening and verification procedures.

We provide evidence of borrower information falsification at both individual variable and aggregate levels. First, we find that both the in-sample goodness-of-fit and the out-of-sample predictive power of our delinquency prediction model are about 50% higher for the Full-Doc subsamples than for the Low-Doc subsamples. These differences suggest that borrower information collected for low-documentation loans is of lower quality, either in terms of inaccurately recorded data or intentionally falsified information, thereby compromising the ability of such information to predict delinquency. Second, certain variables--notably income--exhibit weak or even perverse relations to delinquency probabilities among low-documentation loans. These weak or perverse relations are especially evident in the Broker/Low-Doc subsample, where brokers both apply looser lending standards and are less diligent in verifying borrower information. The most plausible explanation for this observed pattern is information falsification. Through further analysis, we conservatively estimate that the median magnitude of income exaggeration is about 20% among low-documentation borrowers.

Finally, we document significantly higher delinquency rates among Hispanic and black borrowers. The differences in delinquency rates--4 to 11 percentage points higher for Hispanics and 3 to 4 percentage points higher for blacks, relative to white borrowers--are not explained by the full set of individual risk factors collected at loan origination, or by differences in loan pricing. Our analysis--which includes far more detailed data than that used in prior research on the relationship between race/ethnicity and credit--does not support a finding of discrimination, whereby minorities are subjected to higher lending standards or higher pricing for given financial products. Rather, the findings suggest that systematic differences between white and minority borrowers--such as information and experience disparities resulting from a lack of prior home buying experience or exposure to mainstream financial institutions--may explain these delinquency differences.

Our paper builds on a fast-growing literature on the mortgage crisis,⁶ and most closely relates to a few recent empirical papers exploring the causes of the mortgage crisis using large sample micro-level archival data. Mian and Sufi (2008) identify the effects of the increase in the supply of mortgage credit on fueling the housing bubble between 2001 and 2005, and on the subsequent large increase in mortgage defaults. Demyanyk and Van Hemert (2008) and Keys, Mukherjee, Seru, and Vig (2008) both use data from LoanPerformance, a provider of performance data on securitized loans. Demyanyk and Van Hemert (2008) focus on the deterioration in loan quality between 2001 and 2006, while Keys, et al. (2008) focus on how securitization weakens the incentive of lenders to screen loan applicants. Deng, Quigley, and Van Order (2000) analyze mortgage termination risk using large sample of loans purchased by the Federal Home Loan Mortgage Corporation. Commercial or government agency loan databases mentioned above usually do not include borrower demographic characteristics, detailed loan contractual terms, or location (address) information, and usually only include securitized loans. Some earlier papers (e.g., Munnell, Tootell, Browne, and McEneaney (1996)) obtain demographic information from government data sources, such as those reported for compliance with the Home Mortgage Disclosure Act (HMDA). However, loan performance and detailed location information are absent from these data sources, as are certain central economic variables such as the borrowers' credit scores and the loan-to-value ratio.

The contribution of this paper can be summarized as follows. First, the unique dataset allows us to present the most comprehensive and updated predictive model of delinquency in the literature. The comprehensive list of predictors—including data on loan contract terms, property characteristics, and borrower attributes—not only afford us a better understanding of the determinants of loan delinquency, but also provide us an accurate calibration of the information possessed by the bank, thereby facilitating analyses of the moral hazard and adverse selection problems in the loan market. Moreover, with loan performance information updated to early 2009, we are able to capture the full effect of the crisis on the mortgage market. Second, we model the borrower choice of loan types and quantify the agency problems arising from the broker origination channel and from information falsification among low-documentation loans to the current mortgage crisis. Finally, we find evidence of a race/ethnicity effect in mortgage loan performance, underlining the need to examine mortgage lending practices--such as those that disadvantage less experienced borrowers--that may disparately impact minorities.

The rest of the paper is organized as follows. The next section provides a detailed data description. Section II contains a comprehensive analysis of predictive models of loan delinquency. Section III models borrowers' choices of loan origination channel and documentation level, and decomposes the cross-subsample differences in delinquency rates into two components: one reflecting

⁶ An incomplete list includes Chomsisengphet and Pennington-Cross (2006), Dell'Ariccia, Igan, and Laeven (2008), Mayer, Pense, and Sherlund (2008), and Ben-David (2008).

observable borrower characteristics or lending standards, and another reflecting unobservable borrower heterogeneity. Section IV documents and quantifies borrower information falsification among low-documentation loans. Section V discusses the relationship between race/ethnicity and loan performance. Finally, Section VI concludes.

I. Data and Sample Overview

A. Data Sources and Description

As described in the prior section, our proprietary data set contains 721,767 loans funded by the bank between January 2004 and February 2008. Our sample includes prime, Alt-A, and subprime mortgages.

The data set contains all information obtained at loan origination, including the loan contract terms, property data, and borrower financial and demographic data, as well as monthly performance data updated through January 2009. Loan contract information includes the loan terms (such as loan amount, loan-to-value (LTV) ratio, interest rate, and prepayment penalty), loan purpose (such as home purchase or refinance), origination channel (broker versus bank-originated), and documentation requirements.

Property data used in our analysis includes the property address, whether the property will be owner-occupied and used as a primary residence or used as an investment property/second home, and home appraisal value. Borrower data includes protected class demographic variables collected under the Home Mortgage Disclosure Act (HMDA) such as race, ethnicity, gender, and age, as well as all financial and credit information collected at origination: income, cash reserves, expenditures, additional debts, bankruptcy and/or foreclosure status at loan origination, credit score,⁷ employment status, employment tenure (months in current job), self-employment status, and whether there are multiple borrowers (usually used as a proxy for marital status).

Finally, we have monthly performance data for each loan through January 2009, including the monthly unpaid balance and the loan delinquency status: whether the loan payments are current or delinquent, the number of days delinquent, and whether the property is in a state of short sale or foreclosure.

⁷ Fair Isaacs Co. developed the first nationwide, general purpose credit scoring model and released the eponymous FICO score in 1989. Since then, each of the three major credit-reporting bureaus--Equifax, Experian, and TransUnion--have developed proprietary credit scoring models and jointly developed the VantageScore to compete with FICO. Most mortgage lenders use these scores as the primary measure of borrower credit risk. While there is some variation across the models used by the three credit bureaus--depending on the specific credit events reported to and/or collected by each bureau--the credit score used in this study is numerically comparable and analytically equivalent to the FICO score.

We are able to use the recorded property addresses to match approximately three-quarters of the loans to community attributes such as demographics and business opportunities in narrow localities. Using the ArcGIS geo-coding software and Decennial Census geographic boundary files, we match the property addresses to their census tract, zip code, metropolitan statistical area (MSA), and county. The geographic distribution (at the county level) of the properties in our sample is plotted in Figure 1; the sample properties have fair representations in all 50 states, and their distribution is roughly proportional to population density.

[Insert Figure 1 here]

We also obtain the following information at the census tract level from the Decennial Census and the Bureau of Labor Statistics: population count, median age of the residents, percent of residents who are black or Hispanic, and unemployment rate. In addition, we obtain zip-code level average household income information from the Internal Revenue Service's Individual Master File system.

B. Sample Overview

During the sample period, the bank experienced substantial changes in the composition of its loans and borrowers, as did the national mortgage market. Figure 2 reveals several salient patterns. First, the bank experienced a rapid increase in loan production during the mortgage boom, followed by a sharp decline during the housing bust; new loan originations increased from about 20,000 in the first half of 2004 to a peak of over 154,000 in the second half of 2006, followed by precipitous decline starting in the second half of 2007.

[Insert Figure 2 here.]

Figure 2 also shows that the rapid expansion in loan production was driven almost exclusively by increased loan originations through the broker channel, and expansion of low-documentation loans through the broker channel in particular. Broker-originated loans represented 73% of all loan originations in the first half of 2004, increasing to 94% by the second half of 2006; while broker low-doc loans accounted for 39% of originations in early 2004, they comprised 75% of loan originations by late 2006.

Cumulative delinquency rates progressively and substantially increased over the time period in our sample; at 18 months after origination, only 6.7% of loans originated in the first half of 2004 were ever more than 60 days delinquent, as compared to 23.9% of loans originated in the second half of 2007. Demyanyk and Van Hemert (2008) document a similarly deteriorating trend for subprime loans from 2001-2006 using the LoanPerformance database.

We define all of the variables used in this paper in Table 1 Panel A, and we report their mean, median, and standard deviation values at a semi-annual frequency in Table 1 Panel B.

[Insert Table 1 here.]

The time trends in the key determinants of delinquency reflect changes in housing prices, the loosening of lending standards during the boom period (2005 - 2006), and the subsequent tightening of loan underwriting guidelines by the bank starting in 2007. Mean loan-to-value ratios (LTV, the ratio of loan amount to the property's appraised value) decreased from 69% in late 2004 to 65% in early 2007 before climbing to 77% in early 2008, mostly varying inversely with housing prices. Median borrower credit score was 707 in early 2004, ranged from 689-694 in 2006 through early 2007, and subsequently increased in 2007. Simultaneously, median reported income increased from \$5,500 per month in early 2004 to \$6,500 in late 2006, before trending downward. The growth in borrowers' incomes through the end of 2006 may result from the booming economy as well as from borrower income falsification on low-documentation loans. Statistics on borrower job tenure exhibit a U-shape: median job tenure (a proxy for job stability) decreased from 60 to 50 months at the peak of the boom, before bouncing back to 60 months at the end of the sample period.

The housing boom welcomed many first-time homebuyers to the mortgage market. In early 2004, only 7.6% of borrowers in the sample were first-time homebuyers, a figure that climbed to 18.1% by late 2006. As the housing market collapsed and lenders tightened standards, the percent of first-timers fell to 12.7% by the end of 2007. During the sample period, black and Hispanic borrowers gained a significantly higher share of new loan originations. In early 2004, they represented 4.5% and 7.5% of the borrower population, respectively; by early 2007, the percentages were 8.9% and 23.3%. More strikingly, the proportion of blacks and Hispanics who were first-time borrowers increased from 10.3% in early 2004 to more than 25% in late 2006. The national mortgage market experienced a similar increase during the same period in the percentage of first-time homebuyers and the expansion of credit to minority households, who were disproportionately first-time homebuyers. According to national HMDA data on home purchase loans,⁸ 6.6% (10.8%) of borrowers were black (Hispanic) in 2004; the numbers increased to 8.7% (14.4%) in 2006.

C. Sample Representativeness

Given that our analyses build on information from one bank, it is natural to ask how representative this sample is and to what extent our results can be generalized. The large mortgage bank under analysis operated under an "outsource origination to distribution" business model, wherein nearly 90% of loans were broker-originated, and 72% of loans were originated by non-exclusive brokers. These figures are considerably higher than those for mortgage banks with more traditional models; for example, a Wall Street Journal article in 2007 estimates that brokers originate around 60% of all home loans.⁹ In

⁸ Source of information: <http://www.ffiec.gov/hmdaadwebreport/NatAggWelcome.aspx>.

⁹ See "Mortgage Brokers: Friends or Foes?" by James Hagerly, *The Wall Street Journal*, May 30, 2007.

addition, more than 85% of our sample loans were sold to the secondary market, a considerably higher proportion than the 60% figure reported in Rosen (2007) for the 2005-2006 period, but comparable to the national securitization rate of 75-91% reported in “Inside Mortgage Finance” for subprime and Alt-A loans during the same period.¹⁰

We further compare our 2004-2008 sample average statistics (reported in Table 1 Panel B) to those covered by McDash Analytics, the most comprehensive commercial database on mortgage performance, to assess whether the loan and borrower profiles in our bank sample are representative of the general mortgage market. The comparison dataset is used in recent studies such as Pikorski, Seru, and Vig (2009).¹¹ Our sample exhibits a comparable LTV, higher loan amount (about 15% higher on average), and lower credit score (about 5-8 points lower).¹² Finally, low-documentation loans represent just 20% of loans in the McDash database, but represent 70% of our sample. The difference is due to the lender’s specialization in low-documentation loans.

Last, subprime loans are not over-represented in our sample. Nationally, 18-21% of loans originated during 2004-2006 were subprime, while the same proportion in our sample remained flat at 14-15% across all years.¹³ Our sample affords analyses on the full spectrum of the market, thereby complementing prior research focusing on the subprime sector (e.g., Keys, et al. (2008) and Demyanyk and van Hemert (2007)) and highlighting the widespread crisis beyond the subprime sector.

In summary, the bank in our analysis pursued an aggressive expansion strategy relying heavily on broker originations and low-documentation loans in particular. The strategy allowed the bank to grow at an annualized rate of over 50% from 2004 to 2006. Such a business model is typical among the major players that enjoyed the fastest growth during the housing market boom and incurred the heaviest losses during the downturn. By January 2009, the delinquency rate among the bank’s outstanding loans approached 26%; while this figure is significantly higher than the industry average of 10.4%, the delinquency rate of subprime loans is comparable to the industry subprime average of 39%.¹⁴

This particular bank experienced a representative and yet amplified version of the boom-bust cycle experienced in the mortgage industry overall, thereby providing unique insights into the agency problems underlying the mortgage crisis. To avoid generalizing on empirical relations that emerge from

¹⁰ Source of information: http://www.imfpubs.com/data/mortgage_securitization_rates.html.

¹¹ We thank Amit Seru for providing the summary statistics for this dataset.

¹² Part of the difference can be attributed to the fact that McDash over-represents prime loans as it covers about 60% of the entire mortgage market and about 30-40% of the subprime originations.

¹³ Source of information: *The State of the Nation’s Housing, 2008* by the Joint Center for Housing Studies of Harvard University. Webpage: <http://www.jchs.harvard.edu/publications/markets/son2008/son2008.pdf>. The report mostly relies on the credit score cutoff at 640 for subprime classification.

¹⁴ Source of information: Loan Processing Services (LPS). Webpage: <http://www.lpsvcs.com/NewsRoom/IndustryData/Pages/default.aspx>.

the bank's particular loan composition, we conduct our analyses on subsamples partitioned by loan type (origination channel and documentation level), rather than on the pooled sample.

II. Prediction of Loan Delinquency: Model Specification

A. General Framework

The most important question in the mortgage literature is how to predict delinquency. We estimate two predictive models of delinquency, where we maintain the standard definition of delinquency as the borrower being at least 60 days behind in payment, or being in a more serious condition of default (such as short sale or foreclosure). Our first model uses probit regressions to predict the occurrence of delinquency for individual loans at any point in time during the sample period; our second model uses duration analysis to predict the length of time between loan origination and the first occurrence of delinquency.

While our sample includes all loans issued by the bank from January 2004 to February 2008, our performance data is updated through January 2009. Figure 3 plots the cumulative delinquency rates (since origination) of loans by origination date, in half-year intervals. It shows that loans originated during 2006 (2004) have the highest (lowest) cumulative delinquency rates, and more recently originated loans have higher delinquency rates during the first year of their lives.

[Insert Figure 3 here.]

The covariates in our regression analysis include loan contract terms,¹⁵ borrower financial conditions, and borrower demographics. We partition the sample into four subsamples through a two-by-two sorting as outlined in the previous section: Bank/Full-Doc, Bank/Low-Doc, Broker/Full-Doc, and Broker/Low-Doc. All analyses throughout the paper, unless otherwise stated, control for loan origination year fixed effects and report standard errors that are robust to heteroskedasticity and within-cluster correlation of observations at the MSA level¹⁶ to account for common shocks to real estate markets in the same MSA. The effective number of observations for the purpose of computing standard errors of estimated parameters is on the order of the number of clusters, which is 983 in the full sample. Finally, we use the 5% level as the criterion for statistical significance.

We do not include interest rates as regressors in our delinquency analysis because of two major complications. First, interest rates are endogenous to delinquency propensity. Second, our current dataset includes only initial and current interest rates, which may not be informative of the long-term interest rate

¹⁵ Loan maturity is not included in the list of regressors due to a lack of variation; 30-year loans comprise 93% of our sample (the majority of the remainder are 15-year and 40-year loans).

¹⁶ For observations where an address cannot be matched to any MSA, we form the clusters at the state level.

for variable-rate loans originated in recent years. We leave the full analysis of loan pricing to a separate paper. However, in Section V we consider the effects of interest rate on the differential delinquency rates across demographic groups.

B. Probit Analysis

The probit regression specification is as follows:

$$\begin{aligned} \text{Delinquency}_i^* &= X_i\beta + \varepsilon_i; \\ \text{Delinquency}_i &= 1 \text{ if } \text{Delinquency}_i^* \geq 0; = 0 \text{ otherwise.} \end{aligned} \quad (1)$$

In equation (1), Delinquency_i^* is the underlying propensity of delinquency, and Delinquency_i is an indicator variable for actual delinquency.

We conduct the analysis separately for each of the four subsamples, and report the results in Table 2. We report the estimated coefficients of the probit model (β) and standard errors robust to clustering at the MSA level. We also report estimates of the average partial effects (APE), where the APE is defined as:

$$\text{APE} = E(\partial \Pr(\text{Delinquency}_i = 1 | X_i) / \partial X_i). \quad (2)$$

Our estimates of the APE are the empirical analog to the expression above:

$$\widehat{\text{APE}} = \hat{\beta} \frac{1}{n} \sum_{i=1}^n \phi(X_i \hat{\beta}), \quad (3)$$

where $\phi(\bullet)$ is the standard normal probability density function. The APE associated with a covariate is determined by both the underlying sensitivity of delinquency propensity to this covariate (β) and the sample distribution of all covariates (the sample average of $\phi(X\beta)$).

[Insert Table 2 here.]

C. Duration Analysis

In our duration analysis, we define the start of a spell as when the loan is originated; the failure of the spell is when the loan first becomes delinquent, and the duration of the spell is the time from loan origination to the first incident of delinquency. The duration of the spell is right censored if the loan is in good standing at the end of our sample period (the end of January 2009). The duration time is parameterized as follows:

$$\ln(t_j) = X_j\beta + \varepsilon_j. \quad (4)$$

We adopt the log-logistic distribution (very close to the log-normal distribution) for the “accelerated time” $\tau_j = \exp(-X_j\beta)t_j$. Accordingly, (4) can be re-expressed as:

$$\ln(t_j) = X_j\beta + \ln(\tau_j). \quad (5)$$

Moreover, the survival function is:

$$S(t_j) = \left[1 + \{\exp(-X_j\beta)t_j\}^{1/\gamma} \right]^{-1}. \quad (6)$$

In this model, the coefficient β has a semi-elasticity interpretation; that is, $\beta = \partial[\ln(t)] / \partial X$. A positive coefficient means that a higher value of the covariate is associated with a longer time to delinquency or equivalently a *lower* propensity to default within any given time span.

It is worth noting that the parameter γ in the survival function (6) provides flexibility on the duration dependence of the model, which is an attractive feature of the log-logistic specification. If $\gamma \geq 1$, the hazard rate is monotonically decreasing. That is, the instantaneous propensity to delinquency (conditional on the loan being in good standing up to that time) decreases over time. If $\gamma < 1$, then the hazard increases and then decreases over time. Moreover, a lower γ value is associated with a later peak in the higher hazard rate and a higher overall hazard rate for any given value of $X\beta$.

We estimate separately for the four subsamples the duration model using the maximum likelihood method; the results are reported in Table 3. In addition to reporting the estimated β coefficients and their standard errors, we also report the marginal effect of a one-unit change in the covariate (from the mean values) on the expected median duration of the spell (according to the survival function given by (6)).

[Insert Table 3 here.]

Though the probit and duration analyses are closely related, they examine somewhat different aspects of the propensity to delinquency. In the probit analysis, all loans that are delinquent at any point in time during the sample period are treated the same. While the probabilistic results are intuitive, they do not capture the accuracy of duration, i.e., the time from origination to delinquency. On the other hand, a duration analysis does not distinguish a pool of loans with a low occurrence of quick delinquency from another pool of loans with higher delinquency rates but where delinquency tends to occur among more seasoned loans. For these reasons, the two sets of results complement one another. When they are mutually consistent, our discussion will focus on the probit results because they are easier to interpret. The following sections provide a detailed discussion of the results from both tables, along with additional analyses.

III. Loan Types and Attribution of Differences in Delinquency

This section discusses the differences in loan performance across loan type: origination channel (Bank vs. Broker) and documentation level (Full-Doc vs. Low-Doc). We further analyze two related issues: First, which covariates determine a borrower's choice of loan type? Second, how can we decompose the differential delinquency rates across loan types into differences due to observable characteristics versus unobserved heterogeneities?

A. Differences in Loan Performance by Loan Type

A prominent feature of our results is that broker-initiated loans exhibit much higher delinquency rates than bank-initiated loans, as evidenced by the subsample summary delinquency rates at the bottom of Table 2. The difference in the probabilities is greater than 10 percentage points, a difference that is statistically and economically highly significant, indicating serious conflicts of interest in the brokerage channel where the loan originators' incentive is to maximize fees and commissions without bearing the long-term consequences of low-quality loans.¹⁷

The contrasts among subsamples are even more striking in the duration model. The median duration times (in months) reported at the bottom of Table 3 reveal that a loan originated with full documentation by the bank has a median life of 25 years (300 months) before delinquency; the same median lifetime drops steeply to 8.4 years for Bank/Low-Doc loans, and to 7.9 years for Broker/Full-Doc loans. Finally, the median life is a mere 4.6 years for Broker/Low-Doc loans.

The comparison of the delinquency propensity between Bank/Low-Doc and Broker/Full-Doc loans is not straightforward. While the former have a considerably lower overall delinquency rate, their median time to delinquency is comparable to the latter (the difference is not statistically significant). Moreover, the γ estimate (reported at the bottom of Table 3) is in fact smaller for the Bank/Low-Doc subsample than for the Broker/Full-Doc subsample, indicating a higher hazard rate in the former, conditional on covariates. Such a combination implies that, conditional on delinquency, the borrowers from the Bank/Low-Doc channel go into delinquency more quickly. Plausibly, a borrower who will default quickly after loan origination should be easier to screen out than a borrower who defaults years into the life of the loan. Therefore, low documentation leads to financing some of the more "obvious" low-quality borrowers.

B. Choice of Loan Origination Channel and Documentation Level

¹⁷ Using data on loans originated in Florida in 2002, LaCour-Little (2009) shows that brokered loans tend to have higher interest rates (about 20 basis points) than loans available directly from retail lenders. Alexander, Grimshaw, McQueen, and Slade (2002) document that brokered loans originated during 1996-1999 in a multi-lender sample were 15% more likely to be delinquent than loans in the same sample that were originated through the retail channel of the banks. The two studies do not contain the level of borrower detail in this study.

Differences in loan performance by loan type raise the question of how borrowers select into different types of loans. Theoretically, a borrower living in any location can apply for a loan directly from the bank. In regions where the bank does not have branch operations, the loan application can be completed via phone or internet. Therefore, obtaining a loan from a broker represents a choice made by the borrower, or a lack of knowledge about available alternatives. The same can be said for choosing a low documentation loan. Table 4 reports our model results in two panels. Panel A uses only loan and borrower characteristics as regressors, while Panel B adds neighborhood characteristics to the list of covariates. The sample size for Panel B is about 25% smaller due to the additional data requirement.

[Insert Table 4 here.]

Column 1 of Table 4 Panel A indicates that the following variables predict a higher likelihood that a borrower will obtain a loan from a broker rather than from the bank: high debt level, original purchase (as opposed to refinance), first lien, first-time owner, owner-occupied, low income, low credit score, female borrower, minority borrower, young borrower, short employment tenure, and self-employed. All non-white racial groups favor the Broker channel in comparison to whites. Most of these characteristics (except perhaps the first-lien and self-employed variables) are associated, on average, with lower financial sophistication, less experience with mortgages, and lower credit quality. This relation calls attention to the issue of irresponsible lending--lending without due regard to ability to pay, to poorly informed borrowers--as analyzed by Bond, Musto, and Yilmaz (2008) and Inderst (2006).

The variables that predict choosing a low-doc loan have the following contrasts with those that predict choosing a broker. First, borrowers with low loan-to-value (LTV) ratios but high loan size are more likely to choose low documentation. Second, first-time owners and those purchasing owner-occupied properties are less likely to choose low documentation. Third, borrowers with high income and credit scores tend to choose low documentation. Fourth, black borrowers do not appear disproportionately in low documentation loans, while Hispanic and Asian borrowers do. Finally, age is not correlated with documentation level. To summarize, low documentation loans do not necessarily attract less-experienced borrowers. The most prominent summarizing feature of these borrowers seems to be that they are “good on paper.” That is, borrowers who have favorable “hard” information (i.e., information that is quantifiable and could potentially be verified, such as LTV, prior mortgage experience, high income, and high credit score) choose low documentation.

Prior research has shown that lending practices and borrower characteristics are correlated with neighborhood characteristics (e.g., Calem, Gillen, and Wachter (2004), Nelson (2009)). Table 4 Panel B reports the relation between neighborhood characteristics and the respective likelihoods that a borrower will select the broker channel or apply for a low-doc loan. The model’s regressors include average per capita income (*Avgincome*) at the zip code level, and also include the following regressors at the census

tract level: Log population size (*Population*)¹⁸, percentage of residents who are black (*Pctblack*) and Hispanic (*Pcthispan*), median age (*Medage*), and unemployment rate (*Unemprate*). All regressors included in the model reported in Table 4 Panel A are also included in the model reported in Panel B, but are not tabulated for economy of space.

Brokers seem to predominate in neighborhoods with low minority representations and young residents. The combination of results from Panels A and B indicates that minority households in non-minority neighborhoods are the prime clients of mortgage brokers. Low documentation loans, on the other hand, are significantly more popular in minority neighborhoods and in booming neighborhoods (with low unemployment rates) with young populations.

C. Decomposition of Pairwise Subsample Differences in Delinquency

When researchers try to examine the effect of a variable, they often include the variable as a regressor and estimate its contribution in explaining the outcome. Following this logic, we could estimate a regression model that includes loan type as a regressor:

$$Delinquency_i^* = X_i\beta + \lambda LoanType_i + \varepsilon_i, \quad (7)$$

where *LoanType* indicates the origination channel or documentation status. We refrain from conducting such an analysis because a specification like (7) is meant to capture a “treatment effect,” where the relevant question is: if two *ex ante* identical borrowers--along both observable and unobservable dimensions--were assigned to different loan types, how would their delinquency propensity differ *ex post*?

We argue that there is no conventional “treatment effect” of the loan types in our context because all loans are serviced by the bank, regardless of the origination channel and documentation level. As a result, any difference in the outcome that is correlated with loan type should be attributed solely to the “selection effect”; that is, borrowers of different observable and unobservable characteristics are attracted to different loan types, and such characteristics are correlated with delinquency propensities.

The dichotomy between observable qualities and unobserved heterogeneities has implications for understanding why delinquency rates vary across subsamples. For example, if the higher delinquency rates in the Broker subsamples are predictable from observed characteristics (such as LTV and credit score), we could conclude that the Broker channel serves an observably lower-quality clientele, or applies looser lending standards than the Bank channel. If unobserved heterogeneity is responsible for the difference, then we infer that the Broker channel is subject to more severe adverse selection among potential borrowers along unobserved or unquantifiable dimensions (such as income stability, or hidden expenditures), presumably because mortgage brokers are less diligent than bank employees in using

¹⁸ The average and median population size of a census tract is between 5,000 and 6,000 residents.

additional hard or soft information to screen borrowers. The same logic applies to the Full-Doc/Low-Doc comparison.

We apply a non-linear version of the Blinder-Oaxaca (1973) decomposition to the probit model to separate the effects of observable qualities from the effects of unobserved heterogeneities. Let $D = \{0, 1\}$ be the index for the two subsamples for comparison, and let Y be the indicator variable for loan delinquency. More specifically, we will compare loans from the Bank ($D = 0$) and Broker ($D = 1$) channels, controlling for the documentation level, and loans issued as Full-Doc ($D = 0$) and Low-Doc ($D = 1$), controlling for the origination channel. We obtain coefficient estimates for all subsamples from the probit model as specified in equation (1) and reported in Table 2.

The difference in the delinquency rates between two subsamples can be expressed as:

$$\begin{aligned} E(Y|D=1) - E(Y|D=0) \\ = \left\{ E[\Phi(X\beta^0)|D=1] - E[\Phi(X\beta^0)|D=0] \right\} + \left\{ E[\Phi(X\beta^1) - \Phi(X\beta^0)|D=1] \right\}, \end{aligned} \quad (8)$$

or as:

$$\begin{aligned} E(Y|D=1) - E(Y|D=0) \\ = \left\{ E[\Phi(X\beta^1)|D=1] - E[\Phi(X\beta^1)|D=0] \right\} + \left\{ E[\Phi(X\beta^1) - \Phi(X\beta^0)|D=0] \right\}. \end{aligned} \quad (9)$$

Equations (8) and (9) are numerically different but employ the same logic. The left sides of the equations are the difference in the expected value of the outcome variable (delinquency) between the two subsamples. The right sides of the equations feature a sum of two terms. In labor economics, the first term is called the “endowment effect”; that is, the difference in the outcome due to different distributions of the covariates (the X variables) in the two subsamples. The difference due to the endowment is isolated by using the same set of coefficients for both subsamples. The second term is called the “coefficient effect” (in a production function, the coefficients are also referred to as “returns to factors”) and estimates the hypothetical difference in delinquency if the two subsamples had identical covariate distributions but the coefficients remained different. The coefficient effect encompasses two possibilities: a differential sensitivity of the outcome to the covariates in the underlying model, or the effects of missing variables that spill over to the remaining covariates. Both possibilities reflect unobserved heterogeneity.

Equations (8) and (9) differ only because they use a different subsample as the “base” sample. There is no *a priori* argument to favor using one subsample versus the other as the base, so we report both sets of results in Table 5. Table 5 Panel A reports the comparison of Full-Doc ($D = 0$) versus Low-Doc ($D = 1$) loans separately for the Bank and Broker channels. The total difference (the left sides of the above equations) is reported in the bottom row, and is, by construction, 100% of the difference. The “Low-Doc sample as benchmark” comparison applies equation (8) and uses the $D = 1$ subsample as the base; the “Full-Doc sample as benchmark” comparison applies equation (9) and uses the $D = 0$ subsample

as the base. The t-statistics are based on standard errors obtained through the block bootstrap clustered at the MSA level.¹⁹

[Insert Table 5 here.]

The two sets of results are qualitatively similar, so we focus on the first set of results (equation (8)) for discussion. Conditional on the Bank (Broker) channel, Low-Doc loans have, on average, a delinquency rate that is 4.8 (8.0) percentage points higher than for Full-Doc loans. Almost 100% of this difference should be attributed to the “coefficient effect”. The estimated “endowment effect” is small and is not statistically significant; if anything, the “endowment effect” indicates that Low-Doc loans are of slightly better observed quality. We conclude that Low-Doc loans are just as “good on paper” as Full-Doc loans, but encompass more adverse selection along unobserved dimensions.

The comparison between Bank and Broker loans conditional on documentation level (reported in Table 5 Panel B) offers a different picture. Here, the endowment effect accounts for three-quarters (over half) of the total difference in delinquency rates between Bank and Broker loans using the Broker (Bank) subsample as the base sample. Put differently, if the bank and its brokers had loaned to borrowers of the same *observable* quality, more than half of the difference in the incremental delinquency rate between the Broker and Bank subsamples (10.4 percentage points for Full-Doc, and 13.6 percentage points for Low-Doc) would have disappeared.

The implications stemming from the higher delinquency rates among Broker and Low-Doc loans are markedly different. The Low-Doc channel does not necessarily compromise lending standards along verifiable metrics (such as LTV and credit score), but suffers from less careful verification of some reported information (such as income and owner-occupancy status), or less diligent screening of borrowers along hard-to-quantify measures (such as other major expenditures). On the other hand, the Broker channel--while also lacking incentives for careful screening--penetrated a borrower pool that was of significantly worse quality, even by observable, quantifiable, and potentially verifiable standards.

The following hypothetical example illustrates the differences in borrower profiles across loan type. Suppose Borrower A has a high credit score and high income but has major withholding from his income (such as alimony); Borrower B has high income that is difficult to verify (because he is self-employed) or is unwilling to reveal his true income (because of tax reasons); and Borrower C has a low credit score and does not have a stable job or income. Our analysis predicts that borrowers A and B are more likely to choose low-doc loans, while Borrower C is more likely to approach (or be approached by) a mortgage broker.

¹⁹ The conventional delta method for computing standard errors does not apply. The estimator is a function of the model coefficients that depends on the sample distribution of covariates, and thus is a stochastic function of the coefficients. In contrast, the delta method applies when the estimator is a nonstochastic function of the model coefficients.

Among all borrower characteristics, credit score has the highest predictive power for delinquency and is verified for full-documentation as well as for low- or no-documentation loans. Exploring the relationship between credit score and other covariates sheds additional light on the composition of borrowers in different subsamples. The results we report in Table 6 confirm our interpretation of results in Tables 4 and 5. We find that Low-Doc borrowers have, on average, higher credit scores than Full-Doc borrowers. Moreover, credit score and reported income and cash reserves are strongly related in the Full-Doc subsamples, but the relation is much weaker in the Low-Doc subsamples. The fact that reported income and cash reserves may not be certified in the Low-Doc subsample may explain their weakened relationship with credit score, an issue we discuss in more detail in Section IV.

[Insert Table 6 here.]

An examination of credit scores by race reveals that average credit scores are highest among Asian and white borrowers, and lowest among Hispanic and black borrowers. Hispanic borrowers who obtain loans directly from the bank have credit scores that are comparable to those of white borrowers, but those who obtain loans through a broker have credit scores that are on average 2-5 points lower. Black borrowers have average credit scores that are 14-27 points lower than white borrower credit scores, across all subsamples. Section V offers a more detailed analysis of these race/ethnicity effects.

Last, the time trend of credit scores, as shown by the year dummy variable coefficients, is informative; while Bank loans saw steady improvement in credit scores over time from 2004-2008, credit scores for Broker loans deteriorated from 2004-2007, and only recovered in 2008. The findings provide evidence that the bank pursued a growth strategy which relied on penetrating marginal borrowers through the broker channel.

D. Differences within the Broker Channel

We differentiate within the Broker channel between pure brokers and correspondents. Pure brokers act as matchmakers and submit loan applications to a variety of banks for competitive pricing. In contrast, the correspondents in our sample have long-term, established, and near-exclusive relationships with the bank for at least one product type (such as prime loans) and abide by the bank's particular underwriting guidelines in exchange for expedited loan processing. Correspondents in our sample close loans in their own name using a warehouse line of credit advanced by the bank, and then quickly re-sell the loans to the lending bank. Due to the longer and more exclusive relationships, the incentives of the correspondents are more aligned with that of the bank than pure brokers.

To examine the difference between the two groups of brokers, we estimate the probit model (equation (1)) for correspondents and non-correspondents separately, interacted with the Full-Doc/Low-Doc sorting. The double sorting produces four subsamples. We report the results in Table 7.

[Insert Table 7 here.]

A comparison of Table 7 to Table 2 confirms our conjecture. The patterns revealed in the Correspondent subsamples are always between those of the Bank subsamples and those of the Non-Correspondent subsamples, and tend to be closer to the former. For example, total delinquency rates for Correspondent loans are marginally higher than for Bank loans (5 percentage points higher for both Full-Doc and Low-Doc loans), but are much lower than for the Non-Correspondent subsamples (5.7 percentage points lower for Full-Doc, and 15.1 percentage points lower for Low-Doc). Also, there are more commonalities in the relations between loan performance and individual covariates among the Bank and Correspondent subsamples than among the Correspondent and Non-Correspondent subsamples.

IV. Liar’s Loan: Model Predictive Power and Information Falsification

The “liar’s loan” problem includes various forms of borrower information falsification, possibly at the encouragement of brokers who have stronger incentives to close deals than to screen applicants. Such falsification appears primarily among low- or no-documentation loans, where much of the recorded information is self-reported without strict verification. Anecdotal evidence²⁰ suggests that the following falsifications are among the most common: exaggerating income or assets, hiding other major expenditures, and claiming that properties purchased for investment/speculation purposes will be owner-occupied as primary residences.

Despite the mounting anecdotes, there are no formal empirical analyses of borrower information falsification and its impact on loan performance. Our paper fills this void by presenting two pieces of analysis. First, we use model predictive power as an aggregate measure of the quality of information recorded at loan origination. Second, we offer evidence of the falsification of individual variables by exploring how their relationship to loan performance differs between the Full-Doc and Low-Doc subsamples.

A. Model Predictive Power across Different Loan Types

Inaccurately recorded loan and borrower characteristics, whether due to unintentional mistakes or due to intentional falsification, will attenuate the empirical relationship between these variables and loan performance, thereby compromising the model’s fit and predictive power. Because the bank services and

²⁰ See, for example, “My Personal Credit Crisis” by Edmund Andrews, which appeared in the *New York Times* on May 17, 2009. The author provides a detailed description of his personal experience in qualifying for a loan far beyond his financial means by hiding, forging, and strategically managing information with the help of his mortgage broker.

maintains records for all loans in our sample, there is no obvious reason to believe that incidences of random data recording error should vary systematically across the subsamples after loan origination. This leaves intentional falsification (including hiding) of information as the most plausible explanation for differences in model predictive power across loan type.

In Tables 2 and 3, we observe that the goodness-of-fit (i.e., the in-sample model predictive power) is indeed substantially different across the four subsamples. More specifically, the two Full-Doc subsamples have much higher pseudo R-squared statistics (22.1% and 18.2% for Bank and Broker subsamples using probit, or 17.4% and 16.2% using duration, respectively) than the two Low-Doc subsamples (13.6% and 14.6% using probit, or 14.1% and 14.5% using duration), indicating higher quality explanatory variables in the Full-Doc subsamples. Here the reported pseudo R-squared is $(1 - \ln L / \ln L_0)$, where $\ln L$ is the maximized log likelihood value of the probit or duration model using all covariates, and $\ln L_0$ is the maximized log likelihood value of the same model on the same sample, but with a constant as the sole regressor.

The pseudo R-squared discussed above is the most popular goodness-of-fit measure for non-linear models for which there are no obvious empirical analogs to the residuals. Nevertheless, it suffers from two major drawbacks. First, it does not have an interpretation as intuitive as the R-squared metric for linear models, which indicates the percent of variation explained. Second, the in-sample goodness-of-fit should not be equated with model predictive power. When economic agents (the bank or mortgage brokers) make decisions, their predictions are based on information revealed at the time, without knowledge of the full sample. Therefore, an out-of-sample prediction method is more appropriate for our research purposes, because it avoids the look-ahead bias. With these two issues in mind, we develop the following “excess percentage of correct predictions” measure to assess the predictive power of the probit model.

Let P_i denote the predicted probability of delinquency for the i -th observation, where the prediction is made out-of-sample (to be described in more detail later). Let Y_i denote an indicator variable for delinquency, and let \bar{p} denote a cutoff value. Then the objective to maximize “correct predictions” can be expressed without loss of generality as:

$$S = \omega S_1 + (1 - \omega) S_2 - \alpha = \omega \Pr(P_i \geq \bar{p} | Y_i = 1) + (1 - \omega) \Pr(P_i < \bar{p} | Y_i = 0) - \alpha \quad (10)$$

for some $\omega \in (0,1)$, which reflects the relative importance of a type-I error (failure to predict a delinquent loan) and a type-II error (mistakenly predicting that a non-delinquent loan will be delinquent); α is a

constant representing the maximum probability of obtaining a correct prediction with a random guess . The maximization of (10) has a unique solution of \bar{p} :²¹

$$\bar{p} = \frac{(1 - \omega)E(Y)}{\omega[1 - E(Y)] + (1 - \omega)E(Y)} . \quad (11)$$

A natural choice of ω is 1/2, where the objective function weights the two types of prediction errors equally. Under such a criterion, equation (11) simplifies to $\bar{p} = E(Y)$, with the corresponding empirical analog being the sample frequency of delinquency revealed at the time of the evaluation.²² According to this rule, we classify a loan as “predicted to be delinquent” if the out-of-sample predicted probability exceeds the time-adapted sample frequency of delinquency.

Such a classification method has the desirable feature of coinciding with the likelihood ratio rule if the probit model is correctly specified. Let f^D (f^{ND}) be the density functions of the predicted probability of delinquency for the subsample of loans that are *ex post* delinquent (non-delinquent). Then for any value v , $f^D(v) > f^{ND}(v)$ if and only if $v > E(Y)$, as long as the model is correctly specified, i.e., as long as equation (1) holds with the residual ε normally distributed. In other words, the two density functions $f^D(v)$ and $f^{ND}(v)$ have a single crossing at $v = E(Y)$. As a result, $P_i > E(Y)$ implies that the i -th observation is more likely to be drawn from the subsample of *ex post* delinquent loans than from that of the *ex post* non-delinquent loans, and therefore should be classified as “predicted to be delinquent” based on the relative likelihood. The opposite applies when $P_i < E(Y)$.²³

Finally, the percentage of correct predictions should be judged against the benchmark of a non-informative model, which produces correct predictions half of the time in expectation when $\omega = 1/2$. As a result, we set $\alpha = 1/2$ in equation (10) to obtain the “excess percentage of correct predictions.”²⁴

We use the following empirical procedure to calculate the out-of-sample excess percentage of correct predictions. First, we divide each of the four subsamples into semi-year segments by the loan origination date, and pick one semi-year segment at a time to measure the accuracy of the model predictions. We call this the “test sample/period.” Second, for each “test period,” we use all information available up to just before the test period to estimate the model in equation (1) without the year dummy variables²⁵; we call this the “estimation sample/period.” It is important to emphasize that not only do the loans in the estimation sample have to be originated before the test period, but their delinquency status must also be assessed at the beginning of the test sample period. Third, we apply the predictive model

²¹ The proof of equation (11) is in the appendix.

²² Another natural choice of ω is $Pr[Y=1]=E(Y)$, which would lead to maximizing the un-weighted fraction of predictions correctly predicted. Under such a criterion, equation (11) simplifies to 1/2.

²³ The proof of this argument is in the appendix.

²⁴ For general values of ω , the corresponding α parameter is equal to $\max(1 - \omega, \omega)$.

²⁵ Time dummy variables should be omitted from any out-of-sample predictions because they are not applicable for future samples.

using the coefficients estimated from the estimation sample on the test sample to form the predicted probability of delinquency. Finally, equation (10) formulates the calculation of the final measures.

Table 8 reports the percentage of correct predictions by subsample for each semi-year, separately for S_1 , S_2 , and S as defined in equation (10). The test periods start from the first half of 2005 to allow for a prior estimation period.

[Insert Table 8 here.]

Two patterns evident in the table warrant further discussion. First, loan documentation type--not loan origination channel--is the key determinant of the model's predictive power. Figure 4 depicts model predictive power by plotting the time series of the excess percentage of correct predictions (S) by loan type. The model's predictive power in the Bank/Full-Doc and Broker/Full-Doc subsamples is indistinguishable in each semi-year; the same can be said about the model's predictive power in the Bank/Low-Doc and Broker/Low-Doc subsamples. More importantly, the model's predictive power in the Full-Doc subsamples is substantially higher than for the Low-Doc subsamples. The across-time averages are as follows: Bank/Full-Doc (17.2%), Bank/Low-Doc (11.5%), Broker/Full-Doc (18.1%), and Broker/Low-Doc (11.1%). Such a contrast suggests that low documentation loans may allow some borrowers to falsify information in order to qualify for loans or obtain more favorable loan terms. As a result, some of the variables in the regressions could contain measurement errors, compromising their predictive power.

[Insert Figure 4 here.]

Second, the predictive power of the model--especially for the Full-Doc subsamples--declined from 2005 to 2006, before rebounding slightly in 2007. This trend suggests that loans originated during the boom period experienced positive shocks in delinquency that could not be predicted by their characteristics based on information available at the time of loan origination. Rajan, Seru, and Vig (2009) also find that the predictive power of credit score and LTV deteriorated during the high securitization period.²⁶ The difficulty in predicting loan performance based on observed characteristics for loans originated in 2006 indicates the bank may not have been aware it was originating low-quality loans during that time period; this explains why the bank did not tighten its lending standards until 2007, when it began to incur losses from loans originated during the boom.²⁷

B. Evidence of Borrower Information Falsification from Individual Variables

²⁶ We find that the deterioration in model predictive power is more prominent among full-documentation loans, while Rajan, Seru, and Vig (2009) found it to be stronger among low documentation loans. The difference could be due to our use of a larger set of covariates in the prediction and a different metric of model predictive power, and our use of a more recent sample which begins and ends later than theirs.

²⁷ Please also see Figure 3.

B1. Overview

The model's lower predictive power for Low-Doc subsamples relative to Full-Doc subsamples provides strong evidence that the information recorded for low-documentation loans is of lower quality. The lower predictive power is an aggregate measure of the quality of the recorded information, but it does not reveal which particular variables are mis-measured. We now present evidence that borrowers of low-documentation loans tended to falsify particular variables, especially income. We find that such falsification is especially prominent among Broker/Low-Doc loans.

Due to both incentives and the reporting system, falsification is most likely to occur in the following variables. First, borrowers purchasing a second home or investor property could falsely claim that the property will be owner-occupied and used as a primary residence, thereby securing a lower interest rate. While lenders are often able to verify occupancy status for refinance loans by requiring the borrower to submit proof of residence (such as utility bills), lenders are unable to verify occupancy status for home purchase loans at origination. Occupancy fraud is often cited as a major contributor to the surge in delinquencies, as borrowers became over-leveraged from holding multiple mortgages.

Second, low-documentation loans enabled borrowers to falsify employment information--including employment tenure and self employment status--as well as income, asset, expense, liability, and debt information. For many low-documentation loans, lenders do not verify borrowers' financial conditions by requiring a history of bank statements, W-2 forms, asset documentation (such as retirement, savings, or investment account information), or outstanding debt documentation (including student loan information, mortgage statements, credit card statements, and information on judgments/liens resulting from legal action). Borrowers who want to qualify for higher loan amounts or more desirable loan terms through a lower reported debt-to-income ratio could overstate their income and assets, and/or understate expenses and other debt liabilities.

B2. Income Falsification

The coefficients on *Income* in Tables 2 and 3 support the hypothesis that reported income was often falsified by borrowers of Low-Doc loans.²⁸ In the Full-Doc subsamples, higher income is significantly and negatively associated with delinquency, as measured by both lower probability of delinquency and longer duration to delinquency conditional on all other attributes. However, the sign on the *Income* coefficient switches in the Low-Doc sub-samples. Moreover, the coefficients are particularly strong in the Broker/Low-Doc subsample where higher income is associated with significantly higher propensity for delinquency. The most plausible explanation for this contrast is that, when income is not verified, higher income (conditional on all other attributes) may more often be the result of exaggeration

²⁸ In the regression, the *Income* variable is coded as zero when it is missing, and the dummy variable for missing income information, *IncomeMiss*, is set equal to one.

rather than financial strength. Reported income will have a positive sign in the delinquency prediction regressions if the incentive to exaggerate income is negatively correlated with individual credit quality.

The dummy variable for missing income information, *IncomeMiss*, offers corroborative evidence. In the Bank/Full-Doc and Broker/Full-Doc subsamples, only 0.6% and 0.9% of the observations have missing income information, and in these subsamples missing income information does not predict loan performance. Thus, in the Full-Doc subsamples, the sporadic cases of missing income information most likely result from data recording error and not from falsification. In contrast, income is missing for 10.3% and 9.2% of the observations in the Bank/Low-Doc and Broker/Low-Doc subsamples, respectively. Missing income information significantly predicts higher delinquency propensity in the Broker/Low-Doc subsample, where missing income information is associated with a 4.7 percentage point increase in the probability of delinquency, or an 8 month reduction in the time from loan origination to delinquency. The same effect is present but not significant in the Bank/Low-Doc subsample. Thus, purposefully not reporting income information is a low-documentation-only phenomenon. Presumably, borrowers with low or irregular incomes in the Low-Doc subsamples are more likely than comparable High-Doc borrowers to exaggerate or omit their incomes on the loan application.²⁹

In comparing Table 2 and Table 7, it is worth noting that the various perverse relations discussed above for broker-originated loans are mostly driven by non-correspondent brokers. This evidence suggests that correspondents are far less likely to encourage or accommodate borrower information falsification than non-correspondents because the former have stronger reputation concerns due to their exclusive or long-term relationships with the bank.

What is the magnitude of income falsification by borrowers when income is self-reported? While we are not able to pin down the exact number for any individual, it is possible to form some conservative estimates for the average extent of income falsification based on the following identifying assumption:

$$E(\text{Income}^* | X = x, \text{Low-Doc}) \leq E(\text{Income}^* | X = x, \text{Full-Doc}); \quad (12)$$

where *Income*^{*} denotes the borrower's true income, and *X* denotes a vector of borrower characteristics. Formally, equation (12) is implied by the condition that $Pr(\text{Full-Doc} | X, \text{Income}^*)$ is non-decreasing in *Income*^{*}.

All that is required for equation (12) to hold is a relative preference ordering: if Borrower A's true income is more favorable than Borrower B with similar characteristics, then on average A should not have a stronger preference for low-documentation loans than B. In general, such an assumption is

²⁹ Some high-income borrowers may also have an incentive to hide income information when applying for "no ratio" mortgages (a type of low-documentation loan). By not stating their income, ratios such as debt-to-income would be left unreported. Such an omission allows a borrower to achieve higher leverage through multiple mortgages.

plausible because a high certified income is more likely to result in lower interest rates or more favorable loan terms on full-documentation loans, while some of these benefits are forfeited in low-documentation loans because the sensitivity of loan pricing to uncertified income is lower. Self-reported income could still materially affect the qualification of the loan application, providing an incentive for falsification.

The only group for whom equation (12) may plausibly not hold is the self-employed. Self-employed borrowers disproportionately choose low-documentation loans (see the more detailed analysis in Section III and the results in Table 4), not necessarily because they want to exaggerate their income but because their income is often difficult to certify (e.g., they do not have W-2 forms) or they do not wish to reveal their true cash flows for tax reasons. We therefore exclude the self-employed from our estimation of the extent of income exaggeration among borrowers of low-documentation loans.

Our first estimate of the extent of income exaggeration comes from simply comparing borrower income (at the household level) to the average income of the neighborhood where the property is located. We obtain the average per capita adjusted gross income information at the zip code level from the Internal Revenue Service's Individual Master File (IMF) system for the years 2004, 2005, and 2006. A zip code area has, on average, 2,326 households, and the average household size is 3.3 people. We use 2006 data for loans originated in the post-2006 years. The average ratios of borrower household income to the neighborhood average income per capita are 3.6 and 3.3 for the two Full-Doc subsamples, and are considerably higher at 4.3 and 3.8 for the two Low-Doc subsamples. Thus, assumption (12) implies that the average degree to which low-documentation borrowers exaggerate their income is at least 16%-19%, if their true income stands at a ratio to their neighborhood average that is no higher than their full-documentation counterparts.

A more refined estimate incorporates borrower demographics in addition to neighborhood attributes to proxy the true income ($Income^*$). Suppose a borrower's $Income^*$ can be expressed as a linear function of borrower characteristics, neighborhood characteristics, year dummies and an error term, with the error term mean independent of covariates conditional on documentation status. Then such a function could be estimated reliably using the sample of full-documentation loans because there should be no systematic bias in the recorded income given that it is certified; hence, $Income \approx Income^*$. Below is the regression output from full-documentation loans, where the dependent variable is the reported (and certified) household monthly income in \$1,000 units and the t-statistics are reported below the coefficients.

$$\begin{aligned}
Income = & 0.014 * CreditScore - 0.846 * Female + 0.651 * \ln(Age) - 0.416 * Hispanic \\
& [18.01] \quad [-16.49] \quad [13.31] \quad [-1.92] \\
& - 0.430 * Black + 0.575 * Asian + 0.051 * AvgIncome - 0.030 * Unemprate \\
& [-4.31] \quad [5.04] \quad [4.40] \quad [-2.15] \quad (13) \\
& + 0.131 * Y2005 + 0.373 * Y2006 + 0.299 * Y2007 + 0.010 * Y2008 \\
& [2.58] \quad [5.40] \quad [4.76] \quad [0.096] \\
\text{R-squared: } & 6.9\%; \text{ number of observations: } 138,514.
\end{aligned}$$

All coefficients in the above regression are intuitive. Older borrowers and borrowers with higher credit scores tend to have higher income. Female borrowers have lower income on average.³⁰ Black and Hispanic borrowers have lower income on average than white borrowers, and Asian borrowers as a group have the highest income. In addition, borrower income is significantly and positively correlated with the zip-code area average income (*AvgIncome*) and negatively correlated with the census tract unemployment rate (*Unemprate*). Finally, overall borrower income grew from 2004 (the omitted year in the regression) to 2006, and then decreased afterwards.

Resorting to the identifying assumption of (12)--which presumes that the error term from regression (13) is not positively correlated with Low-Doc status--we can estimate the upper bound for the expected true income of low-documentation borrowers by applying the estimated coefficients from (13) to the covariates of these borrowers. We generate an “income exaggeration” variable to capture the difference between the reported *Income* and the estimated *Income**. We find that in dollar terms the average (median) income exaggeration is \$1,830 (\$753) per month; in percentage terms, the average (median) low-documentation borrower reports income that is 28.7% (20.0%) above their estimated true income level. Given that these estimates err on the conservative side, the data suggest serious income falsification among low-documentation borrowers from the benchmark of full-documentation borrowers.

The correlations between estimated true income, estimated income exaggeration and loan performance are all highly statistically significant, and reveal more about the incentives for and consequences of income falsification. First, the correlation between the estimated true income and estimated income exaggeration in percentage terms is -7.9%, indicating a stronger incentive to inflate income when the true income is lower. Second, the correlation between the estimated true income and *ex post* delinquency is -23.5%, recovering the normal inverse relationship between income and delinquency in the Low-Doc subsample that was perverted using reported income (see Tables 2 and 3). Finally, as expected, the correlation between estimated income exaggeration and *ex post* delinquency is positive at

³⁰ This gender effect is not primarily due to the male-female wage gap, but rather to the fact that a female being listed as the sole borrower is a proxy measure for a female head of household; female-headed households have lower income on average than male-headed households.

8.2%. In other words, delinquency risk increases when borrowers inflate income to obtain a loan beyond their true means.

B3. Evidence of Other Information Falsification

Additional important variables for delinquency prediction, which potentially can be falsified in the absence of certification, are *OwnerOccupied* (a dummy variable for whether the property is owner-occupied as a primary residence) and *CashResv* (the borrower's cash reserves in multiples of the monthly mortgage payment, in logs). Mortgages on owner-occupied properties are usually considered to be safer than properties purchased as investments or second homes; the latter are often purchased by borrowers who have higher combined leverage and who have a lower cost of "walking away" from a mortgage that has negative equity value. Cash reserves help pull households through temporary negative income shocks without disrupting mortgage payments.

The coefficients on both variables in Tables 2 and 3 reveal patterns that are generally intuitive: owner occupancy and high levels of cash reserves are associated with significantly lower delinquency propensity. However, the coefficients that represent sensitivity of delinquency propensity to both variables are stronger in the Full-Doc subsamples than in the Low-Doc subsamples,³¹ and the difference is more evident using the duration method than the probit model. Hence, there is some evidence that Low-Doc borrowers may not always truthfully report owner occupancy status and cash reserves, thereby lowering the explanatory power of these variables. Yet the evidence is weaker and less conclusive than that regarding income falsification.

Our conversations with bank officials yield two explanations for the higher quality of cash reserve information relative to income information in explaining delinquency. First, borrowers and brokers have better information about how income affects loan qualification and pricing, so they have a stronger incentive to falsify income. Second, verification of assets is often better than that of income because asset statements are more available than proof of income for a large group of borrowers, especially those who are self-employed or cash compensated.

V. "The Color of Credit:" Race/Ethnicity and Loan Performance

There is a large body of research dedicated to exploring disparate impact on minorities in credit markets and in the mortgage market in particular. A common challenge in this line of research is

³¹ For this context, we resort to the comparison of the β coefficients in equations (1) and (2), rather than the partial effects. This is because the partial effects are a function of both the sensitivity of the outcome to the regressor (the coefficients) and the subsample average outcomes (delinquency rates). See equation (3).

distinguishing between the effects of disparate impact and discrimination, because most researchers pursuing this question do not have access to the full set of variables to predict loan pricing and performance (see Ross and Yinger (2002) for a full analysis of challenges in identifying racial discrimination in the mortgage market).

As an example, the landmark Boston Fed Study (Munnell, Tootell, Browne, and McEneaney (1996)) found that race strongly predicted loan approval among applicants even after controlling for a long list of personal characteristics and individual risk factors, though their estimated race effects were smaller than those found in earlier studies employing a smaller set of control variables. Yet their study did not include other important covariates--such as credit score--which strongly predict loan performance, and did not have information on *ex post* loan performance. Thus, the study was unable to conclude whether the disparate loan approval rates across race resulted from legitimate economic considerations or from discrimination. Our findings complement this line of prior research by including additional covariates and by relating loan performance to race/ethnicity.

In the full sample, the ranking of delinquency rates by race/ethnicity is as follows: white (24.7%), Asian (27.1%), black (37.4%), and Hispanic (40.2%). Controlling for observable characteristics, the black-white (2.8 to 5.2 percentage points) and Hispanic-white (5.9 to 8.3 percentage points) differences are statistically significant at the 1% level in all four subsamples, while the Asian-White differences (-1.1 to 1.1 percentage points) are not significant even at the 10% level. Notably, the difference in the delinquency rates between white and black/Hispanic borrowers is more than 50% higher in the Broker subsamples than in the Bank subsamples.

We must also control for loan pricing in order to attribute these delinquency differences to race/ethnicity. If certain racial/ethnic groups pay higher interest rates conditional on other characteristics, then the heavier payment burden could cause higher delinquency. Such a concern is warranted by prior research on consumer financing. Charles, Hurst, and Stephens (2008) show that blacks pay significantly higher rates when financing a new car, in large part because blacks are more likely to use more expensive financing companies. Similarly, Ravina (2008) finds that black borrowers in an online lending market pay rates that are over 100 basis points higher than comparably risky white borrowers. Much of the difference can be attributed to favorable interest rates obtained in same-race lender-borrower pairings and the underrepresentation of black lenders. In the context of mortgage lending, price differences could occur by pricing a given product differently for borrowers from different demographic groups, but more likely occurs through steering uninformed borrowers into more costly products, such as subprime loans, when more attractive products are available; or through aggressive negotiation strategies used by brokers to enhance their fees and commissions (known in the industry as yield spread premiums).

We next examine the determinants of interest rates to assess the importance of the pricing effect. While we focus on the race/ethnicity variables, we also include all other variables that appear in the delinquency analysis (reported in Tables 2 and 3). Our sample includes both fixed- and adjustable-rate loans, and we have information on the initial and current (updated to 2008) rates. To ensure the rates are comparable across observations, we analyze the following two dependent variables on select samples: the current interest rate on the full sample, and the initial interest rate for loans originated in 2004 and 2005 that have not incurred a rate change up to 2008. The second sample is meant to approximate a sample of fixed-rate loans. We conduct the analysis separately for different loan types, and report the results in Table 9.

[Insert Table 9 here.]

We find no evidence that black or Hispanic borrowers pay higher initial or current interest rates on bank-originated loans, conditional on observable individual risk factors. However, among broker-originated loans, black borrowers appear to pay higher rates, on the order of 10-16 basis points, while there is no clear evidence that Hispanic borrowers are subject to higher loan pricing. While the coefficients on *Black* are significant and positive in the Broker subsamples, the magnitudes are much lower than those documented in other credit markets (e.g., Charles, Hurst, and Stephens (2008) and Ravina (2009)). The estimated gender effect is insignificant throughout, both in terms of loan pricing and loan performance. Our results are closer to findings in Courchane (2007) and Haughwout, Mayer, and Tracy (2009) that there is no significant adverse pricing by race, ethnicity, or gender in the pricing of mortgage credit after controlling for other observable differences.

Our data suggest that loan pricing is an unlikely explanation for the higher delinquency rates observed among black and Hispanic borrowers. Black borrowers exhibit higher delinquency rates relative to white borrowers, even for bank-originated loans for which we find no evidence of unfavorable pricing. The average (median) unpaid balance on loans among black borrowers is \$185,000 (\$150,000). Thus, the estimated black-white difference in interest rate among broker-originated loans--10-16 basis points--amounts to an additional monthly payment of \$15-\$25 (or \$13-\$20) using the mean (or median) balance. It is unlikely that such a difference could be pivotal in loan delinquency. Moreover, Hispanic borrowers exhibit the highest delinquency rates in our sample among all demographic groups, although there is no evidence that they face unfavorable interest rates in comparison to other groups.

Previous work sheds light on the unobserved risk factors that are correlated with race/ethnicity variables. First, blacks and Hispanics have lower savings rates on average than whites of similar age, education and income (Blau and Graham (1990), Charles, Hurst, and Roussanov (2007)). As a result, they accumulate less wealth (often difficult to measure), making them more vulnerable to adverse economic shocks. Second, minorities are less likely to have family or relatives who can help when they

have trouble meeting their mortgage payments (Yinger, 1995). Third, Guiso, Sapienza, and Zingales (2009) offer an interesting explanation for the highest delinquency rates observed among Hispanic borrowers. Based on survey data, the authors find that Hispanics are much less likely (between 18 and 27 percentage points) than blacks or whites to feel morally or socially obligated to continue paying their mortgages when the equity value is significantly below zero.

Historically, policymakers and researchers concerned with mortgage lending discrimination have focused on two key issues: unequal access to credit (i.e., disparities in loan approvals and denials) and pricing disparities. While we do not examine differences in mortgage approvals by race, our analysis suggests that the housing boom fueled a rapid expansion of credit among Hispanic and black borrowers.³² Moreover, the share of first-time borrowers among black and Hispanic households grew from 10% in early 2004 to 25% in late 2006. In addition, we find little evidence of pricing discrimination as a cause for loan delinquency. Taken together, the findings suggest that market dynamics and credit expansionary practices during the sample period may have alleviated some of the inequalities in credit access and pricing. Yet the *ex post* loan performance data suggests that such credit expansion was achieved largely through lowered lending standards, particularly among brokers originating low-documentation loans. The persistence of Hispanic and black race effects in the delinquency models raises further questions, including whether such borrowers were well-informed about the mortgage process and possessed the requisite experience and knowledge to continue making their mortgage payments in full and on time.

VI. Conclusion

This paper uses a unique, proprietary data set from a major national mortgage bank to examine how mortgage loan performance relates to loan origination channel, documentation level, and borrower demographics. Our research aims to identify and quantify the micro-level fundamental causes of the mortgage crisis, and highlights two agency problems. The first agency problem arises between the bank and its mortgage brokers, who originate observably lower quality loans. We find that brokered loans are more than 50% more likely to be delinquent than bank-originated loans, and that approximately three-quarters of this difference can be attributed to lower borrower/loan quality based on observable risk factors. The second agency problem arises between lenders and borrowers, and results in borrower information falsification among low-documentation loans, especially when issued through a broker. We

³² Recall from Table 1 that Hispanic borrowers experienced the fastest growth in newly originated loans during our sample period, followed by black borrowers.

find poor model predictive power and strong evidence of information falsification among low-documentation loans.

Our analysis raises the question of why this major mortgage bank—as well as other market players—allowed such deterioration in borrower and loan quality to persist before tightening its lending standards. A plausible explanation is that the expansion of the secondary mortgage market and the ease of loan securitization weakened the bank’s incentive to screen borrowers by allowing the bank to offload risk. We refer the readers to Keys, Mukherjee, Seru and Vig (2008) for an analysis on the relation between loan performance and the *ex ante* probability of loan securitization, and to Jiang, Nelson, and Vytlačil (2009) for a contrast between the *ex ante* and *ex post* relation of the two.

Appendix:

1. Proof of equation (11):

Let f^D (f^{ND}) be the probability density functions of the predicted probability of delinquency for the subsample of loans that are *ex post* delinquent (non-delinquent), and f be the probability density function for the combined sample.

Suppose the model is correctly specified, i.e., equation (1) holds with the residual ε normally distributed. We have $E(P) = E(Y)$ by the Law of Iterated Expectations. By Bayes Rule and the Law of Iterated Expectations we have:

$$f^D(v) = \frac{vf(v)}{E(Y)}; f^{ND}(v) = \frac{(1-v)f(v)}{1-E(Y)}, \quad (14)$$

for all $v \in [0,1]$.

Equation (14) implies:

$$\Pr(P \geq \bar{p} | Y = 1) = \int_{\bar{p}}^1 f^D(v)dv = \int_{\bar{p}}^1 \frac{vf(v)}{E(Y)} dv = \frac{[1-F(\bar{p})]}{E(Y)} E(P | P \geq \bar{p}). \quad (15)$$

Similarly,

$$\Pr(P < \bar{p} | Y = 0) = \int_0^{\bar{p}} f^{ND}(v)dv = \int_0^{\bar{p}} \frac{(1-v)f(v)}{1-E(Y)} dv = \frac{F(\bar{p})}{1-E(Y)} E(P | P < \bar{p}). \quad (16)$$

We obtain (11) by substituting (15) and (16) into (10).

2. Proof that equation (11) satisfies the likelihood ratio property:

Using equation (14) and the fact $Var(Y) = E(Y)[1-E(Y)]$, we have:

$$f^D(v) - f^{ND}(v) = f(v)Var(Y)[v - E(y)]. \quad (17)$$

Thus,

$$\begin{aligned} f^D(v) - f^{ND}(v) &> 0 \text{ if } v > E(y), \\ &= 0 \text{ if } v = E(y), \\ &< 0 \text{ if } v < E(y). \end{aligned} \quad (18)$$

Therefore, $f^D(v)$ and $f^{ND}(v)$ cross once at $v = \bar{p} = E(Y)$. With such a choice of \bar{p} , we classify a loan as “predicted to be delinquent” if and only if it is more likely to be from the distribution of *ex post* delinquent loans than from that of the *ex post* non-delinquent loans. Hence the classification satisfies the likelihood ratio rule.

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Figure 1. Geographic Distribution of Properties in the Sample

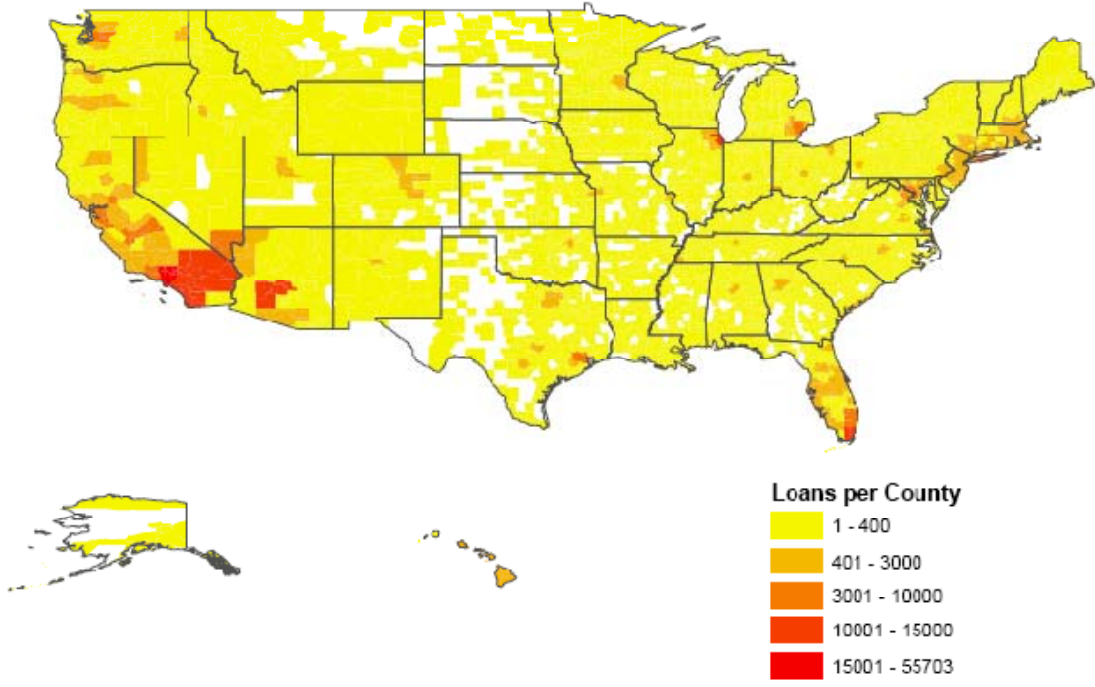


Figure 2. Number of Loans and Composition by Semi-Year: 2004-2008

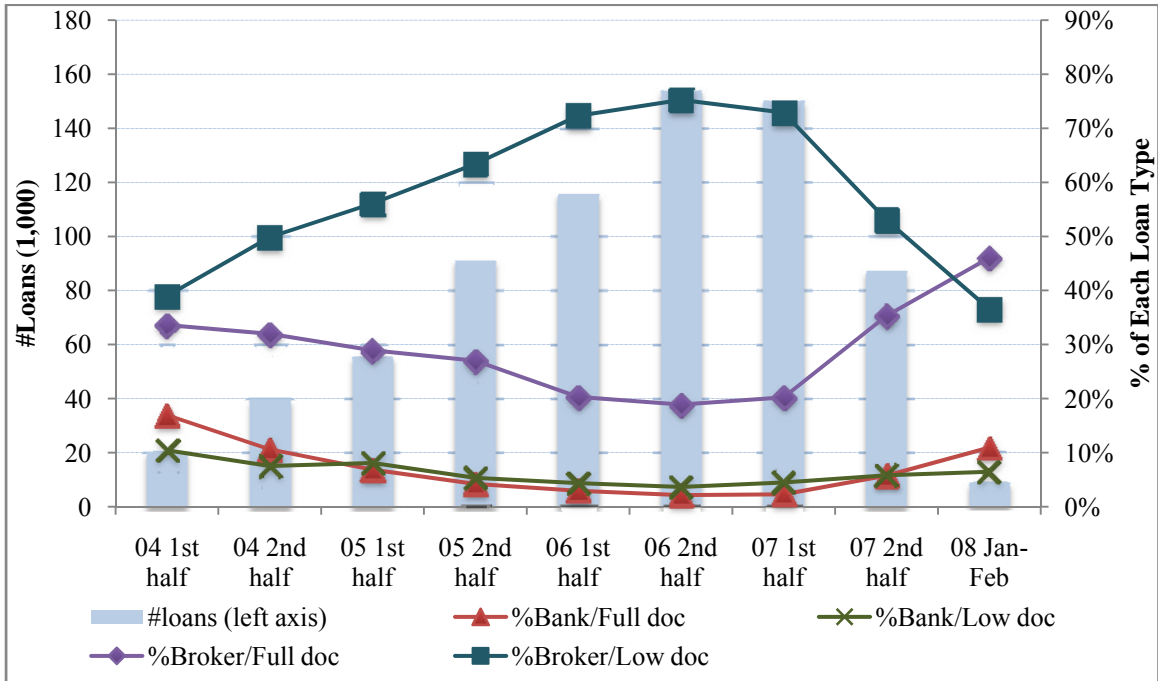


Figure 3. Delinquency Rates since Loan Origination by Semi-Year: Updated to January 2009

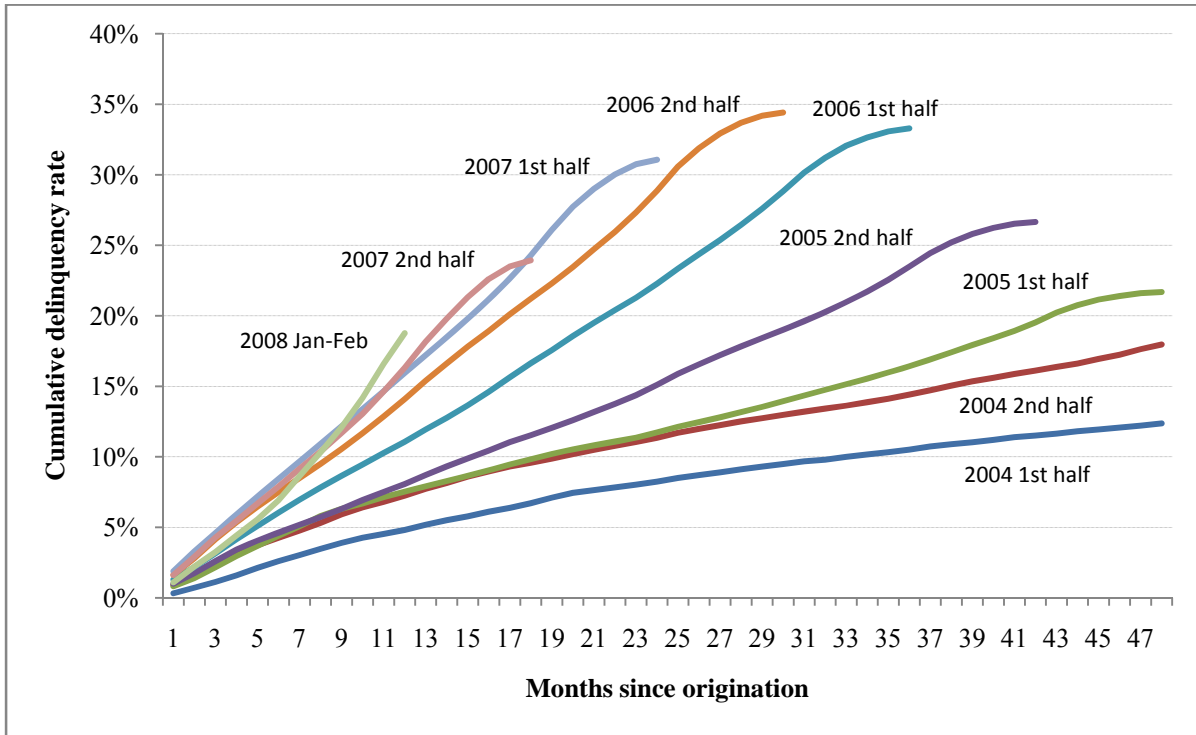


Figure 4. Time Series of Out-of-Sample Model Predictive Power by Loan Type

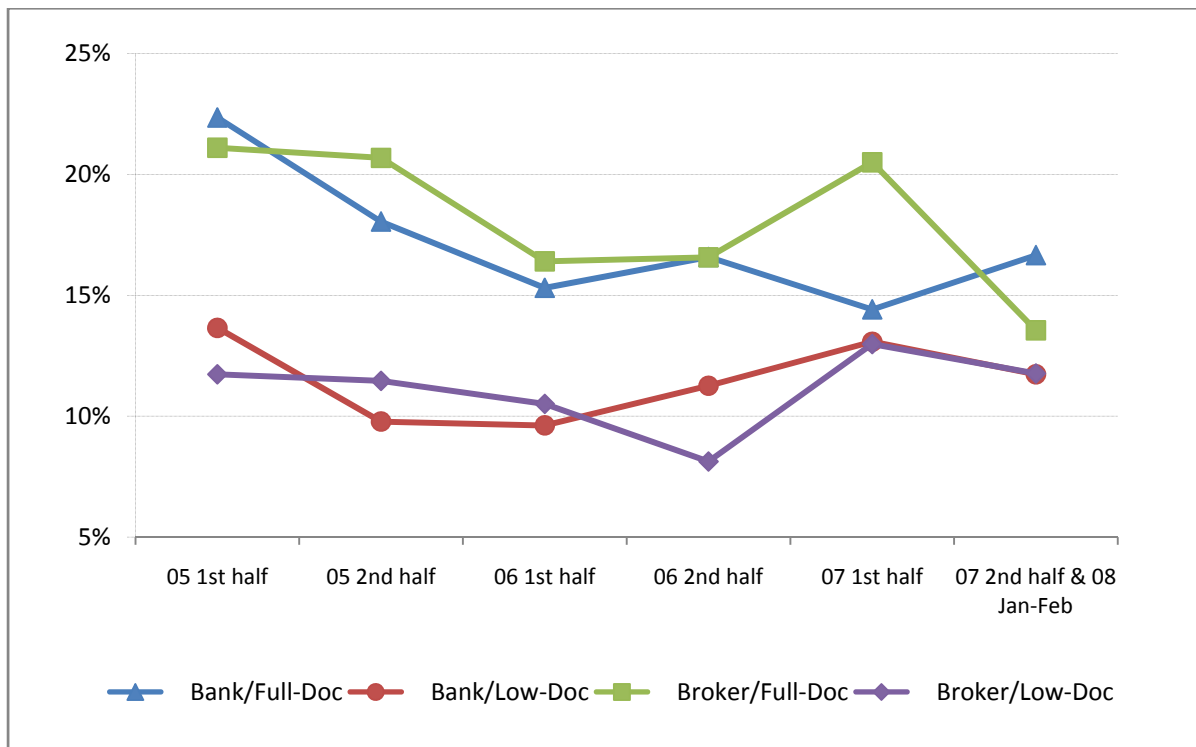


Table 1. Variable Definitions and Summary Statistics

Panel A: Definitions of main variables

	Definition
AddLTV	The ratio of additional loans (including from other banks) secured to the property to the property value
Age	Age of the borrower
Asian	Dummy variable = 1 if the borrower is Asian
Avgincome	Average income per capita of the census tract where the property is located
Black	Dummy variable = 1 if the borrower is black
Cashresv	Cash reserves, in multiples of monthly mortgage payments
Delinquency	Dummy variable for delinquency, defined as being at least 60 days behind in payment
Female	Dummy variable = 1 if the borrower is female
CreditScore	Borrower's credit score
CurrRate	The current interest rate (updated in February 2008) on the loan
FirstTimeOwner	Dummy variable = 1 if the borrower is a first-time mortgage borrower
Hispanic	Dummy variable = 1 if the borrower is Hispanic
Income	Monthly income of the borrower in \$1,000
IncomeMiss	Dummy variable = 1 if the income information is missing
InitialRate	Initial interest rate on the mortgage
Loan	Total loan amount
LTI	Loan-to-income ratio, the percentage of monthly gross income that is used to pay for the mortgage
LTV	Loan-to-value ratio
Medage	Median age of residents in the census tract where the property is located
OneBorrower	Dummy variable = 1 if there is only one borrower on the mortgage
OwnerOccupied	Dummy variable = 1 if the property is the owner's primary residence
Pctblack/Pcthispanic	Proportion of black/Hispanic households in the census tract where the property is located
Population	Population size of the census tract where the property is located
PrepayPenalty	Dummy variable = 1 if there is hard prepayment penalty in the loan contract
Refinance	Dummy variable = 1 if the mortgage is for refinancing
Secondlien	Dummy variable = 1 if the mortgage is a second-lien
SelfEmploy	Dummy variable = 1 if the borrower is self-employed
Subsample1	Bank/Full-Doc subsample
Subsample2	Bank/Low-Doc subsample
Subsample3	Broker/Full-Doc subsample
Subsample4	Broker/Low-Doc subsample
Tenure	Number of months that the borrower has been employed in the current job
TenureMiss	Dummy variable = 1 if the tenure information is missing
Unemprate	Unemployment rate in the census tract where the property is located

Panel B: Summary statistics

This table reports the mean, median and standard deviation (the first, second, and third line of each variable) values of the major variables by semi-year from 2004 to early 2008. Their definitions are in Panel A. “1st” and “2nd” indicate the first and second half of each year.

	04 1st	04 2nd	05 1st	05 2nd	06 1st	06 2nd	07 1st	07 2nd	08 Jan-Feb
Age (years) (average)	44.9	44.2	44	43.3	42.9	42.9	43.8	45.6	45.42
(median)	44	43	43	42	42	42	43	45	45
(std. dev.)	11.6	12.5	12.4	12.3	12.6	12.7	12.7	12.6	12.6
Credit score	703	697.5	698.8	696.9	692.2	695.1	695.5	697.5	699.5
	707	700	699	695	689	692	694	698	701
	60	61.3	58.3	56.2	53	53.6	55.9	59.3	62.2
Income (\$1,000, monthly)	7.1	6.9	6.9	7.3	7.7	8	8.7	8	7.3
	5.5	5.5	5.5	5.8	6.3	6.5	6.3	5.7	5.6
	8.6	11.7	8.6	22.1	9.4	10.5	187.1	21.6	10.1
Initial rate	5.3%	5.5%	4.9%	5.4%	6.1%	6.7%	7.2%	7.2%	6.8%
	5.6%	6.0%	5.8%	6.0%	6.6%	6.9%	6.9%	7.0%	6.8%
	1.7%	2.3%	2.5%	2.7%	3.0%	2.8%	2.2%	1.2%	0.8%
Loan size in \$1,000	235.7	230.9	253.7	263.9	260.2	271.3	275.5	296	282.1
	192	192	217	225	223.2	231.1	232	251.8	256.5
	165.1	162.9	166.1	187.1	189.5	202.8	214	223.1	177.2
Loan-to-income	25.5%	24.4%	25.3%	25.0%	25.3%	26.8%	31.2%	32.4%	34.7%
	23.1%	22.2%	22.9%	23.0%	23.0%	24.9%	30.7%	32.0%	33.7%
	13.8%	13.3%	13.3%	13.4%	14.0%	14.6%	14.5%	15.3%	15.0%
Loan-to-value	69.3%	70.6%	72.6%	69.5%	67.2%	66.9%	65.3%	74.6%	77.1%
	75.0%	78.1%	79.4%	79.4%	79.2%	79.8%	78.4%	80.0%	80.0%
	16.9%	18.3%	14.7%	19.3%	21.8%	22.6%	24.1%	19.0%	17.3%
Tenure (months)	100.2	94	90.7	85.2	81.6	80.8	83.2	91	93.8
	60	60	60	57	50	50	51	60	60
	98.3	95.1	92.4	90	86.7	86.3	89.4	95.2	94.6

	04 1st	04 2nd	05 1st	05 2nd	06 1st	06 2nd	07 1st	07 2nd	08 Jan-Feb
%Asian	5.1%	5.7%	5.6%	5.8%	5.5%	4.8%	5.0%	5.2%	4.2%
%Black	4.5%	6.3%	6.7%	7.2%	8.1%	8.4%	8.9%	9.9%	10.3%
%Black & Hispanic that are first-time owners	10.3%	13.5%	14.1%	19.7%	23.9%	25.2%	24.5%	17.6%	20.9%
%Female	28.8%	32.6%	30.8%	32.5%	32.8%	34.2%	34.7%	35.4%	36.0%
%First-time owner	7.6%	10.8%	11.3%	14.7%	16.8%	18.1%	17.5%	12.7%	15.5%
%Hispanic	7.5%	10.6%	13.1%	15.6%	20.0%	19.2%	23.3%	21.8%	23.5%
%Owner occupied	86.1%	84.2%	84.8%	84.4%	84.6%	86.7%	85.4%	81.8%	88.3%
%Refinance	71.2%	56.0%	59.3%	54.7%	55.4%	54.7%	58.7%	66.9%	65.3%
%Self-employed	18.2%	18.5%	18.2%	18.0%	20.2%	19.7%	21.4%	22.6%	20.5%

Table 2. Delinquency Prediction: Probit Analysis

The dependent variable is loan delinquency, and the estimation method is probit. The definitions of all variables are given in Table 1 Panel A. Reported are the coefficients (Coef), t-statistics (t-stat) that adjust for clustering at the MSA level, and the average partial effects (APE). At the bottom of the table, we report the sample frequency of delinquency, the pseudo R-squared, the number of observations and the number of clusters (at the MSA level).

	1			2			3			4		
	Bank/Full-Doc			Bank/Low-Doc			Broker/Full-Doc			Broker/Low-Doc		
	Coef	t-stat	APE	Coef	t-stat	APE	Coef	t-stat	APE	Coef	t-stat	APE
LTV	1.693	14.61	36.15%	2.480	19.41	56.35%	2.028	17.81	50.99%	3.021	19.15	91.45%
AddLTV	1.467	7.24	31.32%	1.566	7.44	35.57%	1.665	15.98	41.84%	2.975	24.28	90.05%
Loan (log)	0.113	4.08	2.42%	0.178	7.23	4.04%	0.214	8.83	5.38%	0.252	8.78	7.64%
SecondLien	0.245	1.78	5.22%	0.729	6.23	16.56%	0.498	8.07	12.52%	0.297	3.79	9.00%
Refinance	-0.046	-1.08	-0.97%	-0.038	-1.32	-0.86%	-0.050	-2.15	-1.25%	0.097	5.49	2.94%
PrepayPenalty	0.111	2.1	2.37%	0.028	0.7	0.63%	0.005	0.26	0.12%	0.082	6.38	2.49%
FirstTimeOwner	-0.186	-4.2	-3.97%	-0.072	-1.17	-1.63%	-0.010	-0.61	-0.24%	-0.054	-3.81	-1.62%
OwnerOccupied	-0.259	-5.31	-5.53%	-0.275	-8.18	-6.24%	-0.350	-13.75	-8.79%	-0.281	-10.31	-8.51%
OneBorrower	0.267	12.81	5.70%	0.346	15.34	7.87%	0.292	19.32	7.34%	0.298	17.07	9.03%
Income (log)	-0.108	-6.91	-2.30%	0.023	1.32	0.53%	-0.064	-4.33	-1.61%	0.041	4.75	1.26%
IncomeMiss	-0.033	-0.28	-0.71%	-0.006	-0.13	-0.14%	-0.160	-2.97	-4.02%	0.155	6.98	4.71%
CashResv	-0.047	-5.61	-1.01%	-0.027	-3.61	-0.60%	-0.090	-17.94	-2.27%	-0.069	-16.12	-2.10%
CreditScore	-0.009	-53.89	-0.18%	-0.008	-31.84	-0.17%	-0.008	-49.91	-0.21%	-0.007	-71.41	-0.21%
Female	-0.043	-1.71	-0.93%	-0.014	-0.75	-0.32%	-0.003	-0.2	-0.07%	0.003	0.34	0.08%
Hispanic	0.276	5.5	5.89%	0.219	3.78	4.98%	0.391	7.75	9.83%	0.275	10.55	8.33%
Black	0.129	2.74	2.76%	0.156	2.75	3.55%	0.167	5.16	4.21%	0.120	4.53	3.64%
Asian	-0.053	-0.52	-1.13%	-0.052	-1.05	-1.18%	0.022	0.69	0.55%	0.037	1.25	1.12%
Age (log year)	-0.089	-3.65	-1.90%	0.020	1.04	0.45%	-0.020	-1.64	-0.50%	0.005	0.57	0.16%
Tenure(log month)	-0.018	-2.01	-0.38%	-0.045	-5.25	-1.02%	-0.012	-1.87	-0.30%	-0.035	-6.95	-1.06%
TenureMiss	-0.072	-1.16	-1.54%	-0.174	-4.01	-3.95%	-0.251	-7.56	-6.32%	-0.266	-11.52	-8.07%

	1			2			3			4		
	Bank/Full-Doc			Bank/Low-Doc			Broker/Full-Doc			Broker/Low-Doc		
	Coef	t-stat	APE	Coef	t-stat	APE	Coef	t-stat	APE	Coef	t-stat	APE
SelfEmploy	-0.001	-0.03	-0.03%	0.053	2.82	1.20%	0.051	2.44	1.29%	0.000	-0.01	0.00%
2005	0.007	0.2	0.15%	0.155	3.99	3.52%	0.026	0.9	0.65%	0.138	5.28	4.18%
2006	0.018	0.49	0.39%	0.170	4.21	3.86%	0.053	1.13	1.34%	0.265	6.3	8.03%
2007	-0.188	-3.88	-4.02%	0.108	2.14	2.46%	-0.078	-1.48	-1.95%	0.167	3.85	5.05%
2008	-0.263	-4.07	-5.61%	-0.039	-0.49	-0.90%	-0.167	-2.8	-4.20%	0.048	0.88	1.46%
Constant	2.7901	7.82		0.231	0.75		1.00	2.53		-1.51	-4.17	
%Delinquency and (Pseudo) R-squared		0.132	0.221		0.180	0.136		0.236	0.182		0.316	0.146
# obs and # clusters		31,408	807		35,553	778		166,402	963		425,181	949

Table 3. Delinquency Prediction: Duration Analysis

The dependent variable is duration between loan origination and delinquency (or censored at the end of the sample) in months, and the estimation method is a duration model with a log-logistic distribution for the accelerated time. The definitions of all variables are given in Table 1 Panel A. Reported are the coefficients (Coef), t-statistics (t-stat) that adjust for clustering at the MSA level, and changes in the median survival time for a one unit change in a covariate while holding all other covariates at their sample mean levels ($\partial t/\partial x$). At the bottom of the table, we report the *gamma* coefficient and its standard error, the sample mean of median survival time and its standard deviation, the number of observations, and the pseudo R-squared. The number of clusters (at the MSA level) is the same as in Panel A.

	1			2			3			4		
	Bank/Full-Doc			Bank/Low-Doc			Broker/Full-Doc			Broker/Low-Doc		
	Coef	t-stat	$\partial t/\partial x$	Coef	t-stat	$\partial t/\partial x$	Coef	t-stat	$\partial t/\partial x$	Coef	t-stat	$\partial t/\partial x$
LTV	-2.730	-15.02	-804.84	-2.838	-23.39	-284.86	-2.641	-19.51	-249.19	-3.267	-34.08	-178.40
AddLTV	-1.773	-5.49	-522.68	-1.516	-9.27	-152.13	-1.952	-15.67	-184.20	-2.774	-35.27	-151.45
Loan (log)	-0.135	-3.31	-39.84	-0.193	-8.00	-19.33	-0.263	-9.4	-24.77	-0.237	-9.04	-12.95
SecondLien	-0.683	-3.07	-149.30	-0.953	-8.02	-63.67	-0.726	-8.94	-51.86	-0.553	-8.52	-24.73
Refinance	0.092	1.41	26.53	0.032	1.04	3.16	0.098	3.49	9.23	-0.087	-5.99	-4.79
PrepayPenalty	-0.149	-1.79	-41.13	0.014	0.32	1.45	0.064	2.77	6.16	-0.022	-1.98	-1.19
FirstTimeOwner	0.299	4.05	101.03	0.035	0.55	3.58	0.001	0.03	0.06	0.052	4.88	2.91
OwnerOccupied	0.338	4.83	89.73	0.262	8.32	24.87	0.430	10.51	34.62	0.302	9.58	14.87
OneBorrower	-0.417	-12.2	-121.26	-0.378	-14.23	-40.34	-0.370	-24.23	-35.91	-0.299	-13.89	-17.67
Income (log)	0.165	7.21	48.78	-0.009	-0.46	-0.93	0.079	3.86	7.43	-0.040	-4.89	-2.21
IncomeMiss	0.070	0.37	21.37	0.059	1.08	6.01	0.241	3.16	25.57	-0.156	-7.37	-8.26
CashResv	0.076	5.67	22.42	0.026	3.09	2.58	0.129	16.18	12.21	0.075	13.07	4.12
CreditScore	0.015	33.81	4.35	0.009	17.82	0.89	0.012	25.22	1.14	0.007	23.77	0.39
Female	0.072	1.77	21.46	0.012	0.56	1.18	0.005	0.32	0.50	-0.001	-0.15	-0.06
Hispanic	-0.393	-4.91	-98.47	-0.203	-3.65	-18.85	-0.385	-8.47	-31.83	-0.181	-10.12	-9.45
Black	-0.157	-2.08	-43.22	-0.166	-3.19	-15.44	-0.229	-5.38	-19.86	-0.149	-5.42	-7.65
Asian	0.063	0.39	19.15	0.077	1.48	8.06	0.010	0.26	0.98	0.000	0.00	-0.01
Age (log year)	0.187	4.71	55.06	-0.014	-0.71	-1.43	0.039	2.53	3.66	-0.014	-1.79	-0.77

	1			2			3			4		
	Bank/Full-Doc			Bank/Low-Doc			Broker/Full-Doc			Broker/Low-Doc		
	Coef	t-stat	$\partial t/\partial x$	Coef	t-stat	$\partial t/\partial x$	Coef	t-stat	$\partial t/\partial x$	Coef	t-stat	$\partial t/\partial x$
Tenure(log month)	0.025	1.61	7.22	0.045	5.00	4.56	0.009	1.26	0.86	0.028	6.36	1.55
TenureMiss	0.116	1.17	35.85	0.163	3.41	17.38	0.324	9.29	33.03	0.232	9.83	13.42
SelfEmploy	0.038	0.45	11.42	-0.047	-2.24	-4.70	-0.066	-2.27	-6.05	-0.008	-0.86	-0.45
2005	-0.208	-3.45	-58.24	-0.383	-9.17	-34.90	-0.190	-5.07	-17.06	-0.335	-15.5	-16.59
2006	-0.495	-8.25	-127.96	-0.694	-17.66	-61.72	-0.486	-8.4	-41.77	-0.750	-22.47	-38.71
2007	-0.660	-8.28	-170.11	-1.058	-20.27	-91.32	-0.743	-9.98	-64.47	-1.031	-27.05	-50.05
2008	-0.850	-8.76	-173.24	-1.350	-14.5	-75.94	-0.943	-11.44	-58.94	-1.400	-25.28	-41.57
Constant	-1.905	-3.02		3.284	8.35		1.430	2.51		5.192	15.61	
Gamma and std. err		0.866	0.021		0.614	0.021		0.747	0.018		0.577	0.021
Median time (months)		300.1			100.4			94.4			54.6	
#obs and (Pseudo) R-squared		31,400	0.174		35,550	0.141		166,399	0.162		425,180	0.145

Table 4. Choice of Loan Origination Channel and Documentation Level

Panel A: Without neighborhood information

The dependent variable is the choice of broker channel, that of low documentation, and that of the combination of two. The estimation method is probit. The definitions of all variables are given in Table 1 Panel A. Reported are the coefficients (Coef), t-statistics (t-stat) that adjust for clustering at the MSA level, and the average partial effects. At the bottom of the table, we report the average of the dependent variables (the sample frequency of the choices), and the pseudo R-squared.

Dep. Var.	1			2			3		
	Broker			Low-Doc			Broker Issue/Low Doc		
	Coef	t-stat	APE	Coef	t-stat	APE	Coef	t-stat	APE
LTV	0.372	5.14	5.67%	-0.773	-6.82	-19.68%	-0.506	-5.18	-14.91%
AddLTV	3.730	14.92	56.90%	0.411	3.31	10.48%	1.088	8.17	32.09%
Loan (log)	0.088	3.02	1.34%	0.220	11.46	5.61%	0.171	7.69	5.04%
SecondLien	-1.896	-10.84	-28.92%	-0.160	-2.17	-4.06%	-0.497	-5.92	-14.67%
Refinance	-0.146	-5.26	-2.23%	-0.053	-2.2	-1.35%	-0.092	-5.26	-2.72%
FirstTimeOwner	0.331	16.21	5.05%	-0.047	-2.71	-1.19%	-0.004	-0.26	-0.12%
OwnerOccupied	0.126	3.25	1.92%	-0.047	-3.07	-1.20%	0.082	3.1	2.42%
OneBorrower	0.217	18.38	3.31%	0.507	37.65	12.92%	0.449	39.55	13.24%
Income (log)	-0.038	-3.49	-0.57%	0.241	15.01	6.14%	0.218	12.55	6.43%
IncomeMiss	0.128	3.28	1.95%	2.270	56.13	57.80%	1.606	34.22	47.36%
CashResv	-0.015	-1.84	-0.23%	0.003	0.88	0.07%	-0.003	-0.85	-0.09%
CreditScore	-0.001	-14.22	-0.02%	0.002	13.93	0.05%	0.001	9.10	0.03%
Female	0.027	3.67	0.41%	0.150	11.1	3.82%	0.125	10.61	3.70%
Hispanic	0.448	13.53	6.84%	0.432	6.67	11.00%	0.475	8.66	14.02%
Black	0.439	15.57	6.70%	-0.030	-1.15	-0.77%	0.059	2.14	1.75%
Asian	0.485	18.38	7.41%	0.368	18.51	9.37%	0.443	25.73	13.06%
Age (log year)	-0.039	-3.72	-0.59%	0.001	0.06	0.01%	-0.013	-1.87	-0.39%
Tenure(log month)	-0.017	-4.55	-0.26%	-0.055	-9.6	-1.40%	-0.055	-9.53	-1.62%
TenureMiss	0.540	13.61	8.24%	-0.350	-9.66	-8.92%	-0.176	-4.8	-5.18%
SelfEmploy	0.208	8.8	3.18%	1.036	48.57	26.38%	0.775	27.6	22.85%
2005	0.339	12.98	5.18%	0.261	14.42	6.65%	0.306	16.99	9.01%
2006	0.443	12.73	6.77%	0.542	30.15	13.81%	0.544	26.01	16.05%
2007	0.419	17.44	6.40%	0.263	16	6.70%	0.318	15.55	9.38%
2008	0.196	5.3	2.99%	-0.329	-12.57	-8.38%	-0.234	-7.63	-6.89%
Constant	0.188	0.57		-4.213	-18.4		-3.577	-15.06	
E(Dependent Variable)		0.898			0.700			0.646	
#obs and (Pseudo) R-squared		658,544	0.149		658,544	0.265		658,544	0.201

Panel B: With neighborhood information

This table is identical to that in Panel A, with the addition of neighborhood covariates at the census tract or zip-code level. The definitions of all variables are given in Table 1 Panel A. For the economy of space and to avoid repetition, only results regarding the neighborhood variables are reported.

Dep. Var.	1			2			3		
	Broker			Low-Doc			Broker Issue/Low Doc		
	Coef	t-stat	APE	Coef	t-stat	APE	Coef	t-stat	APE
Population(log)	-0.006	-0.98	-0.10%	0.005	0.91	0.12%	-0.001	-0.14	-0.02%
Pctblack	-0.079	-4.69	-1.23%	0.055	2.97	1.39%	0.027	1.38	0.80%
Pcthisp	-0.055	-1.65	-0.86%	0.175	8.88	4.46%	0.143	6.41	4.22%
Medage	-0.002	-3.18	-0.03%	-0.001	-2.67	-0.03%	-0.002	-3.19	-0.04%
Avgincome	0.000	-0.51	0.00%	0.000	0.46	0.00%	0.000	0.66	0.00%
Unemprate	-0.001	-0.29	-0.01%	-0.006	-2.19	-0.15%	-0.007	-2.44	-0.19%
Other controls included?	Y			Y			Y		
E(Dep Var)	89.9%			69.9%			64.6%		
#obs and (Pseudo) R-squared	491,816 0.116			491,816 0.268			491,816 0.200		

Table 5. Non-Linear Blinder-Oaxaca Decomposition of Differences in Delinquency Rates

This table reports the non-linear Blinder-Oaxaca (1973) decomposition to the probit model. The total difference in delinquency rates between two subsamples is decomposed into an “endowment effect” and a “coefficient effect” using equations (8) (using the high average outcome subsample as the base) and (9) (using the low average outcome subsample as the base).

Panel A: Comparison of Full-Doc and Low-Doc subsamples

	Bank			Broker		
	Difference	t-stat	Percentage	Difference	t-stat	Percentage
Low-Doc sample as benchmark						
Endowment Effect	-0.06%	-0.10	-1.20%	-0.89%	-1.62	-11.10%
Coefficient Effect	4.87%	9.13	101.20%	8.91%	12.84	111.10%
Full-Doc sample as benchmark						
Endowment Effect	-2.10%	-2.37	-43.71%	-2.84%	-4.15	-35.47%
Coefficient Effect	6.91%	8.12	143.71%	10.86%	12.94	135.47%
Total Difference	4.81%	5.37	100%	8.02%	8.05	100%

Panel B: Comparison of Bank and Broker subsamples

	Full-Doc			Low-Doc		
	Difference	t-stat	Percentage	Difference	t-stat	Percentage
Broker sample as benchmark						
Endowment Effect	7.84%	8.09	75.69%	10.40%	12.16	76.67%
Coefficient Effect	2.52%	9.46	24.31%	3.16%	8.76	23.33%
Bank sample as benchmark						
Endowment Effect	6.12%	10.28	59.06%	6.93%	9.88	51.10%
Coefficient Effect	4.24%	5.74	40.94%	6.63%	9.45	48.90%
Total Difference	10.35%	10.51	100%	13.56%	13.99	100%

Table 6. Projections of Credit Score on Other Borrower Characteristics

The dependent variable is credit score, and the estimation method is OLS. The definitions of all variables are given in Table 1 Panel A. We report the coefficients (coef) and t-statistics (t-stat) that adjust for clustering at the MSA level.

	1		2		3		4	
	Bank/Full-Doc		Bank/Low-Doc		Broker/Full-Doc		Broker/Low-Doc	
	coef	t-stat	coef	t-stat	coef	t-stat	coef	t-stat
Income (log)	14.91	14.72	3.28	4.43	15.98	17.03	5.86	11.82
IncomeMiss	27.58	6.19	11.25	4.05	32.62	14.45	21.97	17.72
CashResv	13.84	14.45	8.43	14.84	16.77	45.48	8.16	30.13
Female	-11.13	-9.23	-5.16	-8.15	-5.61	-10.37	-3.12	-15.37
Hispanic	0.84	0.36	-2.12	-2.46	-5.39	-4.24	-2.30	-3.41
Black	-23.30	-13.79	-14.31	-7.76	-27.72	-20.47	-18.10	-17.48
Asian	14.03	3.46	9.19	6.02	14.10	11.49	8.35	10.23
Age (log year)	-0.44	-0.29	5.19	7.14	-4.05	-5.33	2.42	5.38
Tenure(log month)	0.90	2.49	1.33	4.58	-1.05	-3.49	0.27	1.67
TenureMiss	11.27	4.9	12.93	8.16	46.20	30.33	19.31	27.43
SelfEmploy	-1.53	-0.76	-3.52	-4.16	-1.78	-1.69	-6.87	-15.09
2005	6.37	4.69	1.45	1.24	-4.71	-3.89	-2.92	-5.57
2006	11.79	4.93	1.96	1.37	-9.58	-9.7	-7.39	-10
2007	18.68	8.43	7.71	5.94	-9.28	-7.07	-4.45	-4.72
2008	18.43	8.38	34.05	13.06	-14.04	-7.68	14.70	16.21
Constant	635.69	151.87	659.44	136.96	647.13	190.28	668.15	391.9
Average Credit Score	683.86		702.10		686.55		699.75	
#obs and R-squared	31,464	0.194	35,685	0.087	168,046	0.202	429,481	0.073

Table 7. Delinquency Analysis: Correspondent and Non-Correspondent Brokers

This table repeats the analysis in Table 2 using loans originated by brokers only, where the Broker channel is decomposed into Correspondent and Non-Correspondent channels.

	1			2			3			4		
	Correspondent/Full Doc			Correspondent/Low Doc			Non-Correspondent/Full Doc			Non-Correspondent/Low Doc		
	Coef	t-stat	APE	Coef	t-stat	APE	Coef	t-stat	APE	Coef	t-stat	APE
LTV	2.035	14.57	45.51%	3.154	16.05	90.78%	2.000	17.35	51.12%	2.973	20.65	91.02%
AddLTV	1.781	8.18	39.84%	3.260	18.82	93.82%	1.707	16.98	43.62%	2.929	25.83	89.66%
Loan (log)	0.140	3.3	3.13%	0.264	6.45	7.61%	0.232	9.22	5.94%	0.255	9.15	7.81%
SecondLien	0.278	2.05	6.22%	0.220	2.31	6.33%	0.490	7.65	12.53%	0.301	3.74	9.23%
Refinance	0.012	0.31	0.26%	0.128	3.72	3.69%	-0.062	-2.55	-1.57%	0.087	5.41	2.66%
PrepayPenalty	0.059	1.37	1.31%	0.068	2.99	1.95%	-0.015	-0.76	-0.38%	0.076	5.52	2.34%
FirstTimeOwner	-0.120	-3.86	-2.69%	-0.098	-4.12	-2.83%	0.003	0.18	0.07%	-0.048	-3.68	-1.47%
OwnerOccupied	-0.366	-8.23	-8.20%	-0.226	-5.64	-6.51%	-0.348	-13.17	-8.90%	-0.288	-10.89	-8.82%
OneBorrower	0.211	8.38	4.73%	0.281	14.01	8.08%	0.299	20.29	7.65%	0.300	17.5	9.18%
Income (log)	-0.059	-2.21	-1.32%	0.020	1.02	0.57%	-0.065	-4.04	-1.67%	0.043	5.24	1.32%
IncomeMiss	-0.042	-0.22	-0.94%	0.053	1.14	1.52%	-0.166	-2.91	-4.24%	0.174	7.8	5.32%
CashResv	-0.095	-8.92	-2.13%	-0.096	-14.94	-2.75%	-0.087	-17.22	-2.23%	-0.063	-13.39	-1.92%
CreditScore	-0.008	-31.1	-0.19%	-0.007	-50.26	-0.20%	-0.008	-45.74	-0.21%	-0.007	-66.9	-0.21%
Female	0.015	0.56	0.33%	0.014	1.15	0.41%	-0.007	-0.47	-0.18%	-0.001	-0.07	-0.02%
Hispanic	0.323	10.01	7.24%	0.360	10.93	10.36%	0.379	7.6	9.69%	0.254	10.11	7.76%
Black	0.152	3.99	3.40%	0.103	3.63	2.98%	0.167	5.19	4.26%	0.127	4.79	3.88%
Asian	0.075	1.49	1.67%	0.143	4.39	4.11%	0.010	0.29	0.25%	0.012	0.42	0.38%
Age (log year)	-0.021	-0.7	-0.47%	0.028	2.23	0.82%	-0.019	-1.58	-0.48%	0.004	0.42	0.12%
Tenure(log month)	0.007	0.74	0.15%	-0.015	-2.03	-0.44%	-0.018	-2.3	-0.45%	-0.041	-8.77	-1.24%
TenureMiss	-0.009	-0.15	-0.19%	-0.129	-4.13	-3.72%	-0.307	-7.87	-7.84%	-0.302	-11.95	-9.24%
SelfEmploy	0.033	0.62	0.74%	0.022	1.06	0.63%	0.057	2.51	1.45%	-0.001	-0.09	-0.03%
2005	0.049	0.97	1.11%	0.154	4.53	4.43%	0.028	0.92	0.71%	0.137	5.31	4.20%
2006	0.031	0.57	0.68%	0.247	5.7	7.10%	0.067	1.34	1.72%	0.271	6.29	8.30%
2007	-0.071	-1.17	-1.58%	0.161	3.28	4.63%	-0.082	-1.54	-2.10%	0.166	3.86	5.07%

	1			2			3			4		
	Correspondent/Full Doc			Correspondent/Low Doc			Non-Correspondent/Full Doc			Non-Correspondent/Low Doc		
	Coef	t-stat	APE	Coef	t-stat	APE	Ceof	t-stat	APE	Coef	t-stat	APE
2008	-0.153	-0.97	-3.42%	-0.094	-0.63	-2.70%	-0.189	-3.15	-4.83%	0.037	0.69	1.13%
Constant	1.706	3.02		-1.888	-4.44		0.83	1.99		-1.484	-3.93	
%Delinquency and (Pseudo) R-squared		0.189	0.171		0.180	0.161		0.246	0.184		0.331	0.143
# obs and # clusters		25,666	657		88,778	672		140,736	955		336,403	936

Table 8. Out-of-Sample Model Predictive Power: Across Loan Types and Over Time

This Table reports the “excess percentage of correct predictions” as defined in equation (10). We report percentage of delinquent loans correctly predicted (S_1), percentage of non-delinquent loans correctly predicted (S_2), and the total percentage of correct predictions in excess of 50% (S). Each measure is reported for the full sample, and separately for the four sub-samples, and is reported by semi-annual intervals, together with the all-sample average.

	05 1st half	05 2nd half	06 1st half	06 2nd half	07 1st half	07 2nd half & 08 Jan-Feb	All-Time Average
% Delinquency correctly predicted (S_1)	54.2%	54.4%	52.2%	42.5%	52.9%	46.1%	50.4%
Bank/Full-Doc	57.6%	46.6%	43.3%	46.7%	40.9%	50.1%	47.5%
Bank/Low-Doc	51.9%	43.3%	42.5%	48.3%	51.4%	44.0%	46.9%
Broker/Full-Doc	61.6%	67.3%	58.9%	56.6%	66.9%	54.2%	60.9%
Broker/Low-Doc	50.7%	51.0%	51.4%	39.7%	50.4%	41.5%	47.4%
% Non-Delinquency correctly predicted (S_2)	76.3%	73.9%	71.9%	76.9%	75.7%	78.9%	75.6%
Bank/Full-Doc	87.1%	89.5%	87.3%	86.5%	88.0%	83.2%	86.9%
Bank/Low-Doc	75.4%	76.2%	76.8%	74.3%	74.8%	79.5%	76.2%
Broker/Full-Doc	80.6%	74.1%	73.9%	76.5%	74.1%	72.9%	75.4%
Broker/Low-Doc	72.7%	71.9%	69.7%	76.6%	75.6%	82.0%	74.7%
Total Excess % of correct prediction (S)	15.3%	14.2%	12.1%	9.7%	14.3%	12.5%	13.0%
Bank/Full-Doc	22.4%	18.0%	15.3%	16.6%	14.4%	16.7%	17.2%
Bank/Low-Doc	13.7%	9.8%	9.6%	11.3%	13.1%	11.7%	11.5%
Broker/Full-Doc	21.1%	20.7%	16.4%	16.6%	20.5%	13.6%	18.1%
Broker/Low-Doc	11.7%	11.5%	10.5%	8.1%	13.0%	11.8%	11.1%

Table 9. Race/Ethnicity and Interest Rates

This table examines the determinants of interest rates, with borrower race/ethnicity as the main variable. In columns 1-4, the dependent variable is the initial interest rate, and the sample includes loans initiated in 2004 and 2005 that have not incurred an interest rate change by 2008 (a proxy for fixed-rate loans). In columns 5-8, the dependent variable is the current interest rate, and we use the full loan sample. Interest rates are expressed in percentage points. We report the coefficients, t-statistics (in brackets) that adjust for clustering at the MSA level.

Dep. Variable Subsample	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Initial Rate for Approximately Fixed-Rate Loans				Current Rate			
	Bank/	Full-Doc Bank/	Low-Doc Broker/Full-Doc Broker/	Low-Doc	Bank/Full-Doc Bank/	Low-Doc Broker/Full-Doc Broker/	Low-Doc	
Hispanic	-0.018	0.049	0.001	-0.019	-0.009	0.008	0.082	-0.059
	[-0.72]	[1.02]	[0.03]	[-1.09]	[-0.24]	[0.21]	[2.29]	[-3.21]
Black	-0.103	0.016	0.130	0.162	-0.058	0.027	0.101	0.115
	[-2.16]	[0.37]	[4.81]	[6.31]	[-1.51]	[0.70]	[5.11]	[5.69]
Asian	0.070	0.093	-0.049	-0.074	0.027	0.039	0.027	0.008
	[1.31]	[2.34]	[-2.40]	[-4.61]	[0.68]	[1.10]	[1.55]	[0.51]
Female	0.051	0.060	0.000	0.018	0.009	0.007	0.006	-0.001
	[3.07]	[3.20]	[0.03]	[2.55]	[0.57]	[0.59]	[0.89]	[-0.35]
LTV	0.751	0.804	0.628	1.165	1.256	1.542	1.229	1.784
	[14.29]	[13.13]	[9.08]	[30.02]	[24.73]	[22.04]	[15.01]	[26.49]
AddLTV	0.378	0.068	-0.480	0.039	-0.230	-1.093	-1.274	-1.577
	[2.83]	[0.48]	[-4.64]	[0.38]	[-1.14]	[-4.61]	[-12.60]	[-17.06]
Loan (log)	-0.378	-0.234	-0.384	-0.235	-0.566	-0.366	-0.444	-0.211
	[-17.13]	[-8.09]	[-19.35]	[-11.44]	[-19.47]	[-19.44]	[-29.07]	[-15.58]
SecondLien	2.400	2.425	3.466	3.715	2.011	3.494	3.734	4.908
	[16.40]	[23.94]	[29.66]	[45.09]	[6.95]	[15.16]	[36.45]	[53.56]
Refinance	-0.109	-0.403	-0.130	-0.111	-0.597	-1.074	-0.103	-0.023
	[-4.75]	[-13.76]	[-5.60]	[-5.67]	[-14.44]	[-25.19]	[-6.10]	[-0.95]
PrepayPenalty	0.145	0.027	-0.143	-0.114	0.453	0.336	0.262	0.088
	[5.59]	[1.07]	[-7.46]	[-9.38]	[13.75]	[13.22]	[9.28]	[3.86]
FirstTimeOwner	-0.169	-0.288	0.040	0.045	-0.500	-0.627	0.047	-0.017
	[-3.43]	[-4.55]	[2.59]	[3.83]	[-11.89]	[-18.38]	[3.01]	[-1.74]
OwnerOccupied	-0.468	-0.368	-0.384	-0.363	-1.225	-0.931	-0.441	-0.227
	[-12.95]	[-10.79]	[-16.70]	[-17.52]	[-14.04]	[-12.68]	[-24.67]	[-8.62]
OneBorrower	0.030	0.066	-0.003	0.065	-0.003	0.021	-0.035	0.054
	[2.12]	[4.52]	[-0.36]	[5.67]	[-0.30]	[1.35]	[-3.22]	[6.19]

Dep. Variable Subsample	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Initial Rate for Approximately Fixed-Rate Loans				Current Rate			
	Bank/ Full-Doc	Bank/ Low-Doc	Broker/ Full-Doc	Broker/ Low-Doc	Bank/ Full-Doc	Bank/ Low-Doc	Broker/ Full-Doc	Broker/ Low-Doc
Income (log)	0.043 [3.74]	0.063 [3.21]	0.021 [2.43]	0.009 [1.55]	0.104 [6.27]	0.176 [10.78]	0.118 [10.72]	0.033 [5.01]
IncomeMiss	0.108 [1.11]	0.044 [1.18]	-0.090 [-1.22]	0.125 [5.81]	0.241 [3.19]	0.068 [1.56]	-0.035 [-0.53]	0.030 [1.46]
CashResv	-0.008 [-1.75]	-0.039 [-3.17]	-0.052 [-4.34]	-0.065 [-11.24]	-0.031 [-5.69]	-0.104 [-10.79]	-0.050 [-7.46]	-0.090 [-32.95]
CreditScore	-0.007 [-21.87]	-0.004 [-13.89]	-0.008 [-20.69]	-0.005 [-19.86]	-0.007 [-25.75]	-0.005 [-18.54]	-0.009 [-43.89]	-0.006 [-26.60]
Age (log year)	0.071 [3.51]	0.020 [1.12]	0.117 [12.49]	0.068 [8.75]	0.016 [1.00]	0.027 [1.89]	0.100 [17.54]	0.100 [21.43]
Tenure (log month)	-0.008 [-1.19]	-0.016 [-2.57]	0.013 [1.98]	0.004 [1.38]	-0.002 [-0.35]	-0.018 [-3.26]	0.006 [1.44]	0.008 [2.47]
TenureMiss	0.030 [0.58]	-0.026 [-0.75]	-0.284 [-7.40]	-0.160 [-4.96]	-0.039 [-1.05]	-0.177 [-6.67]	-0.462 [-16.08]	-0.3847 [-16.61]
SelfEmploy	0.175 [5.48]	0.083 [3.01]	0.045 [2.61]	0.001 [0.06]	0.173 [6.21]	0.043 [2.37]	0.006 [0.38]	-0.053 [-6.63]
2005	0.206 [13.83]	0.144 [6.38]	0.300 [9.52]	0.164 [7.89]	0.284 [11.58]	0.384 [12.61]	0.226 [8.07]	0.231 [11.01]
2006					0.946 [36.70]	0.983 [28.83]	0.704 [31.88]	0.686 [30.25]
2007					0.640 [16.25]	0.673 [16.36]	0.453 [18.79]	0.495 [17.96]
2008					0.329 [5.46]	0.328 [5.32]	0.084 [1.94]	0.202 [7.20]
Constant	15.084 [34.54]	12.203 [24.55]	16.228 [36.07]	12.219 [38.77]	19.107 [48.47]	15.173 [59.25]	17.477 [52.18]	12.739 [46.19]
Observations	12,774	10,169	41,655	72,047	31,408	35,553	166,402	425,181
R-squared	0.525	0.357	0.697	0.665	0.522	0.564	0.576	0.593