Asymmetric Information in Dynamic Contract Settings: Evidence from the Home Equity Credit Market*

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Abstract

Using a unique proprietary panel data set of over 108,000 home equity loans and lines of credit, we analyze the role of contracts and negotiations in distinguishing borrower risks during loan origination. Our results indicate that less credit-worthy applicants are more likely to select credit contracts with lower collateral requirements. Furthermore, adverse selection due to private information persists, even after controlling for contract choice and observable risk attributes. We also assess whether systematic screening *ex ante* to mitigate adverse selection or moral hazard problems can effectively reduce default risks *ex post*. The results show that financial institutions through *ex ante* screening for moral hazard (via increased collateral requirement) can successfully reduce default risks *ex post* by 12 percent. However, *ex ante* screening for adverse selection (via an increased contract interest rate (APR) requirement) increases default risks *ex post* by 4 percent, but the increased profits due to higher APR offsets the higher default risks.

JEL Classification: D1; D8; G2
Key Words: Adverse Selection; Moral Hazard; Dynamic Contracting; Screening; Banking; Home Equity Lending.

In his seminal paper, Akerlof (1970) shows that adverse selection and moral hazard may occur in markets characterized as having asymmetric information between participants. Building on this idea, Stiglitz and Weiss (1981) present a model showing that, in a world with imperfect information, the use of interest rates or collateral in the screening process can introduce adverse selection and reduce overall expected loan profitability. In this classic case, adverse selection refers to the situation where the quality of the average borrower declines as the interest rate or collateral increases. In turn, overall loan profitability may decline as only higher-risk borrowers are willing to pay higher interest rates or post greater collateral. As a result, the use of collateral in the screening process is consistent with lenders sorting borrowers by *observable* risk characteristics.[1]

In contrast, Bester (1985) develops a model showing that lenders attempt to offset the impact of adverse selection by offering a menu of contracts containing combinations of interest rates and collateral levels that allow borrowers to self-select contracts that *ex ante* reveal their risk. The Bester model predicts that high-risk borrowers are more likely than low-risk borrowers to choose contracts with higher interest rates and lower collateral requirements, thus eliminating the impact of adverse selection. The use of a menu of contracts to uncover borrower information is consistent with borrower sorting by *private* (*unobservable*) information.[2]

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[1] See Finkelstein and Poterba (2004, 2006) for a discussion of sorting by observed information and sorting by private information in the insurance-annuity market.

[2] The literature is extensive on adverse selection and moral hazard problems in contractual relationships between lenders and firm agents. Chiappori and Salanié (2003) provide an excellent survey of recent theoretical and empirical studies. Finkelstein and Poterba (2006) present an empirical test of asymmetric information that takes advantages of observable *private* information to distinguish between adverse selection and moral hazard in the insurance market. Dey and Dunn (2006) outline the literature in credit markets surrounding the concepts of sorting by observed risk and sorting by private information. Other empirical studies include Igawa and Kanatas (1990), Ausubel (1991), Calem and Mester (1995), Ausubel (1999), Edelberg, (2003), Davidoff and Welke (2004), Calem, Gordy, and Mester (2006), Dey and Dunn (2006), and Karlan and Zinman (2006).

As noted by Chiappori and Salanié (2000) and Finkelstein and Poterba (2006), distinguishing between adverse selection and moral hazard in empirical tests of asymmetric information is often problematic.[3] For empiricists, this difficulty arises because traditional financial contract data sets and surveys usually contain only information about contracts that are booked and do not provide information regarding the process leading to origination. As a result, prior empirical studies of asymmetric information have ignored the impact that negotiations between contracting parties can have on observed adverse selection and moral hazard. In this paper, we follow more than 108,000 home equity credit applications through the dynamic contracting process and then through post-origination performance, and thus, we are able to observe how the lender mitigates the problem of adverse selection and moral hazard through screening.

Our analysis comprises two parts. First, we focus on establishing the existence of asymmetric information and adverse selection. As Bester (1985) notes, contract choice reveals information about borrower risk. Thus, the screening process begins as borrowers respond to a menu of differential contracts and select the home equity credit contract that best matches their credit requirements. However, the contract menu by necessity is not a continuous risk-based pricing menu, but rather offers a set of coarse interest rate and collateral combinations. As a result, the potential for borrower adverse selection is reduced but not eliminated. Based on the outcome from the initial screening process, we address a set of questions concerning the impact of asymmetric information: First, following the arguments outlined by Bester (1985), do borrowers self-select loan contracts that are designed to reveal information about their risk level? That is, do we observe

[3] In one of the few studies to overcome this problem, Karlan and Zinman (2006) use a novel random experimental design to explicitly distinguish between adverse selection and moral hazard.

borrower sorting by private information? Second, conditional on the borrower's choice of contract type, does adverse selection in the classical Stiglitz and Weiss (1981) framework exist?

The second part of our study uses the outcomes from the dynamic contracting process to analyze the effectiveness of lender actions designed to mitigate the effects of asymmetric information as revealed through the problems of adverse selection and moral hazard.[4] Thus, we focus on the role of collateral in sorting borrowers by risk and motivating greater borrower effort. During the underwriting process, the lender may target certain borrowers for additional screening to reduce the asymmetric information that potentially remains because of private information. The secondary screening provides the lender with the opportunity to gather "soft" information that is not contained on the credit application.[5] For example, soft information may include the nature and extent of the planned remodeling project for borrowers who state on the application that they intend to use the funds for home improvements; it may also include the item intended to be purchased by the borrowers who state on the application that they will utilize the funds for consumption purposes. Thus, based on the nature of the soft information, the lender may counteroffer the borrower with a contract designed to reduce (or price) the information asymmetry. Given that we observe the outcome from this dynamic contracting process, we assess the lender's effectiveness in mitigating problems associated with adverse selection and moral hazard. Specifically, we address the following questions: First, does secondary

[4] We define moral hazard as the behavior change induced by screening on the repayment burden. The behavior change on the repayment burden can also be induced by positive or negative income and wealth shocks. Hence, through out the paper we use moral hazard and repayment burden interchangeably (see, Karlan and Zinman, 2006).

[5] Following Berger et al. (2005), Petersen (2004), and Stein (2002), we characterize information as soft if it is not quantifiable on the credit application, but rather is revealed to the loan officer during the application

screening (at credit origination), designed to mitigate adverse selection and moral hazard, effectively reduce default risks *ex post*? Second, if so, then by how much?

To preview our results, after controlling for borrower age, income, employment, and other observable attributes, we find that borrowers' choice of credit contract does reveal information about their risk. Specifically, we find that less credit-worthy borrowers are more likely to select contracts that require lower amounts of collateral. After controlling for borrower contract choice and other observable risk characteristics, however, we also find that the lender continues to face adverse selection problems because of private information. That is, we find a significant and strong positive correlation between the borrower's choice of collateral pledged *ex ante* and the risk of default *ex post* (consistent with adverse selection). Our results indicate that a borrower who pledges less than 10 percent collateral is 5.6 percent more likely to default in comparison with a borrower who pledges more than 20 percent collateral. These results provide evidence of adverse selection, consistent with the implications of the Stiglitz and Weiss (1981) model. However, these results are not inconsistent with the model presented by Bester (1985), since the contract menu is necessarily coarse. That is, the menu presented to the borrower is not a continuous risk-based pricing menu.

Moreover, we find that the lender's efforts *ex ante* to mitigate adverse selection and moral hazard can effectively reduce credit losses *ex post*. Our results show that counteroffers designed to mitigate moral hazard (via increased collateral requirements) reduce default risk *ex post* by 12 percent, and counteroffers designed to mitigate adverse selection (via increased annual percentage rate (APR) requirements) increase default risk

process. In contrast, "hard" information is easily verifiable (e.g. income or employment status) and thus serves as an input into automated underwriting models.

ex post by 4 percent. However, the increased profits from higher APR all but offset the increased losses from default. As suggested by Karlan and Zinman (2006), finding both adverse selection and moral hazard in the credit markets should lead to practical applications that could translate into investments in screening and monitoring technologies on the margin. Our results show that financial institutions can reduce credit losses using screening devices and counteroffer contracts designed to induce the borrower to reveal her type and effort.

Furthermore, we find it interesting that these mitigation efforts also impose costs in the form of higher prepayment rates. Our results show that the moral hazard mitigation efforts increase the odds of prepayment by 11 percent, while adverse selection mitigation efforts increase the probability of prepayment by approximately 3 percent. Therefore, lenders seeking to minimize credit losses may find it profitable to screen for and design counteroffer contracts to mitigate moral hazard and adverse selection problems. Lenders may, however, also realize losses by requiring higher prepayments, since prepayments may lower the revenue derived from secondary market securitization activity.

Our results provide evidence that a principal can use primary and secondary screening to alleviate adverse selection and moral hazard in a dynamic contract setting where asymmetric information exists and agents have private (unobservable) information. As noted by Chiappori and Salanié (2003), examples of other markets characterized as having similar asymmetric information problems include insurance, managerial incentive contracts, and corporate governance.

The paper proceeds as follows. In Section 1, we provide a brief literature review. Next, in section 2, we describe the home equity origination process. Then, we discuss the data in section 3. In section 4, we provide our outline of empirical methodologies and present our results in assessing adverse selection and moral hazard problems from observable and unobservable information during the underwriting process, as well as through loan origination and post-origination performance. Finally, in section 5, we make our concluding remarks.

1. Literature Review

A number of studies also focus on the role that collateral plays in determining borrower selection of loan contracts. For example, in earlier work, Chan and Thakor (1987) develop a model recognizing that a borrower’s use of collateral may be a positive function of her quality. Furthermore, Igawa and Kanatas (1990) note that the use of collateral may introduce additional default risk through moral hazard if the collateral’s future value can be affected by the borrower’s use of the pledged asset. Their model of optimal contracts provides a framework that allows lenders and borrowers to minimize the impact of moral hazard, which implies a positive relation between borrower credit quality and collateral offered. More recently, Dey and Dunn (2006) use the *Survey of Consumer Finance* (SCF) data to examine the role that collateral plays in distinguishing borrower risk levels in the home equity line of credit and find that riskier borrowers are more likely to pledge lower amounts of collateral. Edelberg (2004) uses the SCF data on automobile and mortgage loan contracts to examine the relationship between interest rates, collateral values, and loan performance. She finds strong evidence that high-risk borrowers self-select *ex post* into contracts with lower collateral levels and higher interest rates, suggesting that adverse selection is present. At the same time, she finds that collateral is used to induce borrower effort, implying the presence of moral hazard. Most recently, Karlan and Zinman (2006) find empirical evidence supporting the significant presence of adverse selection and moral hazard using an innovative field experiment that randomizes *ex ante* loan pricing at solicitation and *ex post* loan pricing at origination. The authors conclude that between 6 percent and 17 percent of the defaults in their sample can be attributed to adverse selection and moral hazard.

With the exception of Karlan and Zinman (2006), who use offers and originated loans, the findings of the previous studies are predicated solely upon originated loans. As noted previously, however, lenders can alter loan contracts during the underwriting process to counter the effects of adverse selection and moral hazard. To overcome this source of bias, we follow a set of loan applications during the underwriting process through loan origination and then through a period of post-origination performance. As a result, we are able to observe directly the borrower's initial contract application as well as the lender's response to that application.

Other empirical research investigating adverse selection problems in the consumer credit market has primarily focused on unsecured lending. For example, in one of the most influential papers to investigate the role of adverse selection problems in the credit card market, Ausubel (1991) empirically documents the *stickiness* of credit card rates relative to the cost of funds, and contends that rates are sticky because cardholders are unable to switch to lower rate cards because of adverse selection problems arising from search and switching costs. Using preapproved credit card solicitations, Ausubel (1999) finds evidence of sorting by observable and unobservable information—consistent with his switching costs rationale. Supporting the view that adverse selection can result from high search costs, Calem and Mester (1995) use data from the 1989 SCF to show that households looking to borrow additional funds hold lower credit card debt. Furthermore, consistent with the impact of switching costs, Calem and Mester (1995) find that households holding larger credit card debt are more likely to be denied future credit and to experience repayment problems on existing credit. Our study using information from the home equity market provides additional insights into the role of asymmetric information in a dynamic contract setting. We now turn to a discussion of the home equity origination process.

2. Home Equity Credit Origination

The market for home equity credit in the form of home equity loans and home equity lines of credit represents a large segment of the consumer credit market. Recent evidence from the *Survey of Consumer Finances* suggests that the home equity lending market increased over 26 percent between 1998 and 2001 to $329 billion.[6] By the end of 2005, home equity lending increased to over $702 billion.[7] With the maturation of the home equity credit market, lenders now offer menus of standardized contracts to meet the needs of heterogeneous consumers and mitigate potential asymmetric information problems.[8]

The home equity credit market presents an ideal framework in which to investigate issues associated with adverse selection and moral hazard because home equity credits are secured by the borrower's home, and the borrower generally faces a menu of differential contracts designed to uncover information about risk preferences. Figure 1 illustrates the

[6] See www.federalreserve.gov/pubs/oss/oss2/2004/scf2004home.html.
[7] See *Inside Mortgage Finance*, an industry publication.

typical home equity loan origination process and describes how adverse selection and moral hazard enter the process. First, a borrower applies for a home equity line or loan in response to a general (nonspecific) advertisement.[9] To counter adverse selection, the lender offers a menu of differential contracts (primary screening) to help borrowers self-select either lines of credit or fixed-term loans having varying interest rates, collateral requirements, and lien requirements. For example, a typical home equity menu may offer a 15-year home equity line of credit with less than 80 percent loan-to-value ratio (LTV) at an interest rate r_1; a 15-year home equity loan with first lien between 80 percent and 90 percent LTV at an interest rate r_2; or a 15-year home equity loan with second lien between 90 percent and 100 percent LTV at an interest rate r_3, where $r_1<r_2<r_3$. As a result, borrowers apply for specific contracts that may reveal information about their risk profiles. For example, through their initial choice, borrowers may indicate their expected tenure and risk.[10]

Next, after the borrower selects a contract, the lender takes one of the following actions: (1) rejects the contract (credit rationing), (2) accepts the contract, or (3) conducts secondary screening and suggests an alternative contract (counteroffer) to induce the borrower to reveal her effort or type. Credit rationing in the classic Stiglitz and Weiss (1981) framework occurs when the observable credit risk characteristics of the borrower are well below the lender's acceptable underwriting standards, since these consumers may

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[8] See Stanton and Wallace (1998) and LeRoy (1996) for a discussion of the mortgage contract and the implications concerning asymmetric information.

[9] See Agarwal et al. (2006) for a review of the various differences between home equity loans and lines of credit.

[10] It is possible that some borrowers may have a first mortgage that implicitly prohibits them from choosing a less than 80% LTV. However, as documented by Agarwal (2006), a significant percentage of borrowers overestimate their house value, allowing them the option to choose from the full menu. We also redid our empirical analysis with a sub-sample of borrowers who have the option to choose the less-than-80 LTV assuming that they did not misestimate their house value. The results are qualitatively similar.

not maximize lender profitability.[11] If the borrower's risk profile meets the lender's minimum underwriting criteria, then the lender accepts the initial contract and originates the loan or conducts secondary screening to counter the asymmetric information that potentially remains because of private information.

Because of the borrower's private information, the lender who accepts the consumer's contract choice may still be susceptible to adverse selection or moral hazard. As a result, the lender may request additional screening and in the process learn new soft information. Based on this information, the lender may propose new contract terms. For example, the lender could induce borrower effort (thus mitigating moral hazard) by requiring that the consumer pledge additional collateral, while at the same time offering a lower interest rate. Alternatively, the lender could propose that the consumer pay a higher interest rate to mitigate potential adverse selection problems. As Igawa and Kanatas (1990) point out, however, the lender's attempt to mitigate adverse selection through the use of higher interest rates may create additional moral hazard problems. At this point, the borrower can either reject the counteroffer and seek alternative sources of funding or accept the counteroffer and contract the loan.

Based on the above description of the origination process, a number of testable hypotheses arise concerning the presence of asymmetric information in the home equity lending market. First, the presence of adverse selection in the home equity lending market implies that we should observe differential responses to the lender's menu, with higher-risk (lower-risk) borrowers selecting loan contracts having higher (lower) LTV ratios and higher (lower) interest rates (Bester, 1985). Second, if borrowers selecting *ex ante* higher (lower) LTV contracts have higher (lower) probabilities of default *ex post*, then the lender

[11] Credit rationing is not from the entire market, thus other lenders may offer the borrowers credit.

still faces adverse selection because of private (unobservable) risk factors Third, examining the counteroffers should reveal the lender's perception of potential moral hazard problems. For example, if the lender counters higher-risk borrowers with a lower LTV ratio, then the lender is attempting to induce the borrowers to reveal their effort and limit moral hazard. Alternatively, if the lender systematically counters higher-risk borrowers with higher interest rates, then the lender is attempting to induce the borrowers to reveal their type, thus mitigating the adverse selection effects. Finally, examining the performance of the loans after origination will reveal the extent to which the lender is successful in limiting the risks associated with adverse selection and moral hazard.

3. Data Description

To assess lender effectiveness in mitigating asymmetric information problems, we collect an administrative data set of home equity contract originations from a large financial institution. The data set is rich in borrower details and includes all variables the lender used in underwriting. These variables include information about the borrower's occupation, credit quality, income, debts, age, and purpose for the loan.

Between March and December of 2002, the lender offered a menu of standardized contracts for home equity credits. Consumers could choose to (1) increase an existing line of credit, (2) request a new line of credit, (3) request a new first-lien loan, and (4) request a new second-lien loan. For each product, borrowers could choose the amount of collateral pledged: less than 80 percent LTV, between 80 percent and 90 percent LTV, and between 90 and 100 percent LTV. Thus, the lender offered twelve LTV combinations, each with an associated interest rate and 15-year term. We observe the borrowers' payment behaviors from origination to March 2005, allowing us to test the effectiveness of systematic screening by lenders for asymmetric information.

As indicated in Table 1, between March and December of 2002, the lender received 108,117 home equity loan applications. Based on the information contained in the application, the lender rejected (rationed credit) 11.1 percent of the applications, accepted 57.6 percent of the applications, and conducted secondary screenings on the remaining 31.3 percent. Secondary screening allows the lender to propose an alternative loan contract to customers whose loan application meets the minimum underwriting standards, yet contains a signal that a potential adverse selection or moral hazard problem may exist. For example, the lender may propose a new contract with lower LTV and/or a different type of home equity product (e.g., switching a loan to a line), in effect lowering the contract rate to induce borrower effort (control moral hazard). Alternatively, the lender may propose a contract with a higher LTV (greater loan amount) and/or a different type of home equity product (e.g., switching a line to a loan), thereby increasing the interest contract rate to control for borrower type (adverse selection). Table 1 reports that 31.4 percent of the 33,860 applicants undergoing secondary screening were offered a new loan at a higher rate and/or different type of home equity product in an effort to mitigate adverse selection, and 68.6 percent of them were offered a new contract with lower LTV and/or a different type of home equity product in an attempt to mitigate moral hazard. [12]

We find considerable differences in applicant response rates depending on whether they were screened for borrower type or effort. Overall, 12,700 applicants (37.5 percent)

[12] Of the adverse selection mitigation counteroffers, 26 percent had a higher LTV with the same home equity type, and 74 percent had the same LTV but were switched from a line to a loan. Of the moral hazard mitigation counteroffers, 63 percent had a lower LTV with the same home-equity type, and 37 percent had the same LTV but were switched from a loan to a line.

declined the lender's counteroffer. Interestingly, we note that the majority of borrowers who reject the counteroffer were screened for adverse selection. For example, 8,129 of the applicants who rejected the counteroffer (64 percent) were screened for adverse selection, while 4,571 of them (36 percent) were screened for effort.

Of the 21,160 applicants who accepted the lender's counteroffer, we note that 15,093 of them (28.7 percent) were screened for adverse selection and offered higher interest rate contracts, while 6,067 of them (71.3 percent) were screened for effort and offered lower interest rate contracts. Finally, we have a pool of 83,411 applicants (77.1 percent of the total 108,117) who were ultimately issued loan contracts.

4. Empirical Methods and Results

Our objective is to assess the role of information asymmetry between the lender and applicant during the underwriting process and the borrower's post-origination repayment behavior. Our empirical analysis is divided into six sequential parts that reflect the dynamic contracting environment. In section 4.1, we investigate the lender's menu of loans offered and estimate a borrower choice model to assess whether borrowers self-select into contracts that are designed to reveal information about their risk level (Bester, 1985). Next, in section 4.2, we examine the likelihood of the lender approving a credit contract, rejecting (rationing) a credit contract, or subjecting an applicant to additional screening based on the contract choice and observable borrower risk characteristics. In section 4.3, we test whether the lender continues to face adverse selection problems within the group of borrowers who were accepted outright (Stiglitz and Weiss, 1981). The objective is to see whether a borrower selecting *ex ante* a higher LTV contract has a higher likelihood of default *ex post*. Then, in section 4.4, we analyze the lender's secondary screening for information asymmetry and the counteroffer contracts designed to further mitigate moral hazard and adverse selection problems. In response to the lender's counteroffer, we estimate the likelihood of a borrower rejecting the counteroffer in section 4.5. Our analysis focuses on whether more credit-worthy borrowers have a greater likelihood of rejecting the counteroffer than the less credit-worthy borrowers. The borrower's ability to accept or reject the counteroffer may reintroduce additional adverse selection problems. Finally, in section 4.6, we evaluate the effectiveness of a lender's *ex ante* mitigation efforts in the secondary screening stage in reducing borrower default risks *ex post*.

4.1 Credit contract choice

We begin by estimating a multinomial logit model to address the question of whether the borrower's initial choice of home equity product provides evidence of asymmetric information between borrower and lender. As outlined in section 2, the borrower faces a menu of home equity contracts at the application stage. Based on her private information regarding credit risks, financing needs, and uncertain expectations for the outcome of her application (the lender's accept/reject decision), the borrower applies for a specific home equity contract. If the choice of collateral amount serves as a borrower-risk-level sorting mechanism during the application process, then we should observe a positive correlation between the borrower's credit quality and collateral choice. We measure the amount of collateral offered to the lender using the borrower's self-reported property value on the application. We calculate the "borrower" LTV ratio using the borrower's initial property value estimate and loan amount requested.[13] Since loan sizes are not constant across borrowers, the LTV ratio provides a mechanism for standardizing the amount of collateral offered per dollar loan requested. Thus, lower LTV ratios are consistent with borrowers offering more collateral per dollar loan.

To formally test whether borrowers with higher (lower) credit quality offer more (less) collateral, we categorize the home equity applications into three groups based on the borrower's choice of LTV and estimate the following multinomial logit model via maximum likelihood:

$$\Pr(LTV_i = j) = \frac{e^{(\alpha_j + \beta_j X_i + \delta_j W_i)}}{\sum_{k=1}^{3} e^{(\alpha_k + \beta_k X_i + \delta_k W_i)}} \qquad (1.)$$

where *j={1,2,3}* corresponds to LTVs less than 80 percent, between 80 percent and 90 percent, and greater than 90 percent, respectively. W_i represents borrower *i*'s credit quality as measured by the borrower's FICO score (Fair, Isaac, and Company credit quality score), and X_i represents a vector of control variables. The control variables are information collected from the loan application and include the borrower's employment status (e.g., employed, self-employed, retired, or homemaker), number of years employed, age and income at the time of application, the property type (single-family detached or condo), the property's status as the primary residence or second home, the tenure in the property, the use of the funds (e.g., for refinancing, home improvement, or debt consolidation), and the current existence of a first mortgage on the property.

[13] Note that we distinguish between the borrower's LTV and the LTV calculated by the lender. The borrower's LTV is based on the borrower's self-declared property value and loan amount request, while the lender's LTV is calculated using the property value from an independent appraisal and the lender-approved loan amount (see Agarwal, 2006).

Table 2 presents the descriptive statistics of the sample segmented by the LTV category (LTV ratio less than 80 percent, LTV ratio between 80 percent and 90 percent, and LTV ratio greater than 90 percent) chosen at the time of application. As expected, we observe that borrowers (or customers) pledging lower collateral per dollar loan (higher LTVs) are, on average, less credit-worthy than borrowers requesting lower loan amounts (lower LTVs). For example, the average FICO score is 708 for borrowers selecting to pledge less than 10 cents per dollar loan (LTV ratio above 90 percent), and the average FICO score is 737 for borrowers choosing to pledge more than 20 cents per dollar loan (LTV ratio less than 80 percent). Furthermore, relative to borrowers pledging more than 20 cents per dollar loan, we observe that, on average, borrowers pledging lower collateral (less than 10 cents per dollar loan) are younger (41 years old versus 51 years old), have shorter tenure at their current address (74 months versus 158 months), have lower annual incomes ($100,932 versus $118,170), have higher debt-to-income ratios (40 percent versus 35 percent), and have fewer years at their current job (7.4 years versus 9.8 years).

Table 3 presents the multinomial logit estimation results of an applicant's LTV contract choice, where the base case is a borrower applying for a contract with an LTV ratio less than 80 percent. The statistically significant coefficients for FICO score indicate that less credit-worthy borrowers (as measured by the borrower's FICO score) are more likely to apply for higher LTV home equity products (pledging less collateral per dollar loan). To place these results into a meaningful economic context, we compare the estimated probabilities of a borrower with a specific FICO score choosing a particular LTV category, holding all other factors constant at their sample means. For example, we find that a lower-credit-quality borrower with a FICO score of 700 is 21.4 percent more likely to apply for home equity product with a LTV ratio that is 90 percent or greater than a higher-credit-quality borrower with a FICO score of 800. Furthermore, a borrower with a FICO score of 700 is 18.9 percent more likely to apply for a home equity product having a LTV ratio between 80 percent and 90 percent than a borrower with a FICO score of 800. The results clearly indicate an inverse relationship between credit quality and collateral pledged, suggesting that adverse selection is present in the home equity market.

In addition to borrower credit scores, we also find that other variables related to borrower risks are related to the borrower's initial LTV choice. For example, a borrower using the proceeds of the loan to refinance an existing debt is 2.9 percent more likely to apply for a home equity product with a 90 percent or greater LTV ratio than to apply for a product with a LTV ratio less than 80 percent.[14] Furthermore, borrowers without a current first mortgage are 7.1 percent less likely to select home equity products with LTV ratios greater than 90 percent than ones with LTV ratios less than 80 percent.[15] We also find that borrowers with lower incomes or higher debt-to-income ratios are more likely to apply for home equity products with higher LTV ratios. For example, every 10-point increase in the borrower's debt-to-income ratio increases the odds by 1.3 percent that she will apply for a product with a LTV ratio greater than 90 percent. In addition, a borrower having a second home is 11.5 percent less likely to apply for a loan with a LTV ratio greater than 90 percent. Finally, we include borrower age at application as a proxy for borrower wealth under the assumption that older individuals tend to have greater personal net wealth than younger persons. The significant negative coefficient on borrower age is consistent with

[14] Similarly, the probability of applying for home equity credit with an LTV ratio between 80 percent and 90 percent is 3.3 percent greater than the odds of applying for a loan with a LTV ratio less than 80 percent if the borrower indicates that the proceeds of the loan will be used to refinance an existing debt.

the hypothesis that younger borrowers (who are thus more likely to have less wealth) are more likely to apply for higher LTV credit.

Finally, although we find that riskier borrowers are more likely to apply for higher LTV home equity products, we also see that the choice of home equity line and home equity loan affects the LTV choice. The results indicate that borrowers applying for a home equity loan are 2.4 percent more likely to choose a greater-than-90-percent LTV ratio than they are to select a less-than-80-percent LTV ratio.[16]

4.2 Lender response to borrower contract choice

We now turn to a formal analysis of the lender's underwriting decisions. After receiving the borrower's application, the lender initially screens the loan using observable information to determine whether the application should be rejected, accepted, or subjected to additional screening for asymmetric information. If the lender systematically screens for adverse selection and moral hazard, then we should observe a positive correlation between the likelihood of additional screening and collateral offered as measured by the LTV ratio, holding all else constant.

We model the outcome (*O*) of the lender's primary screening as a multinomial logit model estimated via maximum likelihood:

$$\Pr(O_i = l) = \frac{e^{(\alpha_j + \beta_j X_i + \delta_j W_i + \gamma_j LTV_i)}}{\sum_{k=1}^{3} e^{(\alpha_k + \beta_k X_i + \delta_k W_i + \gamma_j LTV_i)}}, \qquad (2.)$$

[15] We also note that borrowers without a current first mortgage are 10.5 percent less likely to request a loan with LTV between 80 percent and 90 percent versus a loan with LTV less than 80 percent.

[16] We also estimate a multinomial logit regression over each individual product as described in section 2. The results confirm that borrowers with lower FICO scores choose risky products.

where $O_i=\{1,2,3\}$ corresponds to the lender's accepting the application, rejecting the application, or submitting the application to additional screening, respectively. As before, X_i and W_i represent a vector of control variables and the borrower's credit score, respectively, and LTV_i is the borrower's LTV category. For the underwriting model, we include in X all information that the lender collects on the loan application. In addition, we also use the lender-ordered independent appraisal to calculate the lender's LTV ratio (defined as the requested loan amount divided by the appraisal value).

Table 4 presents the summary statistics for the three primary screening outcomes. Focusing first on the LTV ratio for the set of applications that were rejected (credit rationed), we observe that the lender's LTV estimate averages 8 percentage points higher than the borrower's estimated LTV (82 percent versus 74 percent), indicating that these borrowers tend to overvalue their homes relative to the lender's independent appraisal. In contrast, the difference between the lender and borrower LTV ratios is only slightly higher for the accepted applications (56 percent versus 54 percent) and is virtually identical for the group of borrowers who received a counteroffer from the lender (58 percent). Obviously, collateral risk is one of the key underwriting criteria used by lenders in determining whether a loan application is accepted, and thus, the finding that rejected applications have, on average, higher LTV ratios is not surprising. On the other hand, the higher rejection rate for customers who overvalue their collateral (have lower LTV ratios) suggests that the lender views borrower property value optimism with skepticism—and thus is an indicator of greater default risk.[17]

[17] The relationship between customer property value optimism and credit application rejection is obviously endogenous. Agarwal (2006) provides a detailed analysis exploring the relationship between borrower characteristics and borrower ability to accurately estimate property values.

As expected, credit quality for those who were initially accepted is higher than the credit quality of those who received additional screening as well as for those were rejected. The average FICO score for borrowers who were accepted outright was 737, while the average FICO score for borrowers subjected to additional screening was 729, and the average FICO score for borrowers whose application was rejected was 714. Furthermore, borrowers whose applications were rejected averaged a shorter tenure at their current address (94 months), earned lower annual income ($82,058), had higher debt-to-income ratio (45 percent), and were more likely to be self-employed (12 percent) than borrowers who were accepted outright (152 months tenure, $121,974 annual income, 34 percent debt-to-income ratio, and 8 percent self-employment).

Table 5 provides the multinomial logit estimation results for the lender's underwriting decision. Using loans that were accepted outright as the base case, we estimate the likelihood that a lender will reject an applicant or subject an applicant to additional screening conditional on LTV, borrower risk characteristics, loan characteristics, and other control variables. Turning first to the impact of the lender's estimated LTV ratio, the positive coefficients indicate that applicants in the 80 percent to 90 percent LTV category or greater-than-90-percent LTV category face greater likelihood of being subjected to additional screening or rejected. For example, the reported marginal effects suggest that if the lender-estimated LTV ratio is greater than 90 percent, then the loan application is 18.4 percent more likely to be rejected (only 15.8 percent more likely to be subjected to additional screening) than if the lender-estimated LTV ratio was less than 80 percent. Similarly, applications with lender-estimated LTV ratios between 80 percent and 90 percent are 12 percent more likely to be subjected to additional screening (only 8.7

percent more likely to be rejected) than applications with lender-estimated LTV ratios less than 80 percent. Hence, the lender is more likely to conduct secondary screening than to reject applicants with 80 percent to 90 percent LTV ratios, and more likely to ration applicants with greater-than-90-percent LTV ratios.

Looking at the other risk characteristics, we find that each additional percentage point increase in debt-to-income ratio increases the probability that the lender will reject a loan by 1.8 percent. Borrowers who are *rate* refinancing are 3.7 percent less likely to be screened and 2.6 percent less likely to be rationed. Borrowers selecting a first-lien product are 12.2 percent less likely to be rejected, but 17.1 percent more likely to be subjected to secondary screening. Finally, borrowers who own a condo are 9.1 percent more likely to be screened and 6.5 percent more likely to be rejected, while borrowers who own a second home are 8.6 percent more likely to be screened and 6.1 percent more likely to be rationed. We conjecture that condo owners generally are younger, are less wealthy, and have lower income.

The results from this section are consistent with the lender following standard underwriting protocol. Factors associated with higher default risk (e.g., poor credit quality, high LTV, short tenure in home, lower income, and employment status) correspond to higher probability of credit denial or secondary screening.

4.3 Existence of adverse selection

Consistent with the theory developed by Bester (1985), the results in section 4.1 indicate that borrowers reveal information about their risk level by their self-selection of loan contract offers. In this section, we identify the presence of adverse selection as developed by Stiglitz and Weiss (1981), conditional on the borrower's choice of contract type.

We estimate a competing risks model of loan performance of the 62,251 borrowers whose applications were accepted outright (without additional screening).[18] The presence of borrower adverse selection due to observable and unobservable information is consistent with borrowers who select *ex ante* contracts with higher LTV ratios (pledging less collateral per loan dollar) having higher risk of default *ex post*. This result is consistent with Ausubel (1999) and Karlan and Zinman (2006) when they find that borrowers who select *ex ante* contracts with higher APR are more likely to default *ex post*.

Table 6 presents the estimated coefficients and marginal effects for the model testing for adverse selection on unobserved risks. In terms of model fit, the estimated coefficients for the observable risk characteristics are consistent with our prior expectations. For example, borrower credit quality (as measured by the FICO score) is negatively correlated to the risk of borrower default (lower-quality borrowers are *more* likely to default) and positively correlated to the probability of prepayment (higher-quality borrowers are *more* likely to prepay). In addition, borrowers without a first mortgage and those using home equity credits for rate refinancing or remodeling (investment in the home) are less likely to default. Furthermore, the risk of default declines as borrower tenure in the house increases, but this risk rises for borrowers with higher debt-to-income ratios.

[18] Following standard methods in credit research, we estimate a competing risks model of borrower action, recognizing that each month the borrower has the option to prepay, default, or make the scheduled payment on the loan. We follow the empirical method outlined in Agarwal et al. (2006) and estimate the model based on the maximum likelihood estimation approach for the proportional hazard model with grouped duration data developed by Han and Hausman (1990), Sueyoushi (1992), and McCall (1996). Details of the competing risks model are discussed in Appendix A and the variables definitions in Appendix B.

We include a set of dummy variables denoting borrower choice of contract type (line/loan, lien position, and LTV ratio) to test for adverse selection. If adverse selection based on unobserved risk characteristics is present, then we should find a significant relationship between the LTV ratios and *ex post* default. On the other hand, finding no relation between *ex post* default and LTV would suggest that adverse selection arising from unobservable risk characteristics is not present. The marginal effects in Table 6 indicate a strong relationship between loan outcome (default and prepayment) and contract choice. We are able to test for adverse selection, since these borrowers have self-selected a contract that reveals their risk level, have passed the lender's initial risk screening, and were not subjected to additional screening to mitigate moral hazard or adverse selection (borrowers who were accepted outright by the lender).

The results suggest that borrowers selecting a home equity loan are 5.4 percent more likely to default and 2.1 percent more likely to prepay than borrowers selecting a home equity line. Moreover, borrowers originating a home equity loan or line with a first-lien position are 2.3 percent less likely to default and 2.1 percent less likely to prepay than borrowers who originate a loan or line having a second lien. Again, these results are broadly consistent with expectations. Borrowers with *a priori* expectations of income variability may prefer the fixed-rate home equity loans over the variable-rate home equity lines, and borrowers using home equity products to provide first-lien credit have lower default risks.[19]

[19] A borrower with a second lien also has an obligation towards the primary mortgage. On average, their total debt burden will be higher; this will impact the probability of the default. Moreover, the interest rate for the second-lien product is 30 basis points higher than the first-lien product. This will negatively impact the borrower's debt service burden resulting in higher default rates.

Finally, the results indicate a strong and significant positive correlation between LTV category and the risk of default, even after controlling for all observable risk characteristics captured on the loan application and time-varying default and prepayment option values. For example, we find that borrowers selecting a higher LTV contract (those pledging less collateral per dollar loan) have higher risk of default and higher risk of prepayment *ex post*. Relative to borrowers pledging more than 20 cents per dollar loan (LTV ratio less than 80 percent), those pledging 10 to 20 cents (LTV ratio between 80 and 90 percent) are 2.2 percent more likely to default and 4.5 percent less likely to prepay, while those pledging less than 10 cents per dollar loan (LTV ratio greater than 90 percent LTV) are 5.6 percent more likely to default and 6.6 percent less likely to prepay. Furthermore, the marginal impact of the time-varying collateral variables indicate that borrowers who experience a positive increase in the current LTV ratio (CLTV) from the previous quarter (i.e., a decline in equity due to house price depreciation) are almost 4 percent more likely to default and 1.0 percent less likely to prepay than borrowers who experience a decrease in their LTV from the previous quarter (i.e., an increase in equity due to house price appreciation).[20]

In sum, these results are consistent with the presence of adverse selection in the home equity lending market, since borrowers who originate higher risk contracts have higher default risks. The strong and significant relationships identified between the variables denoting the borrower contract type choice *ex ante* and loan performance *ex post*

[20] No consensus exists regarding the correct specification of the borrower's equity position (*CLTV*) in the competing risks hazard framework. We specified the time-varying equity position (*CLTV*) as a quadratic function to capture any non-linearity in the borrower's equity position. Other researchers have suggested the use of a discontinuous or spline function for *CLTV*. Thus, we also specified the time-varying *CLTV* as a spline function with knots at 80 percent and 90 percent to match the LTV classification at origination. The results under both specifications are qualitatively the same.

suggest that adverse selection is present based on factors the lender did not observe during the origination of the loan.[21]

4.4 Lender's counteroffer to mitigate additional adverse selection or moral hazard

We now turn to a formal examination of the factors affecting the lender's decision to conduct additional screening and counteroffer with contracts designed to mitigate adverse selection or moral hazard. Based on the discussion in section 1, if the new contract has a lower LTV, we define it as a counteroffer designed to mitigate potential moral hazard (in effect increasing the collateral required per dollar loan amount). The counter offer can reduce moral hazard through the following mechanism. During the origination process, the borrower indicates on the application whether the proceeds will be used to refinance existing debt, to make home improvements, or to meet other consumption needs. At the same time, the loan officer collects additional soft information from the consumer concerning her actual needs and intended uses for the loan. For example, a borrower may request a 90 percent LTV loan for the stated purpose of home improvements, and then, during the application process, the borrower reveals to the loan officer the actual nature of the expected home improvements (e.g., a kitchen remodel or major repair). In this context, the actual intended home improvement is soft information, since it is not captured on the loan application or in the loan file. However, based on local knowledge of the market, the loan officer may realize that the loan amount requested far exceeds the usual costs for such an improvement. As a result, the loan officer could then suggest a lower loan amount. The

[21] Agarwal et. al. (2006) note that the default and prepayment behavior of loans and lines are different. Thus, we also estimated the competing risk hazard model for loans and lines independently. While the results

loan officer's motive is to reduce default probability by lowering the debt service burden and curtailing the borrower's ability to consume the excess credit on non-home improvement projects. However, if the consumer insists on the loan amount requested and the loan officer realizes (through the collection of soft information) that the consumer does not need the funds immediately, then the loan officer could suggest a switch in products—from a loan to a line of credit. Under both these counteroffer scenarios, the effective APR is reduced.

In contrast, a counteroffer is designed to mitigate potential adverse selection if the new contract has a higher LTV. When the borrower's estimate of the house value is above the bank's estimate, the loan officer can counteroffer with a contract having either a higher APR (reflecting the higher LTV ratio based on the bank's appraisal) or a lower loan amount to qualify for the original menu selection (holding the original requested LTV ratio constant). If the consumer refuses the lower loan amount offer, then the loan officer counters with a contract having a higher APR to induce the borrower to reveal her type. In this case, the counteroffer is more likely to exasperate the adverse selection problem (Stiglitz and Wiess, 1981), since the better credit consumers will reject the offer.

Table 7 provides summary statistics for the counteroffer contracts. We see that borrowers receiving a counteroffer contract designed to mitigate moral hazard have higher average FICO scores than those receiving a counteroffer contract designed to mitigate adverse selection (727 versus 719). Furthermore, consistent with the goal of risk-based pricing, the average interest rate for adverse selection counteroffers is 271 basis points higher than the average interest rate for moral hazard counteroffers (7.6 APR versus 4.89

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confirm that loans have a higher probability of default and lines have a higher probability of prepayment, estimating the models separately does not impact the findings for the adverse selection dummy variables.

APR). Relative to applicants who received moral hazard counteroffers, we observe a greater share of borrowers who received an adverse selection counteroffer report that they intend to use the funds to finance general consumption (37 percent versus 16 percent), while a smaller proportion of them report that they intend to use the funds to refinance existing debt (38 percent versus 64 percent). Furthermore, those receiving adverse selection counteroffers have slightly higher debt-to-income ratios (40 percent versus 35 percent), and have shorter tenure at their current address (127 months versus 158 months).

To formally test the key determinants of the lender's counteroffer, conditional on subjecting these applicants to secondary screening, we estimate a logit model of the secondary screening outcome via maximum likelihood. As in the model of the lender's initial underwriting process, we include the set of explanatory variables that control for the percentage difference between the lender's LTV estimate and the borrower's LTV estimate, the percentage difference in the loan amount requested by the borrower and loan amount actually approved by the lender, the use of the funds, and other borrower credit-risk factors.

Table 8 presents the results, which clearly indicate systematic differences in the observed risk factors between borrowers receiving counteroffers designed to mitigate adverse selection versus those receiving counteroffers designed to mitigate potential moral hazard. For instance, our empirical results confirm that less credit-worthy borrowers (those with lower FICO scores) are more likely to receive a counteroffer that is designed to mitigate adverse selection. Again, we compare the estimated probabilities for borrowers with specific FICO scores, holding all other factors constant at their sample means. For example, we find that a borrower with a FICO score of 700 is 24.6 percent less likely than a borrower with a FICO score of 800 to receive a counteroffer designed to mitigate adverse selection than one designed to mitigate moral hazard. Furthermore, each additional 1 percentage point increase in the borrower's debt-to-income ratio increases the odds of receiving an adverse selection counteroffer by 2.8 percent.

The effect of the LTV difference also clearly indicates that lenders are more likely to counteroffer borrowers who tend to overvalue their property value relative to the bank's estimated value with contracts designed to mitigate adverse selection. The marginal effects indicate that for every 1 percentage point increase in the lender's LTV ratio over the borrower's LTV ratio, the probability that the lender will counteroffer with a contract designed to mitigate adverse selection rather than moral hazard increases by 3.1 percent.

We also see that lenders are 21.9 percent less likely to counteroffer with a contract designed to mitigate adverse selection for borrowers who are rate refinancing (i.e., non-cash-out refinancing). Furthermore, borrowers who are self-employed are 7.5 percent less likely to be screened for adverse selection, while borrowers who are retired are 6.7 percent more likely to be screened for adverse selection. Finally, borrowers who own a second home are 7.2 percent more likely to be screened for adverse selection, and borrowers who own a condo are 5.3 percent less likely to be screened for adverse selection.

To summarize, the results in this section indicate that lenders do systematically screen borrowers for adverse selection and moral hazard. Riskier borrowers who overvalue their property (relative to the bank's estimate) are more likely to receive a counteroffer designed to mitigate possible adverse selection. That is, the bank increases the contract interest rate by increasing the LTV ratio and switches the borrower from the riskier fixed-rate loan to the less risky variable-rate line-of-credit. On the other hand, borrowers who are refinancing are more likely to receive counteroffers designed to mitigate moral hazard. In this case, the lender counters with a contract designed to induce greater effort by requiring additional collateral in the form of a lower LTV ratio.[22]

4.5 Borrower response to accept/reject lender's counteroffer

We now turn to the decision by borrowers to accept or reject the lender's counteroffer, conditional on receiving a counteroffer. The borrower's decision reveals her opinion regarding the accuracy of the lender's secondary screening, and may also reveal additional asymmetric information. For example, borrowers who feel that the counteroffer incorrectly values their financial condition will reject the counteroffer, since they believe they can obtain a better credit offer from competing lenders. On the other hand, borrowers who feel that the lender correctly identified or underestimated their risk will accept the counteroffer. Thus, the lender's secondary screening and counteroffer may reintroduce the adverse selection problems as described in the Stiglitz and Weiss (1981) model. The good credit risk applicants may reject the counteroffer, but the less credit-worthy applicants eagerly accept it.

We formally analyze the likelihood that an applicant rejects the counteroffer by estimating a logit model of the borrower's response to the lender's counteroffer. Tables 9A and 9B present the likelihood that an applicant rejects the counteroffers designed to mitigate moral hazard and adverse selection, respectively. Overall, we do find that less risky applicants are more likely to reject the lender's counteroffer.

[22] We also modeled the individual counteroffers to switch LTV segments and loan/line products independently (as a 2 x 2 matrix of results). The results are consistent with our reported estimation based on grouped counteroffers.

Turning first to the moral hazard counteroffers, the results in Table 9A show that applicants with higher FICO scores (lower risk) are more likely to reject the counteroffer. All else being equal, the marginal effects suggest that an applicant with a FICO score of 800 is 7.4 percent more likely to reject the counteroffer than a borrower having a FICO score of 700. In addition, borrowers with greater income and longer house tenure (factors generally associated with lower credit risk) are also less likely to accept the offer. We also see that characteristics indicating higher risk are associated with a greater probability of accepting the counteroffer. For example, an applicant who owns a condo is 3.2 percent more likely to accept the counteroffer while an applicant who is rate refinancing or is without a first mortgage is more likely to reject the counteroffer.

Table 9B shows the results for applicants receiving a counteroffer designed to mitigate adverse selection. In contrast to the moral hazard results, we find that the borrower's FICO score is not statistically significant here. However, consistent with the theory that the higher-credit-quality applicant rejects the offer, we see that both applicant income and house tenure are positive and significant. In addition, the results indicate that a borrower who is offered a higher rate than the original contract rate is 1 percent more likely to reject the adverse selection counteroffer. We also see that a borrower who is offered a home equity loan, owns a second home, or is retired is less likely to reject the counteroffer. Furthermore, a borrower who does not have a first mortgage is 24.2 percent more likely to reject the counteroffer.

To summarize, our analysis reveals that in many cases borrowers who are relatively less risky are more likely to reject the bank's counteroffer. These differences can be seen within each counteroffer as well as across the two types of counteroffers. However, we also find a significant relationship between the borrower's probability of accepting a counteroffer and the bank's attempt to mitigate adverse selection or moral hazard by changing the contract interest rate or LTV. As a result, we confirm that the lender's mitigation attempts introduce additional adverse selection problems.

4.6 Effectiveness of lender's adverse selection and moral hazard mitigation efforts

As described in section 4.4, if the lender counteroffers with a contract having a lower LTV ratio (requiring a borrower to pledge more collateral per dollar loan amount) and/or switches the product from a home equity loan to a home equity line of credit, then we denote that the lender attempted to mitigate moral hazard. We designate loans as designed to limit adverse selection if the counteroffer has a higher LTV ratio and/or switches the product from a variable-rate home equity line of credit to a fixed-rate home equity loan. In this section, we evaluate the *ex post* repayment performance of all 83,411 booked applications to determine the effectiveness of the lender's attempts to mitigate adverse selection and moral hazard problems.

Based on the type of counteroffer, we create two dummy variables denoting whether a borrower was subjected to moral hazard mitigation or adverse selection mitigation to determine the effectiveness of the lender's mitigation efforts. Moreover, we create a monthly record of each loan denoting whether the loan defaulted, prepaid, or remained current as of March 2005. During this period, 916 (1.1 percent) of the loans defaulted, and 32,860 (39.4 percent) of the accounts were prepaid.[23]

[23] Default is defined as 90 days past due. Also see Agarwal el. al. (2006) for a discussion of the default and prepayment definitions.

As noted above, the data set contains loan level characteristics, such as the original loan amount, the current LTV ratio (reflecting both the first mortgage and the home equity loan or line), and the contract interest rate. Borrower characteristics include the credit score (FICO score) at origination as well as quarterly updates over the sample period. As a result, we control for the traditional factors associated with borrower prepayment and default and isolate the effects of the lender's attempts to mitigate the impacts of moral hazard and adverse selection. We discuss the set of control variables in Appendix B.

Table 10 presents the estimated coefficients for the competing risks model testing the effectiveness of the lender's adverse selection and moral hazard mitigation efforts (i.e., secondary screening and counteroffer contracts).[24] The results in Table 11 clearly indicate that the lender's *ex ante* mitigation efforts successfully reduced the risks associated with *ex post* default. The marginal effects for the moral hazard mitigation dummy variable indicate that, relative to loans that did not receive additional screening, the probability of default declines by 12.2 percent for loans where the lender *ex ante* required additional collateral and/or switched from home equity loans to home equity lines. In addition, the marginal effects for the adverse selection mitigation dummy variable indicate that, relative to loans that did not receive additional screening, the likelihood of default increases by 4.2 percent for loans where the lender *ex ante* increased the APR.

It is important to understand the economic implications of the moral hazard and adverse selection screening. A 12.2 percent net reduction in defaults in a $700 billion dollar portfolio with a one percent average default rate can save the banks close to $720 million. On the other hand, a higher default rate due to adverse selection screening will cause additional default of $360 million, but this is offset by the higher APR of 180 basis points for an average duration of 18 months on a loan amount of $40,000.

Our findings have additional implications for lenders seeking to maximize the profitability of their loan portfolios. The results clearly indicate that the secondary screening designed to mitigate adverse selection and moral hazard problems can reduce default risk *ex post*. Our findings are consistent with the conclusions of Karlan and Zinman (2006) that financial institutions can reduce credit losses and enhance welfare by investing in screening and monitoring devices. The lender's mitigation efforts are not, however, without costs, because the results in Table 10 also show that the *ex ante* mitigation efforts also significantly alter the odds of prepayment. For example, the marginal effects indicate that the probability of prepayment increases 11 percent for contracts designed to mitigate moral hazard and 2.9 percent for contracts designed to mitigate adverse selection relative to loans that were not subjected to additional screening. The marginal effects indicate that prepayment is substantially higher for loans screened for adverse selection and moral hazard, even after controlling for the effects of changes in interest rates on the option to refinance. Thus, during periods of declining interest rates, loans screened for adverse selection or moral hazard will experience higher prepayment rates than loans not subjected to additional screening.

The results indicate that the lender's mitigation efforts have created an additional incentive for borrowers to refinance into new (perhaps more favorable contracts) during a decline in interest rates. To the extent that the lender's screening alters the sensitivity of

[24] As in section 4.3, we follow the empirical method outlined in Agarwal et al. (2006) and estimate the model based on the maximum likelihood estimation approach for the proportional hazard model with grouped duration data. Details are discussed in Appendix A.

borrowers to changes in interest rates, then this will have a direct impact on secondary market investors and their ability to predict prepayment speeds on a securitized portfolio.

5. Conclusions

In this paper, we address the following questions: Do borrowers self-select into loan contracts that are designed to reveal information about their risk level? If so, do lenders still face adverse selection problems, conditional on borrowers' choices of contract type? Does screening *ex ante* for adverse selection and moral hazard at credit origination reduce default risks *ex post*, and if so, by how much? We answer these questions by analyzing a unique proprietary panel data set of over 108,000 home equity loans and lines of credit from a large financial institution that systematically screened for borrower *type* (adverse selection) and *effort* (moral hazard).

Our empirical analysis suggests that borrower choice of credit contract reveals information about their risk level. Specifically, we find that less credit-worthy borrowers are more likely to select contracts that require them to pledge less collateral, consistent with implications of the Bester (1985) model. We also find, however, that adverse selection due to private information remains after controlling for borrower contract choice and other observable risk characteristics. That is, we find a significant, positive correlation between a borrower's choice of collateral pledged *ex ante* and the risk of default *ex post* (consistent with adverse selection). The significant relationships identified among the variables denoting the borrower contract choice *ex ante* and loan performance *ex post* suggest the presence of adverse selection based on factors not observed by the lender during the origination of the loan; this is consistent with the implications of the Stiglitz and Weiss (1981) model.

Moreover, we find that a lender's efforts *ex ante* to mitigate adverse selection and moral hazard can be effective in reducing credit losses *ex post*. Our results show that secondary screening and counteroffers designed to mitigate moral hazard reduce default risk *ex post* by 12 percent, while additional screening and counteroffers to mitigate adverse selection increases default risk *ex post* by 4 percent. Hence, our results suggest that financial institutions can reduce credit losses using screening devices and counteroffer contracts to induce borrower effort. However, they are less successful in reducing default by screening for adverse selection. It is worth noting that the increased defaults due to adverse selection screening are offset by the increased profitability achieved through higher APR. To put these results into perspective, the home equity market is over $700 billion and has an average default rate of one percent, implying total defaults of approximately $7 billion. We show that secondary screening for moral hazard and adverse selection can reduce these defaults by up to 12.2 percent, indicating a default savings of approximately $720 million and increased profits of $360 million.

We find it interesting, however, that these mitigation efforts also impose costs in the form of higher prepayment rates. The results show that moral hazard mitigation efforts increase the odds of prepayment by 11 percent, and adverse selection mitigation efforts increase the probability of prepayment by approximately 3 percent. Therefore, lenders seeking to minimize credit losses may find it profitable to screen for moral hazard and adverse selection and to design counteroffer contracts to mitigate those problems. They may, however, also realize losses from higher prepayment rates.

The results from this analysis are applicable to a wide variety of financial contracting environments where lenders and borrowers interact prior to loan origination. For example, Sufi (2006) recognizes that syndicated loan market contracts are the result of a complex negotiation between the firm and the lead underwriter. However, his analysis does not address how information asymmetry may affect loan prices. Our analysis clearly indicates that borrower–lender contract negotiations can impact *ex post* default risk and thus should impact *ex ante* loan pricing. Our results are also applicable to other markets, such as insurance, managerial incentive compensation, and corporate governance, that have similar asymmetric information problems.

References

Agarwal, S., 2006, "The impact of homeowners' housing wealth misestimation on consumption and saving decisions," forthcoming, *Real Estate Economics*.

Agarwal, S., B. W. Ambrose, S. Chomsisengphet, and C. Liu, 2006, "An empirical analysis of home equity loan and line performance," *Journal of Financial Intermediation*, 15(4), 444-69.

Agarwal, S., B. W. Ambrose, and C. Liu, 2006, "Credit lines and credit utilization," *Journal of Money, Credit and Banking,* 38(1), 1-22.

Akerlof, G. A., 1970, "The market for 'lemons': Quality uncertainty and the market mechanism," *Quarterly Journal of Economics,* 84(3), 488-500.

Archer, W., D. Ling, and G.A. McGill, 1996, "The effect of income and collateral constraints on residential mortgage termination," *Regional Science and Urban Economics* 26(3-4), 235-261.

Ausubel, L., 1991, "The failure of competition in the credit card market," *American Economic Review* 81(1), 50-81.

Ausubel, L., 1999, "Adverse selection in the credit card market," Working Paper, University of Maryland.

Bennet, P., R. Peach, and S. Peristiani, 2000, "Implied mortgage refinancing thresholds," Real Estate Economics 28(3), 405-434.

Berger, A.N., N.H. Miller, M.A. Petersen, R.G. Rajan, and J.C. Stein, 2005, "Does function follow organizational form? Evidence from the lending practices of large and small banks," Journal of Financial Economics, 76, 237-269.

Bester, H., 1985, "Screening vs. rationing in credit markets with imperfect information," *American Economic Review* 75(4), 850-855.

Calem, P. S., and L. Mester, 1995, "Consumer behavior and the stickiness of credit card interest rates," *American Economic Review* 85(5), 1327-1336.

Calem, P. S., M. Gordy, and L. Mester, 2006, "Switching cost and adverse selection in the market for credit cards: New evidence," forthcoming, *Journal of Banking and Finance*.

Chan, Y. S., and Thakor, A.V., 1987, "Collateral and competitive equilibria with moral hazard and private information," *Journal of Finance,* 42, 345-363.

Chiappori, P.A. and B. Salanié, 2000, "Testing for Asymmetric Information in Insurance Markets," *Journal of Political Economy* 108(1), 56-78.

Chiappori, P. A. and B. Salanié, 2003, “Testing contract theory: A survey of some recent work.” Advances in Economics and Econometrics: Theory and Applications, Eighth World Congress. M. Dewatripont, L. Hansen and P. Turnovsky. Cambridge, Cambridge University Press**:** 115-149.

Davidoff, T., and G.M. Welke, 2004, “Selection and moral hazard in the US mortgage industry,” Working paper, Haas School of Business, UC Berkeley.

Deng, Y., J. M. Quigley, and R. Van Order, 2000, “Mortgage terminations, heterogeneity and the exercise of mortgage options,” *Econometrica.* 68 (2), 275-307.

Dey, S., and L. Dunn, 2006, “An empirical investigation of collateral and sorting in the HELOC market,” Working Paper, Bank of Canada.

Edelberg, W., 2004, “Testing for adverse selection and moral hazard in consumer loan markets,” Finance and Economics Discussion Paper Series, Board of Governors of the Federal Reserve System.

Finkelstein, A., and J. Poterba, 2004, “Adverse Selection in Insurance Markets: Policyholder Evidence from the U.K. Annuity Market,” *Journal of Political Economy*, 112(1), 183-208.

Finkelstein, A., and J. Poterba, 2006, “Testing for Adverse Selection with ‘Unused Observables,’” Working Paper, MIT and NBER.

Gross, D. B., and N. S. Souleles, 2002, “An empirical analysis of personal bankruptcy and delinquency,” *Review of Financial Studies*, 15(1), 319-347.

Han, A., and J.A. Hausman, 1990, “Flexible parametric estimation of duration and competing risk models,” *Journal of Applied Econometrics* 18: 41-50.

Hurst, E., and F. Stafford, 2004, “Home is where the equity is: Mortgage refinancing and household consumption,” *Journal of Money, Credit, Banking*, 36(6), 985-1014.

Igawa, K. and G. Kanatas, 1990, “Asymmetric information, collateral, and moral hazard,” *Journal of Financial and Quantitative Analysis*, 25(4), pp. 469-490.

Karlan, D. and J. Zinman, 2006, "Observing unobservables: Identifying information asymmetries with a consumer credit field experiment" Working paper, Yale University.

LeRoy, S., 1996, “Mortgage valuation under optimal prepayment,” *Review of Financial Studies*, 9, 817-844.

McCall, B.P., 1996, “Unemployment insurance rules, joblessness, and part-time work,” *Econometrica* 64: 647-682.

Peristiani, S., P. Bennett, R. Peach, and J. Raiff, 1997, “Credit, equity, and mortgage refinancings,” *Federal Reserve Bank of New York Economic Policy Review*, July, 83-103.

Petersen, M.A., 2004, “Information: Hard and Soft,” Working paper, Northwestern University.

Stein, J.C., 2002, “Information Production and Capital Allocation: Decentralized versus Hierarchical Firms,” *Journal of Finance,* 57(5), 1891-1921.

Stiglitz, J. E., and A. Weiss, 1981, “Credit rationing in the market with imperfect information,” *American Economic Review*, 71(3), 393-410.

Stanton, R., and N. Wallace. 1998, “Mortgage choice: What’s the point,” *Real Estate Economics* 26: 173-205.

Sufi, A., 2006, “Information Asymmetry and Financing Arrangements: Evidence from Syndicated Loans,” *Journal of Finance* (Forthcoming).

Figure 1: HOME EQUITY MORTGAGE ORIGINATION PROCESS

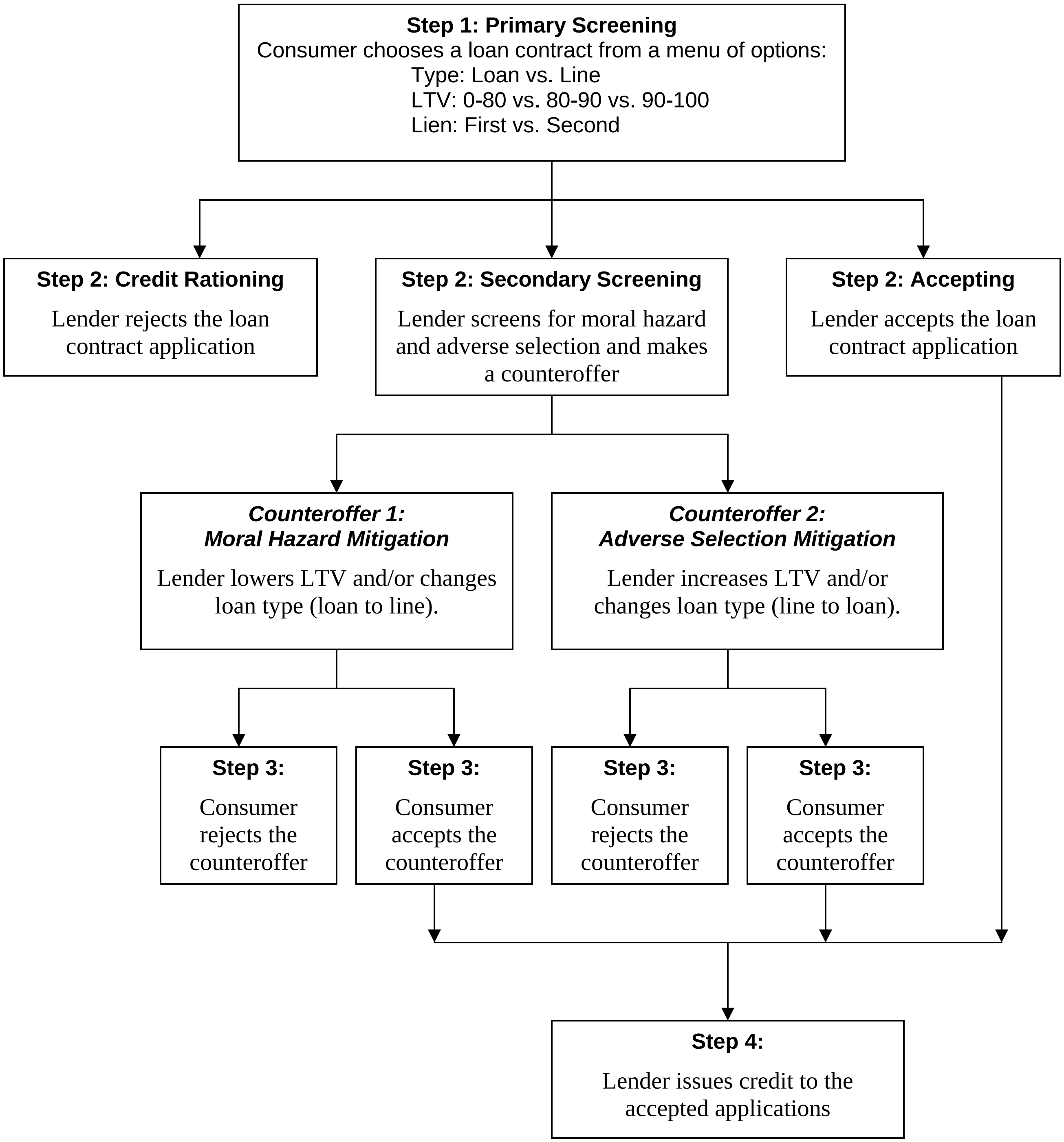

Table 1. Number of accounts

This table shows the number of applications in dynamic contracting settings for the home equity loans and lines-of-credit applications received between March and December of 2002. Panel A shows the initial screening outcome distribution. Panel B shows the distribution of the counteroffers designed to mitigate potential adverse selection or moral hazard. Panel C shows the distribution of the consumers' acceptance or rejection of the counteroffer. Panel D shows the total number of loans originated as a percentage of the total applications.

	Count	%
Total Credit Applications Received (March – December 2002)	108,117	
Panel A: Primary Screening		
Lender Rations Credit	12,006	11.1%
Lender Accepts Credit	62,251	57.6%
Secondary Screening and Counteroffer	33,860	31.3%
Panel B: Secondary Screening		
Counteroffer 1: Lower LTV and/or Change from Loan to Line	23,222	68.6%
Counteroffer 2: Higher LTV and/or Change from Line to Loan	10,638	31.4%
Panel C: Consumer Response to Counteroffer		
Consumer Rejected Counteroffer	12,700	37.5%
Counteroffer 1: Lower LTV and/or Change from Loan to Line	8,129	64.0%
Counteroffer 2: Higher LTV and/or Change from Line to Loan	4,571	36.0%
Consumer Accepted Counteroffer	21,160	62.5%
Counteroffer 1: Lower LTV and/or Change from Loan to Line	15,093	71.3%
Counteroffer 2: Higher LTV and/or Change from Line to Loan	6,067	28.7%
Panel D: Total Loans Originated		
Total Booked	83,411	77.1%

Table 2. Descriptive statistics by LTV category

This table reports the descriptive statistics for the variables used in the analysis of asymmetric information in dynamic contracting settings. The data set is subdivided based on whether the borrower applied for a loan with a loan-to-value (LTV) ratio less than 80 percent, a LTV ratio between 80 percent and 90 percent, and a LTV ratio greater than 90 percent. Loan amount requested is the total credit line or loan amount recorded on the borrower's application. Customer LTV is the loan-to-value ratio based on the customer's self-reported property valuation. FICO is the borrower's credit score at the time of application. "Reason for loan" is the borrower's reported use of funds. Months at address is the total number of months the borrower reports she has resided at the current address. Income is the borrower's reported annual income. Debt to income is the borrower's total debt payment divided by reported income. Employment information indicates whether the borrower is employed, self-employed, retired, or homemaker, as well as the number of years with current employer.

	LTV <80		LTV 80-90		LTV >90	
Variable Name	**MEAN**	**STD**	**MEAN**	**STD**	**MEAN**	**STD**
Loan Amount Requested	$67,503	$50,548	$63,554	$51,222	$54,283	$42,189
Customer LTV	50	21	84	3	98	9
FICO	737	52	718	50	708	49
Reported Reason for Loan:						
Refinancing	41%	49%	42%	49%	48%	50%
Home Improvement	24%	43%	27%	44%	26%	44%
Consumption	35%	46%	32%	41%	27%	45%
Months at Address	158	137	81	92	74	90
Income	$118,170	$182,724	$115,979	$148,723	$100,932	$107,962
Debt to Income	35	19	38	18	40	18
Employment Information						
Employed	79%	24%	89%	18%	91%	18%
Years on the Job	9.78	9.60	7.85	7.72	7.42	7.44
Self Employed	9%	28%	7%	25%	6%	23%
Retired	11%	31%	3%	17%	2%	16%
Homemaker	1%	12%	1%	11%	1%	10%
Borrower Age	51	13	43	11	41	10
Frequency	84,511		15,074		8,532	

Table 3. LTV contract choice by borrower

This table reports the maximum likelihood estimates and marginal coefficients for the multinomial logit model of the borrower's choice of loan-to-value ratio (LTV). The base case is customers applying for a less-than-80 percent LTV. The data set includes 108,117 home equity credit applications.

	Customer LTV between 80 and 90 percent				Customer LTV greater than 90 percent			
Independent variables	**Coefficient**	**Std. Err.**	**p-value**	**Marginal Effects**	**Coefficient**	**Std. Err.**	**p-value**	**Marginal Effects**
Intercept	-7.715	1.803	<.0001		-19.454	2.785	<.0001	
Borrower Characteristics								
FICO	0.038	0.005	<.0001	0.27%	0.087	0.008	<.0001	0.19%
$FICO^2$	-3.0E-05	0.0E+00	<.0001	0.00%	-7.0E-05	1.0E-05	<.0001	0.00%
Log (Income)	-0.032	0.023	0.171	-19.58%	-0.262	0.034	<.0001	-14.40%
Log (Borrower Age)	-1.395	0.062	<.0001	-12.81%	-1.852	0.088	<.0001	-8.74%
Log (House tenure)	-0.303	0.010	<.0001	-2.44%	-0.330	0.015	<.0001	-1.67%
Debt to Income	0.007	0.001	<.0001	0.92%	0.003	0.001	0.015	1.29%
Contract Characteristics								
First Lien Dummy	-0.165	0.109	0.130	-2.89%	-0.543	0.196	0.006	-1.97%
Home Equity Loan Dummy	0.089	0.034	0.009	2.03%	0.448	0.042	<.0001	2.39%
Refinancing	0.096	0.029	0.001	3.32%	0.276	0.042	<.0001	2.90%
Home Improvement	0.003	0.031	0.933	0.04%	0.037	0.046	0.420	0.03%
No First Mortgage	-1.123	0.048	<.0001	-10.52%	-1.805	0.093	<.0001	-7.18%
Second Home	-0.931	0.120	<.0001	-8.00%	-1.207	0.216	<.0001	-11.46%
Condo	-0.047	0.049	0.337	-2.72%	-1.116	0.102	<.0001	-1.86%
Employment Control Variables								
Log (Years on the Job)	-0.043	0.013	0.001	-0.26%	-0.024	0.019	0.200	-0.18%
Self-Employed	-0.234	0.046	<.0001	-2.47%	-0.438	0.072	<.0001	-1.69%
Retired	0.116	0.102	0.254	-0.06%	0.133	0.154	0.388	0.04%
Homemaker	-0.325	0.169	0.055	-3.75%	-0.704	0.274	0.010	-2.56%
Location Control Variables								
CT State Dummy	0.335	0.043	<.0001	3.06%	0.469	0.061	<.0001	2.09%
ME State Dummy	0.816	0.063	<.0001	6.22%	0.985	0.084	<.0001	4.24%
NH State Dummy	0.420	0.068	<.0001	3.83%	0.440	0.096	<.0001	2.62%
NJ State Dummy	-4.1E-04	0.033	0.990	-0.10%	-0.024	0.049	0.617	-0.07%
NY State Dummy	0.034	0.037	0.355	0.77%	0.202	0.051	<.0001	0.52%
PA State Dummy	0.647	0.059	<.0001	6.51%	0.977	0.075	<.0001	4.44%
RI State Dummy	0.295	0.066	<.0001	2.32%	0.287	0.093	0.002	1.58%
Number of Observations		15074				8532		
Pseudo R-square	7.90%							

Table 4. Summary statistics of lender's initial underwriting decisions

This table reports the sample descriptive statistics segmented by the lender's initial underwriting decision: accepted, subjected to secondary screening and counteroffer, or denied. Loan amount requested is the total credit line or loan amount recorded on the borrower's application. Customer LTV is the loan-to-value ratio calculated using the customer's requested loan amount and the customer's self-reported property value. Lender LTV is the loan-to-value ratio calculated using the approved loan amount and the property value determined by the lender's independent appraisal. Annual percentage rate is the effective interest rate on the offered loan. FICO is the borrower's credit score at the time of application. Reasons for loan are the borrower's reported use of funds. Months at address is the total number of months the borrower reports she has resided at the current address. Income is the borrower's reported annual income. Debt to income is the borrower's total debt payment divided by reported income. Employment information indicates whether the borrower is employed, self-employed, retired, or homemaker, as well as the number of years with current employer.

	Application Rejected		**Secondary Screening & Counteroffer**		**Application Accepted**	
	MEAN	STD	MEAN	STD	MEAN	STD
Loan Amount Requested	$68,283	$54,677	$62,470	$46,752	$67,619	$50,288
Customer LTV	74%	24%	58%	27%	54%	23%
Lender LTV	82%	30%	58%	26%	56%	23%
Loan Amount Approved	-	-	$60,010	$47,848	$68,870	$52,158
Annual Percentage Rate	-	-	5.74	0.92	4.68	1.22
FICO	714	54	729	50	737	51
Reported Reason for Loan:						
Refinancing	43%	50%	55%	48%	39%	49%
Consumption	31%	39%	22%	42%	36%	36%
Home Improvement	25%	44%	22%	41%	25%	43%
No First Mortgage	19%	39%	40%	46%	26%	44%
Months at Address	94	107	148	138	152	134
Income	$82,058	$170,174	$110,533	$151,523	$121,974	$213,853
Debt to Income	45	21	37	18	34	19
Employment Information:						
Employed	82%	45%	83%	46%	80%	41%
Years on the Job	8.12	8.27	8.91	8.97	9.79	9.53
Self Employed	12%	33%	7%	25%	8%	27%
Retired	5%	22%	9%	28%	10%	30%
Homemaker	1%	11%	1%	10%	1%	12%
Borrower Age	47	13	49	13	50	12
Number of Observations	12,006		33,860		62,251	

Table 5. Counteroffer and credit rationing by lender

This table reports the estimated coefficients and marginal effects for the maximum likelihood estimation of the multinomial logit model of the lender's initial underwriting decision. The base case is loans that were accepted outright (without additional screening). Lender LTV 80-90 is a dummy variable indicating loans with actual LTV ratios between 80 and 90 percent. Lender LTV 90+ is a dummy variable indicating loans with actual LTV ratios greater than 90 percent. The data set includes 108,117 home equity credit applications.

	Subjected to Secondary Screening and Counteroffer				**Application Rejected**			
Independent variables	**Coeff. Val.**	**Std. Err.**	**p-value**	**Marginal Effects**	**Coeff. Val.**	**Std. Err.**	**p-value**	**Marginal Effects**
Intercept	-10.914	1.210	<.0001		-0.020	1.665	0.990	
Borrower Characteristics								
FICO	0.032	0.003	<.0001	0.08%	0.008	0.002	<.0001	0.09%
$FICO^2$	-2.0E-05	4.0E-06	<.0001	0.00%	-3.0E-04	6.0E-05	0.002	0.00%
Log (Income)	-0.115	0.015	<.0001	-2.55%	-0.018	0.002	<.0001	-3.79%
Log (House tenure)	-0.015	0.007	0.038	-0.32%	-0.067	0.011	<.0001	-0.23%
Debt to Income	0.002	0.001	<.0001	0.95%	0.005	0.001	<.0001	1.78%
Contract Characteristics								
Lender LTV 80-90	1.282	0.021	<.0001	12.01%	1.652	0.033	<.0001	8.67%
Lender LTV 90+	2.223	0.036	<.0001	15.84%	3.921	0.041	<.0001	18.35%
First Lien Dummy	4.846	0.134	<.0001	17.13%	-3.429	0.146	<.0001	-12.18%
Home Equity Loan Dummy	0.379	0.022	<.0001	6.71%	0.959	0.031	<.0001	4.77%
Home Improvement	-0.041	0.021	0.504	-0.17%	-0.028	0.033	0.390	-0.12%
Refinancing	-0.048	0.011	<.0001	-3.68%	-0.174	0.030	<.0001	-2.61%
No First Mortgage	0.021	0.002	<.0001	1.66%	-0.367	0.038	<.0001	-1.18%
Second Home	0.346	0.052	<.0001	8.64%	1.377	0.061	<.0001	6.14%
Condo	0.490	0.032	<.0001	9.07%	1.305	0.041	<.0001	6.45%
Employment Control Variables								
Log (Years on the Job)	-0.031	0.009	0.000	-0.43%	-0.060	0.013	<.0001	-0.31%
Self Employed	0.055	0.030	0.064	3.04%	0.733	0.039	<.0001	2.16%
Retired	-0.246	0.120	0.040	-1.54%	-0.115	0.187	0.541	-1.10%
Homemaker	-0.153	0.044	0.001	-1.75%	-0.216	0.078	0.005	-1.24%
Location Control Variables								
CT State Dummy	-0.072	0.030	0.018	-2.09%	-0.357	0.048	<.0001	-1.49%
ME State Dummy	-0.116	0.048	0.016	-3.90%	-0.737	0.083	<.0001	-2.77%
NH State Dummy	-0.075	0.051	0.138	-1.81%	-0.323	0.079	<.0001	-1.29%
NJ State Dummy	0.004	0.022	0.847	-0.52%	-0.089	0.033	0.007	-0.37%
NY State Dummy	-0.078	0.024	0.002	-1.26%	-0.153	0.037	<.0001	-0.90%
PA State Dummy	-0.005	0.043	0.907	-0.80%	-0.115	0.060	0.057	-0.57%
RI State Dummy	-0.110	0.048	0.021	-1.98%	-0.306	0.075	<.0001	-1.41%
Number of Observations			33,860				12,006	
Pseudo R-square	11.34%							

Table 6. Test of adverse selection on unobservable risk characteristics

This table reports the competing risks hazard model of loan default and prepayment in order to identify the presence of adverse selection in the set of 62,251 applicants who were accepted outright (without secondary screening). The base case is that the loan remains current as of the end of the observation period (March 2005). CLTV is the current (time-varying) loan-to-value ratio based on estimated changes in the underlying house price obtained from the OFHEO MSA level repeat sales indices. PPOption captures the borrower's prepayment option value. LTV difference is a dummy variable denoting a decline in collateral value from the previous quarter. House value difference is the percentage difference between the borrower's initial house value and the lender's independent appraisal. Account age is the number of months since origination and controls for loan seasoning. The model is estimated by maximum likelihood treating both prepayment and default outcomes as correlated competing risk estimated jointly. A bivariate distribution of unobserved heterogeneous error terms is also estimated simultaneously with the competing risk hazard. LOC1 and LOC2 are the location parameters and MASS2 is the mass points associated with LOC1 (MASS1 is normalized to 1).

	Default				Prepayment			
Independent variables	**Coeff. Val.**	**Std. Err.**	**p-value**	**Marginal Effects**	**Coeff. Val.**	**Std. Err.**	**p-value**	**Marginal Effects**
Intercept	24.075	1.173	<.0001		-2.520	0.357	<.0001	
Borrower Characteristics								
FICO	-0.182	0.012	<.0001	-0.49%	0.052	0.003	<.0001	0.15%
$FICO^2$	1.1E-04	9.1E-06	<.0001	0.00%	4.0E-05	1.8E-06	<.0001	0.00%
Log (Income)	-0.377	0.082	<.0001	-9.49%	0.180	0.016	<.0001	1.95%
Log (House tenure)	-0.213	0.031	<.0001	-9.44%	-0.101	0.007	<.0001	-1.74%
Debt to Income	0.026	0.003	<.0001	2.06%	0.017	0.001	<.0001	2.24%
Contract Characteristics								
Lender LTV 80-90	0.354	0.125	0.005	2.22%	-0.553	0.021	<.0001	-4.53%
Lender LTV 90+	1.291	0.180	<.0001	5.57%	-1.709	0.052	<.0001	-6.57%
Home Equity Loan Dummy	1.929	0.192	<.0001	5.38%	0.995	0.051	<.0001	2.07%
First Lien Dummy	-0.653	0.090	<.0001	-2.26%	-0.732	0.107	<.0001	-2.14%
Refinancing	-0.521	0.110	<.0001	-3.70%	0.165	0.018	<.0001	2.77%
Home Improvement	-0.681	0.115	<.0001	-3.36%	0.043	0.021	0.042	1.41%
No First Mortgage	-1.133	0.137	<.0001	-6.79%	-0.120	0.022	<.0001	-3.10%
Second Home	3.140	0.150	<.0001	2.08%	-0.259	0.043	<.0001	-3.10%
Condo	-2.251	0.345	<.0001	-1.26%	0.568	0.034	<.0001	2.46%
Auto Pay	-0.360	0.099	0.000	-4.18%	0.060	0.017	0.001	2.72%
Time-varying Option Variables								
CLTV	0.188	0.368	<.0001	3.98%	-0.489	0.038	<.0001	-1.03%
$CLTV^2$	1.288	0.384	<.0001	8.91%	-0.691	0.061	<.0001	-4.30%
PPOption	1.433	0.262	<.0001	3.05%	1.128	0.215	<.0001	8.12%
LTV_Diff_Dummy	1.012	0.218	<.0001	2.98%	-0.624	0.034	<.0001	-1.14%
HouseVal_Diff	0.345	0.074	<.0001	2.26%	-0.204	0.038	<.0001	-2.10%
Account Age	0.047	0.019	0.013	1.07%	-0.189	0.037	<.0001	-2.71%
Account Age^2	-4.4E-04	9.1E-05	<.0001	-2.55%	1.9E-03	1.9E-05	<.0001	1.02%
Account Age^3	2.0E-06	2.0E-07	<.0001	0.58%	3.0E-06	2.0E-06	<.0001	0.35%
Employment Control Variables								
Log (Years on the Job)	-0.341	0.047	<.0001	-4.03%	-0.072	0.008	<.0001	-1.00%
Self Employed	0.630	0.094	<.0001	0.19%	-0.499	0.026	<.0001	-1.58%
Retired	1.279	0.196	<.0001	0.32%	0.852	0.041	<.0001	2.77%
Homemaker	-0.928	1.153	0.421	-0.65%	-1.111	0.165	<.0001	-2.53%
Location and Economic Control Variables								
Unemployment Rate	0.358	0.023	<.0001	1.62%	0.046	0.005	<.0001	3.80%

CT State Dummy	-1.465	0.249	<.0001	-0.07%	0.201	0.022	<.0001	2.87%
ME State Dummy	-1.974	1.114	0.076	-0.30%	0.677	0.058	<.0001	0.85%
NH State Dummy	0.348	0.109	<.0001	0.47%	0.378	0.059	<.0001	0.79%
NJ State Dummy	-1.203	0.202	<.0001	-0.02%	0.055	0.028	0.052	0.90%
NY State Dummy	0.235	0.105	0.025	0.03%	0.082	0.021	0.000	1.31%
PA State Dummy	1.035	0.116	<.0001	0.13%	0.282	0.039	<.0001	0.97%
RI State Dummy	-1.593	0.473	0.001	-0.16%	0.438	0.043	<.0001	0.31%
Unobserved Heterogeneity Factors								
Loc1	1.479	0.489	<.0001		0.974	0.130	<.0001	
Loc2	1.698	0.572	<.0001		0.899	0.286	<.0001	
Mass2	0.489	0.128	<.0001		0.685	0.184	<.0001	
Time Quarter Dummies	Yes							
Pseudo R-square	13.06%							
Number of Accts/Defaults/Prepay		702				20399		

Table 7. Summary statistics of counteroffers by mitigation type

This table reports the descriptive statistics for the variables used in the analysis of the lender's decision about whether the 33,860 borrower applications who are subjected to secondary screening should receive either a counteroffer designed to mitigate adverse selection or one designed to counteroffer moral hazard. Loan amount requested is the total credit line or loan amount recorded on the borrower's application. Loan amount approved is the actual credit amount offered. Customer LTV is the loan-to-value ratio calculated using the customer's requested loan amount and the customer's self-reported property valuation. Lender LTV is the loan-to-value ratio calculated using the approved loan amount and the property value determined by the lender's independent appraisal. Annual percentage rate is the effective interest rate on the offered loan. FICO is the borrower's credit score at the time of application. Reasons for loan are the borrower's reported use of funds. Months at address is the total number of months the borrower reports she has resided at the current address. Income is the borrower's reported annual income. Debt to income is the borrower's total debt payment divided by reported income. Employment information indicates whether the borrower is employed, self-employed, retired, or homemaker, as well as the number of years with current employer.

	Moral Hazard Mitigation		Adverse Selection Mitigation	
	MEAN	**STD**	**MEAN**	**STD**
Loan Amount Requested	$68,441	$50,808	$47,703	$36,825
Loan Amount Approved	$64,868	$52,049	$47,903	$37,284
Customer LTV	56%	28%	63%	23%
Lender LTV	54%	28%	67%	23%
APR	4.89	0.93	7.60	0.88
FICO	727	48	719	53
Reported Reason for Loan:				
Refinancing	64%	48%	38%	48%
Home Improvement	21%	40%	25%	44%
Consumption	16%	43%	37%	40%
No First Mortgage	48%	48%	22%	41%
Months at Address	158	144	127	126
Income	$118,659	$113,800	$92,797	$94,722
Debt to Income	35	18	40	19
Employment Information				
Employed	84%	46%	82%	45%
Yeas on the Job	8.99	8.94	8.73	9.02
Self Employed	8%	27%	5%	21%
Retired	8%	26%	12%	32%
Homemaker	1%	11%	1%	10%
Borrower Age	49	13	47	13
Frequency	23,222		10,638	

Table 8. Lender's counteroffer to mitigate adverse selection

This table reports the maximum likelihood estimates and marginal effects for the logit model of the lender's decision to mitigate for adverse selection or moral hazard, conditional upon the application being subjected to secondary screening. The base case is the decision to counteroffer to mitigate moral hazard. LTV difference is the difference between the lender LTV ratio and the customer LTV ratio. Loan amount difference is the percentage difference between the customer's loan request and the lender's loan amount offer (customer loan amount less the lender loan offer divided by the customer loan amount). 33,860 applications were subjected to secondary screening.

Independent variables	Coefficient	Std. Err.	p-value	Marginal Effects
Intercept	10.781	2.101	<.0001	
Borrower Characteristics				
FICO	-0.011	0.003	<.0001	-0.41%
$FICO^2$	-1.0E-05	3.0E-06	<.0001	0.00%
Log (Income)	-0.669	0.028	<.0001	-12.07%
Log (House tenure)	-0.022	0.013	0.090	-0.39%
Debt to Income	0.004	0.001	<.0001	2.79%
Contract Characteristics				
LTV Difference	0.005	0.001	<.0001	3.08%
Loan Amount Difference	6.5E-04	4.3E-04	0.385	0.00%
Refinancing	-1.221	0.037	<.0001	-21.94%
Home Improvement	-0.678	0.042	<.0001	-12.17%
No First Mortgage	-0.904	0.035	<.0001	-16.23%
Second Home	0.015	0.086	0.859	7.21%
Condo	-0.296	0.056	<.0001	-5.27%
Employment Control Variables				
Log (Years on the Job)	-0.036	0.015	0.016	-0.65%
Self Employed	-0.420	0.059	<.0001	-7.52%
Retired	0.372	0.073	<.0001	6.69%
Homemaker	-0.310	0.229	0.177	-0.56%
Location Control Variables				
CT State Dummy	0.235	0.054	<.0001	4.24%
ME State Dummy	-0.241	0.083	0.004	-4.35%
NH State Dummy	0.222	0.087	0.011	3.97%
NJ State Dummy	0.414	0.039	<.0001	7.45%
NY State Dummy	0.178	0.044	<.0001	3.21%
PA State Dummy	0.377	0.066	<.0001	6.80%
RI State Dummy	0.275	0.081	0.001	4.92%
Number of Observations	10,638			
Pseudo R-square	13.32%			

Table 9A. Applicants rejecting lender's counteroffer for moral hazard

This table reports the maximum likelihood estimates and marginal effects for the logit model of the borrower's decision to accept or reject the lender's counteroffer designed to mitigate moral hazard. The base case is the decision to accept the lender's counteroffer. LTV difference is the difference between the lender LTV ratio and the customer LTV ratio. Loan amount difference is the percentage difference between the customer's loan request and the lender's loan amount offer (customer loan amount less the lender loan offer divided by the customer loan amount.) APR difference is the difference between the lender's counteroffer interest rate and the interest rate on the application contract. Of the 23,222 borrowers receiving a counteroffer designed to mitigate moral hazard, 8,129 rejected the offer.

	Moral Hazard Mitigation			
Independent variables	**Coefficient**	**Std. Err.**	**p-value**	**Marginal Effects**
Intercept	-7.001	2.781	0.012	
Borrower Characteristics:				
FICO	0.020	0.008	0.011	0.40%
$FICO^2$	-1.0E-05	1.0E-05	0.097	0.00%
Log (Income)	0.334	0.031	<.0001	6.80%
Log (House tenure)	0.139	0.015	<.0001	2.83%
Debt to Income	-0.014	0.001	<.0001	-0.89%
Contract Characteristics:				
LTV Difference	0.003	0.001	0.002	0.65%
Loan Amount Difference	0.003	0.001	<.0001	0.05%
APR Difference	0.012	0.001	<.0001	2.38%
Home Equity Loan Dummy	1.062	0.335	<.0001	5.84%
First Lien Dummy	-1.960	0.355	<.0001	-7.64%
Refinancing	0.142	0.038	0.000	2.88%
Home Improvement	0.052	0.040	0.198	1.06%
No First Mortgage	0.395	0.044	<.0001	8.03%
Second Home	-0.324	0.305	0.576	-0.59%
Condo	-0.155	0.060	0.010	-3.15%
Employment Control Variables				
Log (Years on the Job)	-0.042	0.017	0.013	-0.86%
Self Employed	-0.019	0.008	0.022	-4.39%
Retired	-0.159	0.087	0.068	-1.24%
Homemaker	0.589	0.228	0.010	11.96%
Location Control Variables				
CT State Dummy	-0.419	0.060	<.0001	-8.52%
ME State Dummy	-0.882	0.098	<.0001	-17.92%
NH State Dummy	-0.323	0.100	0.001	-6.56%
NJ State Dummy	-0.076	0.042	0.072	-1.54%
NY State Dummy	-0.165	0.048	0.001	-3.35%
PA State Dummy	-0.169	0.080	0.035	-3.43%
RI State Dummy	-0.447	0.096	<.0001	-9.08%
Number of Obs/Outcome	8,129			
Pseudo R-square	10.14%			

Table 9B. Applicants rejecting lender's counteroffer for adverse selection

This table reports the maximum likelihood estimates and marginal effects for the logit model of the borrower's decision to accept or reject the lender's counteroffer designed to mitigate adverse selection. The base case is the decision to accept the lender's counteroffer. LTV difference is the difference between the lender LTV ratio and the customer LTV ratio. Loan amount difference is the percentage difference between the customer's loan request and the lender's loan amount offer (customer loan amount less the lender loan offer divided by the customer loan amount.) APR difference is the difference between the lender's counteroffer interest rate and the interest rate on the application contract. Of the 10,638 borrowers receiving a counteroffer designed to mitigate adverse selection, 4,571 rejected the offer.

	Adverse Selection Mitigation			
Independent variables	**Coefficient**	**Std. Err.**	**p-value**	**Marginal Effects**
Intercept	-5.986	3.947	0.129	
Borrower Characteristics				
FICO	-0.010	0.010	0.329	-0.18%
$FICO^2$	1.0E-05	1.0E-05	0.109	0.00%
Log (Income)	0.534	0.052	<.0001	9.77%
Log (House tenure)	0.001	0.025	0.982	3.01%
Debt to Income	-0.006	0.002	0.001	-0.91%
Contract Characteristics				
LTV Difference	0.002	0.001	0.128	0.32%
Loan Amount Difference	0.004	0.001	0.001	0.07%
APR Difference	0.165	0.006	<.0001	1.02%
Home Equity Loan Dummy	-4.389	1.371	0.001	-8.28%
First Lien Dummy	-2.996	0.166	<.0001	-5.81%
Refinancing	-0.219	0.074	0.003	-4.01%
Home Improvement	-0.129	0.086	0.133	-2.35%
No First Mortgage	1.382	0.166	<.0001	24.29%
Second Home	-0.245	0.054	<.0001	-4.48%
Condo	-0.203	0.102	0.046	3.71%
Employment Control Variables				
Log (Years on the Job)	-0.070	0.027	0.010	-1.27%
Self Employed	0.055	0.112	0.623	1.01%
Retired	-0.486	0.131	0.000	-8.88%
Homemaker	-0.714	0.431	0.098	-13.06%
Location Control Variables				
CT State Dummy	-0.761	0.102	<.0001	-13.92%
ME State Dummy	-0.736	0.162	<.0001	-13.47%
NH State Dummy	-0.247	0.154	0.109	-4.52%
NJ State Dummy	-0.231	0.073	0.002	-4.23%
NY State Dummy	-0.757	0.081	<.0001	-13.84%
PA State Dummy	-0.346	0.114	0.003	-6.32%
RI State Dummy	-0.317	0.141	0.024	-5.80%
Number of Obs/Outcome	4,571			
Pseudo R-square	12.56%			

Table 10. Effectiveness of lender's effort to mitigate adverse selection and moral hazard

This table reports the competing risks hazard model of loan default and prepayment in order to identify the effect of the lender's efforts at mitigating adverse selection and moral hazard in the set of 83,411 applications that are ultimately booked. The base case is that the loan remains current as of the end of the observation period (March 2005). CLTV is the current (time-varying) loan-to-value ratio based on estimated changes in the underlying house price obtained from the OFHEO MSA level repeat sales indices. PPOption captures the borrower's prepayment option value. LTV difference is a dummy variable denoting a decline in collateral value from the previous quarter. House value difference is the percentage difference between the borrower's initial house value and the lender's independent appraisal. Account age is the number of months since origination and controls for loan seasoning. The model is estimated by maximum likelihood treating both prepayment and default outcomes as correlated competing risk estimated jointly. A bivariate distribution of unobserved heterogeneous error terms is also estimated simultaneously with the competing risk hazard. LOC1 and LOC2 are the location parameters and MASS2 is the mass points associated with LOC1 (MASS1 is normalized to 1).

	Default				Prepayment			
Independent variables	**Coeff. Val.**	**Std. Err.**	**p-value**	**Marginal Effects**	**Coeff. Val.**	**Std. Err.**	**p-value**	**Marginal Effects**
Intercept	40.018	3.500	<.0001		-17.475	0.728	<.0001	
Borrower Characteristics								
FICO	-0.101	0.010	<.0001	-0.50%	0.043	0.002	<.0001	0.20%
$FICO^2$	5.0E-05	1.0E-05	<.0001	0.01%	3.0E-05	0.0E+00	<.0001	0.01%
Log (Income)	-0.142	0.060	0.017	-9.10%	0.248	0.013	<.0001	3.40%
Log (House tenure)	-0.051	0.023	0.028	-10.00%	-0.020	0.006	0.000	-1.40%
Debt to Income	0.019	0.002	<.0001	2.00%	0.015	4.1E-04	<.0001	2.20%
Contract Characteristics								
Moral Hazard Mitigation	-0.184	0.067	0.006	-12.2%	0.649	0.016	<.0001	11.0%
Adverse Selection Mitigation	0.649	0.131	<.0001	4.20%	0.232	0.027	<.0001	2.90%
Home Equity Loan Dummy	3.809	0.152	<.0001	6.40%	1.205	0.039	<.0001	1.90%
First Lien Dummy	-0.272	0.159	0.087	-1.20%	-0.760	0.036	<.0001	-3.10%
Refinancing	-0.372	0.073	<.0001	-3.10%	0.155	0.014	<.0001	3.00%
Home Improvement	-0.408	0.082	<.0001	-4.00%	0.086	0.017	<.0001	2.00%
No First Mortgage	-0.155	0.100	0.121	-5.10%	-0.181	0.019	<.0001	-3.90%
Second Home	1.775	0.107	<.0001	2.00%	-0.133	0.033	<.0001	-2.20%
Condo	-2.773	0.247	<.0001	-1.2%	0.664	0.026	<.0001	2.90%
BorrLender_Diff	-1.237	0.265	<.0001	-6.90%	0.824	0.174	<.0001	7.30%
Time-varying Option Variables								
CLTV	0.118	0.089	0.185	2.10%	-0.307	0.017	<.0001	-5.40%
$CLTV^2$	1.089	0.128	<.0001	1.30%	-0.802	0.032	<.0001	-3.80%
Auto Pay	-0.255	0.070	0.000	-4.00%	0.052	0.013	0.000	5.70%
PPOption	3.007	0.445	<.0001	5.00%	2.096	0.711	<.0001	9.00%
LTV_Diff_Dummy	1.027	0.189	<.0001	2.00%	-0.313	0.090	<.0001	-1.10%
HouseVal_Diff	0.689	0.144	<.0001	2.60%	-0.195	0.028	<.0001	-2.50%
Account Age	6.0E-03	1.6E-03	0.000	1.40%	-6.3E-03	2.9E-04	<.0001	-3.70%
Account Age^2	-3.2E-03	5.8E-04	<.0001	-2.20%	2.0E-04	2.5E-04	0.413	2.40%
Account Age^3	1.0E-05	0.0E+00	<.0001	0.50%	0.0E+00	0.0E+00	<.0001	0.40%
Employment Control Variables								
Log (Years on the Job)	-0.389	0.035	<.0001	-4.00%	-0.008	0.006	0.186	-0.30%
Self Employed	0.295	0.076	<.0001	0.30%	-0.238	0.019	<.0001	-3.70%
Retired	0.913	0.150	<.0001	0.20%	0.544	0.033	<.0001	2.10%
Homemaker	-0.991	1.013	0.328	-0.60%	-1.439	0.145	<.0001	-3.40%
Location and Economic Control Variables								

Unemployment Rate	0.193	0.018	<.0001	1.30%	1.4E-04	4.2E-03	0.973	3.00%
CT State Dummy	-1.791	0.160	<.0001	0.01%	0.157	0.017	<.0001	1.20%
ME State Dummy	-2.814	1.006	0.005	-0.10%	0.254	0.045	<.0001	1.10%
NH State Dummy	0.343	0.073	<.0001	0.10%	0.473	0.076	<.0001	1.00%
NJ State Dummy	-0.749	0.127	<.0001	0.01%	-0.093	0.023	<.0001	-1.00%
NY State Dummy	-0.340	0.078	<.0001	0.01%	0.128	0.017	<.0001	2.20%
PA State Dummy	0.470	0.094	<.0001	0.01%	-0.025	0.030	0.409	-0.30%
RI State Dummy	-1.325	0.330	<.0001	-0.10%	0.252	0.037	<.0001	0.60%
Unobserved Heterogeneity Factors								
Loc1	2.739	0.376	<.0001		1.896	0.349	<.0001	
Loc2	1.358	0.373	<.0001		1.578	0.387	<.0001	
Mass2	0.980	0.088	<.0001		0.635	0.074	<.0001	
Time Quarter Dummies	Yes				Yes			
Pseudo R-square	12.32%							
Number of Obs/Defaults		916				32860		

Appendix A: Competing Risk Model with Unobserved Heterogeneity

In estimating the competing risks hazard model, we follow the procedure outlined in Agarwal et al. (2006) and denote credit commitments that are still current at the end of the observation period as censored. We assume that the time to prepayment, T_p, and time to default, T_d, are random variables that have continuous probability distributions, $f(t_j)$, where t_j is a realization of T_j $(j=p,d)$. The joint survivor function conditional on factors θ_p, θ_d, r, H, X, and Z, $S(t_p,t_d|r,H,X,Z,\theta_p,\theta_d)=Pr(T_p>t_p,T_d>t_d|r,H,X,Z,\theta_p,\theta_d)$, is defined as

$$\begin{aligned} S\left(t_p,t_d \mid r,H,X,Z,\theta_p,\theta_d\right) = \exp(-\theta_p \sum_{n=1}^{t_p} \exp\left(\alpha_{pn} + g_{pn}(r,H,X) + \beta_p' Z\right) \\ - \theta_d \sum_{n=1}^{t_d} \exp\left(\alpha_{dn} + g_{dn}(r,H,X) + \beta_d' Z\right)) \end{aligned} \quad , (3.)$$

where $g_{jn}(r,H,X)$ is a time-varying function of the relevant interest rates (r), property values (H), and borrower characteristics (X), Z represents macro-economic factors (possibly time-varying), and θ_p and θ_d are the unobservable heterogeneity factors.[25] The parameters α_{jn} are the baseline hazard parameters estimated as

$$\alpha_{jn} = \log\left[\int_{n-1}^{n} \lambda_j(t)dt\right], \quad (4.)$$

where $\lambda_j(t)$ is the underlying continuous-time baseline hazard function, and $j=p,d$.

Following Deng, Quigley, and Van Order (2000), we note that the data set consists of M distinct borrower groups, with the distribution of unobservable heterogeneity factors (θ_p and θ_d) modeled by assuming that the unobserved borrower types occur with frequency γ_m, $m=1\ldots M$. Furthermore, following McCall (1996), we note that only the duration

[25] See McCall (1996) appendix B.

associated with a particular termination type is observed ($t=min(t_p,t_d)$). Thus, we define the following probabilities:[26]

$$\begin{aligned} A_p(t \mid \theta_p,\theta_d) = {} & S(t,t \mid \theta_p,\theta_d) - S(t+1,t \mid \theta_p,\theta_d) - .5\{S(t,t \mid \theta_p,\theta_d) \\ & + S(t+1,t+1 \mid \theta_p,\theta_d) - S(t,t+1 \mid \theta_p,\theta_d) - S(t+1,t \mid \theta_p,\theta_d)\} \end{aligned} , \qquad (5.)$$

$$\begin{aligned} A_d(t \mid \theta_p,\theta_d) = {} & S(t,t \mid \theta_p,\theta_d) - S(t+1,t \mid \theta_p,\theta_d) - .5\{S(t,t \mid \theta_p,\theta_d) \\ & + S(t+1,t+1 \mid \theta_p,\theta_d) - S(t,t+1 \mid \theta_p,\theta_d) - S(t+1,t \mid \theta_p,\theta_d)\} \end{aligned} , \qquad (6.)$$

and

$$A_c(t \mid \theta_p,\theta_d) = S(t,t \mid \theta_p,\theta_d). \qquad (7.)$$

The probabilities of mortgage termination by prepayment and default are represented by the functions A_p and A_d, respectively, while A_c represents the probability that the observation is censored due to the ending of the data collection period. The term in braces in equations (3) and (4) is the adjustment factor necessary due to discrete time measurement of duration.

The unconditional probabilities are given by

$$A_j(t) = \sum_{m=1}^{M} \gamma_m A_j(t \mid \theta_{pm},\theta_{dm}), \quad j = p,d,c\,, \qquad (8.)$$

and the log-likelihood function of the competing risks model is given by

$$\log L = \sum_{i=1}^{N} \delta_{pi} \log(A_p(T_i)) + \delta_{di} \log(A_d(T_i)) + \delta_{ci} \log(A_c(T_i)), \qquad (9.)$$

where δ_{ij}, $j=p,d,c$ are indicator variables denoting that the ith loan is terminated by prepayment or default, or is censored. Equation (9) is estimated via maximum likelihood.

[26] The dependence of the functions in equations (3)-(5) on *r, H, X,* and *Z* has been omitted for ease of exposition.

Appendix B: Control Variables Used in Estimation of Competing Risks Models

In modeling the loan performance, we follow the previous empirical studies of mortgage performance and incorporate a set of explanatory variables that capture borrower financial incentives to prepay or default. For example, to approximate the value of the borrower's prepayment option, we follow the approach outlined in Deng, Quigley, and Van Order (2000) and estimate the prepayment option as

$$PPOption_{i,t} = \frac{V_{i,t} - V_{i,t}^{*}}{V_{i,t}}, \tag{10.}$$

where $V_{i,t}$ is the market value of loan i at time t (i.e., the present value of the remaining mortgage payments at the current market mortgage rate), and $V_{i,t}^{*}$ is the book-value of loan i at time t (i.e., the present value of the remaining mortgage payments at the contract interest rate).[27] We calculate $V_{i,t}$ by using the current period t market interest rate on home equity lines and home equity loans, respectively.[28] Since consumers are more likely to prepay and refinance following a decline in the prevailing mortgage rate relative to the original coupon rate, a positive value for *PPOption* is indicative of an "in-the-money" prepayment option. In order to account for any non-linearity in the prepayment option, we also include the square of *PPOption*.

To determine the impact of changing property values on loan and line termination probabilities, we matched each observation with the quarterly OFHEO MSA level repeat sales indices. Based on the estimated changes in house prices, we construct time-varying loan-to-value ratios (*CLTV*) where the loan value is the total outstanding loan balance that

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[27] This is equivalent to the prepayment option value used by Archer, Ling, and McGill (1996) scaled by the mortgage book-value.

[28] Current period *t* home equity line and home equity loan market interest rates were obtained from the Heitman Group (www.heitman.com).

includes the first mortgage.[29] We also include the square of *CLTV* to control for any non-linearity. We include a dummy variable for a positive quarterly change in the loan-to-value ratio (*LTV_Diff_Dummy*) to capture the changes in default option values.[30]

Related to the role of collateral in impacting termination probabilities, we also include the percentage difference between the borrower's initial house value assessment and the lender's independent appraised value (*HouseVal_Diff*). Agarwal (2006) finds that borrowers who underestimate their house value are more likely to refinance without cash and prepay their loans while borrowers who overestimate their house value are more likely to cash out and default on their loans. Thus, the percentage difference in valuation estimates (*HouseVal_Diff*) provides a rough proxy for the borrower's risk aversion.

We capture changes in borrower credit constraints via the time-varying borrower credit score (*FICO*) and include the square of *FICO* to capture any non-linearity present in borrower credit scores. Borrowers with good credit history (higher *FICO* scores) are able to obtain credit with ease; thus, they are able to take advantage of refinancing opportunities. Conversely, borrowers with lower credit scores may be credit-constrained (see Peristiani et al., 1997; and Bennet, Peach, and Peristiani, 2000). Similarly, Agarwal, Ambrose, and Liu (2006) show that liquidity-constrained borrowers (e.g., borrowers with deteriorating credit quality) who have home equity lines are more likely to raise their utilization rates rather than pay down the line.

Local economic conditions may also impact mortgage termination decisions. For example, Hurst and Stafford (2004) note that borrowers with uncertain job prospects may

[29] See Agarwal, Ambrose, and Liu (2006) for a discussion of the potential bias present in the CLTV ratio.
[30] *LTV_Diff_Dummy* is set equal to one if $CLTV_t - CLTV_{t-1}$ is greater than zero. Thus, a positive value for *LTV_Diff_Dummy* indicates that the collateral value has declined from the previous quarter resulting in an increase in the current loan-to-value ratio.

refinance in order to tap into their accumulated equity. Thus, we use the current county unemployment rate (*UnempRate*) as a proxy for local economic conditions. We also include a series of dummy variables that denote the borrower's location (state) to control for unobserved state-specific factors.

We also include a number of variables to control for account seasoning (*AGE* of account, and *AGE*-square), and calendar time effects. $AGE_{i,t}$ is the number of months since origination at time t, and, as Gross and Souleles (2002) point out, allows for loan seasoning. That is, *AGE* accounts for changes in the default propensity as loans mature. In addition, Gross and Souleles (2002) note that the age variables allow the hazard rates to vary with duration. Our quadratic specification of *AGE* allows the default hazard to vary non-parametrically. The dummy variables corresponding to calendar quarters (*Q3:99—Q1:02*) at origination capture unobserved shifts over time in economic conditions or borrower characteristics that may impact the propensity default.

Finally, we include as control variables the information collected from the loan application that indicate the borrower's employment status (e.g., employed, self-employed, retired, or homemaker), number of years employed, the borrower's income at the time of application, the property type (single-family detached or condo), the property's status as primary residence or second home, the tenure in the property, the use of the funds (e.g., refinancing, home-improvement, or debt consolidation), the current existence of a first mortgage on the property, and the borrower's use of an "auto-draft" feature to automatically make the monthly payment.