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

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Abstract

We analyze more than 108,000 home equity loans and lines of credits to study the role of information asymmetry in a credit market where borrowers face a menu of contract options and a lender uses a counteroffer to further mitigate contract frictions. Our results reveal that a less credit-worthy applicant is more likely to select a credit contract that requires less collateral. Further analysis on borrower repayment behavior *ex post* indicates that the lender may face adverse selection due to private information, controlling for observable risk attributes. We also find that systematic screening *ex ante* by a lender to mitigate contract frictions can effectively reduce overall credit losses *ex post*.

JEL Classification: D1; D8; G21
Key Words: Asymmetric Information; Contract Frictions; Screening; Banking; Home Equity Lending.

Adverse selection and moral hazard may occur in markets where participants have asymmetric information (Akerlof 1970). In a credit market with imperfect information, the use of interest rates or collateral in the screening process can introduce adverse selection and reduce a lender's overall expected loan profitability (Stiglitz and Weiss 1981).[1] The use of collateral in the screening process is consistent with lenders sorting borrowers on *observable* risk characteristics. In contrast, lenders can also 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 (Bester 1985).[2] The use of a menu of contracts to uncover borrower information is consistent with borrower sorting on *private* (*unobservable*) information.

Empirical research testing for asymmetric information in credit markets often faces identification challenges, particularly in distinguishing between adverse selection and moral hazard.[3] Traditional financial contract data sets and surveys contain only information about contracts that are already booked and, in turn, cannot identify borrower contract choices *ex ante*. To overcome this problem, Ausubel (1999) uses respondents and non-respondents from credit card solicitations, while Karlan and Zinman (2006) use a novel random experimental design to explicitly distinguish between adverse selection and moral hazard. More recently, Adams, Einav, and Levin (2007) analyze loan demand by subprime auto loan applicants and their subsequent repayment behavior, and they cleverly

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[1] In this classic case, the lender's overall loan profitability declines because the quality of the average borrower declines as the interest rate or collateral increases, since only higher-risk borrowers are willing to pay higher interest rates or post greater collateral. As a result, lenders ration credit.

[2] The Bester (1985) 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 problems of adverse selection – the classic Stiglitz and Weiss (1981) credit rationing.

[3] See Chiappori and Salanié (2000) and Finkelstein and Poterba (2004, 2006) for empirical test of asymmetric information in the insurance market.

disentangle adverse selection and moral hazard by incorporating the residual from the loan amount demand regression into the default regression.

We contribute to the literature by using a unique proprietary data set to study the role of information asymmetry in the home equity credit market where borrowers face a menu of contract options with varying prices (primary screening) and the lender uses counteroffers to further mitigate contract frictions (secondary screening). Primary screening occurs when the applicants self-select contracts based on their individual assessment of their property value and/or other private information. Secondary screening involves the lender targeting certain borrowers with counteroffer contracts designed to mitigate additional contract frictions. We follow more than 108,000 home equity credit applicants through this dynamic contracting process and then through post-origination performance.

More specifically, our empirical analysis comprises two parts. In the first part of our study, we assess the role of asymmetric information during the primary screening of the underwriting process of home equity credits. Given that we are able to observe a borrower's initial contract choice, we first test to see whether a borrower's contract choice reveals information about her risk level. Specifically, do riskier borrowers self-select contracts that require less collateral? Second, conditional on the borrower's initial contract choice *ex ante* and other observable risk characteristics, does the lender continue to face adverse selection on unobservable information?

The second part of our study uses the outcomes from the dynamic contracting process to analyze the effectiveness of the lender's attempt to further mitigate contract frictions by using a counteroffer, focusing on the role of collateral. During the underwriting process, the lender's decision is generally based on "hard" information—quantifiable risk factors (e.g., credit score, loan-to-value ratio, debt-to-income ratio)—that serve as direct inputs into an underwriting model. In addition, the lender may also gather "soft" information that is not directly incorporated into an underwriting model. Such information is often revealed to the loan officer during the application process (see Berger et al. 2005, Petersen 2004, and Stein 2002).[4] Specifically, we assess whether (as well as the extent to which) a counteroffer at the secondary screening stage can effectively reduce default risks *ex post*.

To preview our results, after controlling for borrower age, income, employment, and other observable attributes, we find that the borrower's choice of credit contract does reveal information about his risk level, consistent with the implications of Bester (1985). Specifically, we find that a less credit-worthy borrower is more likely to self-select a contract that requires less collateral. After controlling for observable risk characteristics, however, we find that the lender may continue to face adverse selection problems due to private information. That is, we find a significant and strong positive correlation between the borrower's contract choice to pledge collateral *ex ante* and the risk of default *ex post*. Our results indicate that a borrower choosing to pledge *ex ante* less than 10 percent of collateral is 5.6 percent more likely to default *ex post* in comparison with a borrower choosing to pledge more than 20 percent collateral.[5]

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[4] In this case, soft information may include the nature and extent of a planned remodeling project or the item intended to be purchased with the loan funds. By using soft information, a lender may target certain borrowers for additional screening and may counteroffer with a contract designed to reduce (or price) the impact of information asymmetry. Given that we observe the outcome from this dynamic contracting process and the performance of these loans over time, we evaluate the effectiveness of a lender's effort to mitigate contract frictions.

[5] Given that the home equity menu of contracts is not a continuous risk-based pricing menu, but necessarily offers a set of coarse interest rates and collateral requirements, the problems of adverse selection may be reduced, but cannot be completely eliminated.

Moreover, we find that a lender's efforts *ex ante* to further mitigate contract frictions can effectively reduce credit losses *ex post*. Our results show that a lender's counteroffer that lowers the annual percentage rate (APR) requirement reduces default risk *ex post* by 12 percent, and a counteroffer that raises the APR requirement increases default risk *ex post* by 4 percent. However, we find that a lender's overall profits from the higher APR can more than offset the increase in losses associated with greater defaults, effectively reducing the problems associated with adverse selection. Thus, our results show that financial institutions can reduce credit losses by using screening devices, supporting the conclusions made by Karlan and Zinman (2006) that financial institutions can enhance welfare by investing in screening and monitoring devices.

Furthermore, we find it interesting that these mitigation efforts also impose costs in the form of higher prepayment rates. Our results show that the lower APR requirements increase the odds of prepayment by 11 percent, while the higher APR requirements increase the probability of prepayment by 3 percent. Lenders may, however, also realize losses by requiring higher prepayments, since prepayments may lower the revenue derived from secondary market securitization activity.

The paper proceeds as follows. In Section 1, we provide a brief literature review. In section 2, we describe the home equity origination process, and then discuss the data in section 3. In sections 4 and 5, we provide an outline of empirical methodologies and present our results based on the lender's primary and secondary screening, respectively. Finally, we conclude in section 6.

1. Literature Review

A number of studies followed Stiglitz and Weiss (1981) and Bester (1985) to examine the role that collateral plays in determining borrower selection of loan contracts. In earlier work, for example, Chan and Thakor (1987) develop a model in which a borrower's use of collateral may be a positive function of her credit 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 the collateral offered.

In one of the more recent attempts to document the role of adverse selection and moral hazard in the consumer credit market, 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 *ex post* high-risk borrowers self-select 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, suggesting the presence of moral hazard. Karlan and Zinman (2006) compellingly document 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, respectively. In the most recent study, Adams, Einav and Levin (2007) estimate that about 8 percent and 16 percent of subprime auto loan defaults are due to adverse selection and moral hazard, respectively.

Other empirical research investigating adverse selection problems in the consumer credit market focused on unsecured lending. In one of the most influential papers to provide evidence of adverse selection, 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 due to 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, supporting his switching costs argument. Also supporting the view that adverse selection can result from high search costs, Calem and Mester (1995) use data from the 1989 *Survey of Consumer Finances* to show that households wishing 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.

To model consumer contract choice, Adams, Einav and Levin (2007) use purchasing and down payment decisions of subprime auto consumers, Karlan and Zinman (2006) use randomized loan offers and Ausubel (1999) uses credit card solicitations, while the findings of the other studies are predicated solely upon originated loans. As noted previously, however, lenders can alter loan contracts during the underwriting process to potentially mitigate contract frictions. To overcome the bias of using loans that are already originated, we follow a set of loan applications through the underwriting process and then through a period of post-origination performance. Applicants of home equity credit face a menu of contract options, and we are able to observe directly the borrower's initial contract application as well as the lender's responses to that self-selected contract. The lender's response includes the lender's counteroffer to further mitigate contract frictions. Using information from this dynamic contracting process in the home equity credit market, our study provides additional insights into the role of information asymmetry in a dynamic contract setting in a secured consumer market. Below, we discuss the home equity origination process in detail.

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]

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[6] See www.federalreserve.gov/pubs/oss/oss2/2004/scf2004home.html.
[7] See *Inside Mortgage Finance*, an industry publication.
[8] See Stanton and Wallace (1998) and LeRoy (1996) for a discussion of the mortgage contract and the implications concerning asymmetric information.

The home equity credit market presents an ideal framework in which to investigate the role of information asymmetry because home equity credits are secured by the borrower's home, and the borrower generally faces a menu of contracts having varying interest rates. Figure 1 illustrates the typical home equity loan origination process. First, a borrower applies for a home equity line or loan.[9] To counter the problems due to adverse selection, the lender offers a menu of differential contracts (primary screening) to help borrowers self-select either a line of credit or a fixed-term loan, pledge a certain amount of collateral, and choose a lien type. 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 $r_1<r_2<r_3$. In turn, a borrower's initial contract choice may reveal information about his expected tenure and risk.[10]

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 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

[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 percent LTV. However, as documented by Agarwal (2007), a significant percentage of borrowers overestimate their house value, allowing them the option to choose from the full menu. We also re-estimate our empirical analysis with a sub-sample of borrowers who have the option to choose the less-than-80-percent LTV assuming that they did not misestimate their house value. The results are qualitatively similar.

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

because of private information. Thus, after the borrower self-selects a contract, the lender takes one of the following actions: (1) rejects the contract (credit rationing), (2) accepts the contract, or (3) conducts a secondary screening and suggests an alternative contract (counteroffer) to mitigate contract frictions.

Because of the borrower's private information, the lender may still be susceptible to additional contract frictions. As a result, the lender requiring a secondary screening may use soft information to propose new contract terms. For example, the lender could require that the consumer pledge additional collateral, and in turn, offer the applicant a lower interest rate. Alternatively, the lender could make a counteroffer with a higher interest rate contract. The borrower then accepts or rejects the lender's counteroffer.

As a result of the origination process, a number of testable hypotheses arise concerning the presence of asymmetric information in the home equity lending market. First, evidence of borrower sorting on private information 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 and higher (lower) interest rates (Bester 1985). Second, if borrowers self-selecting *ex ante* higher (lower) LTV contracts have higher (lower) probabilities of default *ex post*, then the lender could still face problems of adverse selection due to private (unobservable) risk factors (Ausubel 1999). Third, examining the counteroffers should reveal the lender's perception of potential contract frictions and the performance *ex post* of the loans that received a counteroffer will reveal the extent to which the lender is successful in mitigating contract frictions.

3. Data Description

We collect an administrative data set of home equity contract originations from a large financial institution. The data set is rich in borrower details, including information about the borrower's credit quality, income, debts, age, occupation status, 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, or (4) request a new second-lien loan. For each product, borrowers could choose the amount of collateral to pledge: more than 20 cents per dollar loan (less than 80 percent LTV), 10 cents to 20 cents per dollar loan (80 to 90 percent LTV), or zero to 10 cents per dollar loan (90 to 100 percent LTV). We observe the customer's choice from 12 combinations of LTV and product type contract, each with an associated interest rate and 15-year term; we also observe the lender's counteroffers, if any, to further mitigate contract frictions. Finally, for loans ultimately booked, we observe the borrowers' payment behaviors from origination through March 2005.

The lender received 108,117 home equity loan applications between March and December of 2002 (see Table I). Based on the information revealed in the application, the lender rejected 11.1 percent of the applications, accepted 57.6 percent of the applications, and conducted a secondary screening on the remaining 31.3 percent. Using soft information learned during the initial application process, the lender can mitigate additional contract frictions by conducting additional screening and proposing an alternative loan contract to customers whose loan application meets the minimum underwriting standards. For example, the lender may propose a new contract with lower

LTV (e.g., greater collateral) and/or a different type of home equity product (e.g., switching a loan to a line), in effect lowering the contract rate. Alternatively, the lender may propose a contract with a higher LTV (e.g., greater loan amount) and/or a different type of home equity product (e.g., switching a line to a loan), thereby increasing the contract interest rate. In Table I, we see that 31.4 percent of the 33,860 applicants subject to a secondary screening were offered a new contract that had a higher rate and/or different type of home equity product, and 68.6 percent of them were offered a new contract that had a lower LTV and/or a different type of home equity product. [12]

We find considerable differences in applicant response rates across the two types of counteroffers. Overall, 12,700 applicants (37.5 percent) declined the lender's counteroffer. Interestingly, we note that the majority of borrowers (64 percent) who rejected the counteroffer were offered a lower APR contract, while 36 percent were given a counteroffer with a higher APR contract. Of the 21,160 applicants who accepted the lender's counteroffer, 28.7 percent received a counteroffer with a higher APR contract, while 71.3 percent received a counteroffer with a lower APR contract. Finally, we have a pool of 83,411 applicants (77.1 percent of the total 108,117) who were ultimately issued home equity contracts.

[12]Of the higher APR 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 higher LTV 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.

4. Empirical Methods and Results: Primary Screening

4.1 Credit contract choice

To assess whether asymmetric information exists between borrower and lender, we begin by estimating a multinomial logit model to test for correlation between the borrower's credit quality and her initial contract choice. Based on her own valuation of the property and other private information regarding her credit risk, 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 from the menu of home equity contracts. 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 using the borrower's initial property value estimate and loan amount requested.[13] Since loan sizes are not constant across borrowers, the LTV provides a mechanism for standardizing the amount of collateral offered per dollar loan requested. Thus, lower LTVs are consistent with borrowers offering more collateral per dollar loan.

To formally test whether higher (lower) credit quality borrowers 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:

[13] Note that we distinguish between the borrower's LTV and the lender's LTV. 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

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

where *j={1,2,3}* corresponds to LTVs less than 80 percent, between 80 percent and 90 percent, and greater than 90 percent, respectively. The W_i represents a borrower *i*'s credit quality as measured by her 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.

Table II presents the descriptive statistics of the sample segmented by the borrower LTV category (LTV less than 80 percent, LTV between 80 percent and 90 percent, and LTV greater than 90 percent) chosen at the time of application. As expected, we observe that borrowers pledging lower collateral per dollar loan (higher LTVs) are, on average, less credit-worthy than borrowers pledging more collateral (lower LTVs). For example, the average FICO score is 708 for borrowers selecting to pledge less than 10 cents per dollar loan (LTV above 90 percent), and the average FICO score is 737 for borrowers choosing to pledge more than 20 cents per dollar loan (LTV 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

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using the property value from an independent appraisal and the lender-approved loan amount (see Agarwal, 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 III presents the multinomial logit estimation results of the applicant's LTV contract choice, where the base case is a borrower applying for a contract with an LTV less than 80 percent. The statistically significant coefficients for FICO score indicate that less credit-worthy borrowers are more likely to apply for higher LTV home equity contracts (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 compared with a higher-credit-quality borrower with a FICO score of 800 is 21.4 percent more likely to apply for home equity contract having an LTV that is 90 percent or greater than a contract having an LTV less than 80 percent. A borrower with a FICO score of 700 compared with a higher-credit-quality borrower with a FICO score of 800 is 18.9 percent more likely to apply for a home equity contract having an LTV between 80 percent and 90 percent than a contract having an LTV less than 80 percent. The results clearly indicate an inverse relationship between borrower credit quality and collateral pledged.

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 than to apply for a

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product with an LTV less than 80 percent.[14] Furthermore, borrowers without a current first mortgage are 7.2 percent less likely to select a home equity product with an LTV greater than 90 percent than one with an LTV less than 80 percent.[15] We also find that borrowers with lower income or higher debt-to-income ratios are more likely to apply for a home equity contract with a higher LTV. In addition, a borrower having a second home is 11.5 percent less likely to apply for a loan with an LTV ratio greater than 90 percent. The significant and negative coefficient on borrower age—a proxy for borrower wealth under the assumption that older individuals tend to have greater personal net wealth than younger persons—indicates that younger borrowers are more likely to apply for higher LTV contracts.

Finally, although we find that overall riskier borrowers are more likely to apply for higher LTV home equity contracts, we note that the choice of home equity line and home equity loan also affects the LTV choice. We see that borrowers applying for a home equity loan are 2.4 percent more likely to choose a greater-than-90-percent LTV contract than a less-than-80-percent LTV contract.[16]

4.2 Lender response to borrower contract choice

We now turn to a formal analysis of the lender's underwriting decisions in response to a borrower's contract choice. After receiving the borrower's application, the lender

[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.
[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 estimated 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. The results are available upon request.

screens the loan using observable information to determine whether the application should be rejected, accepted, or subjected to additional screening for asymmetric information.

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

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

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. Given that the lender's underwriting model uses the lender's independent appraised value of the property, LTV_i is the lender's LTV category, while X_i and W_i represent a vector of control variables and the borrower's credit score, respectively. We include in X all information that the lender collects on a loan application.

Table IV presents the summary statistics for the three primary screening outcomes. Focusing first on the LTV for the set of applications that were rejected, 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 borrowers who were rejected outright tend to overvalue their homes relative to the lender's independent appraisal. In contrast, the difference between the lender's and borrower's 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 for both). Obviously, collateral risk is one of the key underwriting criteria used by lenders. The higher rejection rate for customers who overvalue their collateral (have lower LTVs) suggests that the lender views a borrower's property overvaluation with skepticism.

As expected, credit quality of applicants who were accepted at the outset is higher than the credit quality of those who received additional screening as well as for those were rejected. The average FICO score of applicants who were accepted outright was 737, while the average FICO score of applicants subjected to additional screening was 729, and the average FICO score those who were rejected was 714. Furthermore, rejected applicants 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 applicants who were accepted outright (152 months tenure, $121,974 annual income, 34 percent debt-to-income ratio, and 8 percent self-employment).

Table V 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 the lender will reject an applicant or subject an applicant to additional screening conditional on the lender’s LTV estimate, borrower risk characteristics, loan characteristics, and other control variables. Turning first to the impact of the lender’s estimated LTV ratio, the significant and positive coefficients indicate that applicants in the 80 percent to 90 percent LTV category or applicants in the greater-than-90-percent LTV category are more likely to be subjected to additional screening or rejected than outright accepted. The reported marginal effects suggest that an application with a greater-than-90-percent lender-estimated LTV relative to one with a less-than-80-percent LTV estimate is 18.4 percent more likely to be rejected (and 15.8 percent more likely to be subjected to additional screening) than accepted. Similarly, an application with a lender-estimated LTV between 80 percent and 90 percent relative to a less-than-80-percent LTV is 12 percent more likely to be subjected to additional screening (and 8.7 percent more likely to be rejected) than accepted outright. Hence, the lender is more likely to conduct secondary screening than reject applicants with 80–90 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 again and 2.6 percent less likely to be denied credit. 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.

The results from this section are consistent with standard underwriting protocol. Factors associated with higher default risks (e.g., lower credit quality, higher LTV, and higher debt-to-income) are associated with a higher probability of credit rationing or secondary screening.

4.3 Repayment Behavior Ex post – Testing for 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 the type of contracts they self-select. In this section, we assess the relationship between LTV contract choice *ex ante* and loan repayment behavior *ex post*, conditional on observable borrower/loan attributes. We estimate a competing risks model of the loan performance of the 62,251 borrowers whose applications were accepted outright (without additional screening).[17] The presence of borrower adverse selection due to unobservable information is consistent with borrowers self-selecting *ex ante* contracts with higher LTVs (based on the borrower's own estimate of the property value and loan request.) As a result, these contracts have a higher risk of default *ex post* (see Ausubel 1999).

Table VI presents the estimated coefficients and marginal effects for the competing risk model of loan performance. On the observable risk characteristics first, borrower credit risk quality (as measured by the FICO score) is negatively correlated to the risk of borrower default (borrowers with lower credit risk quality are *more* likely to default) and positively correlated to the probability of prepayment (borrowers with higher credit risk quality are *more* likely to prepay). In addition, default risk rises for borrowers with higher debt-to-income ratios. 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. The risk of default declines as a borrower's tenure in the house increases. Interestingly, borrowers who choose to automatically pay their monthly mortgage directly from their checking account (automatic payment option), relative to those borrowers who pay by invoice, are 4.2 percent less likely to default.

After controlling for the observable risk characteristics, we include a set of dummy variables denoting a borrower's LTV contract choice *ex ante*. If adverse selection due to unobserved risk characteristics is present, then we should find a significant relationship

[17] 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.

between the borrower LTV choice *ex ante* and default risk *ex post*. Testing for adverse selection is possible because these borrowers have self-selected an LTV contract based on their own assessment of the property value as well as other private information, and have passed the lender's initial risk screening without being subjected to additional screening by the lender (borrowers who were accepted outright by the lender). We find a positive and statistically significantly correlation between a borrower's LTV choice *ex ante* and risk of defaulting *ex post*, controlling for all observable risk characteristics captured on the loan application and time-varying default and prepayment option values. For example, relative to borrowers pledging more than 20 cents per dollar loan (LTV less than 80 percent), those pledging 10 cents to 20 cents (LTV 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.

We also find 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 choosing a home equity credit 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. 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.[18]

[18] A borrower with a second lien also has an obligation toward the primary mortgage. On average, his 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.

In sum, borrowers who self-select into a higher risk contract *ex ante* have higher risk of default *ex post*. The positive and significant relationship between borrower contract type choice *ex ante* and loan performance *ex post* suggests that the lender may face problems of adverse selection due to unobservable factors during loan origination.[19]

While we believe the results are consistent with the presence of adverse selection, two alternative possibilities could account for the relationship between contract choice *ex ante* and loan performance *ex post*. First, a simple mechanical process could explain our finding. That is, default is linked to the borrower's debt level at origination. Second, the findings are also consistent with the presence of both moral hazard as well as adverse selection. However, we think neither of these cases plays a substantial role in explaining our findings for the following reason. While it is likely that a borrower who either has more equity in the home or borrows less has a lower risk of default, we control for the current loan-to-value and thus effectively control for the borrower's excess debt capacity. The marginal impact of the time-varying collateral variables indicate that borrowers who face a decline in equity due to house price depreciation (i.e., a positive increase in the current LTV (CLTV)) from the previous quarter are almost 4 percent more likely to default and 1 percent less likely to prepay than borrowers who experience an increase in equity due to house price appreciation.[20]

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

[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.

Furthermore, it is also possible that borrowers pledging less collateral and requesting the credit for rate refinancing could *ex post* increase their utilization of the home equity line of credit, especially since they have less to lose in the event of default (moral hazard). Given that each borrower provides the bank with a reason for taking out credit (rate refinancing, cash-out refinancing, etc.), further assessment of the extent to which borrowers altered their spending behaviors shows that only a small minority of the borrowers changed *ex post* their consumption behaviors. This observation suggests that moral hazard does not significantly explain the observed correlation between a borrower's contract choice *ex ante* and default risk *ex post*.[21] Additionally, following Adams, Einav, and Levin (2007), we estimate the default regression using the residual from equation 1 (credit contract choice model by the borrower) as an explanatory variable. We find a positive and significant coefficient on the residual supporting the presence of adverse selection.[22]

5. Empirical Methods and Results: Secondary Screening

5.1 Lender's counteroffer to mitigate contract frictions

We now turn to a formal analysis of the lender's decision to conduct additional screening and to counteroffer the applicants with contracts designed to further mitigate contract frictions. If the lender changes the contract type from a loan to a line and/or lowers the LTV (in effect the collateral pledged per dollar loan amount is increased) then the counteroffer has a lower APR (we refer to this as counteroffer 1 in Figure 1 and Table VII). The LTV can be lowered for a couple of reasons. First, the lender's estimated house

[21] The results are available upon request.

value may be higher than that of the borrower's own estimate. Second, the lender could use soft information to counteroffer with a smaller credit amount.[23]

We classify a counteroffer having a higher APR as counteroffer 2 (in Figure 1 and Table VII). This could happen because, for instance, if the lender's estimate of the house value is below the applicant's estimate, the loan officer increases the LTV based on the bank's lower appraised value (in effect reducing the collateral pledged per dollar loan). The lender may continue to face adverse selection problems if a greater number of higher risk borrowers accept the lender's higher APR counteroffer, while lower risk borrowers reject the offer.

Table VII provides summary statistics for the two counteroffers. The average interest rate for counteroffer 2 is 271 basis points higher than the average interest rate for counteroffer 1 (7.6 APR versus 4.89 APR). Borrowers receiving a lower APR counteroffer (counteroffer 1) have higher average FICO scores (727 versus 719) than those receiving a higher APR counteroffer (counteroffer 2). Relative to applicants who received a lower APR counteroffer, a greater share of borrowers who received a higher APR counteroffer intend to use the funds to finance general consumption (37 percent versus 16 percent),

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[22] The results are available upon request.

[23] 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 may learn additional soft information from the consumer concerning her actual needs and intended use of the credit. For example, a borrower may request a 90 percent LTV loan for the stated purpose of home improvements, and then, during the application process, reveals to the loan officer a more extended detail description of the expected home improvements (e.g., a kitchen remodel or other major repair). In this context, the actual intended home improvement is soft information not captured in the underwriting model. 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 loan officer's objective is to reduce credit losses 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 scenarios, the counteroffer has a lower APR.

while a smaller proportion intend to use the funds to refinance existing debt (38 percent versus 64 percent). Furthermore, those receiving a higher APR counteroffer 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 a 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 VIII presents the results, which clearly indicate systematic differences in the observed risk factors between borrowers receiving a lower APR counteroffer versus ones receiving a higher APR counteroffer. Results indicate that more credit-worthy borrowers (those with lower FICO scores) are more likely to receive a lower APR counteroffer. For instance, a borrower with a FICO score of 800 compared with a borrower with a FICO score of 700 is 24.6 percent more likely to receive a lower APR counteroffer than a higher APR counteroffer, holding all other factors constant at their sample means.

Equally important, for every 1 percentage point increase in the lender's LTV ratio relative to the borrower's LTV ratio, the lender is 3.1 percent more likely to counteroffer the borrower with a lower APR contract. This result suggests that borrowers who tend to overvalue their home relative to the bank's estimated value are more likely to receive a lower APR counteroffer. We also find that the lender is 21.9 percent less likely to present a lower APR counteroffer to borrowers who are rate refinancing (i.e., non-cash-out refinancing). Furthermore, borrowers who are self-employed are 7.5 percent less likely to receive a lower APR counteroffer, while borrowers who are retired are 6.7 percent more likely to receive such a counteroffer. Finally, borrowers who own a second home are 7.2 percent more likely to receive a lower APR counteroffer, while borrowers who own a condo are 5.3 percent less likely to receive such a counteroffer.

To summarize, the results in this section indicate that lenders do systematically conduct additional screening to further mitigate contract frictions. For example, the lender can lower the contract interest rate by reducing the LTV and/or switching the borrower from the riskier fixed-rate loan to the less risky variable-rate line-of-credit. Overall, we find that riskier borrowers are less likely to receive a lower APR counteroffer. The finding that borrowers who are rate refinancing are less likely to receive a lower APR counteroffer than a higher APR counteroffer may imply that the counteroffer is potentially 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.[24]

5.2 Borrower response to accept higher APR counteroffer

We now turn to the decision by the borrower to accept or reject the lender's counteroffer, conditional on receiving a counteroffer. The borrower's accept/reject decision reveals her valuation of the lender's counteroffer, and in turn, could reveal additional asymmetric information. On the one hand, borrowers who feel that the

[24] 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. The results are available upon request.

counteroffer incorrectly values their financial condition or risk level 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 underestimated their risk will likely accept the counteroffer. Hence, the low-risk applicants will more likely reject a higher APR counteroffer, while the high-risk applicants will eagerly accept it. In turn, the lender's secondary screening and counteroffer may exacerbate the problems of adverse selection as described in the Stiglitz and Weiss (1981) model.

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. Table IX presents the likelihood of an applicant accepting a higher APR counteroffer. Overall, we do find that riskier applicants are more likely to accept the lender's higher APR counteroffer. While the borrower's FICO score is not statistically significant, we find an applicant with higher income and greater house tenure is significantly less likely to accept a higher APR counteroffer. Furthermore, a borrower who does not have a first mortgage is 24.3 percent less likely to accept a higher APR counteroffer. However, a borrower who has a higher debt-to-income ratio, owns a second home/condo, or is retired is more likely to accept a higher APR counteroffer.

5.3 Effectiveness of lender's efforts to further mitigate contract frictions

In this section, we evaluate the *ex post* repayment performance of all the 83,411 borrowers who were booked during both the primary screening and the secondary screening to determine the effectiveness of the lender's attempts to mitigate potential adverse selection and moral hazard problems. Based on the type of counteroffer, we create two dummy variables denoting whether a borrower received a lower APR counteroffer

(counteroffer 1) or a higher APR counteroffer (counteroffer 2) in order to evaluate 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.[25]

Table X presents the estimated coefficients from the competing risks model testing the effectiveness of the lender's mitigation efforts (i.e., secondary screening and counteroffer contracts).[26] As noted previously, we control for the traditional factors associated with borrower prepayment and default and isolate the effects of the lender's attempts to mitigate the impact of contract frictions. Overall, we find that the lender's *ex ante* mitigation efforts can successfully reduce the risks associated with *ex post* credit losses. The marginal effects for the counteroffer 1 (lower APR) dummy variable indicate that, relative to loans that did not receive additional screening, loans that the lender *ex ante* required additional collateral and/or switched the product type from home equity loan to home equity line are 12.2 percent less likely to default *ex pos*t. On the other hand, the marginal effects for the counteroffer 2 (higher APR) mitigation dummy suggest that, relative to loans that did not receive additional screening, loans with a higher APR counteroffer are 4.2 percent more likely to default. Next we show that despite the higher risk of default, the bank's mitigation efforts are still effective in reducing overall portfolio credit losses.

[25] Default is defined as 90 days past due. Also see Agarwal el. al. (2006) for a discussion of the default and prepayment definitions.
[26] 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.

To highlight the economic implications of the two screening mechanisms, we note that the 12.2 percent net reduction in defaults (resulting from counteroffer 1) on a $700 billion dollar portfolio of home equity credit in the U.S., has an average default rate of 1 percent implies a $854 million saving to the bank in default costs. In contrast, the 4.2 percent higher default rate (resulting from counteroffer 2) implies additional default costs of approximately $294 million. However, the higher default costs associated with counteroffer 2 are offset by the higher APR. For example, the increase in APR by counteroffer 2 is about 180 basis points for an average duration of 18 months on a loan amount of $40,000.

Our findings have additional interesting implications for lenders seeking to maximize the profitability of their loan portfolios. The results clearly indicate that the secondary screening can effectively reduce portfolio credit losses *ex post*. Our findings support the conclusions made by Karlan and Zinman (2006) that financial institutions can enhance welfare by investing in screening and monitoring devices. The lender's mitigation efforts are not, however, without costs, because the results in Table X 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 counteroffer 1 and 2.9 percent for counteroffer 2 relative to loans that were not subjected to additional screening. Thus, during periods of declining interest rates, borrowers subjected to additional screening have higher prepayment rates than borrowers 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 borrowers to changes in interest rates, this will have a direct impact on secondary market investors and their ability to predict prepayment speeds on a securitized portfolio.

6. **Conclusions**

We use a unique proprietary data set to study the role of information asymmetry in the home equity credit market, where more than 108,000 applicants face a menu of contract options with varying prices (primary screening) and a lender uses counteroffers to further mitigate contract frictions (secondary screening). Our empirical analysis suggests that a borrower's choice of credit contract reveals information about his risk level. Specifically, we find that less a credit-worthy borrower is more likely to select a contract that requires him to pledge less collateral. We also find, after controlling for other observable risk characteristics, a positive and statistically significant correlation between a borrower's choice of collateral pledged *ex ante* and his risk of defaulting *ex post*. The significant relationship identified among the variables denoting the borrower contract choice *ex ante* and loan performance *ex post* suggest the presence of adverse selection on unobservable factors, consistent with Ausubel's (1999) findings in the credit card market.

Moreover, we find that a lender's efforts *ex ante* to mitigate contract frictions vis-à-vis a secondary screening can be effective in reducing overall portfolio credit losses *ex post*. Our results show that a counteroffer that lowers the APR reduces the default risk *ex post* by 12 percent, while a counteroffer that raises the APR increases the default risk *ex post* by 4 percent. While borrowers with the higher APR counteroffer are more likely to default, it is worth noting that the higher default rate is offset by the increased profitability achieved through higher APR. Hence, our results suggest that financial institutions can reduce credit losses overall and increase profits, using screening devices and counteroffer contracts to induce borrower effort; this supports a conclusion made by Karlan and Zinnman (2006).

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

Finally, we note that 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 (2007) 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. In contrast, 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, which have similar asymmetric information problems.

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Figure 1: HOME EQUITY MORTGAGE ORIGINATION PROCESS

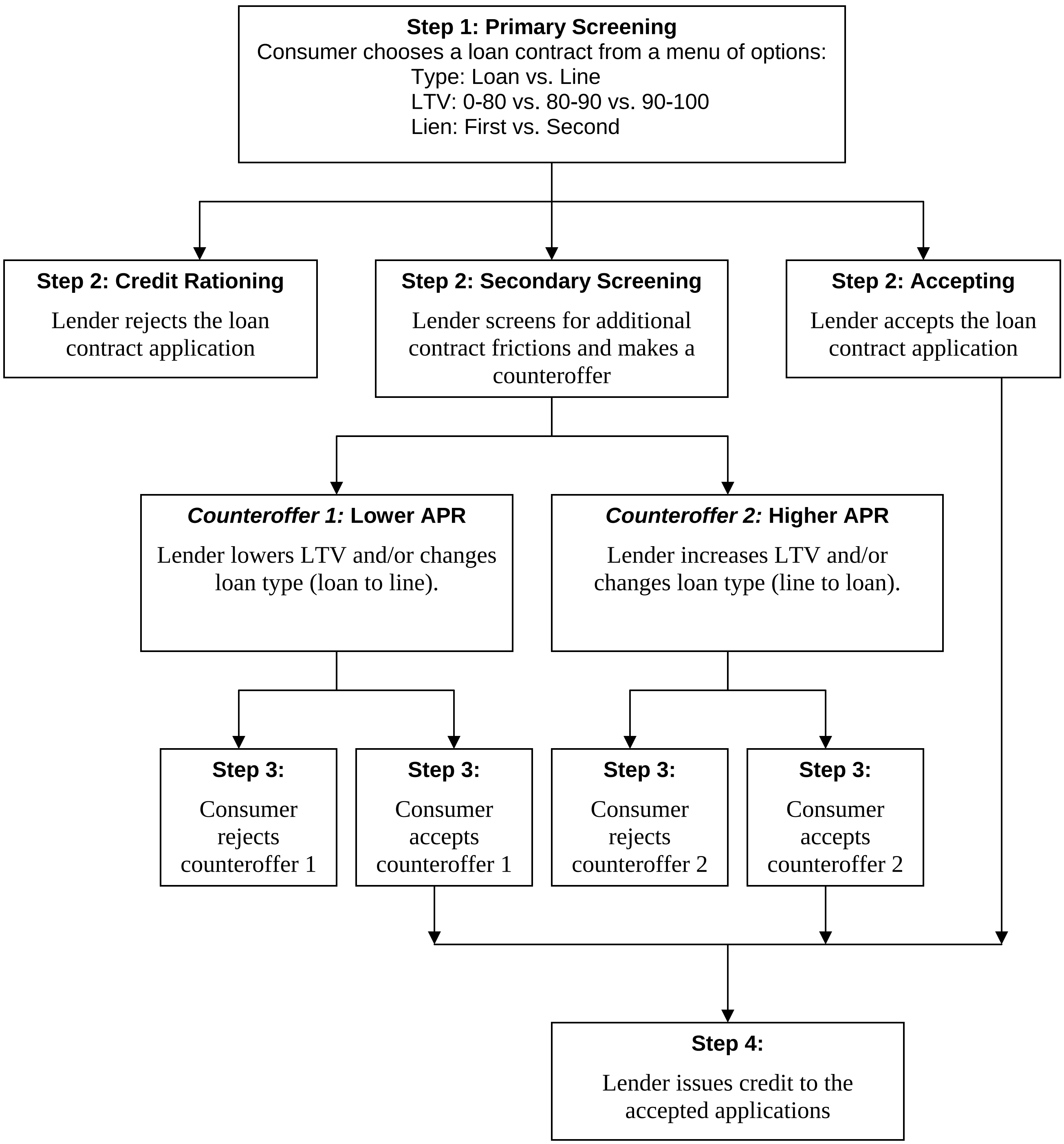

Table I. Number of accounts

This table shows the number of applications in dynamic contract settings for the home equity loans and lines-of-credit applications received between March and December of 2002. Panel A shows the distribution of outcomes from the initial primary screening. Panel B shows the distribution of the counteroffers designed to mitigate contract frictions. 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 II. Descriptive statistics by LTV contract choice

The data set is divided by an applicant's LTV contract choice: (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. Borrwer 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 reported total number of months the borrower 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
Borrower 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 III. LTV contract choice by borrower

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

	Borrower LTV between 80 and 90 percent				Borrower 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 IV. Summary statistics of lender's initial underwriting decisions

This table reports the sample descriptive statistics segmented by the lender's initial underwriting decision: accept, subject to secondary screening and counteroffer, or deny. Loan amount requested is the total credit line or loan amount recorded on the borrower's application. Borrower LTV is the loan-to-value ratio calculated using the applicant's requested loan amount and the applicant'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(APR) is the effective interest rate on the offered loan. FICO is the borrower's credit score at the time of application. Reasons for the 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
Borrower 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 V. Lender's counteroffer and credit rationing decision

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 VI. Test of adverse selection on unobservable risk characteristics

This table reports the competing risks hazard model of loan default and prepayment in order to test for adverse selection in the set of 62,251 applicants who were accepted outright (without secondary screening). The base case is loans that remain 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 own estimate of his house value and the lender's independently appraised house value. 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								
Borrower LTV 80-90	0.354	0.125	0.005	2.22%	-0.553	0.021	<.0001	-4.53%
Borrower LTV 90+	1.291	0.180	<.0001	5.57%	-1.709	0.052	<.0001	-6.57%
Borrower Home Equity Loan Dummy	1.929	0.192	<.0001	5.38%	0.995	0.051	<.0001	2.07%
Borrower 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%
CLTV_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				20,399		

Table VII. Summary statistics by type of counteroffers

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 were subjected to a secondary screening and received a counteroffer designed to mitigate contract frictions. 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. Borrower 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 (APR) 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.

	Counteroffer 1: lower APR		Counteroffer 2: higher APR	
	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
Borrower 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 VIII. Lender counteroffering with a lower APR contract

This table reports the maximum likelihood estimates and marginal effects for the logit model of the lender's decision to mitigate contract frictions using a lower APR counteroffer, conditional upon the application being subjected to secondary screening. The base case is a higher APR 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). 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 IX. Applicants rejecting a higher APR counteroffer

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 2 (higher APR). The base case is the applicant's 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 2 (higher APR), 4,571 rejected the offer.

	Counteroffer 2: higher APR			
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 X. Effectiveness of lender's effort to mitigate contract frictions

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								
Counteroffer 1: lower APR	-0.184	0.067	0.006	-12.2%	0.649	0.016	<.0001	11.0%
Counteroffer 2: higher APR	0.649	0.131	<.0001	4.20%	0.232	0.027	<.0001	2.90%
HouseVal_Diff	0.689	0.144	<.0001	2.60%	-0.195	0.028	<.0001	-2.50%
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%
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%
CLTV_Diff_Dummy	1.027	0.189	<.0001	2.00%	-0.313	0.090	<.0001	-1.10%
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%
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				32,860		

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

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

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.[27] 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

[27] 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:[28]

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

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

and

$$
A_c(t \mid \theta_p,\theta_d) = S(t,t \mid \theta_p,\theta_d). \tag{7.}
$$

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 because of the ending of the data collection period. The term in braces in equations (3) and (4) is the adjustment factor necessary because of discrete time measurement of duration.

The unconditional probabilities are given by

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

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

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

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.

[28] 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

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

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).[29] We calculate $V_{i,t}$ by using the current period *t* market interest rate on home equity lines and home equity loans.[30] 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 control for the impact of changing property values termination probabilities, we matched each observation with the quarterly Office of Federal Housing Enterprise Oversight's (OFHEO) metropolitan statistical areas (MSA) level repeat sales indices. Based on the estimated changes in house prices, we construct time-varying loan-to-value

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

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

ratios (*CLTV*) where the loan value is the total outstanding loan balance that includes the first mortgage.[31] 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 (C*LTV_Diff_Dummy*) to capture the changes in default option values.[32]

With respect to the role of collateral, we also include the percentage difference between the borrower's initial house value assessment and the lender's independent appraised value at origination (*HouseVal_Diff*). Agarwal (2007) 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.

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[31] See Agarwal, Ambrose, and Liu (2006) for a discussion of the potential bias present in the CLTV ratio.
[32] *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.

Local economic conditions may also impact mortgage termination decisions. For example, Hurst and Stafford (2004) note that borrowers with uncertain job prospects may refinance the mortgage 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. The $AGE_{i,t}$ 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.