The Role of Soft Information in a Dynamic Contract Setting: Evidence from the Home Equity Credit Market*

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Abstract

Credit underwriting is a dynamic process involving multiple interactions between borrower and lender. During this process, lenders have the opportunity to obtain hard and soft information from the borrower. We analyze more than 108,000 home equity loans and lines-of-credit applications to study the role of soft and hard information during underwriting. The unique feature of this data is that we are able to follow credit applications from initial contact with the bank through the ultimate disposition of the application. As a result, we are able to distinguish lender actions that are based strictly on hard information from decisions that involve the collection of soft information. Our analysis confirms the importance of soft information and suggests that its use can be effective in reducing overall portfolio credit losses *ex post*.

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

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Abstract

Credit underwriting is a dynamic process involving multiple interactions between borrower and lender. During this process, lenders have the opportunity to obtain hard and soft information from the borrower. We analyze more than 108,000 home equity loans and lines-of-credit applications to study the role of soft and hard information during underwriting. The unique feature of this data is that we are able to follow credit applications from initial contact with the bank through the ultimate disposition of the application. As a result, we are able to distinguish lender actions that are based strictly on hard information from decisions that involve the collection of soft information. Our analysis confirms the importance of soft information and suggests that its use can be effective in reducing overall portfolio credit losses *ex post*.

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Financial institutions utilize information to make decisions about extending credit to potential borrowers as well as determining the type of credit (i.e. the features of the loan contract) to offer. A growing academic literature now recognizes that such information comes in two flavors: hard and soft. Stein (2002) defines hard information as any information that is easily verifiable (e.g. "such as the income shown on the borrower's last several tax returns") while soft information "cannot be directly verified by anyone other than the agent who produces it."[1] Consumer credit scores and corporate bond ratings are examples of hard information that financial institutions often use in determining whether to approve or deny loan applications.[2] In contrast, soft information can not be revealed in a numeric score or easily verified. For example, soft information may be obtained by a loan officer taking a prospective borrower's loan application or acquired via relationships with customers. Soft information can be quite valuable in lending decisions, as it may provide the loan officer with additional insight on the borrower's propensity to repay the loan.

The hardness (or softness) of information plays a central role in financial intermediation. For example, Stein (2002) links information hardness to organizational structure in order to show that hierarchical firms have a competitive advantage in processing "hard" information, suggesting greater consolidation in the banking industry as financial intermediaries increasingly emphasize credit scoring technology.[3] Additionally, Degryse and Cayseele (2000), Chkraborty and Hu (2006), and Brick and Palia (2007), among others, link bank-borrower relationships to the use of collateral and to the pricing of loan contracts, suggesting the importance of soft information.

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[1] Stein (2002), page 1892. See also Petersen (2004) for a discussion of the differences between soft and hard information.
[2] See Mays (2004) for an overview of the development of credit scoring.

Unfortunately, soft information is difficult to observe requiring researchers to rely on proxies to test for its presence. For example, researchers often use the distance between borrower and lender as a proxy for the strength of the borrower-lender relationship, and hence the lender's ability to capture and utilize soft information.[4] Using this measure, Petersen and Rajan (2002) report an increase in distance between small businesses and their lenders during the 1990s and contend that the growing use of hard information is partly responsible. In addition, Del'Ariccia and Marquez (2004) offer a theoretical model that links bank-borrower relationship with distance while Berger et al. (2005) provide empirical support for the relationship between information hardness and bank-borrower distance. Furthermore, Gonzalez and James (2007) provide evidence for the importance of soft information in bank lending based on firm banking relations at initial public offerings. More recently, DeYoung, Glennon, and Nigro (2008) document the relationship between the use of hard information (via credit scoring technology) and increases in borrower-lender distances while Butler (2008) explores the distance between investment bank underwriters and municipal bond issuers as a proxy for the presence and value of soft information.

Although information hardness is clearly important to financial intermediaries, research on the effectiveness of hard versus soft information is somewhat limited. For example, research linking loan origination with loan performance has almost exclusively focused on hard information due to its quantitative nature. Recent studies in this literature include Roszbach (2004), who analyzed the effectiveness of bank credit scoring models

[3] Akhavein, Frame, and White (2005) discuss the growth in small business credit scoring and find that larger banks adopt technology earlier, providing them with comparative advantages in loan originations.

(hard information) in the origination and performance of consumer credit, and DeYoung, Glennon, and Nigro (2008), who link credit scoring to small business loan performance. In addition, a large literature exists in real estate that links mortgage loan performance to hard information captured from the loan application.[5] In contrast, due to the inherent qualitative nature of soft information, empirical studies must rely on various proxies for the presence of soft information. For example, as discussed above, many researchers use geographical distance between borrower and lender as a proxy for the presence of soft information under the assumption that closer geographical distance implies greater use of soft information. More recently, García-Appendini (2007) correlates information on loan types with data on borrower relationships with the lender to infer the presence of soft information. Her study indicates that banks collect soft information through relationships and use this information in credit decisions.[6] Yet, to our knowledge, no study has direct evidence on the actual utilization or effectiveness of soft information. One of the goals of this study is to provide such evidence using a unique dataset that tracks the dynamic contracting environment from loan application through origination. Thus, we address the following question: How extensive is the use of soft information in loan origination?

In addition to using proxies for the presence of soft information, most empirical studies use financial datasets and surveys that contain only information about loan contracts that are already booked.[7] Unfortunately, these sources cannot identify borrower

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[4] See Boot (2000) for a review of the literature on relationship lending. A number of studies including Petersen and Rajan (1994), Berger and Udell (1995), Elsas (2005), and Puri and Rocholl (2007), among others, empirically test the value of lending relationships.

[5] For example, see Deng, Quigley and Van Order (2000) for an application showcasing the utilization of hard information to study loan performance in the context of residential mortgages.

[6] Similarly, Ergungor (2005) examines community bank lending relationships to address the question of whether relationships provide value.

[7] See Roszbach (2004) for a discussion of this issue and the potential bias that it introduces in empirical models of loan performance.

contract choices *ex ante* and thus cannot directly reveal the use of soft information in the loan contracting process or the ultimate impact of this information on the performance of booked loans. In contrast, we observe the role of soft information utilizing a unique, proprietary dataset covering the dynamic contracting process. By examining the complete underwriting process (from loan application to ultimate origination), we directly see the use of soft information in altering loan contracts during the underwriting process. Thus, we show the effect of soft information on the borrower-lender negotiation during loan underwriting. Furthermore, we also match the loan origination data to a complimentary dataset that allows us to observe the loan performance through time. As a result, we can answer the question: how does the outcome of the borrower-lender negotiation affect the performance (default or prepayment) of the booked loan?

The dataset used in this study reveals multiple levels of borrower screening, providing a window into lender use of soft and hard information in the loan underwriting process. Figure 1 illustrates the typical home equity loan origination process: First, borrowers submit an application for a particular home equity loan or line-of-credit offer selected from a menu of contract options with varying prices and terms. At this stage, the lender utilizes hard information obtained from the loan application to conduct an initial screening using an automated underwriting system. The automated underwriting system accepts the application (in which case the loan or line is booked), rejects the application, or refers the application for secondary screening. Credit rationing in the classic Stiglitz and Weiss (1981) framework may occur during this phase 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.[8] In the second stage, applications referred for secondary screening are sent to a loan officer. During this phase, the loan officer gathers additional soft information from discussions with the applicant. For example, the loan officer may learn the extent of a planned remodeling project or the item intended to be purchased with the loan proceeds. Based on the hard information contained in the application and the soft information learned during the negotiation phase, the loan officer proposes a counter offer contract. For example, the loan officer could suggest that the consumer pledge additional collateral, and in turn, offer the applicant a lower interest rate, or alternatively, counteroffer with a higher interest rate contract. At this point, the applicant either accepts or rejects the counter offer. If the counter offer is accepted, the loan is booked. We then follow the post-origination performance of the booked loans to determine the impact of the lender's evaluation of soft information.

The use of credit scoring and automated underwriting models may obscure the importance of soft information in empirical studies that rely only on loan origination data. As described above, a subset of the applicant pool has risk characteristics such that the cost of obtaining soft information outweighs the benefits derived from this information. These applicants are accepted or rejected outright. The value of soft information will only be revealed through the cases where automated underwriting models (using hard information) are unable to make a clear accept/reject decision. Thus, our study directly illuminates the role of soft information as we track all applications through the underwriting process.

To preview our results, after controlling for borrower age, income, employment, and other observable attributes (i.e., hard information), we find that the borrower's choice

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

of credit contract does reveal information about his risk level, consistent with the implications of Bester (1985). Specifically, we find that less credit-worthy borrowers are more likely to self-select contracts that require less collateral.

In the second part of the study, we examine the effectiveness of the lender's use of soft information in designing counter-offer contracts to reduce ex post credit losses. 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 profit from the higher APR can more than offset the increase in losses associated with greater defaults. Thus, our results show that financial institutions can reduce credit losses by using soft information.

Furthermore, we find it interesting that using soft information to craft counter offers also imposes 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 2, we describe the home equity origination process, and then discuss the data in section 3. In section 4 we explore the dynamic contracting environment that results from the borrower-lender negotiations during the primary and secondary screening process. Then, in section 5, we examine the impact of dynamic contracting by estimating the impact of secondary screening on loan repayments. Finally, we conclude in section 6.

2. Home Equity Credit Origination

The empirical setting for our study is the home equity credit market. 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.[9] 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.[10] By the end of 2005, home equity lending increased to over $702 billion.[11] 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.[12]

The home equity credit market presents an ideal framework in which to investigate the role of information because home equity credits are secured by the borrower's home and the borrower generally faces a menu of contracts having varying interest rates. The lender offers a menu of differential contracts to help borrowers self-select a contract type (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 $r_1<r_2<r_3$.

[9] See Agarwal et al. (2006) for a review of the various differences between home equity loans and lines-of-credit.
[10] See www.federalreserve.gov/pubs/oss/oss2/2004/scf2004home.html.
[11] See *Inside Mortgage Finance*, an industry publication.
[12] See Brueckner (1994), Stanton and Wallace (1998) and LeRoy (1996) for a discussion of the mortgage contract and the implications concerning asymmetric information.

3. Data Description

We collected an administrative data set of home equity contract originations from a large financial institution.[13] 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. The database captures all hard information used in the lender's automated underwriting model. 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. 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 1). Based on the hard information revealed in the application, the lender rejected 11.1 percent of the applications, accepted 57.6 percent of the applications, and referred the remaining 31.3 percent to secondary screening. For loans referred to secondary screening, the lender collected soft information and proposed an alternative loan contract. For example, the lender could 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 could 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 1, we see that 31.4 percent of the 33,860 applicants subjected to 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. Of the higher APR 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 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.

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.

[13] At the time the dataset was collected, the financial institution had operations in the New England, Mid-Atlantic, and Florida regions and the FDIC ranked it among the top-five commercial banks and savings institutions.

4. The Dynamic Contracting Environment

This section presents an analysis of the dynamic contracting environment that occurs during primary and secondary screening of home equity contracts. First, we examine the borrower's initial credit contract choice to demonstrate that borrowers reveal information about their credit risk through their response to the lender's credit menu. Next, we examine the lender's initial accept/reject decision based on hard information and the lender's use of soft information. Finally, we examine borrower reaction to the lender's use of soft information (their acceptance or rejection of the counteroffer).

4.1 Initial credit contract choice

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 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.[14] 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

[14] 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-

estimate and loan amount requested.[15] 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:

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

where $j=\{1,2,3\}$ corresponds to LTVs less than 80 percent, between 80 percent and 90 percent, and greater than 90 percent, respectively, W_i represents borrower i's credit quality as measured by her FICO score (Fair, Isaac, and Company credit quality score), and X_i represents a vector of control variables. The control variables are the hard 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.

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than-80-percent LTV assuming that they did not misestimate their house value. The results are qualitatively similar.

[15] 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 using the property value from an independent appraisal and the lender-approved loan amount (see Agarwal, 2007).

Table 2 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 years old versus 51 years old), have shorter tenure at their current address (74 months versus 158 months), have lower annual incomes ($100,932 versus $118,170), have higher debt-to-income ratios (40 percent versus 35 percent), and have fewer years at their current job (7.4 years versus 9.8 years).

Table 3 presents the multinomial logit estimation results of 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, other variables related to borrower risks are also associated with 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 product with an LTV less than 80 percent.[16] 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.[17] 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

[16] 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.

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.[18]

4.2 Lender response to borrower contract choice

We now turn to a formal analysis of the lender's use of hard information in the underwriting decision. We model the outcome (O) of the lender's primary screening as a multinomial logit model estimated via maximum likelihood:

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

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 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 hard information that the lender collected on a loan application.

Table 4 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

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[17] 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.

[18] 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.

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, the credit quality of applicants who were accepted at the outset is higher than the credit quality of those who received additional screening and those who 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 5 provides the multinomial logit estimation results for the lender's underwriting decision. 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 The use of soft information in underwriting

We now turn to a formal analysis of the lender's use of soft information in designing counteroffers. To illustrate how a loan officer could collect useful soft information, consider the following scenario. During the origination process, the borrower

initially requests a 90 percent LTV loan for the stated purpose of making a home improvement, and then, during the application process, reveals to the loan officer a more extended description of the planned home improvement (e.g., a kitchen remodel or other major repair). In this context, the actual intended home improvement is soft information not captured on the loan application. 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 suggest a lower loan amount as her 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 requested loan amount and the loan officer realizes (again 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.

We classify the contracts where the loan officer altered the contract in a way that lowered the APR as counteroffer 1. In contrast, we classify a counteroffer having a higher APR as counteroffer 2 (in Figure 1 and Table 6).

Table 6 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),

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, we estimate a logit model of the secondary screening outcome via maximum likelihood. As in the model of the lender's initial underwriting process, we include the set of explanatory variables that control for the percentage difference between the lender's LTV estimate and the borrower's LTV estimate, the percentage difference in the loan amount requested by the borrower and loan amount actually approved by the lender, the use of the funds, and other borrower credit risk factors.

Table 7 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 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.

4.4 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. On the one hand, borrowers who feel that the 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. As a result, the lender's secondary screening and counteroffer based on soft information 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 8 presents the results for the estimation of this model. Overall, we 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, and/or is retired, is more likely to accept a higher APR counteroffer.

5. The Impact of Dynamic Contracting

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 secondary screening. 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.

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

$$PPOption_{i,t} = \frac{V_{i,t} - V_{i,t}^{*}}{V_{i,t}}, \qquad (3.)$$

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).[19] We calculate $V_{i,t}$ by using the current period *t* market interest rate on home equity lines and home equity loans.[20] 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 on 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 ratios (*CLTV*) where the loan value is the total outstanding loan balance that includes the first mortgage.[21] 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.[22]

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

[19] This is equivalent to the prepayment option value used by Archer, Ling, and McGill (1996) scaled by the mortgage book-value.
[20] Current period *t* home equity line and home equity loan market interest rates were obtained from the Heitman Group (www.heitman.com).
[21] See Agarwal, Ambrose, and Liu (2006) for a discussion of the potential bias present in the CLTV ratio.
[22] *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.

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) with home equity lines are more likely to raise their utilization rates rather than pay down the line.

Local economic conditions may also impact mortgage termination decisions. For example, Hurst and Stafford (2004) note that borrowers having 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, and a series of dummy variables that denote the borrower's location (state) to control for unobserved state-specific factors.

We 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 to default.

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.

Finally, 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 determine the effectiveness of the lender's use of soft information. Moreover, we create a monthly record of each loan denoting whether the loan defaulted, prepaid, or remained current as of March 2005. During this period, 916 (1.1 percent) of the loans defaulted, and 32,860 (39.4 percent) of the accounts were prepaid.[23]

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

Table 9 presents the estimated coefficients from the competing risks model. Overall, we find that the lender's use of soft information 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 use of soft information is effective in reducing overall portfolio credit losses.

To highlight the economic implications of using soft information, we estimate the impact that the counter-offers could have had on the $700 billion dollar portfolio of U.S. home equity credit that existed in 2005 assuming that the portfolio that had an average default rate of 1 percent. First, we note that the 12.2 percent net reduction in defaults arising from counteroffer 1 would have saved approximately $854 million in direct default costs. In contrast, the 4.2 percent higher default rate resulting from counteroffer 2 would have increased default costs by 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 implications for lenders seeking to maximize the profitability of their loan portfolios. The results clearly indicate that the use of soft

information can effectively reduce portfolio credit losses *ex post*. Furthermore, 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 9 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, borrowers subjected to additional screening have higher prepayment rates during periods of declining interest rates than borrowers not subjected to additional screening.

The results indicate that the lender's counteroffers created an additional incentive for borrowers to refinance into new (perhaps more favorable contracts) during a decline in interest rates. The extent that the lender's use of soft information alters the sensitivity of borrowers to changes in interest rates 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 soft information in the home equity credit market, where more than 108,000 applicants face a menu of contract options with varying prices and a lender proposes counteroffers based on soft information. Our empirical analysis suggests that a borrower's choice of credit contract reveals information about his risk level. Specifically, we find that a less credit-worthy borrower is more likely to select a contract that requires him to pledge less collateral.

Moreover, we find that a lender's efforts *ex ante* to mitigate contract frictions by using soft information 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 their higher APR. Hence, our results suggest that financial institutions can reduce credit losses overall and increase profits, by using soft information. We find it interesting, however, that the counteroffers also impose costs in the form of 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 during 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 soft information 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. Furthermore, our analysis clearly shows that, in a market with readily available credit scoring and automated underwriting technology, samples of originated loans will contain loans originated solely through the use of hard information as well as loans that were originated based on soft information. As a result, empirical studies of the effect of soft information that rely on observations of originated loans will be biased. Our results are also applicable to other markets, such as insurance, managerial incentive compensation, and corporate governance, which have a similar dynamic contracting environment.

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Figure 1: HOME EQUITY MORTGAGE ORIGINATION PROCESS

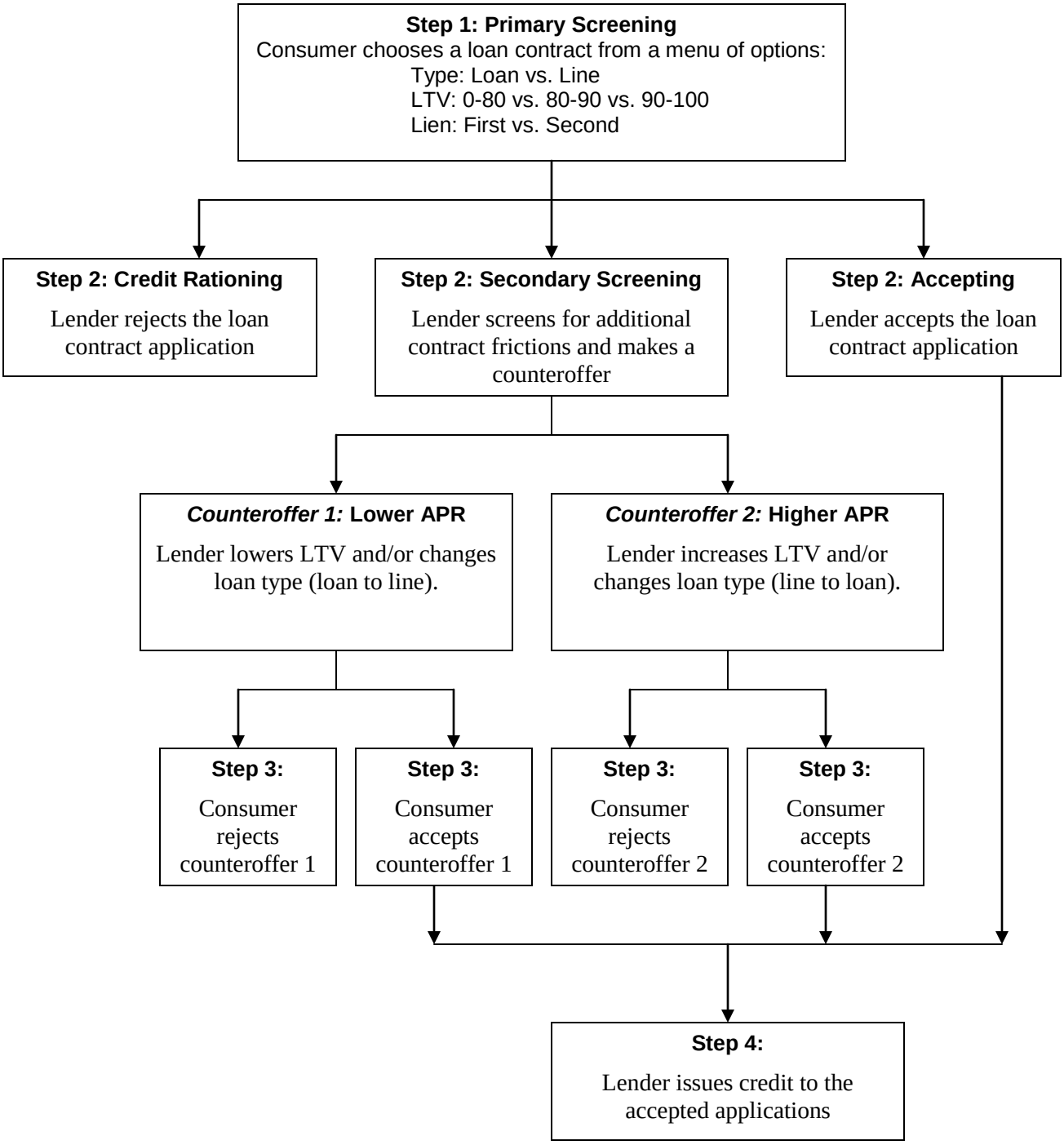

Table 1. Number of accounts

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. Panel C shows the distribution of the consumers' acceptance or rejection of the counteroffer. Panel D shows the total number of loans originated as a percentage of the total applications.

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

Table 2. Descriptive statistics by LTV 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. Borrower 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 3. 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 4. 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 5. 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 6. 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. 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 7. 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 counteroffer with a lower APR, 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 8. 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 9. Effectiveness of lender's use of soft information

This table reports the competing risks hazard model of loan default and prepayment in order to identify the effect of the lender's use of soft information. 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). The model is estimated over the 83,411 applications that are ultimately booked

	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

$$S(t_p,t_d \mid r,H,X,Z,\theta_p,\theta_d) = \exp\Big(-\theta_p \sum_{n=1}^{t_p} \exp(\alpha_{pn} + g_{pn}(r,H,X) + \beta_p' Z) - \theta_d \sum_{n=1}^{t_d} \exp(\alpha_{dn} + g_{dn}(r,H,X) + \beta_d' Z)\Big), \quad (4.)$$

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.[24] The parameters α_{jn} are the baseline hazard parameters estimated as

$$\alpha_{jn} = \log\left[\int_{n-1}^{n} \lambda_j(t)\,dt\right], \quad (5.)$$

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

[24] 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:[25]

$$A_p(t \mid \theta_p,\theta_d) = S(t \mid \theta_p,\theta_d) - S(t+1 \mid \theta_p,\theta_d) - .5\{S(t \mid \theta_p,\theta_d) + S(t+1,t+1 \mid \theta_p,\theta_d) - S(t,t+1 \mid \theta_p,\theta_d) - S(t+1,t \mid \theta_p,\theta_d)\}, \quad (6.)$$

$$A_d(t \mid \theta_p,\theta_d) = S(t \mid \theta_p,\theta_d) - S(t+1 \mid \theta_p,\theta_d) - .5\{S(t \mid \theta_p,\theta_d) + S(t+1,t+1 \mid \theta_p,\theta_d) - S(t,t+1 \mid \theta_p,\theta_d) - S(t+1,t \mid \theta_p,\theta_d)\}, \quad (7.)$$

and

$$A_c(t \mid \theta_p,\theta_d) = S(t \mid \theta_p,\theta_d). \quad (8.)$$

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 (6) and (7) is the adjustment factor necessary because of discrete time measurement of duration.

The unconditional probabilities are given by

$$A_j(t) = \sum_{m=1}^{M} \gamma_m A_j(t \mid \theta_{pm},\theta_{dm}), \; j = p,d,c, \quad (9.)$$

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

$$\log L = \sum_{i=1}^{N} \delta_{pi} \log(A_p(T_i)) + \delta_{di} \log(A_d(T_i)) + \delta_{ci} \log(A_c(T_i)), \quad (10.)$$

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 (10) is estimated via maximum likelihood.

[25] The dependence of the functions in equations (6)–(8) on r, H, X, and Z has been omitted for ease of exposition.