JMCB	jmcb_390	**Dispatch:** 3-18-2011	**CE:** AFL
Journal	**MSP No.**	**No. of pages:** 23	**PE:** Grily Chua

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

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. Our dataset allows us 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 codes: D1, D8, G21
Keywords: information, contract frictions, screening, banking, home equity lending.

FINANCIAL INSTITUTIONS UTILIZE information to make decisions about extending credit to potential borrowers as well as determining the type of credit

The authors thank Regina Villasmil for excellent research assistance and Han Choi for editorial assistance. We also thank Amy Crew-Cutts, Shubhasis Dey, John Driscoll, Dennis Glennon, Robert Hauswald, Bert Higgins, Doug McManus, Donna Nickelson, Karen Pence, Mitch Petersen, Calvin Schnure, Nick Souleles, Matt Spiegel, Jon Zinman, and seminar participants at the 2007 ASSA meeting, the FDIC Center for Financial Research, Maastricht University, MEA, NCAER, the Office of the Comptroller of the Currency, The Pennsylvania State University, and the University of Kentucky for helpful comments and suggestions. The views expressed in this research are those of the authors and do not necessarily represent the policies or positions of the Office of the Comptroller of the Currency; and any offices, agencies, or instrumentalities of the United States Government; the Federal Reserve Board; or the Federal Reserve Bank of Chicago. Ambrose and Liu gratefully acknowledge financial support from the FDIC's Center for Financial Research.

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Received February 3, 2009; and accepted in revised form November 9, 2010.

Journal of Money, Credit and Banking, Vol. 43, No. 4 (June 2011)

(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 cannot 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), Chakraborty 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 (also see Agarwal, Chomsisengphet, Liu, and Souleles (2009)).

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 **Q2** 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) and Agarwal and Hauswald (2010) 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

1. Stein (2002, p. 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.

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.

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 (2008), among others, empirically test the value of lending relationships. **Q3**

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 (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 (also see Agarwal and Hauswald (2010)). 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, empirical studies must rely on various proxies for the presence of soft information due to its inherent qualitative nature. 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 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

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.

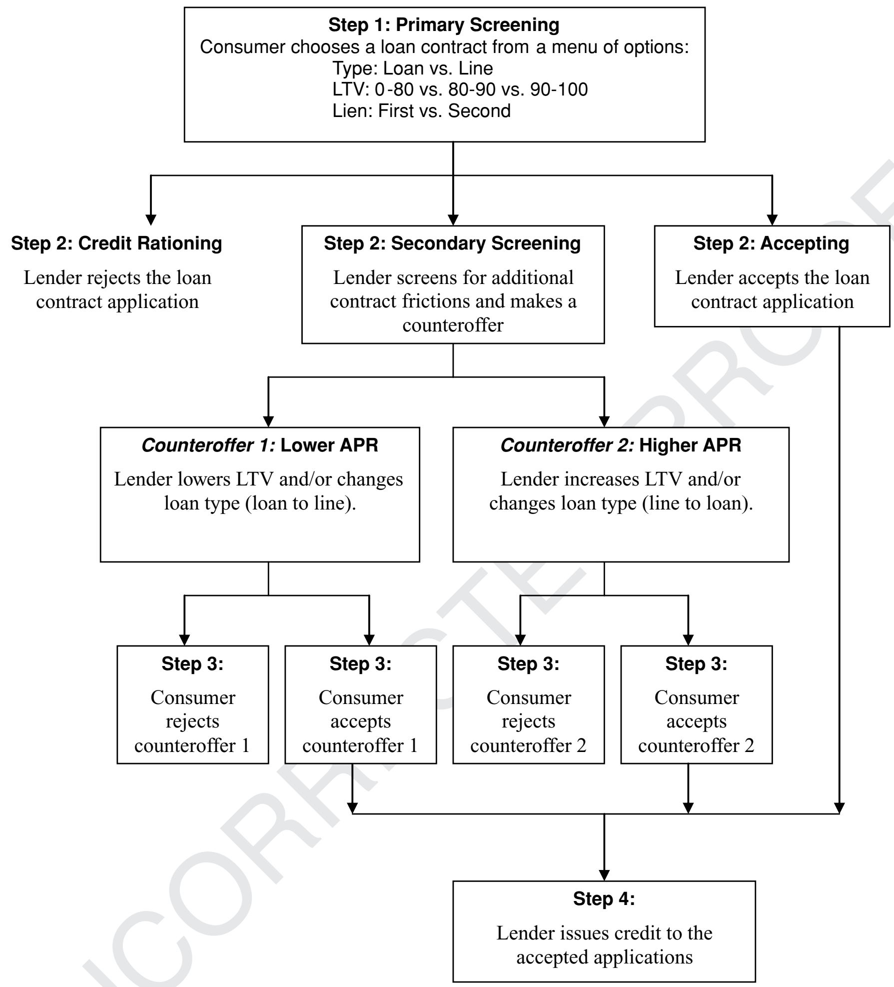

Fig. 1. Home Equity Mortgage Origination Process.

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 counteroffer 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.[9] At this point, the applicant either accepts or rejects the counteroffer. If the counteroffer is accepted, the loan is booked. We then follow the postorigination 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 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 counteroffer contracts to reduce *ex post* credit losses. Our results show that a lender's counteroffer that lowers the annual percentage rate (APR) requirement (e.g., but increasing the collateral) reduces default risk *ex post* by 11%, and a counteroffer that raises the APR requirement increases default risk *ex post* by 4%. However, we find that a lender's overall profit from the higher APR can more

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

9. In the context of this product type (home equity credit), the bank's counteroffer always resulted in a change in the contract interest rate since contract rates are tied to contract features (e.g. loan-to-value ratios and maturity terms.)

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 counteroffers also imposes costs in the form of higher prepayment rates. Our results show that the lower APR requirements increase the odds of prepayment by 10%, while the higher APR requirements increase the probability of prepayment by 3%. 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 describe the home equity origination process, and then discuss the data in Section 2. We explore the dynamic **Q4** contracting environment that results from the borrower–lender negotiations during the primary (Section 3) and secondary screening (Section 4) 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.

1. 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.[10] Recent evidence from the *Survey of Consumer Finances* suggests that the home equity lending market increased over 26% between 1998 and 2001 to $329 billion (see www.federalreserve.gov/pubs/oss/oss2/2004/scf2004home.html.). 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.[13] For example, a typical home equity menu may offer a 15-year home equity line-of-credit with less than 80% loan-to-value (LTV) ratio at an interest rate r_1; a 15-year home equity loan with first lien between 80%

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

11. See *Inside Mortgage Finance*, an industry publication. **Q5**

12. See Brueckner (1994), Stanton and Wallace (1998), and LeRoy (1996) for a discussion of the mortgage contract and the implications concerning asymmetric information.

13. The bank's credit menu (combinations of rate/LTV/contract type) reflects the competitive nature of the lending business as well as the bank's risk/return appetite. The actual selection of the credit menu is determined by competitive forces as well as the bank's other business lines and internal capital ratios.

and 90% LTV at an interest rate r_2; or a 15-year home equity loan with second lien between 90% and 100% LTV at an interest rate r_3, where $r_1 < r_2 < r_3$.

2. DATA DESCRIPTION

We collected an administrative dataset of home equity contract originations from a large financial institution. 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. **Q6** Moreover, the home equity portfolio of the bank was the largest in the nation. Home equity lending practices within the industry were fairly uniform during this time period. We know this because over the years this financial institution merged and/or acquired several financial institutions, and comparing and contrasting the loan underwriting practices of those institutions reveals that they followed similar practices. However, subsequent to the 2002–05 period, financial institutions practiced divergent underwriting practices.

The dataset 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 (i) increase an existing line-of-credit, (ii) request a new line-of-credit, (iii) request a new first-lien loan, or (iv) request a new second-lien loan. For each product, borrowers could choose the amount of collateral to pledge by selecting across three LTV ratio groups: less than 80% LTV, 80–90% LTV, or 90–100% 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% of the applications, accepted 57.6% of the applications, and referred the remaining 31.3% 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% of the 33,860 applicants subjected to secondary screening were offered a new contract that had a higher LTV and/or different type of home equity product, and 68.6% of them were

TABLE 1
Number of Accounts

	Count	%
Total credit applications received (March 2002 to 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

Note: 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.

offered a new contract that had a lower LTV and/or a different type of home equity product. Of the counteroffers that resulted in a higher APR, 26% had a higher LTV with the same home equity type, and 74% had the same LTV but were switched from a line to a loan. Of the counteroffers with a lower APR, 63% had a lower LTV with the same home equity type, and 37% 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%) declined the lender's counteroffer. Interestingly, we note that the majority of borrowers (64%) who rejected the counteroffer were offered a lower APR contract (lower LTV), while 36% were given a counteroffer with a higher APR contract. In no circumstances did the financial institution maintain the same APR offer and make changes to the other terms of the contract offer. This is also consistent with industry practices. Of the 21,160 applicants who accepted the lender's counteroffer, 28.7% received a counteroffer with a higher APR contract, while 71.3% received a counteroffer with a lower APR contract. Finally, we have a pool of 83,411 applicants (77.1% of the total 108,117) who were ultimately issued home equity contracts.

3. INITIAL CREDIT CONTRACT CHOICE

We first 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.[14] 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.[15] 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.[16] 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.

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: **Q7**

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

where $j = \{1,2,3\}$ corresponds to LTVs less than 80%, between 80% and 90%, and greater than 90%, 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,

14. We also examined the lender's initial accept/reject decision based on hard information and the lender's use of soft information and borrower reaction to the lender's use of soft information (their acceptance or rejection of the counteroffer); these results are available upon request from the authors.

15. It is possible that some borrowers may have a first mortgage that implicitly prohibits them from choosing a less than 80% LTV. However, as documented by Agarwal (2007), a significant percentage of borrowers overestimate their house value, allowing them the option to choose from the full menu. We also reestimate our empirical analysis with a sub-sample of borrowers who have the option to choose the less than 80% LTV assuming that they did not misestimate their house value. The results are qualitatively similar.

16. 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).

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 2 presents the descriptive statistics of the sample segmented by the borrower LTV category (LTV less than 80%, LTV between 80% and 90%, and LTV greater than 90%) chosen at the time of application. As expected, we observe that borrowers pledging less collateral (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 a LTV ratio above 90% while the average FICO score is 737 for borrowers choosing a LTV ratio less than 80%. Furthermore, relative to borrowers with LTV ratios less than 80%, we observe that on average borrowers pledging less collateral (90% or higher LTV ratios) 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% versus 35%), 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 choice of LTV, where the base case is selecting a contract with a LTV less than 80%. Although the nonlinear specification for borrower credit score makes interpretation difficult, the combined effect of the statistically significant coefficients for FICO and FICO^2 indicates 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 computed 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. The estimated probabilities indicate that a lower credit-quality borrower (FICO score equal to 700) is 21.4% more likely to apply for home equity contract having an LTV that is 90% or greater than a higher credit-quality borrower (FICO score equal to 800). Furthermore, a borrower with a FICO score of 700 is 18.9% more likely to apply for a home equity contract having an LTV between 80% and 90% than a higher credit-quality borrower (FICO score equal to 800). 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, the marginal effects indicate that refinancing borrowers are 2.9% more likely to apply for a home equity product with a 90% or greater LTV and 3.3% more likely to apply for a home equity product with a LTV between 80% and 90% than borrowers using the proceeds for consumption. Furthermore, borrowers without a current first mortgage are 7.2% less likely to select a home equity product with an LTV greater than 90% than borrowers with a first mortgage.[17] We also find that borrowers with lower income

17. We also note that borrowers without a current first mortgage are 10.5% less likely to request a loan with LTV between 80% and 90% than borrowers with a first mortgage.

Q8

TABLE 2

DESCRIPTIVE STATISTICS BY LTV CONTRACT CHOICE

Variable name	LTV ≤ 80 Mean	LTV ≤ 80 STD	LTV 80–90 Mean	LTV 80–90 STD	LTV ≥ 90 Mean	LTV ≥ 90 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	

NOTE: The dataset is divided by an applicant's LTV contract choice: (LTV) ratio less than 80%, a LTV ratio between 80% and 90%, and a LTV ratio greater than 90%. 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.

Q9

TABLE 3

LTV Contract Choice by Borrower

	Borrower LTV choice							
	LTV between 80% and 90%				LTV greater than 90%			
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	-3.0×10^{-05}	$0.0 \times 10^{+00}$	<.0001	0.00%	-7.0×10^{-05}	1.0×10^{-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	-4.1×10^{-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%							

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

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% less likely to apply for a loan with an LTV ratio greater than 90% than a borrower without a second home. 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% more likely to choose a greater than 90% LTV contract than home equity line-of-credit borrowers.[18]

4. 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. Based on discussions with various loan officers, we construct the following scenario to illustrate how loan officers collect useful soft information. Assume that a borrower initially submits an application requesting a 90% LTV loan for the stated purpose of making a home improvement. Based on the initial screen based on the hard information contained in the loan application, the automated underwriting system refers the application to a loan officer for secondary screening. During the secondary review, the applicant and loan officer discuss the loan request. At this point, the applicant 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 nonhome 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 based on whether the loan officer proposed an increase or decrease in the contract interest rate. We refer to contracts where the loan officer proposed terms that resulted in a lower APR

18. We also estimated a multinomial logit regression over each individual product as described in Section 1. The results confirm that borrowers with lower FICO scores choose risky products. The results are available upon request.

TABLE 4

Summary Statistics by Type of Counteroffers

	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
Years 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	

Note: 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.

as counteroffer 1. In contrast, we classify a counteroffer having a higher APR as counteroffer 2 (in Figure 1 and Table 4).

It is important to recognize that the counteroffers are made based on hard and soft information as the loan officer has access to the information contained in the loan application as well as information learned during the secondary review. Thus, the subsequent analysis based on the counteroffers should reflect an upper bound for the role of soft information since both types of information were utilized in the origination process.

Table 4 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% versus 16%), while a smaller proportion intend to use the funds to refinance existing debt (38% versus 64%). Furthermore, those receiving a higher APR counteroffer have slightly higher debt-to-income ratios (40% versus 35%), and have shorter tenure at their current address (127 months versus 158 months).

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).[19]

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

$$PPOption_{i,t} = \frac{V_{i,t} - V^*_{i,t}}{V_{i,t}}, \tag{2}$$

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).[20] We calculate $V_{i,t}$ by using the current period t market interest rate on home equity lines and home equity loans.[21] 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 nonlinearity 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

19. Details of the competing risk model estimation are provided in Agarwal et al. (2006).

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

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

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 (CLTV) ratios where the loan value is the total outstanding loan balance that includes the first mortgage.[22] We also include the square of CLTV to control for any nonlinearity. We include a dummy variable for a positive quarterly change in the loan-to-value ratio (*CLTV_Diff_Dummy*) to capture the changes in default option values.[23]

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 nonlinearity 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, 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. In addition, we also control for differences across location based on heterogeneity in local housing markets. Thus, we include the average 12-month house price appreciation prior to the application date as measured by the change in the Case–Shiller zip-code level repeat sales index. We also include the volatility in the local zip-code level index prior to the application date. These "external" information sources capturing variation in the local markets are observable at the application date.

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

22. See Agarwal, Ambrose, and Liu (2006) for a discussion of the potential bias present in the CLTV ratio.

23. *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.

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 nonparametrically. 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.[24]

Finally, 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%) of the loans defaulted, and 32,860 (39.4%) of the accounts were prepaid.[25]

Table 5 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 11.1% 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 4.1% 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 counteroffers 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%. First, we note that the 11.1% net reduction in defaults

24. As a robustness check, we also estimated the model for loan secured by primary residences only. The results are not qualitatively different. To conserve space, a table detailing these results is available upon request.

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

TABLE 5

Effectiveness of Lender's Use of Soft Information

Independent variables	Default: Coeff. val.	Default: Std. err.	Default: *p*-Value	Default: Marginal effects (%)	Prepayment: Coeff. val.	Prepayment: Std. err.	Prepayment: *p*-Value	Prepayment: Marginal effects (%)
Intercept	2.813	0.755	<.0001		−1.340	0.523	<.0001	
Borrower characteristics								
FICO	−0.097	0.009	<.0001	−0.40	0.042	0.002	<.0001	0.18
$FICO^2$	0.000	0.690	<.0001	0.00	0.000	0.000	<.0001	0.00
Log (income)	−0.137	0.057	0.016	−8.40	0.245	0.012	<.0001	3.28
Log (house tenure)	−0.048	0.022	0.025	−9.90	−0.019	0.006	0.000	−1.30
Debt-to-income	0.017	0.001	<.0001	1.90	0.015	0.000	<.0001	2.05
Contract characteristics								
Counteroffer 1: Lower APR	−0.175	0.065	0.006	−11.10	0.644	0.015	<.0001	9.99
Counteroffer 2: Higher APR	0.641	0.122	<.0001	4.12	0.230	0.026	<.0001	2.71
HouseVal_Diff	0.653	0.131	<.0001	2.37	−0.193	0.025	<.0001	−2.40
Home equity loan dummy	3.763	0.143	<.0001	6.33	1.147	0.039	<.0001	1.78
First-lien dummy	−0.261	0.157	0.082	−1.10	−0.700	0.034	<.0001	−3.00
Refinancing	−0.354	0.069	<.0001	−2.90	0.148	0.013	<.0001	2.92
Home improvement	−0.386	0.078	<.0001	−3.60	0.084	0.016	<.0001	1.86
No first mortgage	−0.145	0.097	0.110	−4.60	−0.165	0.018	<.0001	−3.50
Second home	1.672	0.100	<.0001	1.98	−0.122	0.030	<.0001	−2.00
Condo	−2.764	0.226	<.0001	−1.00	0.611	0.024	<.0001	2.68
Time-varying option variables								
CLTV	0.058	0.082	0.180	1.48	−0.189	0.015	<.0001	−4.00
$CLTV^2$	0.476	0.121	<.0001	1.09	−0.488	0.012	<.0001	−1.60
CLTV_Diff_Dummy	1.003	0.184	<.0001	1.98	−0.282	0.085	<.0001	−0.90
Auto pay	−0.251	0.068	0.000	−3.90	0.050	0.013	0.000	5.60
PPOption	2.899	0.442	<.0001	4.70	2.005	0.700	<.0001	8.19
Account age	0.006	0.001	0.000	1.28	−0.006	0.000	<.0001	−3.60
Account age^2	−0.003	0.000	<.0001	−2.00	0.0002	0.0002	0.384	2.23
Account age^3	9.247	0.000	<.0001	0.46	0.0000	0.0000	<.0001	0.36

Continued

Q10

TABLE 5

Continued

Independent variables	Default Coeff. val.	Default Std. err.	Default p-Value	Default Marginal effects (%)	Prepayment Coeff. val.	Prepayment Std. err.	Prepayment p-Value	Prepayment Marginal effects (%)
Employment control variables								
Log (years on the job)	−0.350	0.031	<.0001	−3.60	−0.008	0.006	0.176	−0.20
Self-employed	0.276	0.070	<.0001	0.29	−0.228	0.018	<.0001	−3.30
Retired	0.872	0.140	<.0001	0.18	0.532	0.032	<.0001	1.94
Homemaker	−0.908	1.010	0.305	−0.50	−1.390	0.132	<.0001	−3.10
Location and economic control variables								
Unemployment rate	0.185	0.016	<.0001	1.26	0.0001	0.004	0.949	2.87
CT state dummy	−1.706	0.144	<.0001	0.00	0.143	0.017	<.0001	1.15
ME state dummy	−2.799	0.995	0.005	0.00	0.238	0.041	<.0001	1.00
NH state dummy	0.330	0.069	<.0001	0.09	0.463	0.070	<.0001	0.99
NJ state dummy	−0.703	0.115	<.0001	0.00	−0.088	0.021	<.0001	−0.90
NY state dummy	−0.306	0.075	<.0001	0.00	0.118	0.017	<.0001	2.17
PA state dummy	0.439	0.086	<.0001	0.00	−0.023	0.027	0.400	−0.20
RI state dummy	−1.299	0.307	<.0001	0.00	0.227	0.036	<.0001	0.55
Mean home price change	−0.753	0.265	<.0001	−1.20	0.691	0.258	<.0001	1.04
Volatility of home price change	0.374	0.259	0.796	0.17	−0.569	0.163	<.0001	−0.40
Unobserved heterogeneity factors								
LOC1	2.652	0.363	<.0001		1.841	0.347	<.0001	
LOC2	1.230	0.352	<.0001		1.528	0.373	<.0001	
MASS2	0.931	0.084	<.0001		0.617	0.072	<.0001	
Time quarter dummies			Yes				Yes	
Pseudo R-square	12.32%							
Number of defaults/prepay			916				32,860	

NOTE: 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.

arising from counteroffer 1 could have saved approximately $777 million in direct default costs.[26] In contrast, the 4.1% 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 5 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 10% for counteroffer 1 and 2.7% 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 dataset 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 11%, while a counteroffer that raises the APR increases the default risk *ex post* by 4%. While borrowers with the higher APR counteroffer are more likely

26. Our estimates are an upper bound for two reasons. First, counteroffers are made only to a select group of applications. Second, counteroffers are based on both soft and hard information, presumably a counteroffer made on hard information along may go a long way in reducing default.

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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