Discussion paper

CREDIT CYCLE AND ADVERSE SELECTION EFFECTS IN CONSUMER CREDIT MARKETS – EVIDENCE FROM THE HELOC MARKET

By Paul Calem, Matthew Cannon, Leonard Nakamura

July 2011

European Banking Center Discussion Paper
No. 2011-021

This is also a CentER Discussion Paper
No. 2011-086

ISSN 0924-7815

Credit Cycle and Adverse Selection Effects in Consumer Credit Markets –

Evidence from the HELOC Market

Paul Calem
Board of Governors of the Federal Reserve System

Matthew Cannon
CoreLogic

Leonard Nakamura
Federal Reserve Bank of Philadelphia

July 2011

We would like to particularly thank CoreLogic for its support. We would also like to thank Elif Sen for exceptional and tireless research assistance. The views expressed here are those of the authors and do not necessarily reflect those of CoreLogic, the Federal Reserve Bank of Philadelphia, the Board of Governors of the Federal Reserve System, or the Federal Reserve System. This paper is available free of charge at www.philadelphiafed.org/research-and-data/publications/working-papers/.

Credit Cycle and Adverse Selection Effects in Consumer Credit Markets – Evidence from the HELOC Market

Paul S. Calem
Board of Governors of the Federal Reserve System

Matthew Cannon
CoreLogic

Leonard I. Nakamura
Federal Reserve Bank of Philadelphia

Abstract

We empirically study how the underlying riskiness of the pool of home equity line of credit originations is affected over the credit cycle. Drawing from the largest existing database of U.S. home equity lines of credit, we use county-level aggregates of these loans to estimate panel regressions on the characteristics of the borrowers and their loans, and competing risk hazard regressions on the outcomes of the loans. We show that when the expected unemployment risk of households increases, riskier households tend to borrow more. As a consequence, the pool of households that borrow on home equity lines of credit worsens along both observable and unobservable dimensions. This is an interesting example of a type of dynamic adverse selection that can worsen the risk characteristics of new lending, and suggests another avenue by which the precautionary demand for liquidity may affect borrowing.JEL Classification: D14, D82, G21
Keywords: Home equity loan; adverse selection; liquidity; consumption; housing finance

Address correspondence to:

Paul Calem, Division of Banking Supervision and Regulation, Board of Governors of the Federal Reserve System, 20th and C Streets NW, Washington D.C. 20551, phone: (202) 452-2836

Matthew Cannon, Credit Risk Products and Analytics, CoreLogic, 188 The Embarcadero, 3rd Floor, San Francisco, CA, 94105, phone: (215) 893-1503

Leonard I. Nakamura, Research Department, Federal Reserve Bank of Philadelphia, Ten Independence Mall, Philadelphia, PA, 19106-1574, phone: (215) 574-3804,fax: (215) 574-4303
e-mail: Leonard.Nakamura@phil.frb.org.

Credit Cycle and Adverse Selection Effects in Consumer Credit Markets – Evidence from the HELOC Market

1. Introduction

As economic conditions deteriorate during recessions, it is well recognized that existing consumer credits will display higher delinquency and default rates. For example, empirical investigations of mortgage default (Deng et al, 2000) show that as unemployment rates rise, mortgage defaults increase. It is less clear what the effect of rising expectations of worsening economic conditions should be on the pool of borrowers applying for credit or drawing on credit lines.

Neoclassical consumption theories suggest that as consumer expectations of future unemployment rises, expected lifetime wealth will decline, and consumption should fall. This should cause those consumers most likely to experience unemployment to reduce their current expenditures, so that the pool of borrowers should improve in the sense of a shift in composition of the pool toward the higher credit quality range. If this occurs simultaneously with tightening credit standards on the part of lenders, the proportion of higher credit quality borrowers will rise due to constraints on both the demand and supply side.

However, recent empirical research has suggested that households have strong precautionary motives and typically desire to preserve purchasing power. Gross and Souleles (2002a) show that when consumer credit card lines increase exogenously, consumers display a relatively large marginal propensity to consume even if they have substantial credit available on their existing lines. If households worry about their ability to borrow in the future or have concerns about their future liquidity, then it is possible that households whose subjective probability of unemployment has risen may increase their current borrowing. In contrast to the classical view, such households will borrow preemptively when their confidence is low—not to increase their current consumption, but to ensure their access to liquidity in the future. As a consequence, the pool of borrowers may worsen observably, even if credit standards are tightened.[1] Alternatively,

[1] Dick and Lehnert (2010) argue that heightened competition among banks leads to easing of credit standards. Their paper focuses on the historical effects of the lifting of geographic barriers to entry in banking. To the extent that banks have to compete more aggressively for borrowers when credit demand

or in addition, the credit quality of the pool may decline along unobservable dimensions, exacerbating the kind of adverse selection problem highlighted in Brueckner (2000). In this case, as lenders update their estimates of the underlying riskiness of the borrower pool, the analysis in Brueckner (2000) suggests that credit markets will respond procyclically, charging higher risk premiums for larger credit lines or those with higher loan-to-value ratios, and reducing the availability of lower cost credit.[2]

Anecdotal evidence on preemptive borrowing is offered in a recent article in the *New York Times.*[3] The article notes that consumers with home equity lines of credit are finding their lines cut as home prices have fallen, and that one way they can preserve borrowing power is to borrow preemptively. A mortgage loan officer interviewed encourages consumers to preemptively borrow $100 thousand on their home equity line of credit and invest the proceeds in a bank term CD (doing so with a 4 percent interest rate on the home equity line and a 3 percent rate on the CD has a cost of $1000). This cost may be small compared to the transactions cost of selling one's home or other costs due to a period of unemployment.

In this study, we investigate how the credit risk profile of households with newly originated home equity line of credit (HELOC) accounts varies in relation to regional economic conditions during 2002 through 2007, using data provided by the data and analytics firm CoreLogic.[4] This unique database tracking monthly utilization and payment performance of the HELOC accounts of several of the largest U.S. home equity lenders has not previously been available for academic research. We find evidence of both "credit cycle" effects of macroeconomic variables on observable indicators of borrower credit risk, as well as evidence of cyclical adverse selection. On the one hand,

---

weakens, such effects could reinforce the effect of precautionary borrowing motives on the quality of the borrower pool.

[2] To the extent that HELOC markets rely on collateral, improved technology for monitoring collateral would work in the direction of allowing more risk to be accepted. On the other hand, when housing markets become thinner, information about collateral is likely to become less precise, and risks are greater, exacerbating the tightening of credit standards.

[3] See Tedeschi (2008).

[4] CoreLogic is a leading provider of consumer, financial and property information, analytics and services to business and government. The company has developed U.S. real estate, mortgage application, fraud, and loan performance databases combining public, contributory, and proprietary data and is a provider of mortgage and automotive credit reporting, property tax, valuation, flood determination, and geospatial analytics and services. For more information, visit www.corelogic.com.

consistent with the classical view, we observe that lenders and borrowers respond to appreciating home values and other favorable economic conditions by obtaining or expanding home equity credit lines and increasing debt payment-to-income ratios. On the other hand, consistent with adverse selection, we find that all else equal, households drawing on new credit lines when consumer confidence has declined are more likely to fall behind in their payments.

We conduct a comprehensive analysis, employing both panel data and competing risk hazard rate modeling. Panel models estimated with monthly data aggregated to the county level are used to analyze the relationship between average measures of borrower credit risk and economic variables. A competing risk survival analysis of delinquency and prepayment (defined as paying the HELOC balance down to zero) is used to test for adverse selection effects related to the regional index of consumer confidence and local unemployment rate conditions.

In particular, a key contribution of the study is the examination of adverse selection effects tied to changing macroeconomic conditions in the context of consumer credit. Prior studies that have looked at adverse selection in consumer credit markets typically have focused on specific cases where adverse selection effects appear to explain observed patterns of delinquency. For instance, Gross and Souleles (2002b) document an increase in the riskiness of borrowers who were issued new credit cards during the period 1995 through 1997 that was reflected in deteriorating performance but was not detectable using standard credit quality indicators at the time of issuance. Another prominent example is adverse selection tied to the broker origination channel in the subprime mortgage market, which has been cited as a contributing factor in the subprime crisis (Jiang, Nelson, and Vytlacil 2009, Keys et al. 2009).

A secondary contribution of this study is methodological, demonstrating the importance of isolating the effect of exit of lower risk borrowers resulting from prepayments for identifying adverse selection tied to cyclical economic factors. Moreover, we develop new ways of modeling the competing risk of delinquency and prepayment for HELOC accounts, which, compared to closed-end first mortgages, have received relatively little attention in the literature.

The remainder of the paper is organized as follows. Section 2 briefly reviews previous studies focusing on the utilization and credit performance of HELOCs. Section

3 discusses the data used in the study. Section 4 develops the panel data models and presents the estimation results for these models. Section 5 presents the competing risk hazard analysis and discusses the evidence of cycle-driven adverse selection effects. Section 6 provides concluding comments.

2. Literature Review

We are aware of only a few previous studies that have examined the utilization behavior or credit risk of home equity lines of credit specifically or home equity loans together with lines: Agarwal, Ambrose, and Liu (2006); Agarwal, Ambrose, Chomsisengphet, and Liu (2006); and Yamashita (2007). Our study is readily distinguished from these earlier studies by period examined and data source. The first study relies on a sample from a single large financial institution, containing roughly 79,000 HELOCs and 56,000 closed-end home equity loans originated between January 1994 and May 2001 to borrowers located almost entirely in New York, New Jersey, and the New England states. Performance of the loans is tracked through May 2002. The second study relies on a subset of the same sample, consisting of roughly 35,000 HELOCS originated between January 1998 and May 2001. The third study relies on the 1982 through 1993 waves of the Panel Study of Income Dynamics, which is a longitudinal survey of a representative sample of U.S. families begun in 1968.

The study by Agarwal, Ambrose, and Liu (2006) has some similarity to our study in that it offers evidence suggestive of precautionary motives affecting HELOC utilization. The study tests two hypotheses about line utilization. The first is that borrowers with lower FICO scores, who represent those at greater risk of financial shocks, have lower initial utilization. An estimated regression equation for initial utilization supports this hypothesis, even after applying a correction for selection bias (in the accept-reject decision). The second hypothesis is that borrowers who experience credit shocks, represented by those exhibiting a decline in their FICO score, use their lines more. A multinomial logit model representing the competing risks of full prepayment, partial prepayment, and increased utilization indicates that a decline in FICO (lagged four months) results in increased utilization, consistent with the hypothesis.

Agarwal, Ambrose, Chomsingsengphet, and Liu (2006) estimate and compare the responsiveness of prepayment and default of home equity loans, home equity lines, and first mortgages to economic factors. The findings suggest that both equity loans and lines prepay to take advantage of declining interest rates (interest rate refinance) and increasing property values (cash out refinance.) Home equity loans appear almost twice as sensitive as home equity lines to interest rate changes. Prepayment and default are more sensitive to credit shocks for first mortgages and home equity loans than for home equity lines. The latter finding is viewed as consistent with the finding in Agarwal, Ambrose, and Liu (2006) that individuals who face credit shocks are comparatively likely to increase use of a home equity line.

Yamashita (2007) examines how households use second mortgages (both loans and lines) in response to shocks to housing wealth. The empirical results indicate that, on average, house price appreciation is associated with increased second mortgage borrowing, consistent with results from our study. In addition, Yamashita (2007) finds that responsiveness differs across households in relation to age and the ratio of liquid wealth to income. Younger households and those with lower wealth-to-income exhibit a strong reaction to house price appreciation, whereas high wealth-to-income ones do not. These results are interpreted as evidence of the importance of liquidity constraints among homeowners.

3. Data

Our study relies on historical, account-level data on the monthly payment and utilization performance of the HELOC accounts of three of the largest HELOC lenders in the U.S. These data are drawn from CoreLogic's HomeEquity database, a data product covering all HELOC and closed-end junior lien mortgages serviced by the top four U.S. originators and servicers of these mortgage products as well as several smaller banks. [5] Only HELOCs are used in this analysis, since our focus is on utilization of credit lines.

The three lenders included in our study were selected based on extent of coverage of historical performance and account-level characteristics in the database; their identities were kept anonymous in the research data set provided to us. Loan characteristic and dynamic loan performance information are available for these three lenders from January

[5] As of 2010 Q1, the database included 5.4 million active HELOCs.

2002 onward.[6] The data made available to us for this study track account performance through August 2007, which is about when the recent "crisis" period commenced in the mortgage market. Thus, the period of analysis for this study is January 2002 through August 2007; for the hazard models, attention is restricted to loans originated through May 2007.

Account-level characteristics provided in the database include the origination date; maturity date; origination channel (retail, broker, wholesale/correspondent); lien position (first or junior); original credit limit, and combined loan-to-value ratio (of all liens). The data also include the borrower's original FICO score and ratio of (total mortgage and consumer) debt payment to income. In addition, the data provide the index interest rate (generally the prime rate) and margin that together determine the contractual interest rate. (Often, HELOCs are priced using a tiered structure for the margin, such that the margin declines as the balance increases above a specified threshold. Presumably, the reported margin is that associated with the original drawn amount.) The geographic location and type of property (single-family home, condominium, etc.) are also provided.

The database provides monthly performance updates for each HELOC account, including outstanding principal balance, draw amount, and payment status (number of days delinquent). Updated credit limits and refreshed FICO scores are also reported, when they occur.[7] Monthly utilization rates are obtained by dividing the outstanding principal balance by the credit limit.

The database incorporates a substantial number of accounts originated prior to 2002. These lack full performance histories, and their inclusion in our study could introduce survivor bias, since accounts opened and then closed prior to January 2002 are not in the sample. Therefore, we exclude all accounts originated prior to December 2001.

About one-fifth of the remaining accounts were not utilized when they were first opened. Including these accounts in the sample would cloud interpretation of the results, for two reasons. First, this cohort contains substantial unobserved heterogeneity, because it is impossible to distinguish among customers with specific plans to draw on

[6] The database includes loans originated prior to 2002 and their characteristics; however, dynamic performance information is available beginning only in 2002.

[7] When available, a FICO score dated one or two months after origination is utilized as a proxy for the origination FICO score if the origination FICO score is missing. About 98 percent of accounts in the sample had origination FICO reported and another 1 percent had a FICO score dated one or two months after origination.

their credit lines in the future, those with cautionary motives, and those obtaining credit lines primarily for convenience or in response to marketing appeals. Second, there is a lack of comparability between this cohort and customers who utilize their HELOC accounts from the start. For the latter, the date of origination is the same as the date of the first draw on the credit line. For customers whose draws occur later, individual circumstances or broader economic conditions at the draw date may be more relevant to the borrowers' motives and credit quality than circumstances at origination. Moreover, the database contains more information associated with the date of origination. For these reasons, we restrict attention to accounts having a utilization rate of 10 percent or greater and a balance no less than $10,000 within three months of origination.[8]

Standard data quality and consistency checks and edits were applied to the data prior to conducting statistical analysis.[9] No systematic data problems were detected. As is typically the case with industry-supplied data, there is a moderate frequency of missing information on borrower characteristics, particularly origination FICO scores, combined loan-to-value ratios, and debt payment-to-income ratios. The occurrence of missing information for these variables is not correlated with other indicators of credit quality or payment performance such as initial utilization rates, size of the credit line, or subsequent payment delinquency.

Figure 1 plots the number of originations by month in the HELOC sample, from December 2001 through June 2007. The pace of HELOC origination activity increased during the first half of this period, peaked in the second quarter of 2004, and then declined. There appears to be a seasonal component, with origination activity relatively high in the second quarter. Figure 2 shows the geographic distribution of the sample by census division. The Pacific division contains the single largest share, at 40 percent, with another 40 percent distributed roughly evenly across the South Atlantic, Mountain, and East North Central divisions.

Tables 1 and 2 provide descriptive statistics for account-level variables employed in the study, distinguishing among three origination channel categories: retail; wholesale

[8] About 22 percent of accounts in the sample were excluded by these restrictions.

[9] For instance, accounts with initial utilization exceeding 125 percent were excluded. Combined loan-to-value ratios greater than 125 percent and debt payment-to-income ratios greater than 70 percent were set equal to missing. Such cases were rare. We also checked for inconsistencies among reported lien status, credit limit, appraised value, and combined LTV; these were also rare.

or broker; and other.[10] Table 1 focuses on lien status and property type and indicates that the sample is relatively homogeneous along these dimensions. Notably, HELOCs secured by condo or co-op properties, which constitute 12 percent of the sample, were disproportionately originated through the wholesale and broker channels. Table 2 reports means, quartiles, and missing data frequencies for continuous variables. Borrowers can be generally characterized as prime, as indicated by FICO scores at origination well above the 620 threshold typically used to define subprime credits. The average combined loan-to-value ratio for the full sample is 83 percent, exceeding the minimum 80 percent loan-to-value that generally is required to waive private mortgage insurance on a first-lien, prime mortgage. Combined LTVs, utilization rates, payment-to-income ratios, and interest rate margins are higher for wholesale compared to retail, suggesting higher credit risk of loans originated through the wholesale channel. Broker-originated accounts exhibit even higher values for these variables.

Economic data. Our study also employs a variety of economic time series and panel data. These include monthly interest rate data from the Federal Reserve (the bank prime interest rate, federal funds rate, and 10-year Treasury bill rate) and monthly refinance share of first-lien, prime, conventional conforming home mortgage applications from Freddie Mac's Primary Mortgage Market Survey.[11] In addition, we use the Conference Board's monthly regional Consumer Confidence Index for the nine U.S. census regions; quarterly state and metropolitan area (CBSA) house price indexes from the Federal Housing Finance Agency; and monthly state and county unemployment rates from the Bureau of Labor Statistics. State-level house price and unemployment data are used for counties lacking this information at the more local level. We convert the quarterly house price data to monthly data using a rolling weighted average. The difference between the 10-year Treasury bill interest rate and the federal funds rate is employed as a measure of the "yield curve."

[10] Accounts with loan source identified as "Mortgage Broker" were slotted to the broker category; those with source identified as "Wholesale," "Other," or "Unknown" were slotted to the wholesale channel, and those with source identified as "Retail," "Internet," or "Correspondence" were slotted to retail. We combined the more granular loan source classification found in the data on the basis of similar distributions of account characteristics such as combined loan-to-value ratio and credit limit amount, because some of the individual classifications contained too few accounts to model separately.

[11] For information about the Primary Mortgage Market Survey, see http://www.freddiemac.com/pmms/abtpmms.htm

The January 2002 through August 2007 period of analysis encompasses a fair amount of variation and cyclicality in these economic variables. Figure 3 displays the time series of the 10-year Treasury bill interest rate, the federal funds rate and the Freddie Mac refinance share measure for this period. During this period, the prime rate (not shown in the figure) maintained a fairly constant, 3-percentage-point spread above the federal funds rate. Figure 4 shows the median and first and third quartiles of local area unemployment rates where the rankings are point-in-time across all counties represented in the sample, weighting by number of accounts. Figure 5 shows the median and first and third quartiles of local area (CBSA) house price appreciation rates calculated over the prior 12-month period, where again the rankings are point-in-time across localities, weighting by number of accounts. Table 3 provides means, medians and maximum and minimum values of the Consumer Confidence Index for each of the nine census regions. The Mountain, South Atlantic, and West Central are characterized by relatively high mean and median values of the index, while East North Central, Middle Atlantic, and New England census divisions exhibit relatively low mean and median values.[12] Within each range, there is substantial temporal variation in the level of consumer confidence, as reflected in the maximum and minimum values of the index in each region.

4. Panel Models

We begin by investigating the consistency of borrower and lender behavior with neoclassical consumption theory and/or adverse selection effects using panel models. The panel model estimations aggregate home equity lines of credit originations by county-month. Each observation is the average for a given county and month.[13] Observations from Louisiana and Mississippi, where most delinquencies were a consequence of Hurricane Katrina, and observations with fewer than 10 originated HELOCs are excluded. We weight each observation by the number of home equity lines of credit originated in the county and month.

The underlying data aggregate over 3 million home equity lines into some 90 thousand county-month observations, but after eliminating county-months with less than 10 originations and with the exclusion of Louisiana and Mississippi, the data reduce to

[12] Excluding June, July, and August 2007 for consistency with the range of origination dates in the sample used for the hazard analysis does not materially alter the values in Table 3.
[13] Essentially the same results are obtained using median in place of average.

2.8 million accounts aggregating to 29,884 observations.[14] The resulting panel consists of 841 counties over the period from January 2002 to August 2007.

The panel model regression equations relate characteristics of the HELOCs – the quality of the borrower, size of the credit line, pricing, and pace of originations – to economic conditions, including recent county house price appreciation, the yield curve and change in the prime rate, regional consumer confidence, and the forward and backward county unemployment rate change. We include county fixed effects, as well as lagged dependent variables to address autocorrelation. In addition, in alternative specifications we incorporate either a (quadratic) time trend relationship or a set of monthly dummy variables (in the latter case dropping the yield curve and prime rate change).

The relations among the economic factors and borrower and account characteristics observed in the county-level panel data set reflect the net effect of the demand for and supply of credit. Aggregate credit demand can be impacted by cyclical changes in borrower behavior consistent with neoclassical consumption theory as well as behavior reflecting adverse selection. On the supply side, lenders' risk aversion, as reflected by credit policy, will also change over the course of the credit cycle. Given different levels of information, borrowers and lenders may not respond with the same speed to changing economic conditions in altering the demand for and supply of credit.

The time period used in the regression analysis generally corresponds to rising house prices and a lowering of credit standards but also includes the beginning of the decline of house prices and uptick in delinquencies. Evidence of improved borrower credit quality as economic conditions deteriorate is consistent with neoclassical "credit cycle" effects as consumers restrict borrowing and lenders tighten credit standards in response to a decrease in expected future wealth. Similarly, credit cycle effects are consistent with decreased borrower credit quality and relaxed lending standards during periods of robust economic growth. Evidence of deterioration in borrower credit quality as economic conditions deteriorate, however, is consistent with adverse selection and precautionary borrowing motives.

Explanatory variables. The regional consumer confidence index and the county 12-month forward unemployment rate change capture the effects of precautionary

[14] Prior to eliminating Louisiana and Mississippi, the number of county-month observations is 30,369.

motives and adverse selection. Our hypothesis is that precautionary motives and adverse selection are associated with deterioration in the quality of the borrower pool as regional consumer confidence falls or the forward unemployment rate rises.[15] The Conference Board's regional consumer confidence index is a measure of local consumer expectations about labor market conditions. Bram and Ludvigson (1998) argue that the Conference Board's confidence measure is more predictive of consumption behavior than the Michigan survey because it emphasizes labor market conditions and prospects. Garrett et al. (2005) argue that there is some information about regional consumption in the Conference Board's regional consumer confidence indexes. The forward unemployment rate change may be a useful measure of private information on the part of households on the assumption that residents are better forecasters of local employment conditions than lenders. In particular, workers at an establishment that may shut down have a strong incentive to acquire additional information about that likelihood.

The county house price appreciation rate is calculated as the change in the log price over the prior 12 months and thus captures recent increases in the value of the collateral available to be borrowed against. We interpret the yield curve, as in Bernanke and Blinder (1992), as a forward-looking measure of monetary policy. The yield curve is positive when the Federal Open Market Committee has lowered rates and is negative when monetary policy is being aggressively tightened. The prime rate has a direct influence on the cost of credit, since the floating interest rate on the HELOC is typically tied to the prime rate. The variable prime rate plus a fixed margin specified in the HELOC contract determines the interest paid on the HELOC.

Empirical model specifications. Our first set of panel regression equations employs a quadratic specification for time to control for general market trends in addition to the explanatory variables introduced above. A second set appends the (endogenous) dependent variables from the other equations as covariates. A third and fourth set of equations employs a dummy variable for each month instead of the time trend, respectively, without and with inclusion of dependent variables from the other equations. The equations are estimated using ordinary least squares.

[15] There is a very small positive correlation (0.0356) between the CCI and the forward unemployment rate change.

Estimation results for the first set of panel equations are presented in Table 4, and those for the last set are presented in Table 5. For the sake of brevity, we report only these results; consistency of the other two specifications with these is discussed below. The first three columns in each table provide panel model estimation results for three credit quality measures: county average FICO score, average ratio of consumer debt payments to income (backend ratio), and combined loan-to-value ratio, respectively. The next two columns provide the estimation results for two pricing terms: margin and credit limit, respectively. The last column presents the results for the panel model for the rate of origination of new accounts, defined as number of accounts originated in the month and county per number of owner-occupied units in the county based on the 2000 U.S. census.

Because the county-level regressions reflect the aggregate net effect of credit supply and demand over the time period examined, the results suggest a mix of credit cycle effects with precautionary borrowing and adverse selection effects. On the one hand, credit cycle effects tend to dominate along the dimension of house price appreciation, with the regression results indicating increased credit risk during periods characterized by rapidly appreciating home values. On the other hand, some results for credit quality in relation to consumer confidence and/or forward unemployment rate are consistent with precautionary borrowing motives or adverse selection. In the next section of this paper, additional information regarding the payment performance of HELOC loans over time will be utilized to test for adverse selection effects on the part of HELOC borrowers during economic downturns.

Credit quality indicators. We begin with the effects of consumer confidence and forward unemployment rate change on county average FICO score as of the origination date of newly originated HELOCs. The FICO score is an observable measure of the credit quality of the pool of accepted HELOC borrowers. Precautionary borrowing and adverse selection (deterioration in quality of the borrower pool) should be associated with low consumer confidence and a rising 12-month forward unemployment rate. Thus, a positive coefficient on the consumer confidence index and a negative coefficient on the forward unemployment rate change would be consistent with the precautionary borrowing hypothesis.

As seen in Tables 4 and 5, both estimated coefficients consistently support this hypothesis across each of the model specifications. Moreover, both relationships are statistically and quantitatively significant in each of the model specifications.[16]

It is also noteworthy that an increase in the house price index reduces the FICO score at origination, so that rising home values lower the observable quality of borrowers. This is most likely due to lenders being more willing to lend to risky borrowers when collateral is rising in value.

Next, we consider the back-end ratio, a measure of observable borrower quality as well as an indicator of willingness to incur debt. An increase in the back-end ratio implies a more difficult debt burden for the borrower and thus a greater chance the borrower will default, but it may also signal a borrower's confidence with respect to income prospects. Consistent with the latter hypothesis, as seen in Tables 4 and 5, the average back-end ratio is positively related to consumer confidence, consistently across each of the model specifications.

The forward change in the unemployment rate is not statistically significant in relation to the back-end ratio in the specification shown in Table 4. In the specifications that employ time dummy variables, however, as in Table 5, the forward unemployment rate change exhibits a positive and statistically significant relationship to the average back-end ratio, consistent with precautionary borrowing and adverse selection.

An increase in the 12-month house price appreciation rate also raises the back-end ratio. This can be interpreted as a combined demand and supply effect—rising house prices force households to stretch their borrowing and encourage lenders to ease credit conditions.

The combined loan-to-value ratio (combined LTV) at the time of origination of the HELOC, like the back-end ratio, also measures credit quality as well as the borrower's willingness to incur debt and the lender's willingness to extend credit. It is defined as the combined (summed) HELOC credit limit and (where the HELOC is not the first lien) first mortgage balance, as a ratio to the value of the home, at the time of

[16] County-level mean FICO scores, measured at origination, have a mean within-county standard deviation of 9.8. The mean within-county standard deviation of the regional consumer confidence index is 18.4, implying (with the estimated coefficient of .07) an impact of 1.3, or about 13 percent of the FICO within-county standard deviation. One standard deviation in the forward unemployment rate change is somewhat less important, with an impact of 0.4, or about 4 percent of the FICO standard deviation. These are conservative assessments, because the indirect effect via the lagged dependent variable and any cross-county effect are not considered.

origination of the HELOC. The higher the combined LTV, the smaller the homeowner's equity stake in the home and, in general, the greater the credit risk to the lender. The consumer confidence index generally (with the sole exception of the expanded specification in Table 5) does not exhibit a statistically significant relationship to combined LTV. In the specifications that employ time dummy variables, including that shown in Table 5, the forward unemployment rate change exhibits a negative and statistically significant relationship to the average back-end ratio, consistent with reduced borrower willingness to incur debt and lender willingness to extend credit. Credit cycle effects associated with the housing market cycle also are apparent—a recent rise in the house price index (12-month change) lowers the combined loan-to-value ratio.

Pricing variables. The lender's perception of the credit risk associated with a HELOC is reflected in the margin and credit limit. A lender generally will price higher perceived credit risk through a larger margin or lower credit limit or a combination of the two. As previously noted, the margin has a tiered structure, such that it depends on the amount drawn—as the balance increases above a specified threshold, the margin declines. A caveat for the following discussion is that we cannot isolate the potential impacts of tiered pricing on changing margins. Moreover, as with any market price, the margin (likewise, the credit limit) reflects general supply and demand conditions. Also, note that the credit limit reflects not only the perceived credit risk but also the amount of equity the borrower has in the home prior to obtaining the HELOC.

The margin exhibits a statistically significant, inverse relationship to consumer confidence, while the credit limit exhibits a statistically significant, positive relationship to consumer confidence in the Table 4 specification and in its counterpart with monthly dummy variables. As we have seen, the observable credit quality of borrowers (as measured by FICO score and back-end ratio) is positively related to the consumer confidence index, so it would be surprising if the margin and credit limit did not reflect the greater observable riskiness of these loans. As seen in Table 5, the credit limit relationship to consumer confidence is robust to inclusion of the additional loan and borrower characteristics, but the margin relationship switches sign. The latter result suggests that after controlling for these other observables, the credit cycle effect dominates, with stronger demand for HELOC borrowing during periods of elevated consumer confidence placing upward pressure on margins.

In contrast, consistent with precautionary borrowing rather than a credit cycle effect, both margin and credit limit generally exhibit positive and statistically significant relationships to the forward change in unemployment rate.[17] The margin exhibits an inverse relationship to home values, whereas, not surprisingly, credit limits increase with home prices.

New accounts. The pace of origination of new accounts is higher when the forward unemployment rate is rising, consistent with a precautionary motive for obtaining a HELOC, and consistent with the pricing relationships observed above. This relationship is statistically significant across all model specifications.

Mixed results are obtained for the pace of origination of new accounts in relation to the CCI. Arguably, the specifications that incorporate month dummies are more reliable because they address the seasonality in origination activity (apparent in Figure 1). The specification with month dummies indicates a positive and statistically significant relationship of origination activity to the CCI when the (endogenous) account and borrower characteristics are omitted. In this case, the relationship is consistent with a credit cycle effect. Again not surprisingly, an increase in the house price index has a positive impact on the pace of originations, while an increase in the prime rate has a negative impact.

5. Competing Risk Hazard Analysis

We next estimate a hazard model of delinquency that analyzes HELOC payment performance in relation to the macroeconomic context as of the date the borrowing occurred. The hazard that is modeled is 60-day delinquency.[18] The model controls for observable credit characteristics of the borrower and for economic conditions arising ex-post. Specifically, we test whether HELOC borrowers who draw on their credit lines in anticipation of reduced earnings or liquidity—when consumer confidence is low or unemployment elevated—are more likely to become seriously delinquent compared to those drawing on their credit lines under more favorable circumstances, holding observable characteristics constant. Such a relationship would indicate that borrower

[17] The sole exception is lack of statistical significance of the forward change in the unemployment rate in relation to the margin in the specification with time dummy variables without inclusion of the other borrower and account characteristics.

[18] A very small number of accounts (211) that reach charge-off at an earlier stage of delinquency are also treated as terminated.

credit quality declines along unobservable dimensions as the state of the economy worsens, consistent with adverse selection effects tied to preemptive borrowing.

A complicating factor for the empirical analysis is the competing-risk effect of prepayment. Prepayment causes censoring of observations because once a borrower prepays we cannot observe whether a default would have occurred later on. In addition, an increase in the prepayment rate may reduce the credit quality of the remaining pool.[19] The reason is straightforward—borrowers not responding to a drop in interest rates or other motivation to refinance a loan may be those whose credit condition has deteriorated, reducing their access to low-cost credit.

We equate prepayment of HELOC borrowers with termination of the account relationship, rather than simply paying down a balance to zero, because the latter often occurs without the account being closed and, hence, is less often associated with refinancing. The competing risk hazard analysis treats prepayment as censoring. In addition, we control for the potential selection effect of prepayment in a direct and somewhat novel way by including a lagged cumulative prepayment rate (calculated regionally within the HELOC sample, from the date of origination of the account) as an explanatory variable in the delinquency hazard model. Moreover, we estimate a separate prepayment hazard model that, alongside the delinquency model, provides a comprehensive view of HELOC payment performance.

The unit of observation for the hazard model estimation is account and month. Each account's payment status is tracked each month, until termination due to 60-day delinquency, prepayment, or end of the sample period. We exclude from the estimation sample all HELOCs originated after May 2007, in order to ensure at least 3 months of observation of payment performance. We again exclude borrowers located in Louisiana or Mississippi. We include all accounts that reach 60-day delinquency and a 5 percent random sample of all other accounts.

The delinquency and prepayment hazard equations take the "proportional hazard" form:

$$(1) \qquad h(t|\mathcal{X}) = h(t)\ \exp(\beta_1 X_1 + \cdots + \beta_p X_n)$$

[19] This effect, often referred to as "burnout," is also a relevant factor in prepayment modeling. Borrowers who have not responded to prior refinance opportunities are likely to maintain a relatively low likelihood of prepayment. For example, Calhoun and Deng (2002) find a statistically significant burnout effect for both prepayment and default of fixed-rate mortgages.

The hazard rate h(t|x) in (1) is the rate of termination (60-day delinquency or prepayment) at time t conditional on an account surviving until t and conditional on a vector of covariates X; its relation to the cumulative survival probability S(t|X) is:

$$(2) \qquad h(t|X) = -d\log S(t|X)/dt$$

Under the proportional hazard assumption (1), the hazard rate consists of a baseline hazard rate h(t) that depends only on the survival time and a multiplier that is a function of the covariates. The advantage of this approach is that it does not impose any restrictions on baseline hazard rates. Moreover, estimates of the coefficients β_1 through β_p can be obtained by maximizing the partial likelihood function without any need to estimate the baseline hazard rates.[20] This is the approach we take, since we are concerned with testing relationships between the hazard rate and economic covariates, and not with the baseline hazard.

As noted in section 2, there are considerable differences in the risk profiles and payment performance of borrowers based on origination channel. Therefore, we estimate the delinquency and prepayment hazard models separately for each of three origination channel categories: retail, broker, and wholesale. To facilitate the estimation process, we reduce the sample size by selecting all accounts that terminate in 60-day delinquency and from the remaining accounts randomly select one out of every twenty. We apply weights to adjust for the oversampling of delinquent accounts when estimating the hazard model.

Initial borrower and loan characteristics. In testing for adverse selection effects associated with macroeconomic conditions at the time of borrowing, it is necessary to control for the borrower's observable credit risk characteristics. Three key credit risk measures provided in the data and used as explanatory variables for the delinquency model are the combined loan-to-value ratio; the borrower's ratio of (total mortgage and consumer) debt payment to income; and the borrower's credit (FICO) score, each measured as of the date of origination of the HELOC. Reduced borrower equity in the home, as measured by a higher combined loan-to-value ratio; a higher debt payment ratio; and a lower FICO score are widely associated with increased credit risk, both in the academic literature on mortgage default and in mortgage underwriting practice.

[20] See Allison (1995).

Credit line utilization is another factor typically predictive of payment performance.[21] We include a set of indicator variables distinguishing four ranges of credit line utilization as of the date of origination: less than 50 percent; greater than or equal to 50 and less than 75 percent; greater than or equal to 75 and less than 90 percent; and greater than 90 percent.

Figures 6 and 7 illustrate these risk relationships by means of survival curves derived from our HELOC sample. Figure 6 shows survival curves for four FICO and utilization rate groupings (FICO above or below 680 and utilization above or below 90 percent), and Figure 7 shows survival curves for four combined LTV and back-end ratio groupings (LTV above or below 90 percent and back-end ratio above or below 45 percent). For instance, borrowers with an original FICO below 680 and a utilization rate above 90 percent are about 10 times as likely to reach 60 days delinquent within two years following origination as those with FICO scores above 680 and utilization rates below 90 percent. Borrowers with a combined LTV less than or equal to 90 percent and a back-end ratio below 45 percent are about three times as likely to reach 60 days delinquent within two years following origination as those with a combined LTV above 90 percent and backend ratio above 45 percent.

Default risk may also vary by property type. The only identified property type other than a single-family residence that is associated with a substantial number of accounts in the sample is a condo or co-op. We include a dummy variable identifying condo or co-op.

Two additional variables are included as proxies for other observable borrower risk characteristics: the margin (over the index rate) determining the (variable) interest rate, and the log of the original credit limit. In general, lower risk borrowers would receive more favorable credit terms, including a lower interest rate and higher credit limit. However, these variables are also influenced by other factors. For example, the margin can be affected by points and fees paid at origination (not reported in the data), and by the borrower's financial savvy and wherewithal to negotiate a lower rate.

Initial economic conditions. The economic variables of interest are those that proxy for borrower expectations about earnings or liquidity at the time the account is opened (and initially utilized). Two such variables are included in the model: the

[21] See, for example, Board of Governors of the Federal Reserve System (2007)

regional consumer confidence index, and the local area unemployment rate as of the origination date. We also estimate a specification that additionally includes the 12-month forward (from date of origination) change in the unemployment rate as a proxy for expected change in employment conditions. (Alternatively, the 12-month forward change may be considered a control for ex-post economic conditions.) In the presence of adverse selection effects tied to preemptive borrowing, HELOC borrowers who draw on their credit lines when consumer confidence is low or unemployment elevated or rising would exhibit higher ex-post delinquency rates.

Time-varying economic factors. The model incorporates three time-varying indicators of ex-post economic conditions: local area house price appreciation, change in the prime rate, and the yield curve measure. The first two are measured as change over the previous 12 months, or for accounts aged less than 12 months, since the date of origination.[22] We focus on the 12-month change (as opposed to the longer-term cumulative change since origination) because, over the longer term, HELOC borrowers might adapt to changing house values or interest rates through adjustments in account utilization, mitigating the impact on credit risk.[23] House price appreciation is measured as the change in the log of the local price index, while the prime rate change is the simple difference.

It is well known from the literature on mortgage default and delinquency that default rates are inversely related to local area house price appreciation. The rate of change in house prices is a key factor that determines the change in the borrower's equity in the home, affecting the borrower's incentive to default, and more generally is a proxy for local housing market and economic conditions affecting mortgage credit risk.

A rise in the prime rate increases the borrower's monthly payments and therefore may increase the likelihood of delinquency. The yield curve reflects expectations of changing interest rates, which might affect the incentive to default. For instance, a borrower experiencing financial difficulties may make less effort to keep current on the HELOC payment if interest rates are expected to rise, thus exacerbating the borrower's financial situation. Alternatively, the yield curve may proxy for general economic conditions.

[22] As discussed below, results are robust to replacing the 12-month change with change since the date of origination.
[23] For example, borrowers might adapt to longer-term house price declines by reducing their account utilization.

As noted, the competing risk effect of prepayments is addressed by including a lagged cumulative prepayment rate (calculated at the census division level), as an explanatory variable in the model. Specifically (for a given census division), let N_τ denote the number of open accounts in the sample as of month τ and let $C_{\tau,\tau+n}$ denote the number that close (exit from the sample) between month τ and month τ+n (that is, they are in the sample in month τ but no longer present in τ+n). To an account originated in month τ and surviving into month τ+n, we assign the lagged cumulative prepayment rate:

(3) $PPR_{\tau,\tau+n} = 1 - (C_{\tau,\tau+n})/ N_\tau$

Prepayment equation. While the focus of this study is delinquency, it is important to understand prepayment behavior as well, since the two are interrelated in several ways. First, as already noted, higher prepayment speeds typically are associated with declining credit quality of borrowers remaining in the pool. Second, faster prepayment in effect reduces the average maturity of a pool, which implies lower cumulative default rates (although conditional default rates of borrowers remaining in the pool are higher). Third, many of the same borrower characteristics and economic factors that are directly related to delinquency may also affect the propensity to prepay. Therefore, alongside the delinquency model we estimate a prepayment hazard model.

Studies of default and prepayment of first mortgages find that both exhibit relationships to some of the same variables. In general, higher–credit-risk prime borrowers tend to have slower prepayment speeds, reflecting such factors as reduced mobility, or vulnerability to income, credit, liquidity, or employment setbacks that might impede the ability to refinance at favorable credit terms.[24] Studies also find that house price appreciation, while reducing the risk of default, tends to increase the likelihood of prepayment, which may reflect borrowers cashing out equity or shopping around for better credit terms based on their improved equity position. Thus, the prepayment model includes as explanatory variables each of the initial borrower and loan characteristics and the time-varying measure of local area house price appreciation described above.

[24] For example, Calhoun and Deng (2002) find that borrowers with higher original LTV or smaller original loan amounts, which are viewed as proxies for net worth and income, have lower prepayment speeds, controlling for the borrower's current equity position and the value of the prepayment option. Comparative behavior of prime and subprime borrowers is not so readily characterized in relation to credit risk, because of important differences with respect to a number of factors. These include prevalence in the subprime market of prepayment penalties and of hybrid ARM loans with interest rate resets; ability of many subprime borrowers to qualify for a lower interest rate as their credit standing improves; and comparative propensities to refinance to cash out equity as home values appreciate.

Three additional time-varying factors are included in the prepayment model—the change in the prime rate, the yield curve measure and the monthly national refinance share of first-lien, prime, conventional conforming home mortgage applications. An increase in the prime rate could make HELOC borrowing less attractive compared to the alternatives and motivate prepayment. The yield curve may capture the incentive to refinance the variable rate HELOC into a fixed rate home equity loan (or consolidate the HELOC into a fixed rate first mortgage) as determined by the spread between long- and short-term interest rates. Refinancing of first-lien mortgages may influence HELOC prepayment because borrowers may choose to consolidate their mortgage debt when refinancing their first mortgages.

Hazard equation estimates. Results from estimation of the delinquency hazard equations are provided in Table 7, in separate columns by origination channel. For the sake of brevity, we show results only for the two larger channels: retail and wholesale/other.[25] Qualitatively the same results are obtained for the broker channel. Looking first at the consumer confidence index and local unemployment rate, we find that households drawing on new credit lines when unemployment is elevated or confidence is low are more likely to fall behind in their payments. In addition, likelihood of delinquency is positively related to the 12-month forward change in unemployment. These relationships are observed consistently across origination channels and are statistically significant. Overall, the results are consistent with adverse selection associated with preemptive borrowing when household confidence in the economy has declined.

Other estimated coefficients of the delinquency hazard equations are generally as expected. Likelihood of delinquency is strongly related to the house price and interest rate environment; slower house price growth, an increase in the prime rate, or expectations or rising interest rates (a steeper yield curve) are associated with increased delinquency on HELOC borrowing. The likelihood of delinquency increases with the payment-to-income and combined loan-to-value ratios and is inversely related to FICO score. Higher priced credit (a larger margin) and higher utilization rates are associated with an increased likelihood of delinquency. We also observe evidence of selection effects associated with prepayment—likelihood of delinquency increases with cumulative

[25] Results for the broker channel are available from the authors upon request.

prepayments of a cohort of borrowers as defined by origination date and geographic region. This effect is stronger for the retail channel than for wholesale (and broker), possibly because non-retail channels are subject to additional selection effects tied to the actions of the loan originator (the broker or correspondent institution) that might make the prepayment effect less pronounced.

Results from estimation of the prepayment hazard equations are provided in Table 8, again only for the two larger channels. (Again, results are qualitatively the same for the broker channel.) Prepayment of HELOC balances is very closely tied to market interest rate conditions as measured by the yield curve and changes in the prime rate. Since HELOC payments are tied to the prime rate, an increase in the prime rate over the past 12 months and expectations of further increases as represented by a steeper yield curve are associated with higher prepayment frequencies. Also not surprisingly, prepayment of HELOC balances is very closely tied to refinancing of first-lien mortgages. We also observe that higher credit risk HELOC borrowers, as indicated by a lower FICO score, higher combined loan-to-value ratio, and higher payment-to-income ratio, tend to have slower prepayment rates. Interestingly, consistent with precautionary motives, an increase in the local unemployment rate subsequent to the account origination date is associated with slower prepayment.

Model robustness. We explored various alternative specifications and observed no substantial impact on the estimation results. First, we dropped the yield curve measure, to address a potential concern about overfitting. None of the other estimated coefficients were substantially changed. Second, we substituted change since date of origination for the 12-month change in the prime rate and for measuring house price appreciation. Again, the estimates were robust. Third, we substituted a set of indicator variables for ranges of combined loan-to-value in place of the continuous measure; results were essentially unchanged. Finally, we replaced the unemployment rate as of the date of origination with the change in the unemployment rate over the 12 months prior to origination as our proxy for borrower expectations about earnings or liquidity. As with the level of unemployment, a rise in the unemployment rate prior to the date of origination is associated with an elevated risk of delinquency on the account; other estimated coefficients were not substantially affected by this substitution.

6. Conclusions

When the expected unemployment risk of households increases, we have shown that riskier households tend to borrow relatively more. As a consequence, the pool of households that borrow on home equity lines of credit worsens along both observable and unobservable dimensions. This is an interesting example of a type of dynamic adverse selection that can worsen the risk characteristics of new lending and suggests another avenue by which the precautionary demand for liquidity may affect borrowing.

One potential consequence of this occurrence is that lenders have to tighten credit standards not only because the risk appetite of the lenders has fallen either due to reduced capital or increased regulatory oversight, but because the inherent risk underlying observable characteristics is greater. That is, lenders may engage in observably procyclical behavior in response to expected unobservable changes in the borrowing pool.

It has long been recognized that procyclical behavior of this type can exacerbate the cyclicality of credit markets and weaken the mechanisms that stabilize asset markets. To the extent that these procyclical behaviors exist in the interaction between borrowers and lenders, regulators may wish to seek countercyclical channels to strengthen the stability of markets.

References

Agarwal, Sumit, Brent W. Ambrose, and Chunlin Liu (2006), "Credit Lines and Credit Utilization," *Journal of Money, Credit, and Banking* 38(1), pp. 1-22.

Agarwal, Sumit, Brent W. Ambrose, Souphala Chomsisengphet, and Chunlin Liu (2006), "An Empirical Analysis of Home Equity Loan and Line Performance" *Journal of Financial Intermediation* 15(4), pp. 444-469.

Allison, Paul D. (1995), *Survival Analysis Using the SAS System: A Practical Guide*, Cary, North Carolina: The SAS Institute, Inc.

Bernanke, Ben S., and Alan S. Blinder (1992), "The Federal Funds Rate and the Channels of Monetary Transmission," *American Economic Review* 82(4), 901-21.

Board of Governors of the Federal Reserve System (2007), "Report to the Congress on Credit Scoring and Its Effects on the Availability and Affordability of Credit." http://www.federalreserve.gov/boarddocs/rptcongress/creditscore/creditscore.pdf

Bram, Jason, and Sydney C. Ludvigson (1998), "Does Consumer Confidence Forecast Household Expenditure? A Sentiment Index Horse Race," Federal Reserve Bank of New York *Economic Policy Review* 4(2) pp. 59-78.

Brueckner, J.K. (2000), "Mortgage Default with Asymmetric Information," *Journal of Real Estate Finance and Economics* 20, pp. 251-274.

Calhoun, Charles A., and Yongheng Deng (2002), "A Dynamic Analysis of Fixed And Adjustable Rate Mortgage Terminations," *Journal of Real Estate Finance and Economics* 24(1/2), pp. 9-33.

Deng, Yongheng, John M. Quigley, and Robert Van Order (2000), "Mortgage Terminations, Heterogeneity, and the Exercise of Mortgage Options," *Econometrica* 68(2), pp. 275-307.

Dick, Astrid, and Andreas Lehnert (2010), "Personal Bankruptcy and Credit Market Competition," *Journal of Finance* 65(2), pp. 655-686.

Garrett, Thomas A., Ruben Hernandez-Murillo, and Michael T. Owyang (2005), "Does Consumer Sentiment Predict Regional Consumption?," Federal Reserve Bank of St. Louis *Review*, March/April, pp.123-135.

Gross, David B., and Nicholas S. Souleles (2002a), "Do Liquidity Constraints and Interest Rates Matter for Consumer Behavior? Evidence from Credit Card Data," *Quarterly Journal of Economics* 117(1), pp. 149-85.

Gross, David B., and Nicholas S. Souleles (2002b), "An Empirical Analysis of Personal Bankruptcy and Delinquency," *Review of Economic Studies* 2002(1), pp. 319-47.

Jiang, Wei, Ashlyn Nelson, and Edward Vytlacil, (2009), "Liar's Loan? Effects of Loan Origination Channel and Loan Sale on Delinquency," manuscript, Columbia University.

Keys, Benjamin J., Tanmoy Mukherjee, Amit Seru, and Vikrant Vig (2009), "Financial Regulation and Securitization: Evidence from Subprime Loans," *Journal of Monetary Economics,* July, 700-720.

Tedeschi, Robert, "Opening the Tap on Home Equity," *New York Times*, October 31, 2008. http://www.nytimes.com/2008/11/02/realestate/02mort.html

Yamashita, Takashi (2007), "House Price Appreciation, Liquidity Constraints, and Second Mortgages," *Journal of Urban Economics* 62, pp. 424-440.

Figure 1: Number of Originations by Month in the HELOC Sample

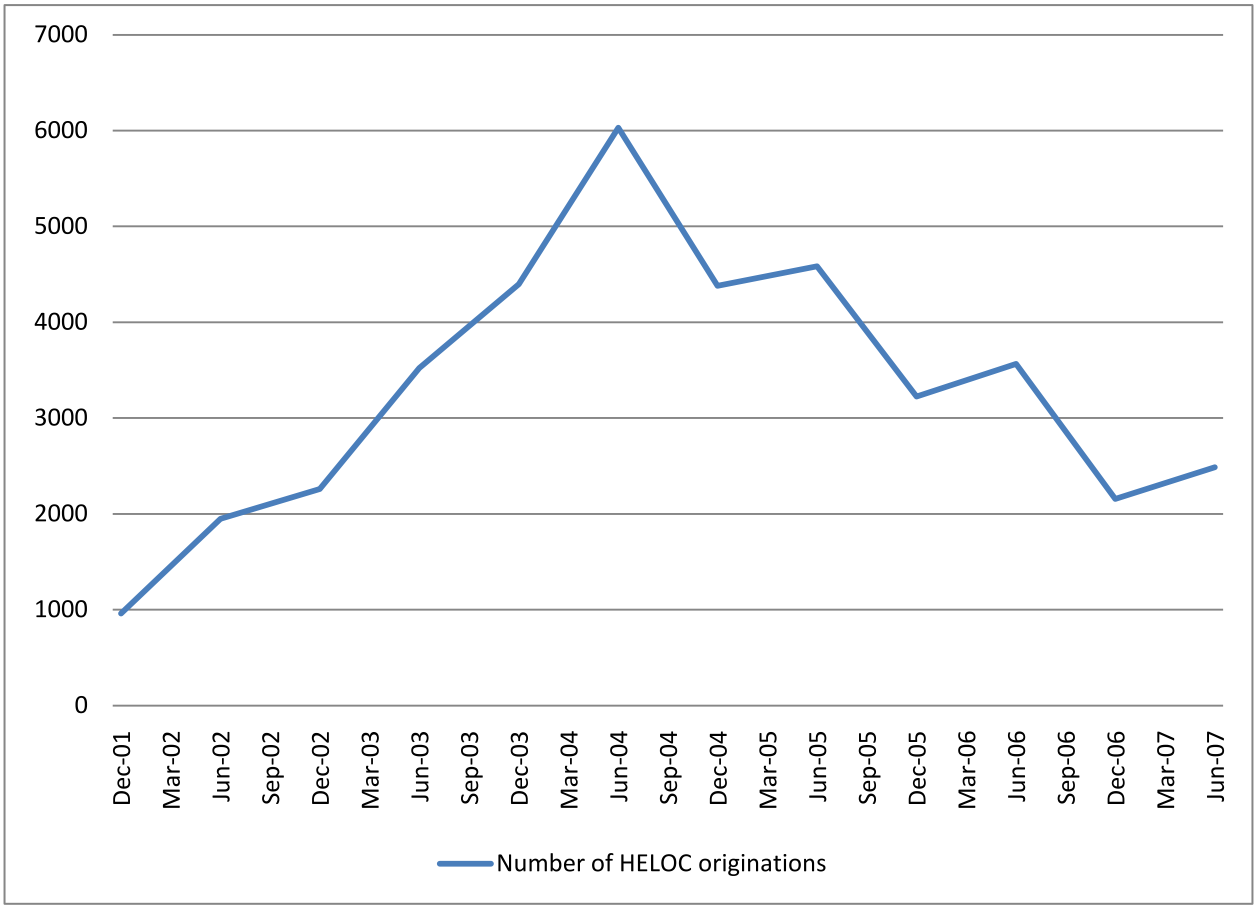

Figure 2: Regional Distribution of the HELOC Sample

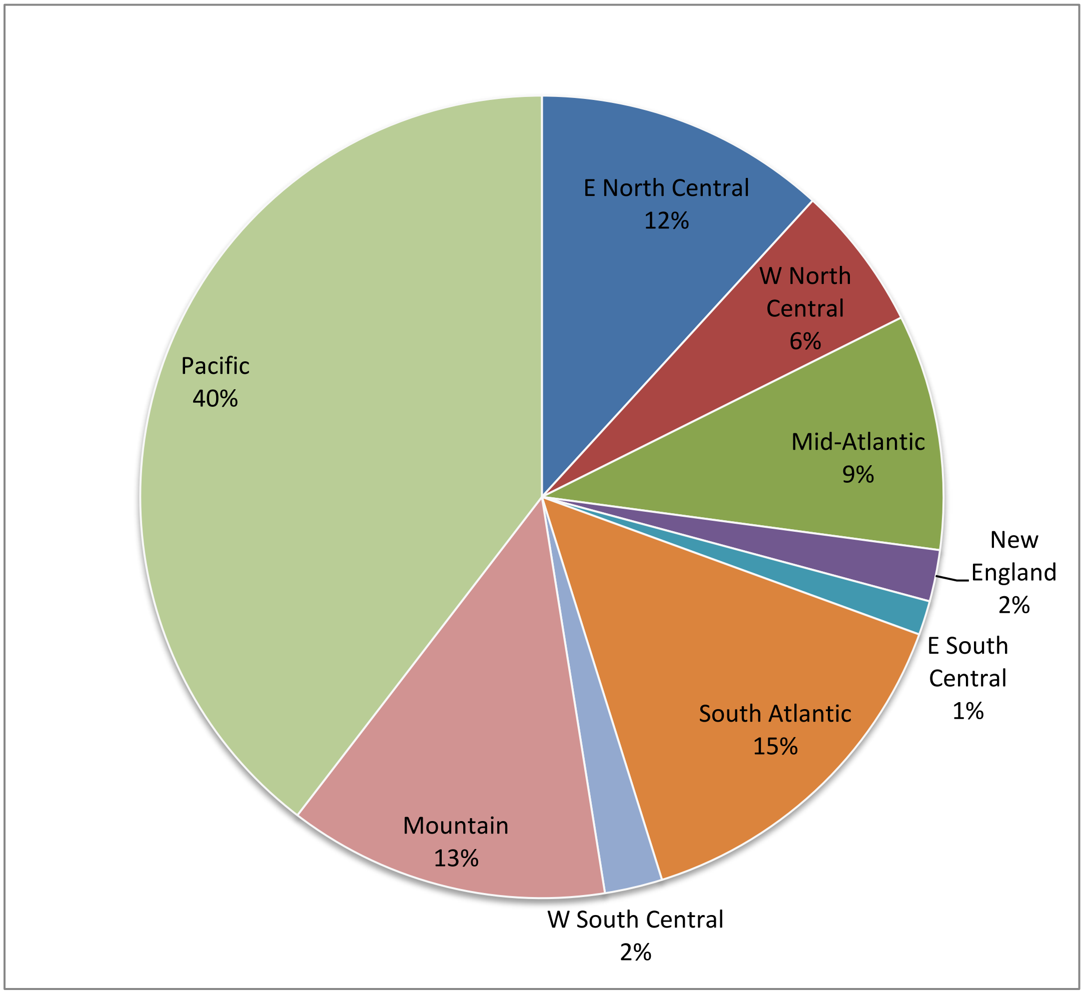

Figure 3: Interest Rates and Refinance Share

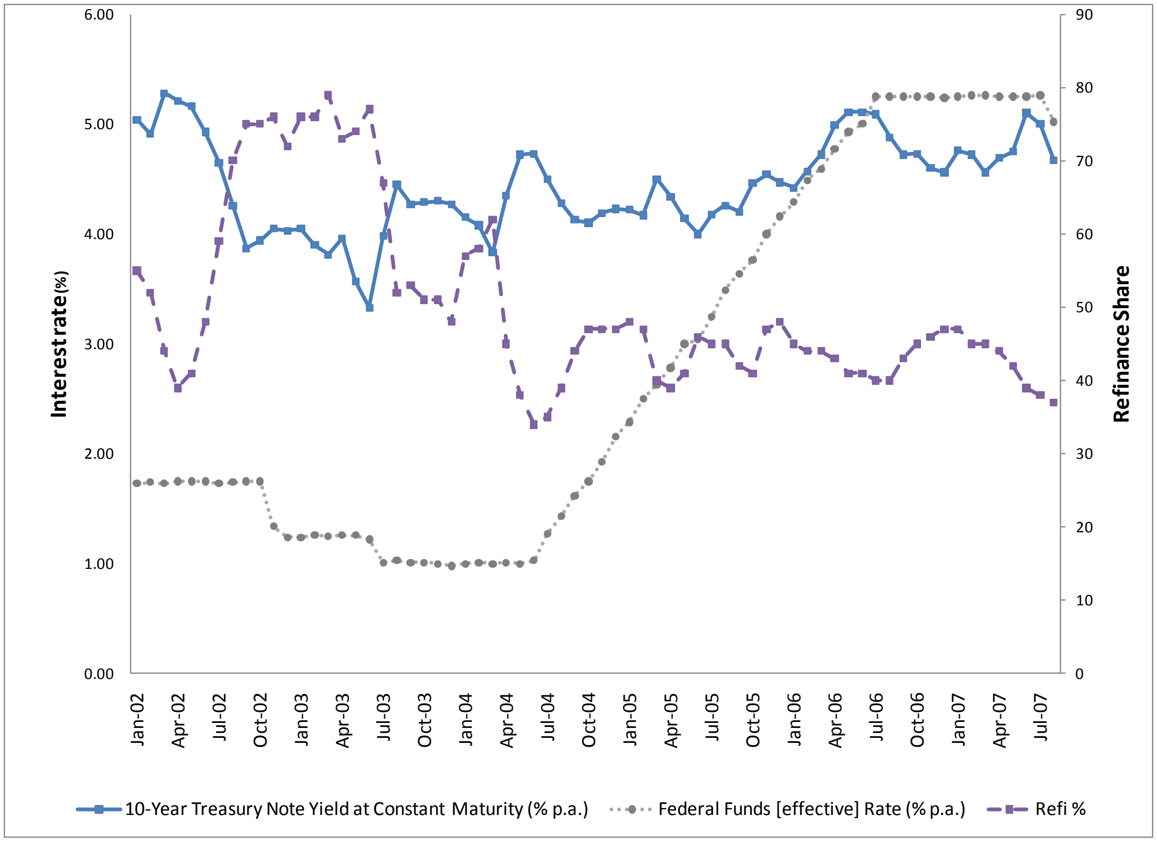

Figure 4: County Unemployment Rates

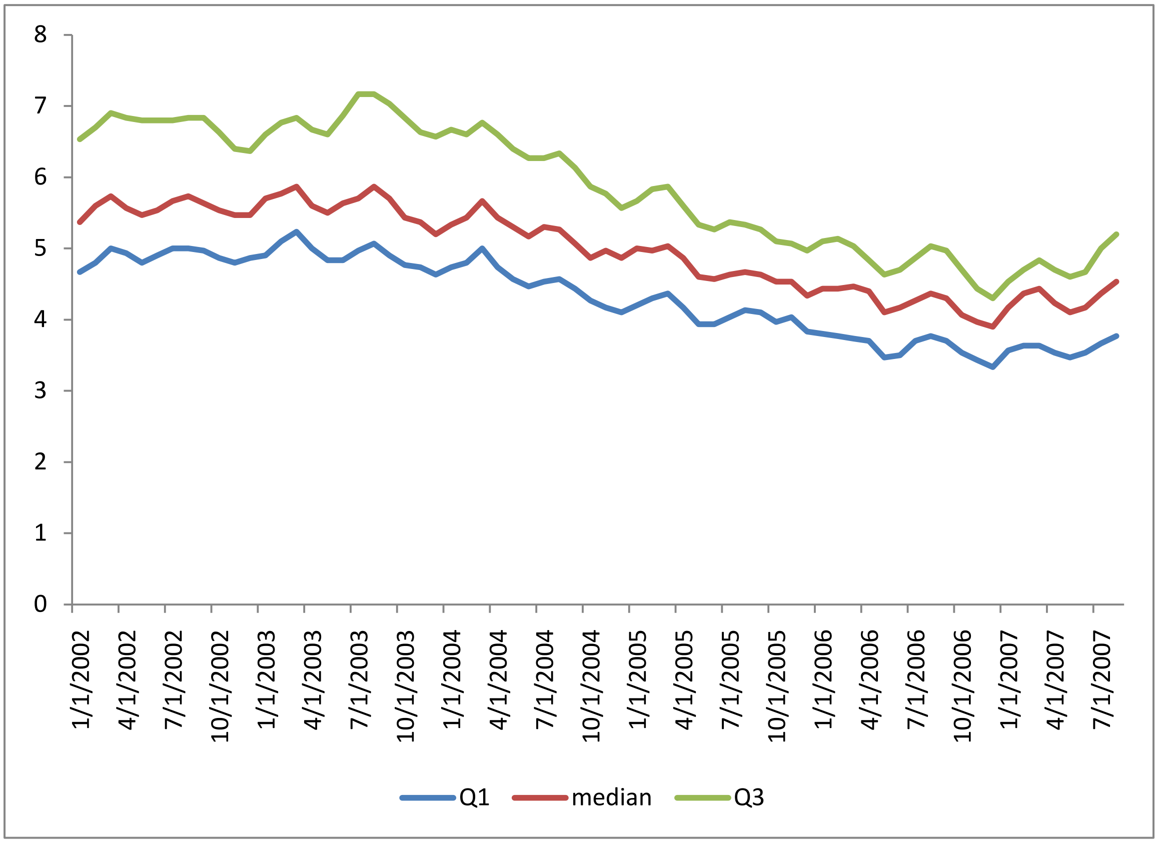

Figure 5: Local Area House Price Appreciation

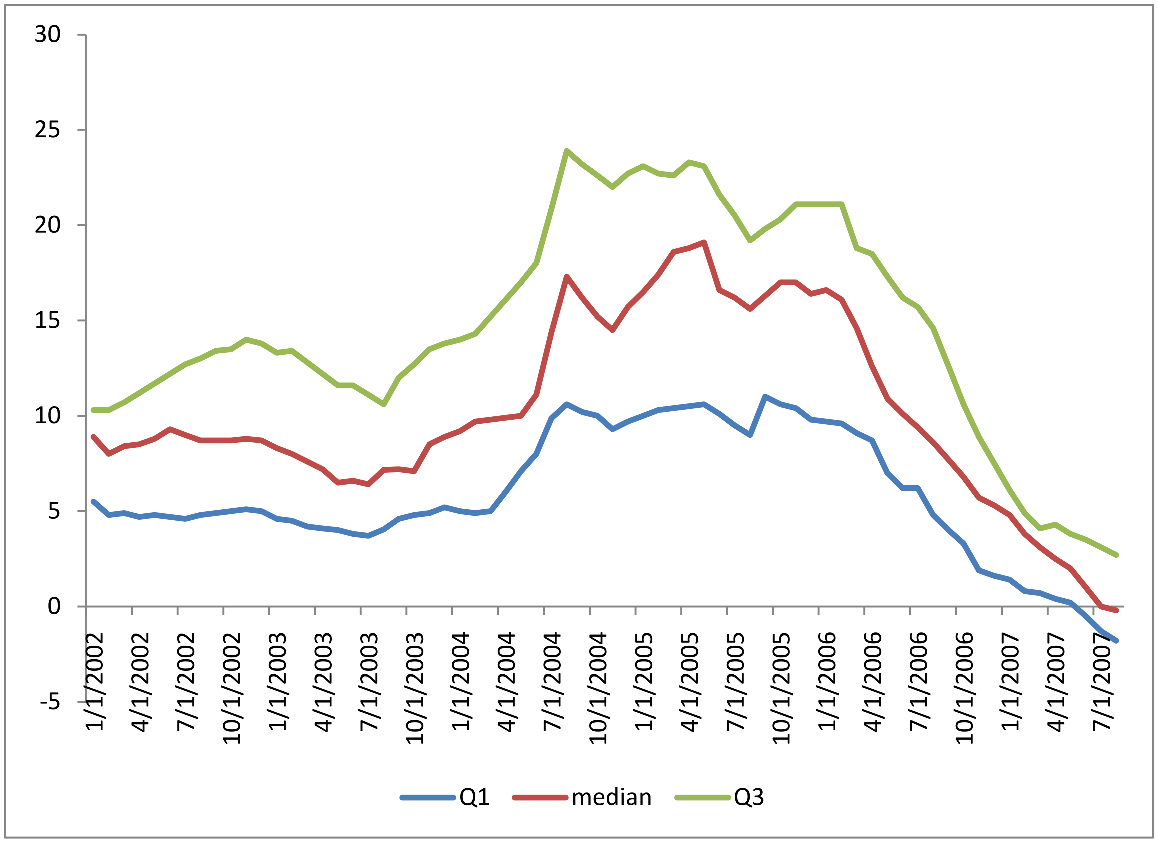

Figure 6: Survival Curves by FICO and Utilization Strata

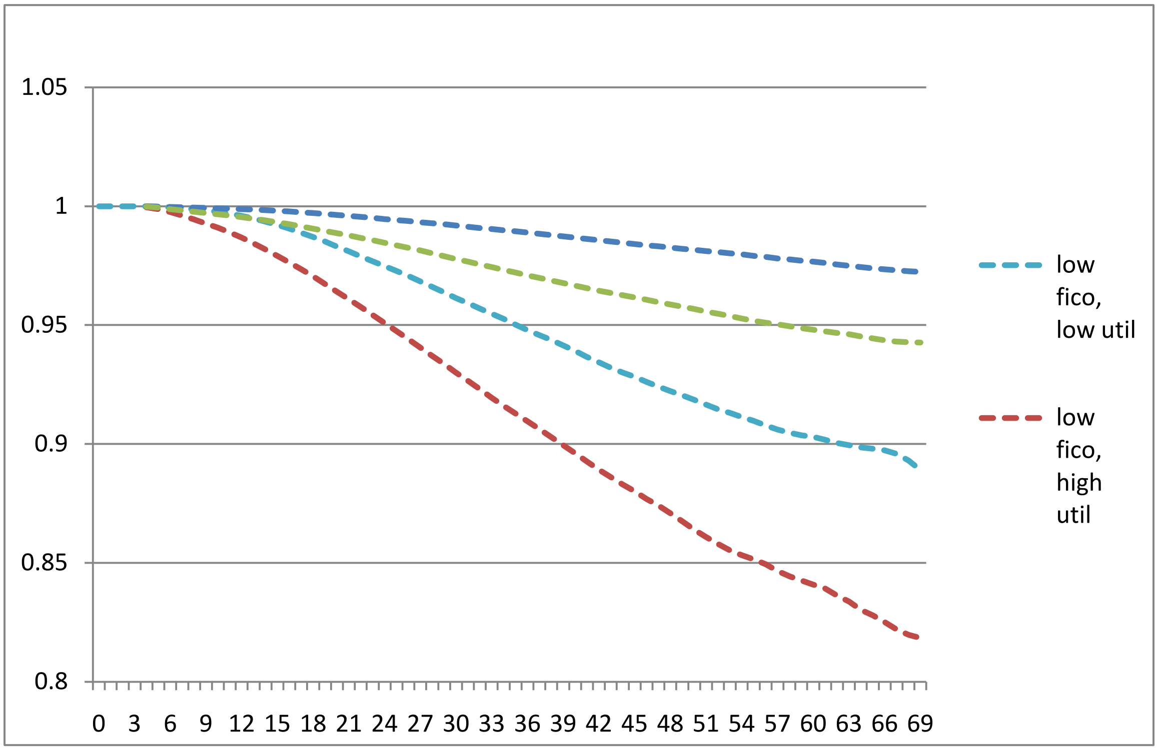

Figure 7: Survival Curves by Combined LTV and Back-end Ratio Strata

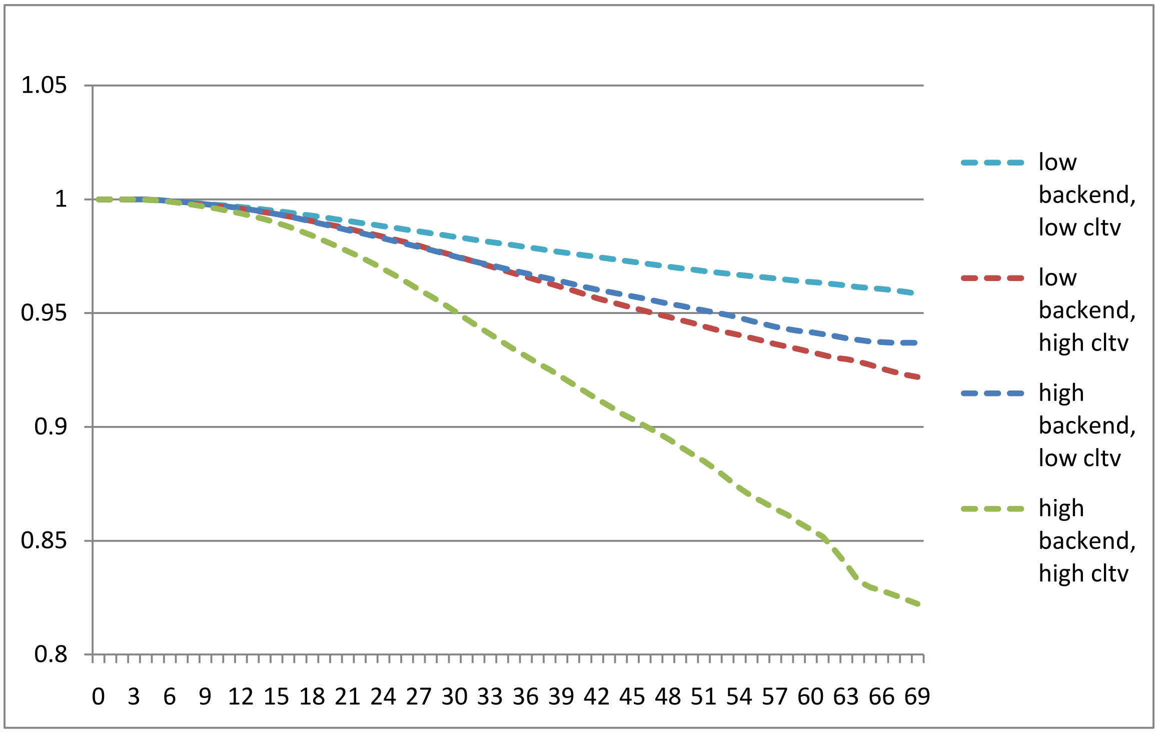

Table 1: Summary Statistics for Categorical Variables

	Retail	Broker	Wholesale
Total count	99,163	11,419	119,583
Lien Status			
% junior lien	98.2	99.3	99.8
% first lien	1.8	0.7	0.2
Property Type			
% unknown	0.01	0.7	5.5
% condo or co-op	6.9	23.9	15.6
% non-condo/co-op	93.1	75.4	78.9

Table 2: Summary Statistics for Continuous Variables

	Number of Accounts	Mean	Median	25th percentile	75th percentile
Retail	99,163				
Credit Limit	99,163	\$90,695	\$60,000	\$36,150	\$106,000
Initial Utilization	99,163	68.25%	75%	42%	99%
Combined LTV	97,719	77.9%	80.0%	71.1%	90.0%
FICO at Origination	98,591	716.4	717	678	757
Payment-to-Income	98,233	35.1%	36.4%	26.3%	45.3%
Margin	98,978	0.81	0.35	0.00	1.49
Broker	11,419				
Credit Limit	11,419	\$71,738	\$53,600	\$33,475	\$85,250
Initial Utilization	11,419	93.4%	100%	100%	100%
Combined LTV	11,340	90.2%	90.0%	88.1%	99.75%
FICO at Origination	11,372	719.5	717	690	750
Payment-to-Income	11,282	37.6%	38.8%	32.0%	44.1%
Margin	11,254	1.63	1.63	0.88	2.25
Wholesale/Other	119,583				
Credit Limit	119,583	\$79,423	\$52,800	\$30,420	\$100,000
Initial Utilization	119,583	80.0	100%	61%	100%
Combined LTV	118,907	83.8%	89.1%	77.9%	95.0%
FICO at Origination	118,188	725.5	728	693	761
Payment-to-Income	108,632	36.25%	37.3%	29.9%	43.6%
Margin	116,889	1.14	1.00	0.38	1.63

Table 3: Monthly Regional Consumer Confidence Index: Jan 2002 – Aug 2007

	Mean	**Median**	**Min**	**Max**
Census Division				
East North Central	76.6	76.8	58.2	107.4
West North Central	93.7	95.2	60.2	118.8
Middle Atlantic	80.7	82.9	54.7	99.1
New England	86.9	87.7	56.8	111.4
Mountain	112.8	115.8	59.9	144.3
Pacific	101.2	103.3	63.0	128.4
South Atlantic	110.0	112.2	70.8	132.7
East South Central	95.7	99.3	59.7	122.5
West South Central	110.5	111.2	62.3	132.9

Table 4. Panel regressions with county fixed effects

	FICO	Back-end	Combined LTV	Margin	Credit Limit	New Accounts
Lagged Dependent Variable	0.223** (38.88)	0.359** (64.91)	0.472** (91.00)	0.492** (97.54)	0.533** (105.80)	0.517** (99.57)
CCI	0.067** (20.63)	0.009** (9.56)	-0.001 (-0.74)	-.001** (-7.12)	104.7** (19.78)	-0.007** (-27.07)
Forward change in unemployment	-0.834** (-9.65)	-0.042 (-1.68)	-0.036 (-1.13)	0.013** (6.03)	938.7** (6.99)	0.053** (7.93)
House price change	-0.113** (-13.98)	0.025** (10.52)	-0.077** (-25.32)	-0.002** (-11.40)	176.2** (13.96)	0.025** (37.96)
Controls						
Prime change	0.389** (2.90)	0.262** (6.66)	-0.146** (-2.95)	-0.048** (-14.06)	1037.4** (5.00)	-0.153** (-14.69)
Yield curve	0.146 (1.09)	-0.036 (-0.91)	-0.019 (-0.38)	0.037** (11.08)	1538.5** (7.41)	0.065** (6.23)
Time	0.041 (1.33)	-0.038** (-4.23)	0.128** (11.16)	0.010** (12.68)	237.2** (4.95)	0.056** (22.97)
Time squared	-0.000 (-0.06)	0.001** (7.91)	-0.002** (-10.55)	-0.000** (-11.82)	1.971** (2.65)	-0.005** (-12.21)
Within R-square	0.171	0.557	0.332	0.738	0.782	0.652

T-statistics in parentheses.
Significance: **1 % *5%

Table 5. Panel regressions with county fixed effects and time dummies

	FICO	**Back-end**	**Combined LTV**	**Margin**	**Credit Limit**	**New Accounts**
Lagged Dependent Variable	0.140** (25.91)	0.287** (51.83)	0.370** (72.62)	0.280** (59.17)	0.446** (88.81)	0.671** (148.57)
CCI	0.0473** (10.13)	-0.00429** (-3.00)	0.00678** (3.89)	0.00052** (4.93)	114.7** (15.37)	0.0002 (0.85)
Forward change in unemployment	-0.734** (-8.92)	0.0648* (2.57)	-0.090** (-2.92)	0.00694** (3.74)	1347.1** (10.25)	0.0325** (6.82)
House price change	-0.166** (-20.21)	5.19e-05 (0.02)	-0.0606** (-19.76)	-0.00085** (-4.58)	131.7** (10.01)	0.0143** (28.41)
FICO		-0.0564** (-30.89)	0.0439** (19.41)	-0.00712** (-54.72)	93.11** (9.62)	-0.0011** (-3.07)
Back-end	-0.579** (-30.74)		0.017 (1.49)	0.00132** (3.06)	-19.77 (-0.65)	-0.0045** (-4.12)
Combined LTV	0.379** (25.45)	0.00735 (1.60)		0.0198** (62.49)	-71.25** (-2.97)	0.00092 (1.07)
Margin	-12.75** (-52.25)	0.248** (3.16)	5.292** (58.62)		-17370.8** (43.91)	-0.101** (-6.84)
Credit Limit	2.66e-05** (7.87)	-6.76e-07 (-0.65)	-2.63e-06* (-2.07)	-3.30e-06** (-44.60)		1.87e-06** (9.48)
Within R-square	0.324	0.606	0.442	0.828	0.811	0.844

Table 6: Estimation Results for the Delinquency Hazard Model

	Retail				Wholesale			
	Hazard Ratio / Chi-square		Hazard Ratio / Chi-square		Hazard Ratio / Chi-square		Hazard Ratio / Chi-square	
Initial economic conditions								
CCI	0.807**	16.5	0.752**	28.7	0.849**	8.4	0.792**	16.9
Unemployment	1.042**	64.4	1.057**	113.7	1.032**	38.1	1.050**	89.7
Forward change in unemployment			5.222**	121.8			7.736**	191.0
Time-varying factors								
House price change	0.507**	2292.8	0.534**	1871.0	0.570**	1605.5	0.602**	1257.3
Yield curve	1.244**	407.2	1.207**	298.2	1.269**	702.6	1.213**	429.2
Prime rate change	1.843**	3199.4	1.804**	2905.1	1.636**	2208.3	1.608**	2014.8
Prepay percentage	11.14**	309.0	14.41**	369.2	2.124**	28.0	2.573**	43.1
Utilization rate at origination								
< 50%	0.462**	1299.0	0.466**	1273.1	0.531**	552.4	0.531**	554.4
≥ 50% and < 75%	0.578**	645.2	0.580**	637.3	0.650**	262.4	0.652**	258.8
≥ 75% and < 90%	0.678**	311.3	0.680**	305.2	0.714**	152.2	0.719**	146.6
Other risk characteristics								
Payment-to-income	1.879**	111.9	1.884**	112.6	3.181**	179.4	3.160**	177.4
Log credit limit	0.996	0.1	0.993	0.5	0.967**	8.5	0.970**	7.0
FICO	0.881**	5647.2	0.880**	5698.1	0.884**	3635.1	0.884**	3263.1
Combined LTV	4.321**	594.4	4.385**	606.2	2.286**	144.8	2.319**	150.0
Margin	1.224**	1161.0	1.221**	1135.4	1.309**	1087.8	1.315**	1116.4
Condo-Co-op	1.232**	56.0	1.240**	58.9	0.990	0.2	1.002	0.0
Estimation summary statistics								
No. of observations	92,269		89,953		102,050		99,824	
Event count	18,372		18,332		17,520		17,485	
Likelihood ratio	22466.8		22212.3		15718.7		15636.8	
Wald chi-square	22731.9		22399.1		15878.3		15828.0	

Significance: **1 % *5%

Table 7: Estimation Results for the Prepayment Hazard Model

	Retail				Wholesale			
	Hazard Ratio / Chi-square		Hazard Ratio / Chi-square		Hazard Ratio / Chi-square		Hazard Ratio / Chi-square	
Initial economic conditions								
CCI	1.091**	118.3	1.053**	41.1	0.900**	234.5	0.908**	194.3
Unemployment	1.002**	7.5	0.998	2.7	0.998**	9.6	0.996**	25.6
Forward change in unemployment			0.723**	159.0			0.871**	43.5
Time-varying factors								
House price change	0.997**	1.8	1.013**	29.7	1.021**	126.2	1.032**	278.4
Yield curve	1.241**	13129.7	1.222**	10978.9	1.343**	49669.4	1.325**	43240.9
Prime rate change	2.049**	162025.6	1.989**	140530.8	1.763**	148120.4	1.719**	128109.6
PMMS refinance %	1.059**	81876.4	1.058**	76224.0	1.033**	64601.6	1.032**	58239.6
Utilization rate at origination								
< 50%	0.987**	18.3	0.992**	7.3	1.011**	15.3	1.013**	22.1
≥ 50% and < 75%	0.994	3.1	0.998	0.2	0.997	1.3	1.001	0.2
≥ 75% and < 90%	0.985**	15.7	0.991*	6.3	1.002	0.3	1.006	2.9
Other risk characteristics								
Payment-to-income	0.957**	23.6	0.954**	27.0	0.958**	17.1	0.954**	20.7
Log credit limit	1.015**	86.1	1.011**	49.7	1.002	2.8	1.000	0.0
Log FICO	1.002**	68.0	1.002**	68.9	1.002**	46.6	1.001**	29.2
Combined LTV	0.909**	177.0	0.906**	190.1	0.951**	50.7	0.959**	36.0
Margin	0.995**	21.3	0.999	0.3	0.998	3.5	0.998	1.8
Condo-Coop	1.010*	4.0	1.003	0.3	0.983**	38.7	0.981**	44.1
Estimation summary statistics								
No. of observations	92,269		89,953		102,050		99,824	
Event count	35,696		35,603		52,411		52,253	
Likelihood ratio	465851.4		416492.9		384829.7		337606.9	
Wald chi-square	373295.0		340229.9		299900.9		268177.2	

Bold type indicates statistical significance at the 5% level or greater.