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Credit Lines and Credit Utilization

While much is known about the characteristics of consumers or businesses that obtain credit lines, relatively little is known empirically about credit line utilization after origination. This study fills that gap by testing two interrelated hypotheses concerning borrower credit quality and credit line utilization. The empirical analysis confirms that borrowers with higher expectations of future credit quality deterioration originate credit lines to preserve financial flexibility. Furthermore, we estimate a competing risks model that confirms our predictions concerning changes in borrower credit line utilization in response to borrower credit quality shocks.

JEL codes: G2, R2, D12

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THE LITERATURE ON BANK credit commitments (or lines of credit) to businesses is extensive, and the link between firm quality and credit lines is well documented.¹ For example, Qi and Shockley (2003) find that higher quality firms finance via loan commitments, while Shockley and Thakor (1997) find that loan commitment costs decline with credit quality. Furthermore, Klapper (2002) finds that higher risk firms are more likely to use secured lines of credit than unsecured lines. In addition, Berger and Udell (1995) discuss the use of credit

1. In this paper, we consider “formal” lines of credit as opposed to “informal” lines of credit. An informal line of credit does not contractually commit the lender to provide funds, whereas a formal credit line involves an explicit contractual commitment on the part of the lender to provide funds to the borrower.

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23 commitments by small firms and find support for theoretical models showing
24 that relationship lending produces information about borrower quality. Berger and
25 Udell (1995) document that those firms with longer bank relationships borrow at
26 lower rates than firms with shorter relationships. They also note that their results
27 are consistent with the theory that banks accumulate private information about
28 borrower quality and utilize this information in setting loan contract terms.² In two
29 early studies of credit commitments, Melnik and Plaut (1986b) examined the com-
30 position of the credit line commitment contract and document that the size of the
31 commitment is positively related to the commitment cost as well as the quality of
32 the borrowing firm, while Melnik and Plaut (1986a) examined the relationship
33 between firm default risk and pricing in commitments and spot loans. These empirical
34 findings are broadly consistent with the theoretical model developed by Dinç (2000),
35 but are counter to the theoretical predictions of Sharpe (1990), who posits that less
36 risky firms will have higher interest rates than higher risk firms.

37 In addition, a number of studies have examined the role of credit lines in overcom-
38 ing information asymmetry problems between borrowers and lenders. For example,
39 in a study of business credit lines Boot, Thakor, and Udell (1987, 1991) show that
40 loan commitments eliminate welfare losses resulting from asymmetric information.
41 In addition, Berkovitch and Greenbaum (1991) demonstrate that business credit
42 lines (or loan commitments) solve the traditional underinvestment problem through
43 the imposition of usage fees and maximum loan amounts, while Duan and Yoon
44 (1993) determine that firms can utilize loan commitments as a credible signal of
45 project quality.

46 As this brief review demonstrates, much is known about the implications of
47 originating credit commitments, as well as the characteristics of firms that originate
48 them. However, few studies have empirically tested the predictions concerning risk
49 and credit commitment utilization. This study seeks to fill this gap in the literature
50 using information on consumer credit lines. Although consumer and business credit
51 lines are distinct, the contractual features of consumer and business credit lines are
52 remarkably similar. Thus, consumer credit lines provide an interesting market to
53 empirically test the theoretical predictions concerning credit utilization and risk that
54 have been derived from studies of business credit.

55 We use objective measures of credit risk to estimate the impact of changes in
56 risk on borrower credit utilization. Furthermore, we also examine the conditions
57 that lead borrowers to payoff their lines of credit. Our results are consistent with
58 theoretical predictions that are derived from models of business credit lines that
59 suggest that credit utilization increases during periods of economic distress. As a
60 result, this study provides additional evidence concerning the link between borrower
61 credit quality and bank loan commitments by utilizing a unique panel data set
62 of borrower-specific consumer loan commitment contracts containing independent
63 objective measures of credit quality.

2. Thakor (1982) establishes that lines of credit effectively allow lenders to sort firms based on risk while Duan and Yoon (1993) show that firms can utilize credit lines as a signaling mechanism of future growth prospects. Furthermore, Houston and Venkataraman (1996) show that firms will have preferences for credit lines based on firm risk characteristics and uncertainty regarding future projects. (AQ2)

64 In Section 1, we outline the distinction between bank loans and lines of credit.
65 We also discuss the differences between consumer and business credit lines and the
66 implications of these differences in the subsequent empirical analysis. In Section 2,
67 we outline the testable hypotheses and in Section 3 we discuss the data. Section 4
68 follows with the empirical results, robustness checks, and a brief discussion of
69 policy implications. Section 5 concludes.

70 1. CREDIT LINES AND TERM LOANS

71 The differences between bank loans and lines of credit with respect to business
72 credit are well documented. According to Strahan (1999), banks provide firms with
73 lines of credit to meet short-term liquidity needs, while also providing “term loans”
74 to finance long-term investments. In general, the distinction between a term loan
75 and a line of credit centers on two aspects of the contract. First, credit lines are
76 usually variable-rate debt in which the bank commits to provide a fixed amount to
77 the borrower, while term loans carry fixed as well as variable interest rates. Second,
78 the borrower pays interest only on funds drawn against the commitment.³

79 Strahan (1999) notes that credit lines expose banks to both liquidity risk and
80 credit risk, while term loans only involve credit risk. Liquidity risk refers to the
81 bank’s commitment to provide funds to the borrower over the life of the contract,
82 while credit risk refers to the risk that the borrower may default on the loan. Of
83 course, both liquidity risk and credit risk are interrelated since borrower credit risk
84 usually increases during periods when liquidity risk is greatest. In general, Strahan
85 (1999) finds that banks structure the price and terms of commitments and loans to
86 reflect these risks. That is, less risky firms have lower interest rates and longer terms
87 than higher risk firms.⁴

88 In consumer lending, the distinction between bank loans and lines of credit is
89 equivalent. Home equity credit is generally classified into home equity loans [i.e.,
90 “spot” loans] and home equity lines. A home equity spot loan is a closed-end note
91 extended for a specified length of time that requires repayment of interest and
92 principal in equal monthly installments. The interest rate on these loans is usually
93 fixed at the time of origination. On the other hand, a home equity line is an open-
94 end revolving credit agreement that permits the consumer to borrow up to the amount
95 of the line. The interest rate on credit lines varies with an index (often the prime
96 rate).⁵ Furthermore, most lines are open for 5 years, and during this time period
97 they require payment of interest only. After 5 years, the line is closed and converted
98 to a fixed-term loan requiring payment of both interest and principal in equal
99 monthly installments.

3. In addition, business credit line contracts often have a provision assessing a fee on the unutilized portion of the commitment (Melnik and Plaut, 1986b).

4. This is consistent with the findings of Berger and Udell (1995). Credit line pricing is the subject of an extensive literature (see James, 1981, and Melnik and Plaut, 1986a, 1986b, among others).

5. DeMong and Lindgren (1995) document that 90% of all credit lines are variable rate.

100 With respect to consumer bank spot loans and lines of credit, Canner, Durkin,
101 and Luckett (1998) document that consumers with credit lines typically own rela-
102 tively more expensive homes, have higher income, and have substantially greater
103 equity in their homes than borrowers with bank loans. In fact, they show that median
104 household income for line borrowers in their sample was \$10,000 more than that
105 for loan borrowers. Furthermore, the median home equity among the line borrowers
106 in their sample was \$76,000, as opposed to \$35,000 for loan borrowers. Finally,
107 Canner, Durkin, and Luckett (1998) note that 23% of the loan borrowers were below
108 the age of 34, compared to only 6% of the line borrowers. Manchester and Poterba
109 (1989) report similar findings regarding second mortgage borrower characteristics
110 contained in the Survey of Income and Program Participation. The financial strength
111 of the line borrowers is also reflected in the statistics on delinquency rates. For
112 instance, according to the American Bankers Association statistics, less than 1% of
113 the lines, as opposed to 1.25% of the loans, are delinquent.⁶

114 While consumer and business credit lines are relatively similar with respect to
115 key contract features, a number of important differences exist. For example, unlike
116 business credit lines, consumer credit lines do not contain material adverse
117 change clauses that allow lenders to withdraw the line if credit quality declines after
118 origination.⁷ In addition, consumer credit lines do not have upfront commitment
119 fees or overuse penalties, which are common in business credit lines.

120 2. HYPOTHESES DEVELOPMENT AND EMPIRICAL METHODOLOGY

121 One of the primary advantages of credit lines over term spot loans is that credit
122 lines provide borrowers with financial flexibility. In studying bank commitments to
123 businesses, Avery and Berger (1991) provide evidence that a primary motive for
124 using credit commitments is to provide flexibility during adverse credit market
125 conditions. Kanatas (1987) notes that credit commitments provide firms with a
126 guarantee of credit, and thus can be viewed as hedging instruments. Furthermore,
127 Hawkins (1982) notes that credit lines provide firms with a mechanism for managing
128 fluctuations in working capital.

129 A second advantage of credit lines over spot term loans is that credit lines provide
130 borrowers with access to funds in the event that deterioration in credit quality
131 precludes future borrowing in the spot market. For example, Avery and Berger
132 (1991) indicate that credit lines provide risk-averse firms with access to credit in
133 the event of a future decline in credit quality.

134 Since the primary purpose of credit lines is to provide future financial flexibility,
135 the majority of borrowing firms do not utilize the full credit line at origination. For

6. According to the Survey of Consumers conducted from May to October 1997, other differences exist between line and loan borrowers. For instance, 49% of the households who prefer a loan are sensitive to interest rates, whereas 43% of households cite the "ease of use" for choosing lines, as opposed to 1% who select loans.

7. Lenders are able to convert the credit line into a fixed-term loan (effectively restricting further draw down of the line) if the borrower becomes delinquent on the line payments.

136 example, Martin and Santomero (1997) note that firms typically utilize only 65%
137 of their credit line, implying that the average firm with a credit line has access to
138 significant future credit.

139 While much is known about the characteristics of consumers or businesses that
140 obtain lines of credit, relatively little is known empirically about line utilization (or
141 takedown) after origination. Given that one of the primary reasons for originating
142 a credit line is to provide flexibility in the event of future credit shocks, we hypothe-
143 size that initial credit utilization will be lower for borrowers with higher *a priori*
144 expectations of a future credit deterioration. That is, in equilibrium, borrowers who
145 value the flexibility afforded by ready access to credit will preserve the option
146 for future credit by retaining the option to increase their credit line utilization.
147 However, borrowers with low expectations of future credit demand should utilize
148 a greater percentage of total credit availability, all else being equal.⁸

149 In addition to credit utilization at origination, Greenbaum and Venezia (1985)
150 note that borrower credit line takedowns after origination are an increasing function
151 of borrower risk. Thus, if borrowers originate credit lines in anticipation of future
152 credit shocks, then we should observe an inverse relationship between changes in
153 borrower credit quality after origination and credit utilization at origination. That
154 is, borrowers who experience credit shocks are more likely to take down their
155 credit line after origination.

156 Unlike business credit lines, consumer credit lines also have characteristics similar
157 to mortgages, in that the credit line is collateralized by the borrower's principal
158 residence. Traditional mortgage pricing models recognize two explicit options em-
159 bedded in the mortgage contract, the right to prepay and the right to default. In
160 addition, the now ubiquitous mortgage option pricing models recognize that the
161 interaction of the explicit termination options create an additional implied option
162 to substitute one method of termination with another.⁹ Traditional mortgage pricing
163 models recognize that the primary sources of uncertainty, interest rates, and house
164 prices determine the option values. Given that consumer credit lines are secured by
165 the underlying property and are prepayable at the borrower's option, we expect to
166 find similar relationships between the termination options and volatility of interest
167 rates and property values.

168 As with traditional mortgages, the options embedded in credit lines have significant
169 interaction effects that create difficulties in empirically isolating the factors associated
170 with line performance. As discussed above, a credit commitment gives the borrower
171 an explicit right to draw down funds against the commitment over the term of the
172 loan. However, the borrower also has the option to pay off the existing balance of
173 the commitment at any time prior to the loan termination. Analyzing these options
174 requires recognizing the implicit interactions embedded in the exercise of each

8. This is consistent with the theoretical models of credit lines as developed in Campbell (1978), Hawkins (1982), Melnik and Plaut (1986a, 1986b), and Sofianos, Wachtel, and Melnik (1990).

9. See Kau and Keenan (1995) for a review of the literature and issues associated with traditional mortgage pricing models.

175 option. For example, the incentive to prepay increases during periods of declining
176 interest rates as borrowers seek to convert their variable-rate lines to fixed-rate
177 loans, with the incentive to prepay being greater for borrowers with higher loan
178 amounts, all else being equal. However, a decline in interest rate levels coupled
179 with a downward sloping yield curve is usually correlated with overall weakness
180 in the economy, indicative of declining credit quality. This suggests that the
181 borrower's ability to refinance (and hence prepay the line) may decline at the
182 same time as the borrower's credit commitment utilization increases. Further-
183 more, the subsequent probability of default and corresponding loss associated with
184 default should also rise as credit utilization increases. This is embodied in the "credit
185 risk" component of credit commitments, as discussed by Strahan (1999).

186 To summarize, we identify two interrelated testable hypotheses concerning the
187 relationship between borrower credit risk and credit line utilization. First, initial
188 credit utilization will be lower for borrowers with expectations of future credit
189 quality deterioration. Second, credit line utilization (takedown) after origination will
190 be correlated with changes in borrower credit quality.¹⁰ The next section presents
191 the data used in testing these hypotheses.

192 3. DATA

193 The data are from a large financial institution (proprietary in nature) that originates
194 home equity lines. Our sample consists of 34,384 credit lines issued to owner-
195 occupants and originated from January 1998 to May 2001. The loans are typical
196 credit lines that are open for the first 5 years, during which time the borrower is
197 only required to make interest payments on the utilized line balance. After the fifth
198 year, the line is closed and converts to a fixed-rate term loan with a remaining term
199 of 5 or 15 years. At this point, the borrower is required to make fixed monthly
200 payments of principal and interest for the remaining period of the line. Consistent
201 with other mortgage loans, the borrower may prepay the line at any time. We require
202 that credit lines have at least 12 months of performance data to be included
203 in the analysis, and we track the performance of each credit line from origination
204 to May 2002.

205 The credit lines are originated in nine northeastern states, with the majority located
206 in Massachusetts (64.1%), Connecticut (9.9%), and New York (9.8%). Table 1
207 reports the geographic distribution of the credit lines, and Table 2 reports the

10. A third interrelated hypothesis is that credit utilization will also vary inversely with borrower expectations of future liquidity needs. That is, borrowers with highly variable incomes (or consumption patterns) may originate credit lines in order to tap into their home equity during periods of low income. Unfortunately, our data set does not contain information on expectations of borrower liquidity (such as self-employment status or other assets), and thus we are unable to directly test this hypothesis. However, in Section 4.3, we examine the relationship between credit utilization and household wealth and income levels as a robustness check against our results concerning credit utilization and changes in credit quality.

TABLE 1
GEOGRAPHIC DISTRIBUTION OF CREDIT LINES

State	Percentage (%)
CT	10.0
MA	64.2
NH	5.7
NJ	5.2
NY	9.9
PA	0.6
RI	0.5

NOTE: This table reports the geographic distribution at the state level of the 34,384 credit lines issued to owner-occupants from January 1998 to May 2001.

208 descriptive statistics for the lines at origination. We note that the average loan-to-
 209 value (OLTV) ratio at origination (calculated as total debt (credit line plus first-
 210 mortgage debt) divided by house value) is 48% and the average borrower credit score
 211 at origination is 724.¹¹ The average interest rate spread at origination is 2.3%.¹²

212 4. EMPIRICAL TESTS

213 4.1 Initial Credit Utilization

214 The theoretical expectation is that borrowers take out credit lines in order to meet
 215 unexpected cash-flow shocks. Consistent with this expectation, we see that the
 216 average credit line was \$46,392, while the average amount utilized at origination
 217 (line balance) was \$24,459. Furthermore, we note that the average credit line utiliza-
 218 tion at origination was 61%. This indicates that many borrowers had significant
 219 potential credit available.

220 Borrower credit (FICO) scores provide lenders with an objective indicator of
 221 future borrower default propensity, with higher scores indicating lower risk of future
 222 default. To confirm the link between current and future credit quality, we exam-
 223 ine the relationship between current borrower FICO score and future changes in
 224 FICO scores. In order to maintain a consistent analysis window, we track changes
 225 in borrower FICO scores at quarterly intervals over 12 and 24 months.¹³ To measure
 226 the change in borrower credit quality, we calculate the percent change in the borrower's
 227 FICO score over the 12- or 24-month window. Thus, FICO_CHANGE is defined
 228 as $(\text{FICO_NEW} - \text{FICO_OLD})/\text{FICO_OLD}$, where FICO_OLD is the borrower's

11. Borrower credit scores are provided by Fair, Isaac and Company (FICO). Higher scores indicate higher credit quality.

12. The interest rate spread is defined as the line annual percentage rate at origination less the 10-year Treasury rate.

13. Since we require that all observations have at least 12 months of data, the 12-month analysis includes all borrowers. However, some borrowers will leave the sample during the second year after origination, and thus, the 24-month analysis will be biased towards borrowers with longer loan tenures. It is unclear what impact this selection bias will have on the 24-month credit change analysis.

TABLE 2
DESCRIPTIVE STATISTICS OF CREDIT LINES AT ORIGINATION

Variable	Mean	Standard deviation
Line amount	\$46,392	\$34,820
Line balance	\$24,459	\$23,944
Loan-to-value (OLTV) (%)	47.90	34.48
APR spread (%)	2.26	0.91
Utilization (U) (%)	60.99	37.77
FICO	724	79
Unemployment rate (%)	3.16	1.19

NOTES: This table describes the characteristics at origination of the 34,384 credit lines issued to owner-occupants from January 1998 to May 2001. Line amount is the maximum credit amount available under the credit line agreement. Line balance is the amount of credit accessed (taken down) at origination. Loan-to-value equals the total debt (credit line amount plus first-mortgage debt balance) at credit line origination divided by the collateral property value. APR spread is the credit line annual percentage rate at origination less the 10-year Treasury rate. Utilization is the line balance at origination divided by the line amount. FICO is the borrower's Fair, Isaac and Company credit score at origination. Unemployment rate is the unemployment rate for the borrower's county during the quarter when the credit line was originated.

229 FICO score at origination and FICO_NEW is the borrower's FICO score at either
 230 month 12 or 24. Since we are interested in the probability that credit scores will
 231 deteriorate over the subsequent period, we set positive changes in FICO to zero.
 232 Thus, FICO_CHANGE is a simple measure of credit deterioration. To test whether
 233 borrowers with lower FICO scores at line origination experience a higher credit
 234 quality decline, we estimate the following equation:

$$\text{FICO_CHANGE}_i = f(\text{FICO}_i, \text{State}_i), \quad (1)$$

235 where FICO_i is borrower i 's credit quality score at origination and State_i is a series
 236 of dummy variables controlling for location. Equation (1) is estimated as a Tobit
 237 model, and our hypothesis is that credit decline (FICO_CHANGE) will be negatively
 238 related to borrower FICO score at line origination. Table 3 reports the results for
 239 both the 12- and 24-month analysis. The significantly negative coefficient for FICO
 240 indicates that borrowers with high initial FICO scores encounter smaller subsequent
 241 drops in their credit quality score than borrowers with lower initial credit quality
 242 scores.¹⁴ To put these results into perspective, the estimated coefficient for FICO
 243 for the 24-month window indicates that the probability of credit deteriorating for a
 244 borrower with a FICO score of 800 at origination is 6.2% while the probability of
 245 credit deterioration for a borrower with a FICO score of 650 at origination is 17.3%.

14. We conducted two robustness tests to validate our finding that future credit risk is a function of current credit risk. First, we create a dummy variable denoting borrowers whose FICO scores at the end of the analysis window are lower than at origination. This specification is a simple test for the probability of a decline in credit quality. Estimation results (based on a logit model) confirm that borrowers with higher initial credit scores have a lower probability of a decline in credit quality. Second, we constructed a dummy variable that equals one if the borrower experienced any decline in FICO score over the analysis window. This specification tests for any reduction in credit quality. Results from all specifications show that the relationship is robust. The results are reported in the Appendix.

TABLE 3
TOBIT REGRESSION OF CHANGE IN CREDIT QUALITY

Variable	12-month window			24-month window		
	Coefficient value	Standard error	p-value	Coefficient value	Standard error	p-value
Intercept	-0.070	0.046	0.133	-0.316	0.037	<0.0001
FICO at origination	-2.0E-04	1.0E-04	0.012	-0.001	0.000	<0.0001
State Dummy CT	-0.010	0.013	0.411	-0.019	0.012	0.110
State Dummy MA	-0.010	0.013	0.431	-0.008	0.012	0.507
State Dummy NH	-0.004	0.016	0.811	-0.010	0.014	0.455
State Dummy NJ	0.010	0.013	0.437	0.009	0.012	0.482
State Dummy NY	0.009	0.013	0.466	0.009	0.011	0.458
State Dummy PA	0.103	0.153	0.583	0.014	0.026	0.586
Likelihood ratio	81.1			90.2		
Number of observations	34,384			32,948		

NOTES: This table presents the Tobit regression analysis of change in borrower credit quality to test the hypothesis that borrowers with lower credit scores at credit line origination experience a greater subsequent decline in credit quality. The dependent variable is defined as $(\text{FICO_NEW} - \text{FICO_OLD})/\text{FICO_OLD}$ if less than zero and is set to zero otherwise. FICO is the borrower's credit quality score.

246 Based on the results reported in Table 3, in equilibrium, borrowers with low
 247 *a priori* expectations of future credit quality deterioration (i.e., borrowers with high
 248 initial FICO scores) should value the flexibility of credit lines less than borrowers
 249 with higher risk (borrowers with lower FICO scores). Thus, to test the hypothesis that
 250 borrowers with high *a priori* expectations of future credit quality decline request
 251 credit lines in excess of current consumption requirements, we examine the distribu-
 252 tion of credit utilization based on credit quality. Table 4 reports the mean credit
 253 utilization and loan-to-value ratios at origination for the sample segmented by FICO
 254 score. We segment the sample into quartiles based on FICO scores. The average
 255 initial credit utilization ratio for borrowers in the top quartile of the FICO distribution is
 256 81%, while the initial credit utilization for the borrowers in the bottom quartile of
 257 the FICO distribution is 35%. This is consistent with our hypothesis that borrowers
 258 with higher *a priori* expectations of future credit needs (lower FICO scores) conserve
 259 their credit resources by utilizing lower amounts of their credit line at origination.
 260 In addition, we see that the average origination loan-to-value ratios for the bottom
 261 and top quartiles are 25% and 66%, respectively. Based on the *F*-test of differences
 262 in sample means, we can reject the null hypothesis that average utilization rates are
 263 equal across borrower FICO quartiles.

264 In addition to the simple means test, we also test the initial credit utilization
 265 hypothesis by estimating the following regression:

$$U_i = \beta_0 + \beta_1 \text{OLTV}_i + \beta_2 r_i + \beta_3 \text{FICO}_i + \sum_{k=1}^6 \delta_k \text{State}_{ki} + \varepsilon_i, \quad (2)$$

266 where U_i is borrower i 's credit line utilization at origination, OLTV_i is the original
 267 loan-to-value, r_i is the current mortgage interest rate, FICO_i is the borrower's credit
 268 signal at origination, and State_i is a series of dummy variables controlling for the
 269 borrower's location. The relationships between FICO score, loan-to-value ratio, and

TABLE 4

DISTRIBUTION OF CREDIT UTILIZATION AND LTV RATIOS AT ORIGINATION BY FICO SCORE

FICO scores	Credit utilization	Loan-to-value
FICO quartile (range: 449–698)	35.26 (35.03)	25.12 (29.30)
FICO quartile (range: 699–735)	55.84 (36.87)	42.28 (32.75)
FICO quartile (range: 736–766)	71.29 (33.42)	57.36 (31.50)
FICO quartile (range: 767–831)	80.8 (28.70)	66.55 (29.15)
<i>F</i> -test	30.23	19.2

NOTES: This table reports the means and standard deviations of the borrower's credit line utilization at origination and loan-to-value ratio at origination by FICO quartile range. Credit utilization is the line balance at origination divided by the line amount and loan-to-value equals the total debt (credit line amount plus first-mortgage debt balance) at credit line origination divided by the collateral property value.

270 initial credit line utilization identified in Equation (2) may result from a form of
 271 sample selection bias present in the data due to the underwriting process governing
 272 credit line originations. That is, low FICO score borrowers may have compensat-
 273 ing factors (such as significant equity) that would lead to a finding that low credit score
 274 borrowers have lower utilization rates.

275 In order to control for this potential bias, we estimate the two-stage “treatment (AQ1)
 276 effects” model (see Greene 1997). This procedure involves estimating the following
 277 credit line origination accept/reject equation

$$\text{ACCEPT}_i = \gamma Z_i + \xi_i, \quad (3)$$

278 where Z_i is a vector of underwriting characteristics utilized by the lender in determin-
 279 ing whether to accept or reject the credit line application and ξ_i is an error term.
 280 In order to estimate this model, we supplemented the credit line data set with
 281 underwriting data on 14,923 credit line applications that were rejected over the same
 282 origination window (January 1998 to May 2001). The underwriting characteristics
 283 include the borrower's FICO score, loan-to-value ratio, debt-to-income ratio, an
 284 indicator variable denoting prior borrower fraud, an indicator variable denoting prior
 285 borrower bankruptcy, an indicator variable denoting prior borrower delinquency, an
 286 indicator variable denoting whether the borrower has a prior foreclosure, and finally
 287 an indicator denoting the presence of prior liens on the property (other than the senior
 288 mortgage). We estimate Equation (3) as a probit model with the following form:

$$\Pr(\text{ACCEPT}_i = 1) = \frac{\phi(-\gamma Z_i)}{1 - \Phi(-\gamma Z_i)} \quad (4)$$

289 and

$$\Pr(\text{ACCEPT}_i = 0) = [1 - \Pr(\text{ACCEPT}_i = 1)]. \quad (5)$$

290 ϕ is the standard normal probability density function (pdf) and Φ is the standard
 291 normal cumulative distribution function (cdf). We compute the inverse Mills ratio
 292 (λ_i) as

$$\lambda_i = \frac{\phi(\hat{\gamma}Z_i)}{\Phi(\hat{\gamma}Z_i)}. \quad (6)$$

293 Flannery and Houston (1999) note that if ε_i and ξ_i are jointly normally distrib-
294 uted, then

$$E(\varepsilon_i | \text{ACCEPT}_i) = \rho\sigma_\xi E(\xi_i | \text{ACCEPT}_i), \quad (7)$$

295 where ρ is the correlation between ε_i and ξ_i , and σ_ξ is the standard deviation of ξ_i .
296 Thus, in the second step, we estimate Equation (2) via least squares with λ_i included
297 as an explanatory variable:

$$U_i = \beta_0 + \beta_1 \text{OLTV}_i + \beta_2 r_i + \beta_3 \text{FICO}_i + \sum_{k=1}^6 \delta_k \text{State}_{ki} + \alpha \lambda_i + \varepsilon_i, \quad (8)$$

298 The inverse Mills ratio coefficient (α) is a measure of $(\rho\sigma_\xi)$ in Equation (7) and an
299 insignificant parameter estimate for λ indicates that sample selection bias is not
300 present. However, Willis and Rosen (1979) show that including λ corrects for
301 selectivity bias in the sample observations.

302 Table 5 presents the estimated coefficients for the line acceptance Equation (3)
303 and the utilization Equation (8). Panel A shows the estimates for the underwriting
304 model. Given that we include all the factors utilized by the lending institution in
305 determining borrower acceptability, it is not surprising that all the coefficients
306 are highly significant with the appropriate sign. For example, the probability of
307 acceptance increases with borrower credit quality and decreases with the loan-to-
308 value ratio, the debt-to-income ratio, and the indicators of past credit problems
309 (delinquency, foreclosure, bankruptcy, fraud, and other liens).

310 Table 5, Panel B, reports the second-stage results with asymptotically corrected
311 standard errors for the utilization model including the inverse Mills ratio to control

TABLE 5
SAMPLE SELECTION CORRECTION

Panel A. Probit Model				
Variable	Coefficient value	Standard error	<i>t</i> -statistic	<i>p</i> -value
Intercept	-1.744	0.142	-151.0	<0.0001
FICO score	0.004	0.000	609.6	<0.0001
OLTV	-0.010	0.000	-690.6	<0.0001
Debt to income	-0.015	0.001	-877.8	<0.0001
Fraud indicator	-3.102	0.288	-115.8	<0.0001
Prior delinquency	-1.266	0.041	-954.7	<0.0001
Prior bankruptcy	-2.352	0.123	-363.8	<0.0001
Prior foreclosure	-2.318	0.269	-74.3	<0.0001
Liens	-0.790	0.081	-94.6	<0.0001
Log likelihood	-9594			
Number of accounts accept/decline	34,384/14,923			

NOTES: This table reports the maximum-likelihood parameter estimates for the first-stage probit model of whether the credit line application is accepted or rejected. The dependent variable is a dummy variable equal to 1 if the application is accepted and 0 otherwise. The independent variables are as follows: FICO score is the borrower's credit quality score at application; OLTV is the proposed loan-to-value ratio; debt-to-income is the borrower's proposed total debt to income; fraud, delinquency, bankruptcy, and foreclosure are indicator variables of prior borrower credit problems; and liens indicates whether the borrower has additional outstanding debt.

TABLE 5
SAMPLE SELECTION CORRECTION

Panel B. Second-stage OLS Regression with Consistent Asymptotic Standard Errors				
Variable	Coefficient value	Standard error	t-statistic	p-value
Intercept	56.077	3.119	17.980	<0.0001
OLTV	0.183	0.006	29.154	<0.0001
APR	-1.262	0.226	-5.584	<0.0001
FICO	0.008	0.002	3.411	0.001
State Dummy CT	2.999	1.089	2.752	0.006
State Dummy MA	-5.700	0.931	-6.123	<0.0001
State Dummy NH	-0.091	1.210	-0.075	0.940
State Dummy NJ	2.390	0.130	18.364	<0.0001
State Dummy NY	2.367	0.117	20.162	<0.0001
State Dummy PA	2.509	0.230	10.926	<0.0001
λ	11.152	1.332	8.372	<0.0001
R^2	0.121			
Number of observations	34,384			

NOTES: This table reports the OLS regression estimates of the following equation:

$$U_i = \beta_0 + \beta_1 \text{OLTV}_i + \beta_2 r_i + \beta_3 \text{FICO}_i + \sum_{k=1}^6 \delta_k \text{State}_{ki} + \alpha \lambda_i + \varepsilon_i.$$

The dependent variable is credit line utilization at origination. OLTV_{*i*} is the original loan-to-value (total debt divided by property value), *r_i* is the current mortgage interest rate, FICO_{*i*} is the borrower's credit signal at origination, and State_{*i*} is a series of dummy variables controlling for the borrower's location. The inverse Mills ratio (λ) is defined as $\lambda_i = \phi(\hat{\gamma}_i) / \Phi(\hat{\gamma}_i)$, where γ are the parameter coefficients of the first-stage probit model reported in Panel A.

312 for sample selection bias. The positive and significant parameter estimate for FICO
 313 confirms our hypothesis that borrowers with higher credit quality signals have higher
 314 initial credit utilization rates. This is consistent with our expectation that borrowers
 315 with lower credit signals (low FICO scores)—and thus a higher probability of
 316 encountering a future liquidity shock (and are less likely to be able to handle such
 317 a shock)—preserve flexibility by utilizing a lower amount of credit at origination
 318 relative to borrowers with higher credit quality signals. For example, the parameter
 319 estimates indicate that a borrower with an FICO score of 650 would utilize 34.8%
 320 less credit at line origination than a borrower with an FICO score of 800. We also
 321 note that initial utilization decreases with increases in mortgage interest rates (*r*).
 322 Furthermore, initial utilization also increases with loan-to-value. The significantly
 323 positive coefficient for λ indicates that a simple OLS model of credit line utilization
 324 without including λ would suffer from omitted variables bias.¹⁵ In addition, since
 325 the coefficient for λ is positive, this suggests that credit line utilization is larger
 326 than that estimated under a simple OLS regression.

327 4.2 Changes in Borrower Credit Quality and Credit Line Performance

328 To test the “credit risk” hypothesis—that subsequent credit utilization and credit
 329 line performance are related to changes in borrower credit—we compare the ex-
 330 post origination performance of credit commitments to determine whether higher

15. See Flannery and Houston (1999) for a discussion of the interpretation of the inverse Mills ratio in the context of the impact of bank examinations on market value.

331 risk borrowers do indeed take advantage of the flexibility afforded by credit lines.
 332 Thus, we estimate a competing risks model of borrower actions, recognizing that
 333 the borrower has the ability to draw additional funds from the commitment (increase
 334 utilization), partially prepay the line, fully pay off the line, default, or maintain
 335 the current level of utilization. In estimating the competing risks model, we denote
 336 credit commitments that are still current at the end of the observation period as
 337 censored. Thus, we define $T_j (j = 1, \dots, 5)$ as the latent duration for each commitment
 338 to end by partially prepaying, fully prepaying, defaulting, increasing credit utiliza-
 339 tion, or being censored, and the observed duration, τ , is the minimum of the T_j .

340 Conditional on a set of explanatory variables, x_j , that include personal characteris-
 341 tics as well as market conditions at the time of origination, the pdf and cdf for T_j are

$$f_j(T_j | x_j; \theta_j) = h_j(T_j | x_j; \theta_j) \exp(-I_j(r_j | x_j; \theta_j)), \quad (9)$$

$$F_j(T_j | x_j; \theta_j) = 1 - \exp(-I_j(r_j | x_j; \theta_j)), \quad (10)$$

342 where I_j is the integrated hazard for outcome j :

$$I_j(T_j | x_j; \theta) = \int_0^{T_j} h_j(s | x_j; \theta_j) ds \quad (11)$$

343 and h_j is the hazard function.

344 The joint distribution of the duration and outcome is

$$f(\tau, j | x; \theta) = h_j(\tau | x_j; \theta_j) \exp(-I_0(\tau | x; \theta)), \quad (12)$$

345 where $x = (x_1, x_2, x_3, x_4, x_5)$, $\theta = (\theta_1, \theta_2, \theta_3, \theta_4, \theta_5)$, and $I_0 = \sum I_j$ is the aggregated
 346 integrated hazard. Thus, the conditional probability of an outcome is

$$\Pr(j | \tau, x; \theta) = \frac{h_j(\tau | x_j; \theta_j)}{\sum_{j=1}^5 h_j(\tau | x; \theta)}. \quad (13)$$

347 In order to simplify estimation, we specify a separate exponential hazard function
 348 for each mortgage outcome

$$h_j(\tau_j | x_j; \theta_j) = \exp(x_j' \beta_j) \quad (14)$$

349 and estimate Equation (14) in a multinomial logit framework.

350 In estimating Equation (14), we recognize that we initially observe each credit
 351 line as being current. In subsequent quarters, we observe whether the borrower
 352 continues the current credit utilization, increases the utilization, partially prepays
 353 the line (decreases utilization), fully prepays the line, or defaults on the line. We
 354 classify borrowers as increasing their credit utilization if the credit line amount
 355 increased more than 20% in any given quarter, and we classify a partial prepayment if
 356 the credit line amount declined by more than 20% but less than 100% in any given
 357 quarter. Although arbitrary, we chose the 20% cutoff criteria in order to focus
 358 on substantial changes in borrower credit line utilization rather than *de minimus*

359 changes in credit utilization.¹⁶ Obviously, full prepayment occurs if the credit line
360 is closed and the full amount paid off. Over the sample period, very few borrowers
361 defaulted, and thus, we are unable to estimate the default hazard. However, we
362 include a dummy variable for a positive quarterly change in the loan-to-value
363 (LTV_DIFF_Dummy) to capture the changes in default option values. Quarterly
364 current loan-to-value (CLTV) ratios were estimated by multiplying the loan-to-value
365 at origination (OLTV) by the change in local house prices since origination.
366 We use the zip code level Case-Shiller Home Price Index as a proxy for changes
367 in local house prices. Furthermore, we observe the quarterly change in borrower
368 credit quality (FICO score), the change in market interest rates, and the change in
369 the county unemployment rates. Our proxy for the market interest rate is the average
370 interest rate charged by lenders on new first mortgages. We also include the county
371 unemployment rate as a proxy for local economic risk factors and state dummy vari-
372 ables to control for unobserved differences in local economic risk factors.

373 We use the credit score level and a dummy variable for a change in borrower
374 credit score as a proxy for credit quality shocks. According to our theoretical
375 predictions, a decline in a borrower's credit score (indicating a credit shock) should
376 be associated with a higher probability of credit utilization and a lower probability
377 of prepayment. Furthermore, we anticipate that increases in interest rates and declines
378 in estimated house values will be associated with lower probabilities of prepayment.
379 Finally, assuming that local unemployment rates also serve as a proxy for borrower
380 credit shocks, we should see lower prepayment probabilities and higher credit
381 utilization probabilities for borrowers in areas with rising unemployment rates.
382 Table 6 presents the estimated coefficients for Equation (14), and Table 7 presents
383 the marginal effects, showing the impact of a change in a variable (holding all else
384 constant) on the outcome probabilities at month 48.

385 *Full prepayment.* Looking first at the probability of prepayment, we see that, with
386 the exception of the dummy variables for a positive change in LTV and unemployment
387 over the previous quarter (LTV_DIFF_Dummy and Unemp_DIFF_Dummy), all the
388 borrower and economic risk factors are statistically significant. The marginal effects
389 table provides a better indication of the economic significance. For example, we
390 see that a 10% decline in borrower credit quality results in a 7.2% decline in
391 the probability of prepayment, and a 10% increase in the LTV (reflecting a decrease
392 in the house value) corresponds to a 12.9% decrease in the probability of prepayment
393 at month 48. Consistent with theoretical expectations about the impact of changes
394 in market interest rates, a 1 percentage point decline in the average mortgage interest
395 rate is associated with a 10% increase in the probability of prepayment. This indicates
396 that borrowers do take advantage of dips in interest rates to convert variable-rate
397 lines into fixed-rate loans. Finally, we note that a 1 percentage point increase in
398 the unemployment rate corresponds to a 5.9% drop in the probability of prepayment.
399 Overall, the results follow expectations concerning the importance of borrower

16. We also tried alternate specifications, and the results were qualitatively similar. Results are available from the authors upon request.

TABLE 6
 COMPETING RISKS MODEL COEFFICIENT ESTIMATES OF CREDIT LINE OUTCOMES

	Prepay			Decrease utilization			Increase utilization		
	Coefficient value	Standard error	p-value	Coefficient value	Standard error	p-value	Coefficient value	Standard error	p-value
Intercept	9.814	3.214	0.002	-6.268	0.468	<0.0001	-3.968	0.500	<0.0001
State Dummy CT	0.934	0.688	0.175	-0.237	0.085	0.005	-0.130	0.080	0.104
State Dummy MA	1.491	0.663	0.024	-0.239	0.078	0.002	-0.124	0.072	0.087
State Dummy NH	1.302	0.815	0.110	-0.537	0.099	<0.0001	-0.010	0.099	0.920
State Dummy NJ	-6.852	460.900	0.988	-0.489	0.742	0.510	-8.799	58.790	0.881
State Dummy NY	-1.369	1.172	0.243	-0.188	0.321	0.558	-0.187	0.330	0.572
State Dummy PA	-7.413	280.100	0.979	-1.049	0.730	0.151	-0.128	0.750	0.865
Age	0.069	0.062	0.267	-0.017	0.009	0.046	0.013	0.009	0.144
Age (square)	0.001	0.001	0.537	1.1E-04	1.4E-04	0.424	-1.5E-04	1.5E-04	0.317
CLTV_Diff_Dummy	-0.061	0.176	0.727	-2.001	0.039	<0.0001	-1.591	0.028	<0.0001
CLTV	-0.025	0.003	<0.0001	-0.004	4.9E-04	<0.0001	-0.057	0.001	<0.0001
FICO_Diff_Dummy	0.320	0.137	0.031	0.033	0.025	0.186	-0.049	0.021	0.031
FICO (lagged 4 months)	0.001	1.8E-04	0.013	0.003	3.1E-04	<0.0001	-0.001	3.0E-04	0.014
APR_Diff_Dummy	-1.907	0.694	0.006	0.257	0.094	0.006	0.159	0.050	0.021
APR	-1.456	0.709	0.040	0.250	0.096	0.010	0.167	0.040	0.031
Unemp_Diff_Dummy	-0.679	0.701	0.332	-0.127	0.092	0.169	-0.086	0.094	0.356
Unemployment	-0.456	0.134	0.001	-0.175	0.019	<0.0001	-0.005	0.019	0.795

NOTES: This table shows results of a proportional hazard model of prepayment, increasing utilization, and decreasing utilization using monthly date for home equity lines of credit from January 1998 to May 2002. Increased utilization is defined as increasing the credit line amount more than 20% in any given quarter. Decreased utilization is defined as decreasing the credit line amount by more than 20% but less than 100% in any given quarter. Although arbitrary, we chose the 20% cutoff criteria in order to focus on substantial changes in borrower credit line utilization. The independent variables control for calendar time, credit risk, current loan-to-value ratio, interest rates, and county unemployment rates both at the level and differences. The competing risks model is estimated as a multinomial logit via maximum likelihood.

TABLE 7

IMPACT OF CHANGES IN VARIABLE VALUES ON PREDICTED OUTCOME PROBABILITIES

Marginal effects	Age 48 months
Prepayment	
FICO 10% drop	-7.23%
CLTV 10% increase	-12.91%
APR 1% point drop	10.03%
Unemployment 1% point increase	-5.93%
Increase utilization	
FICO 10% drop	15.57%
CLTV 10% increase	-23.89%
APR 1% point drop	-2.71%
Unemployment 1% point increase	-3.13%
Decrease utilization	
FICO 10% drop	-7.81%
CLTV 10% increase	-3.28%
APR 1% point drop	-0.49%
Unemployment 1% point increase	-0.48%

NOTES: This table reports the impact of a change in the indicated variable on the probabilities of prepayment and credit utilization holding all other variables constant that their sample mean.

400 characteristics on the exercise of financial options. For example, the decline in
 401 prepayment following a reduction in credit quality is consistent with borrowers
 402 preserving current credit given the lower likelihood of qualifying for future credit.

403 *Partial prepayment.* Turning to the probability of a decrease in utilization (or
 404 partial prepayment), we again find that a decline in borrower quality is associated
 405 with a decline in the probability of a partial prepayment. A 10% decline in borrower
 406 FICO scores results in a 7.8% drop in the probability of decreasing the credit line
 407 by month 48. Interestingly, however, the risk factor associated with changes in
 408 property value is negatively associated with partial prepayment. The marginal effects
 409 indicate that a decline in house values (proxied by a 10% increase in LTV) results in
 410 a 3% decline in the probability of paying down part of the credit line. Again, this
 411 is consistent with the theory that the ability to refinance is reduced during periods of
 412 declining property value. Furthermore, our model indicates that changes in interest
 413 rates and unemployment rates, while statistically significant, have very small eco-
 414 nomic impacts on partial prepayment.

415 *Increased utilization.* Finally, turning to the probability of an increase in utiliza-
 416 tion, we see that a 10% decline in borrower credit quality corresponds to a 15%
 417 increase in the probability that the borrower will draw against the credit line. This is
 418 consistent with our hypothesis that borrowers experiencing a credit shock (proxied
 419 by a decline in credit quality) are more likely to increase their credit line utilization.
 420 However, the estimated coefficients imply that a 10% decline in property value
 421 results in a 23.9% decline in the probability of increased utilization. This is not
 422 consistent with the hypothesis that borrowers facing credit shocks (or asset value
 423 deterioration) will increase their credit line utilization. On the other hand, this finding
 424 is consistent with the theory that borrowers rationally manage their overall debt

425 exposure in the face of changes in asset value. That is, borrowers do not actively
426 increase their debt burden and thus increase the probability of optimal default when
427 property values fall. We also see that a decline in market interest rates and an increase
428 in the local unemployment rate each result in a lower probability of an increase in
429 utilization. The marginal effects indicate that a 1 percentage point decrease in the
430 interest rate results in a 2.7% drop in the probability of the borrower increasing
431 the credit line utilization. Although it implies that borrowers respond to changes in
432 price, an interesting question is why credit utilization increases rather than declines as
433 the cost of credit increases. In the meantime, contrary to our expectations, borrowers in
434 areas experiencing an adverse economic shock (increasing unemployment rates)
435 have a lower probability of increasing their credit utilization.

436 *4.3 Robustness Checks*

437 We conduct several robustness checks. Specifically, we are concerned that an
438 increase in utilization might just be a reflection of the permanent income hypothesis
439 and not necessarily a response to credit shocks.¹⁷ Hence, we control for both
440 financial and demographic characteristics of the borrower. Specifically, we control for
441 household wealth and income at account origination. Since both income and wealth
442 can be endogenous to changes in utilization, we control for them at account origina-
443 tion. We construct three control variables denoting low, medium, and high income
444 and wealth. Table 8 reports the distributions of the various segments, with 62%
445 of households having a net worth between \$50,000 and \$70,000, while 59% of
446 households have a gross income between \$40,000 and \$80,000. We define both
447 of these categories as medium wealth. Wealth for the low and high categories is
448 evenly distributed at 18%, while the low-income and high-income categories repre-
449 sent 12% and 27% of the households, respectively.¹⁸

450 Table 9 provides results for the determinants of net worth and income on pre-
451 payment, partial prepayment, and increased utilization. High income and wealth
452 categories are the control segments. We also interact the credit score with both income
453 and wealth. Income, wealth, and their interaction with credit scores are statistically
454 insignificant for prepayment. Income variables are also insignificant for increased
455 utilization. The results show that low- and medium-wealth households tend to
456 increase utilization in comparison to high-wealth individuals. Moreover, the interac-
457 tion of low- and medium-wealth households with credit score shows that an increase
458 in credit constraints within each wealth category also increases utilization. Finally,
459 even after controlling for both wealth and income, we show that households change
460 their credit line utilization in response to credit shocks.¹⁹

17. The permanent income hypothesis suggests that borrowers originate lines or loans depending upon their income or wealth level.

18. We chose the wealth and income cutoff levels based on examination of the distribution of borrower wealth and income for the sample. Furthermore, these variables were originally coded in discrete \$10,000 increments, limiting our ability to construct continuous variables.

19. In other specifications we also control for education, marital status, and other demographics. Though these variables are not populated for 100% of the sample, the results show that credit constraints, as measured by a drop in credit scores, are a significant determinant of increases in utilization of the credit line.

TABLE 8
DISTRIBUTION OF INCOME AND NET WORTH AT ORIGATION

Variable	Range	Percentage (%)
Low income	\$40,000–	12.56
Medium income	\$40,001–\$80,000	59.71
High income	\$80,001+	27.72
Low net worth	\$50,000–	18.59
Medium net worth	\$50,001–\$70,000	62.56
High net worth	\$70,001+	18.85

NOTE: This table reports the distribution of borrower income and net worth at credit line origination.

461 4.4 Potential Policy Implications

462 We identify two interesting relationships between borrower credit risk and credit
 463 line utilization. First, initial credit utilization is lower for borrowers with higher
 464 *a priori* expectations of a future credit deterioration. Second, there exists an inverse
 465 relationship between changes in borrower credit quality after origination and credit
 466 utilization. These results have direct implications for the treatment of credit line
 467 exposure at default (EAD) under the Basel II Capital Accord.²⁰ Specifically, our
 468 results show that a decrease in credit quality (increase in risk) results in a significant
 469 increase in credit line utilization. Consequently, the results indicate that EAD may
 470 be significantly higher in the event of credit line default. In other words, without
 471 considering the correlation between the borrower's probability of default (credit
 472 quality) and corresponding EAD (credit utilization), economic capital models may
 473 underestimate the impact of credit loss severity. Furthermore, due to the analogous
 474 treatment of EAD in consumer and commercial lines of credit, and since the new
 475 Basel II Capital Accord regulations require lenders to set aside capital based on
 476 risk, the results should provide some guidance to bank regulators concerning the
 477 need to evaluate credit line portfolios during periods when borrower credit quality
 478 is deteriorating.

479 The results also have potential implications on the effectiveness of monetary
 480 policy. Credit lines have the potential to provide borrowers with insurance against
 481 unexpected changes in monetary policy that might adversely impact either the pricing
 482 or availability of future credit. For example, central banks often act to curtail credit
 483 availability in an effort to slow economic growth in the face of inflation concerns.
 484 Yet, our results indicate that borrowers respond to rising interest rates by increasing
 485 credit line utilization. This implies that growth in credit line borrowing may limit
 486 the ability of the monetary authority to execute changes in policy that attempt to

20. One of the key features of the Basel II Accord is the Advanced Internal-Ratings-Based (A-IRB) method for determining a bank's minimum regulatory capital charge. The A-IRB method is designed to align bank minimum capital requirements with the economic risks associated with the bank's investments.

TABLE 9
COMPETING RISKS MODEL COEFFICIENT ESTIMATES OF CREDIT LINE OUTCOMES CONTROLLING FOR INCOME AND WEALTH

	Prepay		Decrease utilization		Increase utilization		p-value
	Coefficient value	Standard error	Coefficient value	Standard error	Coefficient value	Standard error	
Intercept	4.740	3.829	-3.267	0.675	-2.192	0.780	0.005
State Dummy CT	0.801	0.691	-0.221	0.085	-0.110	0.081	0.171
State Dummy MA	1.487	0.663	-0.250	0.078	-0.170	0.073	0.019
State Dummy NH	1.400	0.816	-0.565	0.099	-0.124	0.099	0.212
State Dummy NJ	-7.012	4.54.700	-0.440	0.742	-8.789	57.879	0.879
State Dummy NY	-1.399	1.172	-0.183	0.321	-0.279	0.331	0.399
State Dummy PA	-7.419	291.900	-1.059	0.730	-0.119	0.748	0.873
Age	-0.068	0.062	-0.018	0.009	0.014	0.009	0.130
Age (square)	0.001	0.001	1.2E-04	1.4E-04	-1.6E-04	1.5E-04	0.278
CLTV_Diff_Dummy	-0.049	0.176	-2.003	0.039	-1.600	0.029	<0.0001
CLTV	-0.026	0.003	-0.004	0.000	-0.057	0.001	<0.0001
FICO_Diff_Dummy	0.317	0.177	0.083	0.015	-0.051	0.016	0.002
FICO (lagged 4 months)	0.008	0.004	0.001	2.3E-04	-0.001	2.6E-04	0.001
APR_Diff_Dummy	-1.908	0.694	0.258	0.094	0.161	0.080	0.035
APR	-1.493	0.710	0.250	0.097	0.149	0.051	0.021
Unemp_Diff_Dummy	-0.686	0.701	-0.131	0.092	-0.083	0.094	0.374
Unemployment	-0.459	0.134	-0.175	0.019	-0.004	0.002	0.013
Net worth low	4.487	3.570	2.463	0.684	-0.321	0.104	0.017
Net worth medium	5.092	3.009	2.510	0.584	-0.818	0.383	0.023
Income low	-0.222	3.160	-1.197	0.557	3.147	0.649	<0.0001
Income medium	5.175	3.057	1.395	0.487	-0.969	0.563	0.085
FICO x net worth low	0.006	0.005	0.004	0.001	-1.1E-04	1.1E-04	0.009
FICO x net worth medium	0.006	0.004	0.003	0.001	-0.001	4.0E-04	0.012
FICO x income low	-4.5E-04	0.004	0.002	0.001	-0.004	0.001	<0.0001
FICO x income medium	0.007	0.004	0.002	0.001	-0.001	0.001	0.121

Notes: This table shows results of a proportional hazard model of prepayment, increasing utilization, and decreasing utilization using monthly date for home equity lines of credit from January 1998 to May 2002. Increased utilization is defined as increasing the credit line amount more than 20% in any given quarter. Decreased utilization is defined as decreasing the credit line amount by more than 20% but less than 100% in any given quarter. Although arbitrary, we chose the 20% cutoff criteria in order to focus on substantial changes in borrower credit line utilization. The independent variables control for calendar time, credit risk, current loan-to-value ratio, interest rates, county unemployment rates both at the level and differences, as well as borrower wealth and income. The competing risks model is estimated as a multinomial logit via maximum likelihood.

487 slow consumer spending. However, since credit lines are usually variable-rate debt,
488 it is hard to quantify whether the effectiveness of monetary policy will be constrained.
489 Further research is necessary to determine the impact of monetary policy on borrow-
490 ers who have credit lines.²¹

491 5. CONCLUSIONS

492 The literature on credit lines provides two interrelated hypotheses concerning
493 borrower credit risk and credit line utilization. First, initial credit utilization will be
494 lower for borrowers with higher expectations of future credit quality shocks. Second,
495 credit line utilization will be correlated with changes in borrower credit quality.
496 Using an objective measure of credit risk, the borrower's credit score, we are able to
497 estimate the impact of changes in risk on credit utilization. We also examine the
498 conditions that lead borrowers to prepay or pay down their credit lines.

499 Our analysis confirms that borrowers with greater expectations of a decline in
500 future credit quality originate credit lines to preserve financial flexibility. Further-
501 more, our results indicate that borrowers with lower credit scores at origination
502 utilize a lower percentage of their credit line than borrowers with higher credit
503 scores. Since we also document that borrowers with lower credit scores are more
504 likely to experience a subsequent decline in credit quality, we interpret the results
505 as suggesting that borrowers with lower credit quality scores recognize the benefits of
506 maintaining financial flexibility by retaining unused credit line utilization. In contrast,
507 borrowers with low expectations of a need for additional future credit utilize a
508 higher proportion of their credit lines at origination.

509 Our results show that borrowers who experience a decline of 10% in their FICO
510 score (credit quality) after origination increase their credit line utilization by 15.5%.
511 Furthermore, we also show that a 10% decline in borrower credit quality lowers
512 the probability of prepayment by 7.2%. These findings are consistent with the
513 theoretical "credit risk" prediction discussed by Strahan (1999).

514 Finally, we note that our results have two policy implications. First, for bank
515 regulators implementing the Basel II Capital Accord, our results suggest that capital
516 regulations for credit lines should reflect the possible changes in default exposure
517 as borrowers alter their credit utilization in response to changes in credit profiles.
518 Second, our results imply that the increasing prevalence of credit line borrowing
519 has implications for the ability of central banks to affect changes in consumer
520 behavior via monetary policy.

21. We thank the referee for providing the insight concerning policy implications of our results research.

APPENDIX

TABLE A1
ALTERNATE SPECIFICATIONS OF CREDIT QUALITY CHANGES

	12-month window			24-month window		
	Coefficient value	Standard error	p-value	Coefficient value	Standard error	p-value
Logit model estimation of the probability that borrower FICO score at the end of the observation window is less than the FICO score at origination						
Intercept	-8.424	2.098	<0.0001	-8.388	0.995	<0.0001
FICO at origination	-0.010	0.003	0.001	-0.010	0.001	<0.0001
State Dummy CT	-0.121	0.527	0.819	-0.071	0.260	0.785
State Dummy MA	-0.289	0.532	0.588	-0.136	0.248	0.583
State Dummy NH	-0.213	0.602	0.723	-0.256	0.301	0.394
State Dummy NJ	0.374	0.538	0.487	0.187	0.260	0.471
State Dummy NY	0.593	0.512	0.246	0.128	0.243	0.599
State Dummy PA	0.723	0.513	0.168	0.258	0.352	0.969
Likelihood ratio	74			129		
Number of observations	34,384			32,948		
Logit model estimation of the probability that borrower FICO score at the end of the observation window is less than the FICO score at origination						
Intercept	-6.100	1.664	2.00E-04	-8.356	0.831	<0.0001
FICO at origination	-0.008	0.002	2.00E-04	-0.012	0.001	<0.0001
State Dummy CT	-0.031	0.422	0.942	-0.254	0.234	0.278
State Dummy MA	-0.092	0.414	0.824	-0.169	0.222	0.447
State Dummy NH	-0.258	0.497	0.604	-0.364	0.264	0.167
State Dummy NJ	0.429	0.442	0.331	0.289	0.232	0.212
State Dummy NY	0.083	0.417	0.843	0.185	0.219	0.398
State Dummy PA	0.645	0.624	0.923	0.437	0.561	0.436
Likelihood ratio	92			147		
Number of observations	34,384			32,948		

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