CHAPTER 6

ASYMMETRIC INFORMATION AND THE AUTOMOBILE LOAN MARKET*

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Introduction

Information revelation can occur through a variety of mechanisms. For example, corporate finance research has established that a firm's dividend policies provide investors with information about future growth prospects.[1] In addition, research on residential mortgages indicates that borrowers reveal their expected tenure through their choice of mortgage contracts.[2] As a result, lenders offer a menu of mortgage interest rate and point combinations in an effort to learn about borrower potential mobility.[3] Similarly, lenders may anticipate how consumer debt will perform by observing the consumption choices that are being financed. With the proliferation of risk-based pricing in credit markets, lender's ability to further differentiate between borrower credit risks, based on consumer choice of goods, offers lenders a potentially important source to enhance profitability, as well as the potential to extend credit to a wider range of borrowers.[4]

In this study, we use a unique dataset of individual automobile loans to assess whether borrower consumption choice reveals information about future loan performance. For most Americans, the automobile is the second largest asset purchased (after housing), and as Grinblatt, Keloharju, and Ikaheimo (2004) observe, automobiles are highly visible consumption goods in which interpersonal effects clearly influence purchase decisions. Furthermore, in a study of the automotive leasing market, Mannering, Winston, and Starkey (2002) report that individual characteristics (e.g., income, education, etc.) impact consumer choice among methods for acquiring vehicles (either through leasing, financing, or cash purchase). As a result, the auto loan market provides an interesting laboratory for studying whether consumers reveal information about their expected performance on financial contracts through the type of product they purchase.

Insurers have long recognized that automobile makes and models appeal to different clienteles, and that these clienteles have heterogeneous risk profiles and accident rates. As a result, insurers routinely price automotive insurance based on car make and model. For example, insurance premiums on Volvos are not necessarily lower than premiums on BMWs due to any discernable difference in car safety, but rather result from the clientele that purchase these cars. That is, the typical Volvo driver may be less aggressive, and thus less prone to accidents, on average, than the typical BMW driver. Given that individual risk behavior is revealed in the automobile insurance market, a natural question arises as to whether consumption decisions also reveal individual financial (or credit) risk behavior. In other words, does the type of automobile purchased reveal information about the consumer's propensity to prepay or default on the loan that finances that purchase?

To answer this question, we adopt a competing-risks framework to analyze auto loan prepayment and default risks using a large sample of individual automobile loans. To the best of our knowledge, Heitfield and Sabarwal (2004) conduct the only other study of default and prepayment for automobile loans. Unlike Heitfield and Sabarwal (2004), who use performance data from sub-prime auto loan *pools* underlying asset backed securities, we use conventional (non-sub-prime) individual auto loan *level* data that provides individual loan and borrower characteristics (e.g., borrower income and credit risk score) and individual automobile characteristics (e.g., auto make, model, and year).

Our results can be summarized as follows. First, we find that factors that traditionally predict automobile default and prepayment continue to perform as expected. Specifically, we find that (1) a decline in borrower credit risk lowers the likelihood of default and raises the probability of prepayment; (2) an increase in the loan-to-value ratio increases the risk of default and lowers the likelihood of prepayment; (3) an increase in borrower income increases the probability of prepayment, whereas an increase in local area unemployment increases the risk of default; (4) a decrease in the market interest rate increases both the probability of prepayment and default. Finally, we also find that vehicle manufacturer location (America, Europe, and Japan) significantly impacts both the prepayment and default behavior of borrowers, and increases the model explanatory power by 52 percent. In an extended model, we also find significant dispersion in prepayment and default rates across the specific automobile manufacturers.

These results provide evidence that the type of automobile purchased reveals the consumer's propensity to prepay or default on the loan used to finance that purchase. Since knowledge of the type of automobile purchased is available to the lender at the point of origination, our results suggest that lenders could utilize this information in risk-based pricing by moving away from the standard "house-rate" loan pricing for auto loans. Risk-based pricing could not only help the bank achieve a lower capital allocation, but also provide credit access to higher-risk borrowers.

The remainder of this chapter is structured as follows. A brief discussion of the auto loan market is presented first. The next section describes the data, which is followed by the section that provides the methodology for empirical estimation. The subsequent section describes the regression results for the prepayment and default model for auto loans. The next section discusses the results in light of recent studies of the changes in vehicle manufacturer market share. The final section offers concluding remarks.

The Market for Auto Loans

According to Aizcorbe, Kennickell, and Moore (2003), automobiles are the most commonly held nonfinancial asset. For example, in 2001, over 84 percent of American households owned an automobile.[5] In contrast, approximately 68 percent of American households owned their primary residence.[6] Furthermore, loans related to automobile purchases are one of the most common forms of household borrowing (Aizcorbe and Starr-McCluer 1997; Aizcorbe, Starr, and Hickman, 2003). Consistent with the high penetration of automobile ownership among households and the average automobile purchase price, Dasgupta, Siddarth, and Silva-Risso (2003) note that the vast majority of auto purchases are financed. In fact, Aizcorbe, Starr, and Hickman (2003) report that in 2001 over 80 percent of new vehicle transactions were financed or leased. As a result, given the size of the U.S. automotive market, it is not surprising that automobile credit represents a sizeable portion of the fixed-income market. For example, in 2002, debt outstanding on automobile loans was over $700 billion, and a growing percentage of this debt is held in "asset backed securities."

Financing for automobile purchases comes from three primary sources: dealer financing, leasing, and third-party loans. Based on a sample of auto sales in Southern California between September 1999 and October 2000, Dasgupta, Siddarth, and Silva-Risso (2003) report that 24 percent of the transactions were leased, 35 percent of the sales were dealer-financed, and the remaining 40 percent of the cash transactions were most likely financed from third-party lenders (credit unions or banks). Furthermore, using a national sample of 654 households that purchased new vehicles, Mannering, Winston, and Starkey (2002) find that 51.6 percent financed, 28.1 percent paid cash, and 20.3 percent leased. Based on these surveys, clearly third-party financing represents a sizable portion of the automobile credit market.

One of the key features of the third-party auto loan market is the standard practice of using a "house rate" for pricing loans, such that all qualified borrowers with similar risk characteristics pay the same rate at any given point in time. In other words, prospective borrowers secure a loan before they contract to buy. The lender simply underwrites the loan based on the borrower's credit score and required downpayment.[7] With the loan commitment in hand, the borrower then shops for a particular vehicle. As a result, these lenders do not incorporate information about the purchase decision into the loan pricing.

In contrast, before lenders originate a mortgage, typically they have information on the underlying asset as well as the borrower's personal characteristics. Thus, information about the underlying asset often plays a role in determining the mortgage contract rate. For example, lenders know that a borrower who seeks a loan above the government-sponsored enterprise "conforming loan limit" is almost certainly purchasing a high-valued asset, while a borrower who requests an FHA-insured mortgage is likely purchasing a lower-valued home. Since standard mortgage-pricing models show that the volatility of the underlying property value is important in determining the probability of mortgage termination, borrowers originating mortgages on properties with higher volatilities pay higher contract rates.[8]

Extending this analogy to the auto loan market, if third-party lenders required information about the car being purchased prior to approving the loan, then they could price that into the loan. Currently, this is not the practice. Thus, our study suggests an avenue for lenders to potentially increase auto loan profitability by utilizing the information about the car being purchased when they set their loan terms.

Data

The data comes primarily from a large financial institution that originates *direct* automobile loans.[9] Our data consists of 6,996 loans originated for purchase of new and used automobiles. The loans have fixed interest rates and are originated with four- or five-year maturities. We observe the performance of these loans from January 1998 through March 2003, providing a monthly record for each loan until it either prepays, defaults, pays in full at maturity, or is still current as of the last month of the observation period (right censored). We classify a loan as prepaid if, prior to maturity, the borrower pays off a loan having a balance greater than $3,000.[10] Following standard industry practice, we classify a loan as being in default when the payment is 60 days past due.[11] We removed loans from the analysis if (1) they originated after March 2002, (2) they were made to lender employees, and (3) the automobile was stolen or fraud was suspected. Using our default and prepayment definitions, we find that 1,216 loans had prepaid (17.4 percent), 251 loans had defaulted (3.6 percent), and 5,529 loans were still active as of the last date of the study period.

Loan characteristics include automobile value, automobile age, loan amount, loan-to-value (LTV), monthly payments, contract rate, time of origination (year and month), as well as payoff year and month in the cases of prepayment and default. We also have access to the automobile model, make, and year. Borrower characteristics include credit score (FICO score), monthly disposable income, and borrower age. The majority of the loans originated in eight northeast states.

Since the purpose of our study is to determine whether the type of vehicle reveals information about future loan performance, we classify the cars by manufacturer headquarter location (i.e., American, Japanese, or European). Although this is a crude initial classification of the auto market, classification of automobiles along this basic dimension follows the prevailing consumer sentiment of the automotive market. Obviously, this classification system no longer matches the global automotive manufacturing landscape. For example, BMW has manufacturing plants at 23 sites in 15 countries; Chrysler (one of the Big Three U.S. manufacturers) merged with the German firm Daimler-Benz in 1998 to form DaimlerChrysler, and General Motors

(GM) is the largest shareholder of South Korean manufacturer, Daewoo. However, most consumers still perceive the foreign/domestic classification when referring to automobiles. For example, the Toyota Camry is generally referred to as a Japanese car even though it is manufactured in Georgetown, Kentucky, and Chrysler products are still perceived as American even though Chrysler is a unit of DaimlerChrysler.

Following standard practice, we differentiate cars by their make and model. Automotive make refers to the car manufacturer (e.g., BMW, Toyota, Ford, etc.), model defines the particular car (e.g., BMW 325, Toyota Camry, etc.), and vintage denotes the model year.[12]

Table 6.1 presents the sample descriptive statistics and also reports a series of pair-wise t-statistics testing the null hypothesis that the sample means are equal across manufacturer location. At this basic classification level, we find significant differences. For example, given the concentration of European manufacturers in the U.S. luxury-auto segment, we find that the average price for European cars ($27,269) is significantly greater than the average cost for American or Japanese cars ($19,441 and $21,149, respectively). Consistent with this pricing pattern, we also observe that European cars have higher loan amounts. Since lenders offer a "house rate" for automotive loans, we note that no significant difference exists in loan interest-rate spreads at origination.[13]

Table 6.1 also reports borrower characteristics. For example, on average, borrowers who purchased American cars were older (45 years versus 41 and 38 for European and Japanese buyers, respectively), borrowed more relative to the purchase price (80 percent versus 65 percent and 76 percent for European and Japanese buyers, respectively), and had higher credit scores (720 versus 715 and 708 for European and Japanese buyers, respectively). We also see that European car purchasers had higher monthly incomes on average ($4,625) than either American ($4,024) or Japanese ($4,114) buyers.

Table 6.2 shows the sample distribution by loan outcome and manufacturer location. We note that differences appear in loan performance based on automotive type. For example, 19.9 percent of the loans on European cars were prepaid versus 18.1 percent of loans on American cars and 15.5 percent of loans on Japanese cars. Also interesting is that European and Japanese car loans have lower default rate (2.9 percent) than American car loans (4.7 percent). In the next section, we present a more formal analysis of loan performance.

Methodology

Following the standard practice in mortgage performance analysis, we estimate a competing-risks model of auto loan prepayment and default. The competing-risks framework has the advantage of explicitly recognizing the mutually exclusive nature of prepayment and default. That is, if the borrower exercises the prepayment option then this necessarily means that the borrower is unable to exercise the option to default and vice versa. In the mortgage literature, recent studies such as Deng et al. (2000), Ambrose and Sanders (2005), and Calhoun and Deng (2002) use this competing-risks framework, while Heitfield and Sabarwal (2004) employ the same method in analyzing pool-level auto loan data.[14] As with Gross and

Table 6.1 Descriptive statistics—means and standard deviations

Cars Make	*Price*	*Loan Amt.*	*Mth. Pymt.*	*Rate Spread*	*Income*	*Credit Score*	*LTV*	*Unemp.*	*Owner Age*	*Frequency*
American cars (U.S.)	\$19,441	\$15,765	\$324	0.95	\$4,024	720	80%	4.36	45	2780
Std	\$4,637	\$3,338	\$615	0.56	\$2,022	61	17%	1.04	14	
Japanese cars (JP)	\$21,149	\$16,347	\$323	0.97	\$4,114	708	76%	4.15	38	2873
Std	\$4,929	\$3,087	\$535	0.58	\$2,109	62	17%	1.05	12	
European cars (EU)	\$27,269	\$17,708	\$353	0.96	\$4,625	715	65%	4.14	41	1343
Std	\$7,483	\$4,215	\$676	0.57	\$2,196	61	17%	1.06	12	
All cars	\$21,597	\$16,177	\$329	0.96	\$4,173	714	74%	4.23	41	6996
Std	\$6,091	\$3,445	\$596	0.57	\$2,102	61	17%	1.06	13	
T-test U.S.-JP	−13.41⋆	−6.81⋆	0.03	−1.31	−1.63	7.12⋆	8.84⋆	7.57⋆	21.10⋆	
T-test U.S.-EU	−41.17⋆	−16.03⋆	−1.38	−0.04	−8.69⋆	2.44⋆⋆	26.55⋆	6.28⋆	9.56⋆	
T-test JP-EU	−31.57⋆	−11.80⋆	−1.54	1.00	−7.24⋆	−3.29⋆⋆	19.57⋆	0.23	−7.50⋆	

Note: ⋆ significant at the 1 percent level, ⋆⋆ significant at the 5 percent level, ⋆⋆⋆ significant at the 10 percent level.

Table 6.2 Auto loans by outcome

	American	*Percentage*	*Japanese*	*Percentage*	*European*	*Percentage*	*Total*	*Percentage*
Good accounts	2146	77.19	2346	81.66	1037	77.22	5529	79.03
Default	130	4.68	82	2.85	39	2.90	251	3.59
Prepayment	504	18.13	445	15.49	267	19.88	1216	17.38
Total	2780	100	2873	100	1343	100	6996	100

Souleles (2002) and Heitfield and Sabarwal (2004), we use the discrete outcome interpretation of duration models as presented by Shumway (2001).

In the competing-risks framework, we first recognize that during our observation period a borrower prepays, defaults, or else remains current through the end of the time period of study (censored). We define T_j ($j = 1,2,3$) as the latent duration for each loan to terminate by prepaying, defaulting, or being censored, and the observed duration, τ, is the minimum of the T_j.

Conditional on a set of explanatory variables, x_j, that include personal risk characteristics, market conditions at the time of origination, and characteristics of the consumption choice, the probability density function (*pdf*) and cumulative density function (*cdf*) for T_j are

$$f_i(T_j|x_j;\theta_j) = h_j(T_j|x_j;\theta_j)\exp(-I_j(r_j|x_j;\theta_j)) \tag{1}$$

$$F_j(T_j|x_j;\theta_j) = 1-\exp(-I_j(r_j|x_j;\theta_j)) \tag{2}$$

where I_j is the integrated hazard for outcome j:

$$I_j(T_j|x_j;\theta) = \int_0^{T_j} h_j\,(s|x_j;\theta_j)\,ds, \tag{3}$$

r_j is an integer variable taking values in the set $\{1,2,3\}$ representing the possible loan outcomes, and h_j is the hazard function.

The joint distribution of the duration and outcome is

$$f(\tau,j|x;\theta) = h_j(\tau|x_j;\theta_j)\exp(-I_0(\tau|x;\theta)) \tag{4}$$

where $x = (x_1,x_2,x_3)$, $\theta = (\theta_1, \theta_2, \theta_3)$ and $I_0 = \Sigma\ I_j$ is the aggregated integrated hazard. Thus, the conditional probability of an outcome is

$$\Pr(j|\tau,x;\theta) = \frac{h_j(\tau|x_j;\theta)}{\sum_{j=1}^{3} h_j(\tau|x;\theta)}. \tag{5}$$

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

$$h_j(\tau_j | x_j;\theta_j) = \exp(x'_j \beta_j). \tag{6}$$

and estimate (5) in a multinomial logit framework.

Since our purpose is to determine the information content of borrower consumption decisions on loan performance, we follow Gross and Souleles (2002) and separate x_j into components representing borrower risk characteristics, economic conditions, and consumption characteristics. Specifically, we assume that

$$x'_j \beta_j = \beta_0 \tau_t + \beta_1 age_{jt} + \beta_2 risk_{jt} + \beta_3 econ_{jt} + \beta_4 car_{jt} \tag{7}$$

where τ_t represents a series of dummy variables corresponding to calendar quarters that allows for shifts over time in the propensity to default or prepay; age_{jt} is a third order polynomial in loan age that allows for nonparametric variation in the prepayment and default hazard; $risk_{jt}$ represents a set of borrower characteristics, including credit score, that reflect the lender's underwriting criteria; $econ_{jt}$ is a set of variables capturing changes in local economic condition, and car_{jt} is a set of variables identifying information concerning the type of car purchased.

In equation (7), the combination of the age variables (age_{jt}) and the risk measures ($risk_{jt}$) account for borrower risk in the auto loans. As Gross and Souleles (2002) point out, "age_{jt} allow for duration dependence in the baseline hazard" while the initial risk characteristic ($risk_{j0}$) "allows this hazard to shift across accounts that start the sample period with different risk characteristics."[15]

To establish a baseline to judge the importance of product information on loan performance, we first estimate a restricted model of prepayment and default with only age_{jt} and τ_t:

$$x'_j \beta_j = \beta_0 \tau_t + \beta_1 age_{jt}. \tag{8}$$

Since age_{jt} represents a third-order polynomial, the corresponding prepayment and default hazards are nonparametric. By incorporating the quarterly time dummy variables, we are able to determine whether the baseline hazards of prepayment and default have shifted over time.

Next, we extend the analysis to include borrower risk characteristics and local economic conditions:

$$x'_j \beta_j = \beta_0 \tau_t + \beta_1 age_{it} + \beta_2 risk_{jt} + \beta_3 econ_{jt}. \tag{9}$$

Equation (9) represents the traditional loan performance specification and is extensively used in the analysis of mortgage and credit card performance. We then extend this model to the full specification described in (7) that includes information about the asset securing the loan. By comparing the model log-likelihood ratio statistics, we can determine the marginal impact of incorporating consumer consumption information in evaluating the likelihood of loan default or prepayment.

In modeling the termination probability of auto loans, we incorporate a set of explanatory variables that capture the financial incentives associated with prepayment. For example, to approximate the value of the borrower's prepayment option, we follow the standard approach followed in the mortgage literature, as outlined in Deng, Quigley, and Van Order (2000), and estimate the prepayment option as

$$PPOPTION_{j,t} = \frac{V_{j,t} - V^{*}_{j,t}}{V_{j,t}} \tag{10}$$

where $V_{j,t}$ is the market value of loan j at time t (i.e., the present value of the remaining payments at the current market rate), and $V^{*}_{j,t}$ is the book value of loan j at time t (i.e., the present value of the remaining payments at the contract interest rate). We calculate $V_{j,t}$ by assuming that the current market rate at time t is the average auto loan interest rate in month t as reported in the Informa interest rate survey. Since consumers are more likely to prepay following a decline in the prevailing interest rate relative to the original contract rate, a positive value for *PPOPTION* is indicative of an "in-the-money" prepayment option. In order to account for any nonlinearity in the prepayment option, we also include the square of *PPOPTION*.

To determine the impact of differences in auto depreciation rates on loan termination probabilities, we estimated the depreciation schedule for each auto manufacturer based on the five-year blue-book values reported by the National Automobile Dealers Association (www.nada.com). For example, to determine the average expected depreciation for Subaru vehicles, we collected the estimated market value during the fall of 2003 for the base-level Forrester, Impresa, and Legacy models beginning with the 1998 model year through the 2002 model year. This provides a rough estimate of the yearly change in value for a base-level model experiencing an average driving pattern. For each model, we calculate the yearly depreciation experienced by the baseline car and then average the expected depreciation by manufacturer. Unfortunately, given the heterogeneous nature of the models from year to year, we are unable to match all models to a set of used car values. Thus, we assume that all models within each manufacturer follow a similar depreciation schedule. Obviously, our valuation algorithm is only an approximation since individual cars will vary based on the idiosyncratic driving habits of the borrowers.

Based on these estimated changes in value, we construct monthly loan-to-value ratios (*CLTV*). We expect *CLTV* to be positively related to default since higher depreciation in auto values, holding other things constant, serves to increase the loan-to-value ratio. Given the significant depreciation in auto values upon purchase, many borrowers have an auto loan balance greater than the current car value. Thus, including *CLTV* allows for a direct test for the link between auto quality and credit performance. That is, if an auto manufacturer produces a disproportional number of low-quality cars, then the secondary market value for the manufacturer's cars will reflect this lower quality. We also include the square of *CLTV* to control for any nonlinearity.

In addition to changes in the auto value relative to the debt burden, we also capture changes in borrower credit constraints via the time-varying borrower credit score (*FICO*). Borrower credit history is one of the key determinants of auto loan approval. Thus, we expect the *FICO* score to be negatively related to default, implying that borrowers with lower current *FICO* scores are more likely to default on their auto loans. We also include the square of *FICO* to capture any nonlinearity present in borrower credit scores.

Local economic conditions may also impact borrower loan termination decisions. For example, borrowers who lose their jobs are more likely to default due to inability to continue the loan payments. We use the county unemployment rate (*UnempRate*), updated monthly, as a proxy for local economic conditions. Finally, we include a series of dummy variables that denote the borrower's location (state) to control for unobserved heterogeneity in local economic conditions.

As discussed earlier, the set of variables included in *car* represents information about the purchase decision that is available to the lender at the time of loan origination, but is not utilized in the underwriting decision. By incorporating this set of information into the model, we can ascertain whether data about the consumption decision contains predictive value concerning the performance of debt. Although rather obvious, we also include the auto purchase price in the performance model. Since the lender provides the loan commitment prior to the purchase decision, the lender does not know the actual purchase price. We also include the square of the purchase price to control for any nonlinear effects. Next, we incorporate a dummy variable that is set equal to one if the purchase price is above the average purchase price for that car manufacturer. This variable is designed to flag borrowers who are purchasing higher-valued cars relative to other cars sold in that brand. Finally, in separate models we include a series of dummy variables that control for either the type of auto manufacturer (American, Japanese, or European) or specific auto manufacturer (e.g., BMW, GM, Toyota, etc.).

Results

As outlined earlier, we first estimate the baseline survival function of the cumulative likelihood of automobile loans surviving (i.e., not prepaying or defaulting) by manufacturer location. Figures 6.1 and 6.2 present the baseline survival curves for prepayment and default by manufacturer location (America, Japan, or Europe), respectively. Figures 6.3 and 6.4 present the baseline survival curves for, prepayment and default by vehicle make (Benz, VW, Chevy, Dodge, Honda, Toyota), respectively. While over 20 different automobile makes are in our dataset, we present only the results for select automobile makes.

Considering prepayment first, figures 6.1 and 6.3 show clearly that at any given age, European automobiles (Benz and VW) have a lower survival rate than either American or Japanese, and the prepayment survival rates for American and Japanese automobiles are statistically indifferent. This implies that at a given age, the prepayment rate of European automobiles is higher than that of American and Japanese, and American and Japanese automobiles have relatively the same prepayment rates.

Figure 6.1 Prepayment probability of European (EU), Japanese (JP), and American (US) automobiles

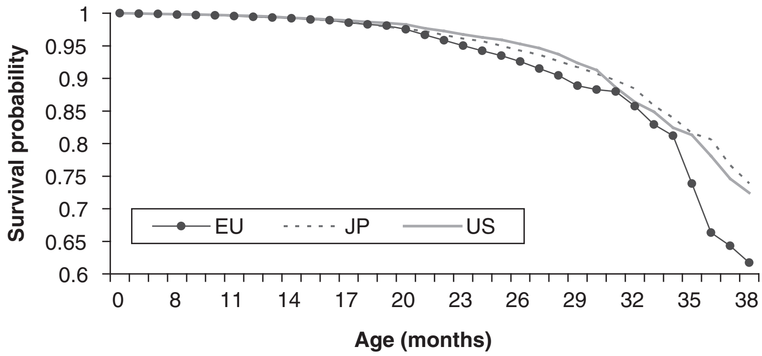


Figure 6.2 Default probability of European (EU), Japanese (JP), and American (US) automobiles

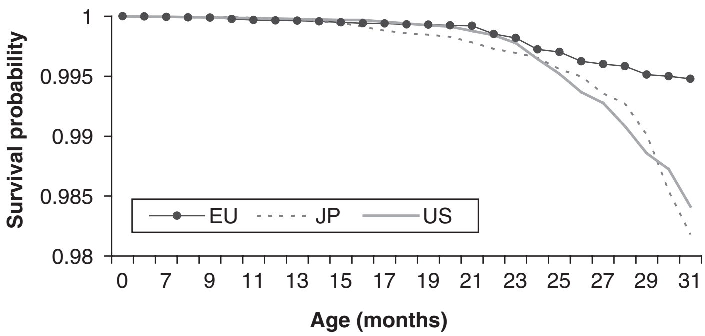


Figure 6.3 Prepayment probability of select automobile makes

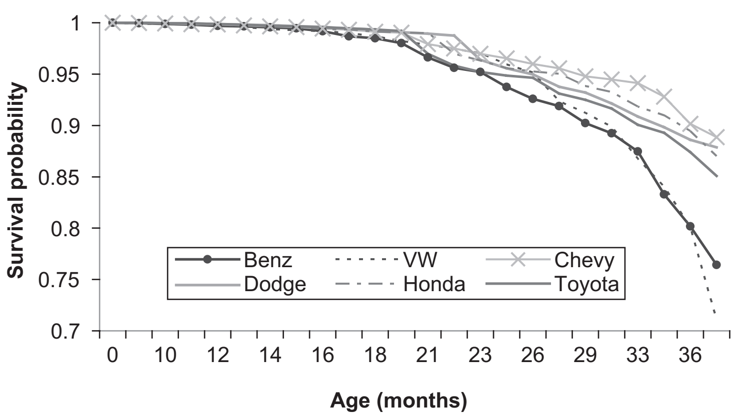
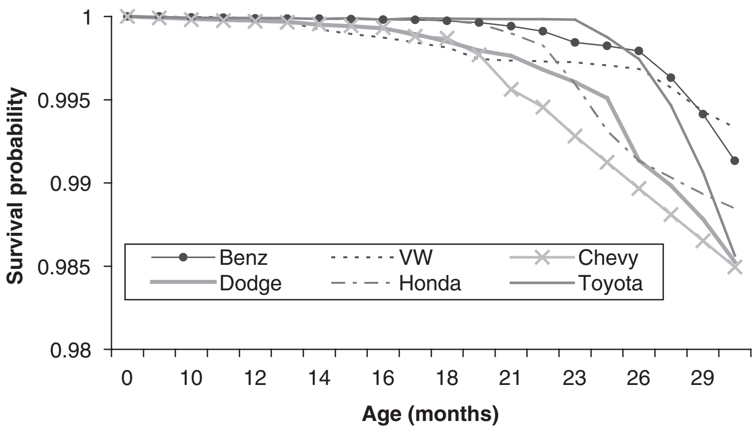


Figure 6.4 Default probability of select automobile makes



Figures 6.2 and 6.4 show the baseline default survival curves. Unlike the baseline prepayment survival curves, the default survival curves for European automobiles are higher (Benz and VW) than American and Japanese, implying that European cars have lower default risk relative to the American or Japanese cars. Once again, we do not find significant differences between the default survival rates for American and Japanese automobiles. Next, we present a more formal analysis to determine the prepayment and default behavior of automobile types.

Table 6.3 presents the estimated coefficients for the competing-risks models. Model 1 is the baseline case as represented in equation (8). Based on the log-likelihood statistic for this model, the pseudo R^2 is 8.2 percent.[16] The statistically significant coefficients for *AGE*, *AGE2*, and *AGE3* indicate that the prepayment and default hazards follow a distinctly nonlinear pattern. Each subsequent model reflects the inclusion of a new set of explanatory variables.

Model 2 corresponds to equation (9) and represents the introduction of borrower risk characteristics and local economic conditions into the specification. Again, this model represents the traditional loan performance model. Adding borrower and local risk characteristics doubles the model's explanatory power, raising the pseudo R^2 from 8.2 to 16.6 percent.

Turning to the individual risk variables, we find the expected relation between current borrower credit score and the probability of default or prepayment. The negative and significant credit score coefficient on the default model indicates that the likelihood of borrower default declines as borrower credit quality increases. Examining the marginal effect of credit score indicates that a 20-point increase in borrower credit quality reduces the likelihood of default by 9.9 percent.[17] On the prepayment side, the positive and significant coefficient for credit score indicates that a 20-point increase in credit quality raises the probability of prepayment by 3.3 percent. These marginal effects clearly demonstrate the asymmetric response to changes in borrower credit quality on auto loan performance. We also find that

Table 6.3 Competing Risks Models

	Model 1		Model 2		Model 3		Model 4	
Variable	*Default*	*Prepayment*	*Default*	*Prepayment*	*Default*	*Prepayment*	*Default*	*Prepayment*
Intercept	−7.194300	−2.910700	−10.330200	−12.129600	−10.757800	−12.650300	−10.984600	−12.863500
	−11.79	−11.19	−3.62	−5.81	−3.75	−6.02	−3.75	−6.09
Monthly incomet$_0$			−0.000400	0.000010	−0.000380	0.000020	−0.000390	0.000020
			−3.81	2.00	−3.62	3.28	−3.61	2.00
Monthly income$_{t0\ (sq)}$			0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
			3.86	−0.70	3.68	−0.83	−3.55	−0.79
Credit score$_{t\text{-}6}$			−0.032400	0.022500	−0.032100	0.022900	−0.029400	0.023100
			−3.76	3.82	−3.75	3.88	−3.41	3.91
Credit score$_{t\text{-}6(sq)}$			0.000040	−0.000020	0.000040	−0.000020	0.000040	−0.000020
			0.57	−4.71	5.69	−4.70	5.67	−4.69
Unemployment$_{t\text{-}6}$			0.136600	−0.084500	0.136800	−0.087300	0.109800	−0.088500
			1.85	−2.20	2.14	−2.27	1.95	−2.30
CLTV$_{t\text{-}6}$			5.129400	−9.708600	5.136400	−9.649800	4.765600	−9.672500
			2.78	−11.41	2.76	−11.34	2.62	−11.36
CLTV$_{t\text{-}6(sq)}$			3.142500	−9.849800	3.119800	−9.793600	2.762100	−9.828800
			1.60	−10.92	1.58	−10.86	1.44	−10.90
Payment$_{t\text{-}6}$			0.000191	0.000299	0.000192	0.000294	0.000193	0.000294
			2.25	6.23	3.00	6.13	2.12	6.13
Car value$_{t0}$			0.000046	0.000013	0.000092	0.000053	0.000134	0.000040
			2.19	1.70	2.19	3.12	2.63	2.11

Continued

Table 6.3 Continued

	Model 1		*Model 2*		*Model 3*		*Model 4*	
Variable	*Default*	*Prepayment*	*Default*	*Prepayment*	*Default*	*Prepayment*	*Default*	*Prepayment*
Car value$_{t0(sq)}$			0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
			−1.14	−0.02	−1.47	−2.13	−2.05	−1.47
PPOption$_{t-6}$			0.407300	0.587300	0.368000	0.606200	0.346600	0.612100
			3.06	3.57	2.75	3.68	2.52	3.71
PPOption$_{t-6(sq)}$			0.009750	0.188500	0.019400	0.192500	0.021500	0.194300
			0.68	3.58	1.36	3.65	1.43	3.68
Owner age			−0.091900	−0.042800	−0.093500	−0.045200	−0.091400	−0.044600
			−3.85	−4.56	−3.88	−4.81	−3.70	−4.69
Owner age^2			0.000929	0.000398	0.000941	0.000411	0.000937	0.000415
			3.48	3.90	3.51	4.03	3.39	4.03
Loan age	−0.182300	0.161600	−0.109900	0.197700	−0.108300	0.197600	−0.098200	0.197400
	−2.45	4.42	−3.29	5.33	−1.30	5.33	−1.18	5.32
Loan age^2	0.006320	−0.009430	0.003220	−0.010100	0.003130	−0.010100	0.002750	−0.010100
	2.26	−6.01	2.90	− 6.39	1.00	−6.39	0.89	−6.39
Loan age^3	−0.000075	−0.000150	−0.000047	−0.000140	−0.000046	−0.000140	−0.000042	−0.000140
	−2.34	−7.14	−1.31	−6.67	−1.28	−6.67	−1.17	−6.67
Buick dummy							−1.733700	−0.069800
							−1.00	−0.42
Cadillac dummy							−0.549700	0.379300
							−2.48	2.62
Chevy dummy							−0.150100	−0.328000
							−0.52	−3.52

Chrysler dummy	−0.936900	0.473700
	−0.90	2.68
Dodge dummy	1.045200	−0.358100
	3.74	−3.36
Geo dummy	−1.115200	1.178300
	−0.91	1.14
GM dummy	−0.442000	0.263900
	−0.88	2.07
Lincoln dummy	0.591700	0.111200
	4.01	0.74
Oldsmobile dummy	0.813400	0.210100
	2.24	1.14
Plymouth dummy	0.046600	0.427800
	1.76	2.39
Pontiac dummy	0.527400	0.377500
	2.38	2.52
Saturn dummy	1.814300	−0.204200
	3.87	−0.85
Audi dummy	−1.489800	0.218300
	−1.95	3.05
BMW dummy	−0.247100	0.106400
	−2.20	2.07
Jaguar dummy	−0.862600	0.396700
	−1.44	2.50

Continued

Table 6.3 Continued

	Model 1		*Model 2*		*Model 3*		*Model 4*	
Variable	*Default*	*Prepayment*	*Default*	*Prepayment*	*Default*	*Prepayment*	*Default*	*Prepayment*
Benz dummy							0.194300	0.021900
							2.16	3.07
Saab dummy							−0.721300	0.225600
							−3.08	1.52
Wolkswagen dummy							0.012400	0.024600
							0.04	0.21
Accura dummy							0.071900	−0.084200
							0.21	−2.69
Honda dummy							−0.004120	−0.092600
							−2.35	−1.97
Infinity dummy							−0.214800	0.342100
							−1.89	2.24
Isuzu dummy							1.105700	−0.173300
							3.15	−0.80
Lexus dummy							−0.270200	0.444600
							−2.42	2.94
Mazda dummy							0.333600	0.077600
							2.09	0.50
Mitsubishi dummy							0.226300	0.302900
							1.94	2.27

Nissan dummy							0.4359	0.1295
							2.01	1.31
Subaru dummy							−1.8415	0.0183
							−4.24	0.10
European auto dummy					−0.148100	−0.231600		
					−3.71	−4.06		
Japan auto dummy					−0.262600	−0.323000		
					−2.28	−2.92		
Above avg. car dummy					0.345900	0.094300	0.533400	−0.054200
					2.00	1.48	2.68	−0.76
Used car dummy	0.213500	0.008340	0.154100	0.040900	0.114000	0.042900	0.165600	0.034500
	1.92	0.20	1.36	0.98	0.99	1.00	1.40	0.79
CT dummy	0.320800	−0.494400	−0.366100	−0.536300	−0.359300	−0.540000	−0.315800	−0.550100
	1.96	−7.86	−2.08	−8.21	−2.04	−8.27	−1.77	−8.39
FL dummy	−1.138400	−0.093300	−1.991100	0.020200	−1.347700	−0.001480	−1.897400	−0.021900
	−1.03	−0.49	−1.53	0.11	−1.12	−0.01	−2.03	−0.11
ME dummy	−2.717600	−0.165800	−2.493900	−0.124500	−2.516300	−0.146300	−2.402200	−0.157200
	−2.70	− 1.47	−2.46	−1.07	−2.48	−1.26	−2.35	−1.35
NH dummy	−1.678000	−0.000070	−1.518500	−0.047600	−1.518000	−0.062700	−1.603900	−0.064500
	−3.29	0.00	−2.94	−0.53	−2.94	−0.70	−3.07	−0.71
NJ dummy	−0.945200	−0.379900	−0.996400	−0.314200	−1.006900	−0.317300	−1.080200	−0.323100
	−3.91	−5.43	−3.92	−4.01	−3.96	−4.04	−4.18	−4.10
NY dummy	−0.039300	−0.499800	0.275700	−0.366100	0.260200	−0.388700	0.234000	−0.394800
	−0.30	−9.70	1.51	−4.61	1.43	−4.88	1.24	−4.94
PA dummy	−1.384400	−0.338900	−0.939600	−0.238900	−0.962600	− 0.236700	−0.860700	−0.251500
	−1.38	−1.48	−0.92	−1.02	−0.94	−1.01	−0.84	−1.07

Continued

Table 6.3 Continued

	Model 1		*Model 2*		*Model 3*		*Model 4*	
Variable	*Default*	*Prepayment*	*Default*	*Prepayment*	*Default*	*Prepayment*	*Default*	*Prepayment*
RI dummy	0.564700	−0.193800	0.460400	−0.105100	0.462100	−0.103300	0.452800	−0.089900
	2.57	−1.76	1.97	−0.90	1.97	−0.89	1.87	−0.77
Q399 dummy	−1.120600	−0.031700	−0.777500	−0.044200	−0.773500	−0.045300	−0.749500	−0.039500
	−3.10	−0.35	−2.12	−0.48	−2.11	−0.49	−2.04	−0.42
Q499 dummy	−1.093300	−0.260400	−0.883200	−0.335700	−0.873900	−0.337500	−0.839500	−0.334600
	−3.21	−2.72	−2.56	−3.40	−2.53	−3.42	−2.43	−3.39
Q100 dummy	0.531200	0.007800	0.234200	−0.013500	−0.231300	−0.011200	−0.221200	−0.010200
	2.11	0.09	0.91	−0.16	−0.89	−0.13	−0.85	−0.12
Q200 dummy	0.277000	−0.180800	0.107200	−0.178300	0.103900	−0.172800	0.104400	−0.172400
	1.26	−1.99	0.46	−1.88	0.45	−1.82	0.45	−1.82
Q300 dummy	0.114500	−0.087900	0.376700	−0.024400	0.374000	−0.016600	0.353800	−0.017400
	0.57	−1.01	1.68	−0.26	1.66	−0.18	1.57	−0.19
Q400 dummy	0.403500	0.989700	0.114100	1.065300	0.108500	1.074100	0.093200	1.072900
	1.73	17.15	0.44	15.13	0.41	15.21	0.36	15.20
Q101 dummy	−0.192300	0.049300	0.341600	0.134100	0.333200	0.142500	0.351100	0.141200
	−0.84	0.55	1.27	1.28	1.23	1.35	1.29	1.34
Q201 dummy	−0.220400	−0.159600	0.228800	−0.077100	0.221100	−0.068300	0.214200	−0.072000
	−0.94	−1.60	0.84	−0.69	0.81	−0.61	0.79	−0.64
Pseudo- R^2	0.08		0.16		0.23		0.26	
Number of observations	290685/6996		290685/6996		290685/6996		290685/6996	

Note: The table provides the coefficient values and the t-statistics (below the coefficient value).

borrower income has the expected impact on prepayment and default. The significantly negative coefficient for monthly income in the default model suggests that borrowers with higher incomes at loan origination are less likely to default. Conversely, higher-income borrowers are more likely to pay off their loan prior to maturity.

The impact of the current loan-to-value ratio also follows the anticipated pattern. The positive and significant coefficient in the default model indicates that the probability of default increases as the loan-to-value ratio increases. Since these loans are positive amortizing loans, an increase in the current loan-to-value implies that the underlying asset (the car) value has declined. On the prepayment side, the significantly negative coefficient suggests the opposite effect. That is, a decline in the asset's value reduces the likelihood of prepayment.

The coefficients for the variable measuring the borrower's incentive to prepay are significant and have the expected signs. Recall that the variable *PPOPTION* captures the borrower's financial incentive to prepay as reflected in the relative difference between the current market loan rate and the contract interest rate. Since positive values of *PPOPTION* indicate that the borrower's prepayment option is "in-the-money," the significantly positive coefficient for *PPOPTION* in the prepayment model indicates that borrowers are more likely to pay off their auto loan when interest rates decline. Not surprisingly, we find that *PPOTION* is significant in the default model, suggesting that current interest rates have a considerable impact on the borrower's default decision.

Finally, we note that the local unemployment rate is significantly positive in the default model. We use the unemployment rate as a proxy for local economic conditions, with higher unemployment rates implying worsening economic conditions. Thus, the positive coefficient in the default model implies that during periods of greater economic uncertainty, the probability of auto loan default increases; however, we note that the coefficient for unemployment is not significant in the prepayment model.

Model 3 represents our first attempt to include information beyond the traditional risk factors associated with loan performance. In Model 3 we include two dummy variables denoting whether a European or Japanese automobile secures the loan. We find that including these dummy variables in the loan performance model increases the pseudo R^2 by 28.5 percent (from 16.6 to 23.2 percent), supporting our hypothesis that the consumer consumption decision provides information about the performance of the debt securing the car. The marginal effects indicate that loans secured by European and Japanese cars are 50 percent and 56 percent, respectively, less likely to default than loans secured by American cars. We also find that loans on European cars are 18.8 percent less likely to prepay than loans secured by American cars, while loans on Japanese cars are 11.7 percent less likely to prepay than loans secured by American cars. From a risk-reward trade-off standpoint, the results suggest that loans to borrowers who purchase Japanese cars have the lowest default risk, while loans to borrowers of European cars have the lowest prepayment risk (most likely to be carried to maturity). We note that the variables controlling for the car purchase price are not significant in the prepayment or default models.

As a final test of the information value related to the consumption decision, we incorporate a series of dummy variables for each auto manufacturer (Toyota is the base case) in Model 4. We find that incorporating greater specificity about the type of car purchased provides only marginal improvement in assessing the probability of a loan prepaying or defaulting. We note that the pseudo R^2 for Model 4 increases only 10.8 percent (from 23.1 to 25.9 percent). However, the individual coefficients reveal that significant dispersion exists in the performance of auto loans after controlling for manufacturer. For example, we see that loans on Saturns have default hazards that are 22 times higher than the default hazard of Toyotas. Furthermore, the individual responses show that the hazards are not monolithic. For example, although the results from Model 3 indicate that loans on U.S. cars have significantly higher default rates, incorporating individual manufacturer control variables shows that five of the American auto manufacturers have significantly higher default hazards than Toyota, while one has significantly lower default hazards. In addition, we find significant variation within the foreign vehicle segment. For example, the model coefficients indicate that loans on Mazdas are six times more likely to default than loans on Toyotas.

The results clearly show that significant variation exists in the default hazard rates on auto loans across manufacturer, even after controlling for the usual factors considered by lenders at the time of loan origination. Furthermore, since this information is available to the lender at the point of origination, our results suggest that lenders could utilize this information in risk-based pricing by moving away from the standard "house-rate" loan pricing for auto loans.

Implications for U.S. Auto Manufacturers

Our results on auto loan performance combined with recent empirical work on automotive brand loyalty suggest a bleak future for U.S. auto manufacturers. For example, Train and Winston (2004) find that U.S. automakers lost significant market share to European and Japanese automakers between 1990 and 2000 and that this loss in market share is partly due to declining consumer brand loyalty toward U.S. automakers. Train and Winston's (2004) analysis suggests that the primary reason for this shift in consumer demand is the perception that U.S. automakers no longer provide a sufficient price/quality trade-off. As a result, U.S. automakers have increasingly relied on price reductions and financing incentives to retain market shares.

If we assume that the auto loan performance observed from our sample represents the general market, then the empirical results reported in this study question the American automotive manufacturers' reliance on financing incentives to retain market share. Our results indicate that loans on American cars have default rates that are approximately 50 percent greater than loans on European or Japanese cars. All else being equal, this finding suggests that loans secured by American cars should have significantly higher interest rates to compensate for the higher default risk. Thus, to compensate for the low credit risk premium earned on their loan portfolios (as a result of low- or zero-interest rate financing incentives), American automobile manufacturers must price their products above the equilibrium quality adjusted clearing price. This finding implies that cash purchasers of American cars are, in effect, subsidizing the poor credit performance of buyers who finance the purchase of American cars. As a result, we should observe a greater percentage of cash buyers opting for European or Japanese cars where the product price does not incorporate the expected losses on the loan pool. Mannering, Winston, and Starkey (2002) present evidence consistent with this prediction. In their study of the automobile leasing market, Mannering et al. (2002) find that consumers who pay cash are more likely to acquire a Japanese vehicle.

Conclusions

This chapter uses a unique dataset of individual automobile loan performance to assess whether borrower consumption choice reveals information about future loan performance. Automobiles are a highly visible consumption good and are directly marketed to appeal to targeted demographic groups. Insurers have long recognized that automobile makes and models appeal to different clienteles, and that these clienteles have heterogeneous risk profiles and accident rates. Given that individual risk-behavior self-selection is evident in the automobile market, a natural question arises: Does this self-selection also reveal information about the consumer's propensity to prepay or default on the automotive loan?

We use a unique dataset consisting of 6,996 new and used automobile loans originated by a large financial institution between January 1998 and March 2002. The loans are fixed-rate notes and have four- and five-year maturities. We observe the performance of these loans from January 1998 through March 2003, creating a monthly record denoting whether the loans are paid-in-full, prepaid, defaulted, or still current at the end of the sample period. In addition to the loan performance, we observe a number of loan characteristics including the automobile value and age at origination, loan amount, and automotive make, model, and year. We also observe a number of borrower characteristics including credit score, income, and age.

Our results show that the factors that traditionally predict default and prepayment continue to perform as expected. Specifically, we find that (1) a decline in borrower credit risk lowers the probability of default and raises the probability of prepayment; (2) an increase in the loan-to-value increases the probability of default and lowers the probability of prepayment; (3) an increase in borrower income increases the probability of prepayment, whereas an increase in local area unemployment increases the probability of default, and (4) a decrease in the market interest rate increases both the probability of prepayment and default. We also find that automobile manufacturing location (America, Europe, and Japan) significantly impacts both the prepayment and default behavior of borrowers; including the location dummies increased the pseudo-R^2 by 28 percent. Finally, we control for individual automobile-make dummies and find them to be significant drivers of default and prepayment.

Our results provide evidence that the type of automobile a consumer purchases reveals information about the consumer's propensity to prepay or default on the loan used to finance that purchase. Since the information on the type of automobile purchased is available to the lender at the point of origination, we suggest that lenders could use this information by moving away from the standard "house-rate" loan pricing for auto loans. Instead, lenders could profitably pursue risk-based pricing based on the type of car the borrower purchases.

Notes

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1. See Miller and Rock (1985) for a discussion of dividend policy as a mechanism for managers to signal the value of the firm.
2. For example, Brueckner and Follain (1988) and Quigley (1987) discuss the tradeoffs between mortgage contract terms and expected tenure.
3. See Stanton and Wallace (1998) and LeRoy (1996) for a discussion of the mortgage menu problem and the implications concerning asymmetric information about borrower expected mobility.
4. Edelberg (2003) provides empirical evidence that the greater use of risk-based pricing during the 1990s has resulted in an increase in the level of credit access for high-risk borrowers.
5. Automobile ownership statistics are fairly stable across various demographic characteristics such as income, age, race, employment, net worth, and homeownership.
6. U.S. homeownership data is reported in "Census Bureau Reports on Residential Vacancies and Homeownership" available at http://www.census.gov/hhes/www/housing/hvs/.
7. For example, a borrower with an acceptable credit score may be offered a loan up to $20,000 conditional on making a 5 percent downpayment. Thus, if the borrower purchases an $18,000 car, the lender provides a $17,100 loan.
8. In an empirical analysis of house-price volatility, Ambrose, Buttimer, and Thibodeau (2001) show that house-price volatility displays a U-shaped pattern when ranked by house value.
9. Automobile loans can be classified into two broad categories, "direct" and "indirect." Direct loans are issued directly to the borrower, and indirect loans are issued through the dealer. In case of indirect loans, the financial institution contracts with the automobile dealership to provide loans at fixed interest rates. However, they have to compete with automobile finance companies that can provide the loan at a much cheaper rate, even if they have to bear a loss on the loan. For example, a GM finance company could take a loss on the financing of a GM automobile if GM profits on the automobile sale. Hence, financial institutions usually cannot compete in the market for indirect automobile loans. As a result, our study focuses only on direct automobile loans.
10. Our results are robust to alternative definitions of prepayment (e.g., early payoffs greater than $2,000 or $4,000) and default (90 days past due).
11. Since financial institutions try to repossess automobiles once accounts are 60 days past due, our definition is consistent with practice.

12. Dasgupta, Siddarth, and Silva-Risso (2003) and Train and Winston (2004) use this breakdown.
13. The interest-rate spread is defined as the loan annual percentage rate (APR) at origination less the corresponding one-year Treasury rate.
14. Competing-risks models are well developed in the labor economics literature. For example, see Mealli and Pudney (1996), Burdett, Kiefer, and Sharma (1985), Narendranathan and Stewart (1993), and Flinn and Heckman (1982).
15. Gross and Souleles (2002: 330).
16. The pseudo R^2 is calculated from the ratio of the model log-likelihood statistic to the restricted model log-likelihood statistic, where the restricted model is a model with only an intercept term.
17. The marginal effect is calculated as $e^{\beta} - 1$.

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