Determinants of automobile loan default and prepayment

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Introduction and summary

Automobiles, meaning cars and light trucks, are the most commonly held nonfinancial assets among Americans. In 2001, the share of families that owned automobiles was over 84 percent—higher than the share that owned primary residences at 68 percent. Further, automobile ownership statistics are fairly stable across various demographic characteristics, such as income, age, race, employment, net worth, and homeownership. So how do we pay for all these automobiles? Roughly three-quarters of automobile purchases are financed through credit, and loans for automobile purchases are one of the most common forms of household borrowing.[1] In 2003, debt outstanding on automobile loans was over $1,307 billion.[2] According to past studies on auto sales, third party financing (direct loans) accounts for the largest portion of the automobile credit market, with dealer financing (indirect loans) second and leasing third.[3]

What are the risks that lenders in the automobile market face? The first, most obvious risk is default—that is, the person who took out a loan to buy a car or truck fails to pay it back. A second significant risk for lenders in this market is prepayment risk—that is, the car or truck purchaser pays off the loan early, reducing the lender's stream of interest payments. (Hereafter we use the terms automobiles, autos, and cars, as well as vehicles, interchangeably.)

At present, the third party auto loan market relies on a "house rate" for pricing loans, such that all qualified borrowers with similar risk characteristics pay the same rate. The lender does *not* rely on any information about the automobile's make and model to price the loan. Rather, the lender simply underwrites the loan based on the borrower's credit score and required down payment.[4] This contrasts with current practices in the auto insurance market and the mortgage market. Auto 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 auto make and model. Also, before mortgage lenders originate loans, typically they have information on the underlying assets (for example, a house) as well as the borrowers' personal characteristics. Thus, information about the underlying assets often plays a role in determining mortgage contract rates. Given the current practices in the auto insurance market and mortgage market, the question naturally arises as to whether incorporating information on automobile make and model would help third party lenders refine their loan pricing models. Specifically, if we assume that the choice of auto make and model reveals individual financial (or credit) risk behavior of the borrower, what does this tell us about the borrower's propensity to prepay or default on his loan?

Studying individual risk behavior in the auto loan market may be important for investors, as well as lenders. Over the years, a growing percentage of the stock of automobile debt has been held in "asset-backed securities." Pricing these contracts is complicated by

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the borrower's options to default and prepay, which are distinct but not independent. Thus, one cannot calculate accurately the economic value of the default option without simultaneously considering the financial incentive to prepay.

In perfectly competitive markets, we expect well-informed borrowers to make decisions about whether to pay their auto loans early or late (or on time) in a way that increases their wealth. For example, individuals can increase their wealth by defaulting on an auto loan when the market value of the auto debt equals or exceeds the value of the automobile. Alternatively, individuals can prepay their auto loan to take advantage of declining interest rates.[5]

In this article, we use a competing risks framework to analyze the prepayment and default options on auto loans, using a large sample of such loans. To the best of our knowledge, there are two other studies, Heitfield and Sabarwal (2003) and Agarwal, Ambrose, and Chomsisengphet (2007), that provide competing risks models of default and prepayment of automobile loans.

Here, we document several interesting patterns. For example, a loan on a new car has a higher probability of prepayment, whereas a loan on a used car has a higher probability of default. In addition, we find that a decrease in the credit risk of an auto loan holder, as measured by the FICO (Fair Isaac Corporation) score, lowers the probability of default and raises the probability of prepayment. We also find that an increase in the loan-to-value ratio (LTV) increases the probability of default and lowers the probability of prepayment. An increase in income raises the probability of prepayment, whereas a rise in unemployment increases the probability of default. And a decrease in the market rate (the three-year Treasury note rate) increases both the probabilities of prepayment and default. These findings are roughly in line with what we would expect.

Interestingly, we also find that loans on most luxury automobiles have a higher probability of prepayment, while loans on most economy automobiles have a lower probability of default. This indicates that consumer choices regarding automobile make and model provide information about the probabilities of default and prepayment, even holding traditional risk factors (FICO score, LTV, and income) constant.

In the next section, we describe our data. Then, we discuss our methodology and describe the regression results from the model for auto loan prepayment and default.

Data

The proprietary data that we analyze are from a large financial institution that originates *direct* automobile loans.[6] We focus on direct loans in this article because this is the market where lenders compete. Direct loans are issued directly to the borrower, and indirect loans are issued through the dealer. In the case of indirect loans, financial institutions have agreements with automobile dealerships to provide loans at fixed interest rates. However, they have to compete with automobile finance companies that can provide the loans at a much cheaper rate, even if they have to bear a loss on the loans. For example, a General Motors Corporation (GM) finance company can afford to take a loss on the financing for a GM automobile while making a profit on the automobile sale. Hence, financial institutions cannot compete in the market for indirect automobile loans.

Our original sample consists of over 24,384 direct auto loans. Auto loans are issued with four-year and five-year maturities as well as fixed rates. We observe the performance of these loans from January 1998 through March 2003, such that a monthly record of each loan is maintained until the automobile loan is either paid in full (at loan maturity), prepaid, defaulted, or stays current. Certain accounts are dropped from the analysis for the following reasons: Loans were originated after March 2002; loans were written for the financial institution's employees; and loans were associated with fraud or with stolen automobiles. We also drop loans that were paid in full. In addition, once the loan has been defaulted or has been prepaid, subsequent monthly records are removed from the data set. Finally, we have a total of 20,466 loans with 4,730 prepayments (23.11 percent) and 534 defaults (2.61 percent) during the study period.[7]

Loan characteristics include automobile value, automobile age, loan amount, LTV, monthly payments, contract rate, time of origination (year and month), and payoff year and month for prepayment and default. We also have access to the automobile make, model, and year. Finally, we know whether the loan was issued toward the purchase of a used or new automobile. Borrower characteristics include credit score (FICO score),[8] monthly disposable income, and borrower age. The market rate used in this analysis is the three-year Treasury note rate. We also include the unemployment rate in the county of residence of the borrower. A majority of the loans originated in eight northeastern states—Connecticut, Maine, Massachusetts, New Hampshire, New Jersey, New York, Pennsylvania, and Rhode Island.

TABLE 1

Summary statistics for auto loans at origination, 1998–2003

	75 percent level	Median	25 percent level
Blue book value *(dollars)*	22,125	17,875	14,875
Loan amount *(dollars)*	20,544	14,027	10,547
Monthly payment *(dollars)*	318	229	158
Annual percentage rate	9.75	8.99	8.49
Monthly income *(dollars)*	5,062	3,416	2,357
FICO score	761	723	679
Loan-to-value ratio *(percent)*	92.86	78.47	70.90
Unemployment rate *(percent)*	5.40	4.50	2.60
Owner age *(years)*	50	40	31
Auto age *(years)*	7	4	1
Loan age *(months)*	50	54	59

Notes: Blue book value means an auto's market value. FICO score means Fair Isaac Corporation score, which is a credit score with a range of 300–850 (see note 8 for further details).

TABLE 2

Summary statistics for loans on all, used, and new autos at origination, 1998–2003

	All autos	Used autos	New autos
Blue book value *(dollars)*	17,875	14,283	28,382
Loan amount *(dollars)*	14,027	10,624	24,583
Monthly payment *(dollars)*	229	193	324
Annual percentage rate	8.99	9.00	8.74
Monthly income *(dollars)*	3,416	3,333	3,665
FICO score	723	722	726
Loan-to-value ratio *(percent)*	78.47	74.37	87.18
Unemployment rate *(percent)*	4.50	4.50	4.50
Owner age *(years)*	40	39	40
Auto age *(years)*	4	6	0
Loan age *(months)*	54	52	60

Notes: All values are medians. Blue book value means an auto's market value. FICO score means Fair Isaac Corporation score, which is a credit score with a range of 300–850 (see note 8 for further details).

Table 1 presents summary statistics for all loans. The median loan amount is $14,027, with a median LTV of 78 percent and a median annual percentage rate (APR) of 8.99 percent. The median FICO score is 723 in our sample, which also happens to be the national median score in 2005 (see note 8). The median monthly disposable income is $3,416. Finally, the median owner, loan, and car ages are 40 years, 54 months, and 4 years, respectively. The blue book value (the car's market value)[9] at loan origination ranges from $4,625 to $108,000. These statistics are comparable with the overall statistics for a typical auto loan portfolio.

Next, table 2 compares these median statistics on all auto loans with the median statistics for loans on used cars, as well as loans on new cars. The median FICO scores are 722 and 726 for loans on used and new vehicles, respectively. The median LTV ranges from 74 percent for loans on used automobiles to 87 percent for loans on new automobiles. Finally, the median loan amount is about two and a half times for new cars as compared with that for used cars. These statistics reveal the differences between the borrowers who buy new and used automobiles. Despite these differences, the credit risk characteristics between the borrowers for new versus used autos are not significantly different, as reflected by the similar FICO scores.

Table 3 presents the distribution of loans on used and new automobiles by loan outcome. The first row shows the number of loans that are current at the end of the sample period—that is, those that are not defaulted or prepaid. While 20 percent of loans on used autos and 32 percent of loans on new autos are prepaid, only 2.77 percent of loans on used vehicles and 2.13 percent of loans on new vehicles are defaulted.[10] Overall, 75 percent of all loans are originated for used cars and 25 percent are originated for new ones. The descriptive statistics show that a higher percentage of borrowers who have loans for new automobiles prepay, while a slightly higher percentage of borrowers who have loans for used automobiles default.

Table 4 presents the distribution of the auto loans across the various states. Thirty-three percent of the loans originated in New York, 22 percent in Massachusetts, and 1 percent in Florida, while 3 percent originated across the 41 states (and the District of Columbia) not listed individually in the table.

Table 5 presents the distribution of the loan origination by quarter. Since most U.S. and European automobile manufacturers typically introduce the new versions of their established models (as well as brand new models) in the third quarter, 41 percent of all auto loans in the sample originated in that quarter. Next, 26 percent of the loans originated in the first quarter. The earned income tax credit (EITC) refunds, which

TABLE 3

Loans on all, used, and new autos, by loan outcome, 1998–2003

	All autos		Used autos		New autos	
	Number	Percentage	Number	Percentage	Number	Percentage
Good accounts	15,202	74.28	11,843	77.20	3,359	65.54
Prepayment	4,730	23.11	3,073	20.03	1,657	32.33
Default	534	2.61	425	2.77	109	2.13
Total	20,466	100.00	15,341	100.00	5,125	100.00

Note: Good accounts are loans that are current at the end of the sample period—that is, those that are not defaulted or prepaid.

TABLE 4

Auto loans, by state, 1998–2003

State	Number	Percentage
Connecticut	3,256	15.91
Florida	199	0.97
Maine	782	3.82
Massachusetts	4,418	21.59
New Hampshire	1,099	5.37
New Jersey	2,536	12.39
New York	6,669	32.59
Pennsylvania	296	1.45
Rhode Island	643	3.14
Other states and District of Columbia	568	2.78
Total	20,466	100.00

Note: The percentage column does not total because of rounding.

typically become available to recipients in the first quarter, might help explain why 26 percent of the loans originated then.[11] Finally 18 percent of all auto loans originated in the second quarter, and 15 percent originated in the fourth quarter.[12] Since a majority of the loans in our sample are for used car purchases, this suggests that consumers even tie their used automobile buying decisions to the introduction of the new automobiles. This is evident from the distribution of the loans for used car purchases by quarter. The distribution is fairly similar to that of the loans for new car purchases. Finally, table 6 provides a distribution of the auto loans by auto make. Loans on Chevy automobiles constitute the largest percentage, and those on Jaguar and Porsche automobiles constitute the smallest shares.

Variables

In our regression results for default and prepayment, the dependent variable can take on the following values: Current = 0, prepay = 1, and default = 2. We regress this variable against a variety of independent variables that control for the economic environment as well as various borrower risk factors.

We first isolate variables to capture the prepayment option. To approximate the prepayment option, we follow the approach outlined in Calhoun and Deng (2002) and construct an auto loan prepayment premium that is defined as $PPOption_{t-6} = (r_{ct-6} - r_{mt-6})/(r_{mt-6})$, where r_{ct-6} is the coupon rate on the existing auto loan and r_{mt-6} is the three-year Treasury note rate.[13] We expect $PPOption_{t-6}$ to be positively related to prepayment behavior—that is, consumers are more likely to prepay and trade in their cars with the decline in the prevailing three-year Treasury note rate relative to the original loan coupon rate.

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 market values for autos reported by the National Automobile Dealers

TABLE 5

Loan originations for all, used, and new autos, by quarter, 1998–2003

	All autos		Used autos		New autos	
	Number	Percentage	Number	Percentage	Number	Percentage
First quarter	5,289	25.84	4,034	26.30	1,255	24.49
Second quarter	3,714	18.15	3,157	20.58	557	10.87
Third quarter	8,478	41.42	6,053	39.46	2,425	47.32
Fourth quarter	2,985	14.59	2,097	13.67	888	17.33
Total	20,466	100.00	15,341	100.00	5,125	100.00

Note: The percentage columns may not total because of rounding.

TABLE 6

Auto loans, by auto make, 1998–2003

Auto make	Number	Percentage
Acura	608	3.0
Audi	270	1.3
BMW	538	2.6
Buick	475	2.3
Cadillac	573	2.8
Chevy	2,097	10.2
Chrysler	390	1.9
Dodge	1,342	6.6
Geo	467	2.3
General Motors	449	2.2
Honda	1,919	9.4
Hyundai	125	0.6
Infinity	218	1.1
Isuzu	157	0.8
Jaguar	78	0.4
Jeep	1,591	7.8
Lexus	187	0.9
Lincoln	283	1.4
Mazda	400	2.0
Mercedes-Benz	722	3.5
Mitsubishi	433	2.1
Nissan	1,674	8.2
Oldsmobile	386	1.9
Plymouth	358	1.7
Pontiac	628	3.1
Porsche	75	0.4
Rover	147	0.7
Saab	286	1.4
Saturn	293	1.4
Subaru	340	1.7
Toyota	1,963	9.6
Volkswagen	994	4.9
Total	20,466	100.0

Notes: BMW means Bayerische Motoren Werke (Bavarian Motor Works). The percentage column does not total because of rounding.

Association (NADA) on its website (www.nada.com). For example, to determine the average expected depreciation for Subaru cars, we collected the estimated market value during the fall of 2003 for Subaru's base-level Forester, Impreza, and Legacy models from 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 (as determined by the NADA). For each model, we then calculate the simple yearly depreciation experienced by the base car model (without considering possible upgrades or add-ons), and we 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 assumed that all models for each manufacturer follow a similar depreciation schedule. Obviously, our valuation algorithm is only an approximation, since the values of individual cars will vary based on the idiosyncratic driving habits of the borrowers.

Based on these estimated changes in car prices, we construct the monthly loan-to-value ratio (*CLTV*). We expect the monthly loan-to-value ratio to be positively related to default probability because the higher depreciation in the auto value (holding other things constant) serves to increase the loan-to-value ratio. Given the significant depreciation in auto value 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 disproportionate number of low-quality cars, then the secondary market value for the manufacturer's cars will reflect this lower quality.

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 probability, implying that borrowers with lower current FICO scores are more likely to default on their auto loans.[14]

Local economic conditions may also affect borrower loan termination decisions. For example, borrowers facing possible job losses are more likely to default because they may be unable to continue making loan payments. We use the county unemployment rate (*Unemployment*), updated monthly, as a proxy for local economic conditions; the unemployment rate is for the county of residence of the borrower. Finally, we include a series of dummy variables that denote the borrower's location (state) to control for unobserved heterogeneity in local economic conditions.

We also control for other variables, such as the age of the borrower, state-specific effects, account seasoning (time since loan origination), and calendar time effects. Lastly, we also control for the make, model, and year of the automobile. It is well documented that different auto makes and models have different depreciation functions, so an auto make dummy will help isolate the auto make's specific depreciation. For example, Aizcorbe, Corrado, and Doms (2000) and Corrado, Dunn, and Otoo (2003) use fixed effects models by assigning dummy variables for each automobile make, which can be used as a proxy for the measurement of the physical characteristics of the automobile make. Since the characteristics of an automobile are fixed, the dummy variables capture the cross-sectional variation in the auto's market values.

Methodology

Using a loan-level model, we empirically evaluate the effect of market changes in interest rate exposure on prepayment risk for an automobile loan portfolio. We also do this for the effect of liquidity constraints—as measured by FICO scores—and the effect of unemployment on default risk. Previous empirical prepayment and default models using loan-level data are typically based on techniques of survival analysis (originally used in biological studies of mortality).[15] Kalbfleisch and Prentice (1980) and Cox and Oakes (1984) provide a classic statistical treatment of the topic. For further details, see the appendix.

Since our primary purpose is to determine how borrower consumption decisions can affect 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

$$1)\qquad x_j'\beta_j = \beta_0\tau_t + \beta_1 State_i + \beta_2 risk_{it} + \beta_3 econ_{it} + \beta_4 car_{it},$$

where τ_t represents a series of dummy variables corresponding to calendar quarters that allow for shifts over time in the propensity to default or prepay; $State_i$ represents a series of dummy variables corresponding to the state of residence of the borrower; $risk_{it}$ represents a set of borrower characteristics, including credit score, that reflect the lender's underwriting criteria; $econ_{it}$ is a set of variables capturing changes in local economic conditions; and car_{it} is a set of variables identifying information concerning the type of car purchased.

Empirical results

We look at the results from the competing risks model that capture the determinants of auto loan prepayment and default. Table 7 presents the results.[16] We control for state dummies, loan age, owner age, and quarter time dummies.

The results (estimated coefficients) in the first column of data show that the probability of default is higher in the first, second, third, and fourth quarters of 2000. However, the probability of default is lower in the first and second quarters of 1999. Also, the results in the fourth column show the probability of prepayment is higher in the first, second, third, and fourth quarters of 2002, but the probability of prepayment is lower in the fourth quarter of 2000. These results highlight the effects of macroeconomic conditions on default and prepayment probabilities. Because of weakening macroeconomic conditions in 2000, there were more defaults and fewer prepayments. However, with dropping interest rates and subsequent attractive automobile offers—some of which featured no closing costs, zero percent financing, and no down payment—prepayment and trade-in rates in 2002 were much higher. These results are consistent with the literature on consumer durable goods purchases, transactions costs, and liquidity constraints.[17]

Next, we look at the automaker control variables. The competing risks model contains 31 dummy variables denoting the various automakers. The estimated coefficients provide interesting insights into the prepayment and default behavior of the borrowers with respect to the makes of the automobiles they eventually purchase. Specifically, we find that loans for most luxury automobile makes, such as Lexus, BMW, and Cadillac, have a higher probability of prepayment, while loans for most economy automobile makes, such as Geo, Buick, and Honda, have a lower probability of default. It is interesting that some luxury automobiles (for example, Jaguar and Saab) have higher probabilities of default *and* prepayment. This implies that certain luxury automobiles have a premium in the used car market; luxury vehicles in the used car market are preferred by liquidity-constrained consumers.

We interpret the results from the ninth and tenth rows (*Owner age* and *Owner age*^{2}) of table 7, and find that younger borrowers (those below the median age of 40) have a higher probability of default than the older borrowers (those at the median age of 40 and above). We also find that the older borrowers have a higher probability of prepayment than their younger counterparts. The results also confirm that younger borrowers are liquidity constrained and thus more likely to own a used automobile. Account seasoning (time since loan origination) increases both the probabilities of default and prepayment—our interpretation of the results from the eleventh and twelfth rows (*Loan age* and *Loan age*^{2}) of table 7. These results are intuitive.

Finally, we look at some of the important determinants of default and prepayment as indicated by the option value theory. First, the results show that the auto loan prepayment premium ($PPOption_{t-6}$) is positive and statistically significant for the probability of prepayment and also, surprisingly, for the probability of default. The first result indicates that the higher the difference between the auto loan rate and the market rate is, the higher the probability of prepayment and trade-in. Again, this result is consistent with the literature on consumer durable goods purchases. A trade-in at lower interest rates both lowers the monthly payments out of disposable income and increases the share of durable goods in household wealth. However, it is a little surprising that a bigger

TABLE 7

Competing risks model of auto loan termination through default and prepayment

	Default			Prepayment		
	Coefficient value	Standard error	*p* value	Coefficient value	Standard error	*p* value
Intercept	6.8050	0.6265	0.0001	–5.3690	0.3243	0.0001
New auto dummy	–0.0261	0.0113	0.0224	0.0540	0.0258	0.0331
Monthly income$_{t0}$/1,000	–0.0200	0.0170	0.3608	0.0280	0.0072	0.0001
FICO$_{t-6}$	–0.0166	0.0004	0.0001	0.0010	0.0003	0.0001
Unemployment$_{t-6}$	0.2262	0.0783	0.0039	0.1613	0.0414	0.0001
CLTV$_{t-6}$	1.0110	0.2958	0.0006	1.4485	0.1338	0.0001
Payment$_{t-6}$	0.0002	0.0001	0.0166	0.0002	0.0000	0.0001
PPOption$_{t-6}$	0.2917	0.0754	0.0001	0.0419	0.0178	0.0380
Owner age	–0.0941	0.0137	0.0001	–0.0338	0.0066	0.0001
Owner age^2	0.0009	0.0002	0.0001	0.0003	0.0001	0.0001
Loan age	0.0316	0.0147	0.0311	0.1293	0.0083	0.0001
Loan age^2	–0.0013	0.0002	0.0001	0.0023	0.0002	0.0001
1999:Q1 dummy	–0.4023	0.2131	0.0591	0.1148	0.0796	0.1492
1999:Q2 dummy	–0.5659	0.2080	0.0065	0.0029	0.0803	0.9714
1999:Q3 dummy	0.0793	0.1726	0.6459	0.1267	0.0761	0.0962
1999:Q4 dummy	0.1832	0.1722	0.2876	–0.1608	0.0825	0.0514
2000:Q1 dummy	0.3297	0.1727	0.0562	–0.0198	0.0824	0.8100
2000:Q2 dummy	0.3799	0.1782	0.0331	0.9646	0.0695	0.0001
2000:Q3 dummy	0.4669	0.1892	0.0136	0.0047	0.0905	0.9586
2000:Q4 dummy	0.5381	0.1905	0.0047	–0.3303	0.1005	0.0010
2001:Q1 dummy	0.1727	0.2017	0.3919	–0.1096	0.0983	0.2650
2001:Q2 dummy	0.3351	0.1927	0.0821	0.0978	0.0942	0.2989
2001:Q3 dummy	0.1187	0.1909	0.5340	–0.0554	0.0990	0.5755
2001:Q4 dummy	0.2523	0.1711	0.1402	0.4236	0.0842	0.0001
2002:Q1 dummy	0.1721	0.1588	0.2784	0.1738	0.0933	0.0625
2002:Q2 dummy	–0.0476	0.1628	0.7701	0.2261	0.0967	0.0194
2002:Q3 dummy	0.2841	0.1579	0.0720	0.3618	0.0891	0.0001
2002:Q4 dummy	0.1600	0.1567	0.3072	0.4911	0.0863	0.0001
Connecticut dummy	–0.3784	0.1035	0.0003	–0.5174	0.0505	0.0001
Florida dummy	0.3926	0.2116	0.0636	–0.2428	0.1551	0.1175
Maine dummy	–0.3781	0.1885	0.0449	–0.1795	0.0846	0.0339
New Hampshire dummy	–0.7172	0.1870	0.0001	–0.1575	0.0677	0.0200
New Jersey dummy	–0.4121	0.1482	0.0054	–0.1850	0.0672	0.0059
New York dummy	0.1724	0.1406	0.2201	–0.2060	0.0785	0.0087
Pennsylvania dummy	–0.5487	0.4691	0.2421	–0.2002	0.1775	0.2595
Rhode Island dummy	0.0493	0.1593	0.7570	–0.2028	0.0962	0.0350
Acura dummy	–0.4570	0.2379	0.0547	0.0951	0.1089	0.3828
Audi dummy	–1.7109	0.7163	0.0169	0.3795	0.1553	0.0145
BMW dummy	–0.1186	0.2486	0.6334	0.4202	0.0969	0.0001
Buick dummy	–1.0463	0.4209	0.0129	–0.1134	0.1158	0.3272
Cadillac dummy	0.2226	0.2694	0.4087	0.3811	0.1233	0.0020
Chevy dummy	–0.1028	0.1296	0.4275	0.1509	0.1586	0.3241
Chrysler dummy	–0.1220	0.3140	0.6976	0.2540	0.2335	0.3121
Dodge dummy	0.3696	0.1240	0.0029	0.1048	0.0691	0.1295
Geo dummy	–1.3232	0.7141	0.0639	–0.2126	0.2185	0.3305
General Motors dummy	–0.1937	0.2665	0.4672	0.2865	0.2008	0.3234
Honda dummy	–0.3666	0.1407	0.0092	–0.0533	0.0686	0.4369
Hyundai dummy	–0.4782	0.4664	0.3052	–0.1337	0.2423	0.5812
Infinity dummy	–0.4485	0.4590	0.3286	0.3301	0.1558	0.0404
Isuzu dummy	0.2555	0.2619	0.3292	–0.0585	0.1777	0.7419
Jaguar dummy	1.1264	0.5201	0.0303	0.7451	0.3425	0.0296
Jeep dummy	–0.0876	0.1508	0.5615	0.0910	0.0711	0.2008
Lexus dummy	0.0036	0.2906	0.9902	0.6604	0.1302	0.0001
Lincoln dummy	0.5613	0.2093	0.0073	0.1187	0.1241	0.3388
Mazda dummy	0.1673	0.1734	0.3344	–0.1009	0.1149	0.3798
Mercedes-Benz dummy	0.3848	0.1656	0.0201	0.0950	0.0908	0.2953
Mitsubishi dummy	0.0848	0.1833	0.6437	0.1854	0.0998	0.0633
Nissan dummy	–0.1012	0.1368	0.4596	–0.0020	0.0730	0.9779

TABLE 7 (CONTINUED)

Competing risks model of auto loan termination through default and prepayment

	Default			Prepayment		
	Coefficient value	Standard error	*p* value	Coefficient value	Standard error	*p* value
Oldsmobile dummy	0.0114	0.2588	0.9647	–0.0152	0.1196	0.8988
Plymouth dummy	–0.1911	0.2723	0.4828	–0.0039	0.1213	0.9744
Pontiac dummy	0.4209	0.1408	0.0028	0.0680	0.0933	0.4665
Rover dummy	0.4033	0.5117	0.4306	0.2235	0.2367	0.3451
Saab dummy	0.6634	0.2367	0.0051	0.3294	0.1153	0.0043
Saturn dummy	–0.3285	0.2982	0.2707	–0.0927	0.1454	0.5235
Subaru dummy	–0.5246	0.3898	0.1784	0.0388	0.1343	0.7726
Toyota dummy	–0.0780	0.1376	0.5707	–0.1041	0.0688	0.1305
Volkswagen dummy	–0.1601	0.1741	0.3579	0.1278	0.0759	0.0922
Log likelihood ratio	1,389					
Number of accounts	20,466	534			4,730	

Notes: FICO score means Fair Isaac Corporation score, which is a credit score with a range of 300–850 (see note 8 for further details). LTV means loan-to-value ratio. BMW means Bayerische Motoren Werke (Bavarian Motor Works). Porsche is excluded from the regression analysis because there are no defaults on loans for Porsches in the sample.

difference in the loan rate and the market rate also increases the probability of default. One possible explanation is that liquidity-constrained consumers, who have bad credit risk profiles, are priced out of the low market rates, but the option to default remains valuable.

Monthly payments, or the debt service burden ($Payment_{t-6}$), are also positively related to both the probability of prepayment and probability of default. We expect that a higher debt service burden for liquidity-constrained consumers could lead to a higher probability of default; however, it could also lead to a higher probability of prepayment for consumers who do not have liquidity constraints.[18] Monthly income ($Monthly\ income_{t0}$) is negatively related to default but positively related to prepayment. This result is consistent with theory. The county unemployment rate ($Unemployment_{t-6}$) is positively related to both the probabilities to default and prepay. Once again we expect a higher unemployment rate to lead to a higher default probability, but higher unemployment could also lead some to prepay and cash out equity from their automobiles. These results are largely consistent with Heitfield and Sabarwal (2003).

Next, we look at the monthly loan-to-value ratio ($CLTV_{t-6}$), the FICO score ($FICO_{t-6}$), and the new auto indicator. All three of these are measures of liquidity constraints. As expected, liquidity-constrained consumers are more likely to have a high LTV and a low FICO score, and they are more likely to buy used automobiles. The results show that the FICO score is negatively related to default probability, LTV is positively related to default probability, and the new auto indicator is negatively related to default probability. Moreover, a higher FICO score and a new auto indicator lead to a higher probability of prepayment, and a higher LTV leads to a higher probability of prepayment. (Heitfield and Sabarwal [2003] do not control for LTV, FICO, automobile age, automobile make, and income, so we cannot compare our results with theirs.)

Marginal effects

Table 8 presents the marginal effect of a borrower owning a new automobile on prepayment and default rates of auto loans over a 30-month period. This table also shows the marginal effects of changes in FICO score, LTV, auto loan prepayment premium, income, and county unemployment rate on the prepayment and default rates of automobile loans over a 30-month span. The results show that a borrower owning a new automobile reduces the probability of default by as much as 15 percent but raises the probability of prepayment by 13 percent. An increase of 20 points in the FICO score lowers the probability of default by 12 percent but raises the probability of prepayment by 8 percent. These results suggest that an increase in the credit risk profile or an ease in liquidity constraints reduces one type of hazard (default) but increases another type of hazard (prepayment). A 5 percent drop in LTV reduces the probability of default by 4 percent but increases the probability of prepayment by 7 percent. This would indicate that a drop in LTV raises the overall wealth of the household. Next we note that a 10 percent increase in income raises the probability of prepayment by 8 percent. These results are consistent with the theoretical literature on consumer durable goods purchases and liquidity

TABLE 8

Marginal effects on auto loan termination through default and prepayment over a 30-month period

	Default	Prepayment
	(percent)	*(percent)*
New auto	–15	13
FICO score increase by 20 points	–12	8
Loan-to-value ratio decrease by 5 percent	–4	7
Auto loan prepayment premium increase by 1 percent	3	6
Income increase by 10 percent	0	8
County unemployment rate increase by 1 percent	9	3

Notes: FICO score means Fair Isaac Corporation score, which is a credit score with a range of 300–850 (see note 8 for further details). For details on the calculation of the auto loan prepayment premium, see p. 20. The county unemployment rate is for the county of residence of the borrower.

constraints (Eberly, 1994). A 1 percent increase in the county unemployment rate significantly increases the probability of default by as much as 9 percent. This is a fairly striking result and suggests that liquidity constraints can significantly increase default rates. Finally, a 1 percent decrease in the market interest rate in relation to the auto loan annual percentage rate—that is, a 1 percent increase in the auto loan prepayment premium—increases prepayment probability by 6 percent. The results also suggest that the decrease in the market rate will increase the probability of default by 3 percent. One possible explanation for these results could be that liquidity-constrained consumers may not be able to get favorable interest rates on their loans.

Conclusion

Automobiles are highly visible consumption goods that are often purchased on credit. In this article, we use a unique proprietary data set of individual automobile loans to assess whether borrower consumption choice reveals information about future loan performance. Given that individual self-selection is evident in the automobile market (as in the auto insurance market and the mortgage market), a natural question arises as to whether this self-selection also reveals information about the consumer's propensity to prepay or default on an auto loan. We adopt the competing risks framework to analyze these auto loan prepayment and default risks empirically, using a sample of 20,466 individual loans that were issued toward the purchases of both new and used automobiles.

Our results can be summarized as follows. A loan on a new car has a higher probability of prepayment, whereas a loan on a used car has a higher probability of default. A decrease in the credit risk of a loan holder, as measured by the FICO score, lowers the probability of auto loan default and raises the probability of prepayment. An increase in the LTV increases the probability of default and lowers the probability of prepayment. An increase in income raises the probability of prepayment, whereas a rise in unemployment increases the probability of default. A decrease in the market rate (the three-year Treasury note rate) increases both the probabilities of prepayment and default. And perhaps most interestingly, we also find that loans on most luxury automobiles have a higher probability of prepayment, while loans on most economy automobiles have a lower probability of default.

Clearly, this study has some limitations. We are only looking at direct auto loans that were originated, for the most part, in Northeast states by a single lender. However, our results imply that lenders could improve the pricing of automobile loans by considering the type of car collateralizing the loan. Although the use of auto make/model information in loan pricing is probably not feasible because of the multitude of make/model combinations, the results from this study suggest that controlling for differences in default and prepayment patterns based on broader auto types (for example, luxury versus economy) could improve loan pricing.

NOTES

[1]Aizcorbe, Kennickell, and Moore (2003), pp. 16–17, 19; Aizcorbe, Starr, and Hickman (2003) report that in 2001 over 80 percent of new vehicle transactions were financed through loans or leases.

[2]See the Federal Reserve's G.19 statistical release (www.federalreserve.gov/releases/g19/Current). While this release also includes debt on mobile homes, education, boats, trailers, or vacations, a vast majority of the debt is on automobiles.

[3]For example, 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 were financed through auto dealers, and the remaining 40 percent were most likely financed from third party lenders (credit unions or banks).

[4]For example, a borrower with an acceptable credit score may be offered a loan up to $20,000 conditional on making a 5 percent down payment. Thus, if the borrower purchases an $18,000 car, the lender provides a $17,100 loan.

[5]Over the years, several studies using loan-level data have investigated the economic drivers of default and prepayment risks on residential mortgages. See Kau et al. (1992, 1995); Deng (1997); Deng and Quigley (2002); Deng, Quigley, and Van Order (2000); Pavlov (2001); Calhoun and Deng (2002); and Ambrose and Sanders (2003).

[6]We obtained the sample and permission to use it for our article from a large financial institution under the condition that we keep the institution's identity confidential.

[7]In our sample, prepayment is defined as an account that pays off the loan in full before loan maturity, while a default is defined as 60 days past due. We tried alternative definitions for both prepayment ($2,000, $3,000, and $4,000) and default (90 days past due). However, the results are qualitatively the same. Since financial institutions try to repossess the automobile once the account is 60 days past due, our definition is consistent with current practice.

[8]FICO scores have a range of 300–850. In 2005, the median FICO score was 723 (see www.businessweek.com/magazine/content/05_48/b3961124.htm). Typically, a FICO score above 800 is considered very good, while a score below 620 is considered poor. As reported on the Fair Isaac Corporation website (www.myfico.com), there is a 400-basis-point interest rate spread for a 15-year home equity loan between borrowers with FICO scores above 760 and those with scores below 580; those with the higher FICO scores obtain a loan with a lower interest rate.

[9]The *Kelley Blue Book*, produced by the Kelley Blue Book Company Incorporated, has become so authoritative and popular that the term "blue book value" has become synonymous with a car's market value.

[10]According to the American Bankers Association (ABA), the national delinquency rate of 30 days past due for all direct automobile loans was 2.4 percent in 2002. This statistic is consistent with the default rates in table 3. It is interesting to note that the delinquency rate for indirect automobile loans was around 1.9 percent in 2002. The lower delinquency rates for indirect loans can be explained as follows. The ABA does not report the loan performance information for auto finance companies and financial institutions that compete in the indirect loans market and that have very stringent origination guidelines. This highlights the point that a study on automobile defaults should distinguish between direct and indirect loans.

[11]Goodman-Bacon and McGranahan (2008) document that EITC eligible households receive over 80 percent of the EITC payments, which averaged $2,113 in 2004, in the first quarter of the year. They also show that these households tend to spend a sizable portion of their EITC refunds on automobile purchases.

[12]The distributions of loan origination for both new and used automobiles are similar.

[13]We lag the three-year Treasury note rate by six months to avoid endogeneity. We also conduct similar analyses with both five-year and one-year Treasury note rates; the results are qualitatively similar. In fact, we lag all other variables by six months as well.

[14]In a separate regression, we also include the square terms of *CLTV* and *FICO* to control for any nonlinearity in explaining the prepayment and default rates. These results are not reported in this article.

[15]These techniques have also found frequent application in industrial engineering failure time studies.

[16]We conducted an exhaustive robustness test by including quadratic specifications for the various risk variables, discrete dummies for some of the continuous variables, and log transformations. Though the results are not reported, they are qualitatively similar.

[17]Accordingly, about half of the households adjust their durable stock to a target share of their total wealth and then allow it to depreciate until it reaches a critical share of wealth; at this point they purchase a new durable good so that the stock once again equals the target share of wealth (Attanasio, 1995; and Attanasio, Goldberg, and Kyriazidou, 2000).

[18]Heitfield and Sabarwal (2003) find debt service coverage to be positively related to default but negatively related to prepayment.

APPENDIX

In automobile loan termination analysis, we consider that loans "die" prior to scheduled maturity from either default or prepayment. Survival data consist of not only a response variable that measures the duration of a particular event but also a set of independent variables that may explain duration of a particular event. We use duration models to analyze the underlying distribution of the failure time variable and to assess the effect of various explanatory variables of the failure time. Duration models estimate the probability of a particular terminating event of the real world. Hazard models are a type of duration model that deals with events that may happen at various times in the future.

Let prepayment or default be the termination events of an automobile loan. A loan given in period t_0 has different probabilities of prepayment and default in one year, two years, … , t years. In duration analysis, we are interested in describing the probability distribution of observed automobile loan duration across an individual loan. The basic idea behind the hazard model is that it estimates the conditional probabilities of prepayment and default at time t, assuming payments are being made from loan inception up to time $t – 1$, conditional on the baseline hazard as well as other factors affecting the prepayment and default behavior of the auto owner. Hence, we include explanatory variables for factors that could affect the probabilities of prepayment and default, such as LTV and FICO score.

Let τ be a random variable describing time to exit (in months since origination) due to prepayment or default. Let $p(\tau < t) = F(t)$, $\forall t \geq 0$ be the distribution function of τ at time t. Let $f(t) = dF/dt$ be the probability density function for τ. Then, we can define the hazard function (the probability of a loan terminating) at time t with the following equation:

$$\text{A1)}\quad h(t) = p(t \leq \tau < t + dt \mid \tau \geq t)$$

$$= \frac{p(t \leq \tau < t + dt, \tau \geq t)}{p(\tau \geq t)}$$

$$= \frac{p(t \leq \tau < t + dt)}{p(\tau \geq t)} = \frac{f(t)}{1 - F(t)}.$$

Setting $1 - F(t) = \overline{F}(t)$ with initial condition $\overline{F}(0) = 1$, then

$$\text{A2)}\quad h(t) = \frac{f(t)}{\overline{F}(t)} = \frac{-d\overline{F}(t)/dt}{\overline{F}(t)} = -\frac{1}{\overline{F}(t)} \times \frac{d\overline{F}(t)}{dt}$$

represents a differential equation in t with the following solution,

$$\text{A3)}\quad \overline{F}(t) = \exp\left\{-\int_0^t h(s)ds\right\}.$$

This gives the survivor function, $\overline{F}(t)$, and the distribution function, $F(t) = 1 - \overline{F}(t)$, of τ in terms of the hazard function, $h(t)$. From equations A1 and A2, we obtain the unconditional density function of τ:

$$\text{A4)}\quad f(t) = h(t)\exp\left\{-\int_0^t h(s)ds\right\}.$$

The parametric specification of the hazard function (log-logistic functional form) is as follows. Substituting equation A3 into equation A1 yields:

$$\text{A5)}\quad h(t) = \frac{\lambda^{1/\gamma} t^{(1-\gamma)/\gamma}}{\gamma(1 + (\lambda t)^{1/\gamma})}.$$

From equation A2, we have

$$\text{A6)}\quad \overline{F}(t) = \frac{1}{1 + (\lambda t)^{1/\gamma}}.$$

And from equation A3, we have

$$\text{A7)}\quad f(t) = \frac{\lambda^{1/\gamma} t^{(1-\gamma)/\gamma}}{\gamma(1 + (\lambda t)^{1/\gamma})^2}.$$

Covariates are introduced in the model by setting $\lambda = \exp(-x'\beta)$, where x is a matrix of independent variables ($FICO_{t-6}$, $CLTV_{t-6}$, $PPOption_{t-6}$, $Unemployment_{t-6}$, etc.) and β is a vector of parameters to be estimated. Gamma (γ) is an ancillary parameter also estimated from the data. Estimation is by maximum likelihood allowing for right-side censoring and left-side truncation.

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