

A Puzzle in the Relation Between Risk and Pricing of Long-Term Auto Loans

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First version: September 2017
This version: June 2020

Keywords: Auto loans; loan terms; long-term auto loans.

JEL classification: G21.

The views expressed in this paper do not necessarily reflect the views of Fannie Mae, the Office of the Comptroller of the Currency, the U.S. Department of the Treasury, or any federal agency and do not establish supervisory policy, requirements, or expectations. The authors would like to thank the excellent research support by Andrew Goad and Qun Wang, and the valuable comments from the editor (Mark Carey) an anonymous referee, Fredrick Andersson, Michel Becnel, John Court, Matthew Engelhart, Marcey Hoelting, Steven Jones, Rodney Hansen, Min Qi, Lan Shi, Natalie Tiernan, Chris Henderson, and seminar participants at the Office of the Comptroller of the Currency, the World Bank Long-Term Loan conference, the 2016 Interagency Risk Quant Forum, and the Philadelphia 2017 auto loan workshop. The authors take responsibility for any errors.

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Abstract Long-term auto loans have become increasingly popular in the past decade. After controlling for borrower and loan characteristics available from the credit bureau data and macroeconomic conditions, we find that auto loans with terms longer than five years have higher delinquency rates than shorter-term loans during each year in their lifetimes. However, the yield curve among auto loans is inverted after controlling for the loans' delinquency and prepayment risks, and the interest rates on the long-term loans are lower than those justified by their higher delinquency risks. The reasons behind this puzzle deserve additional investigation in the future.

1 Introduction

Auto loans have captured the media's attention in recent years because of the rapid increase in loan originations and their record high balances in the US. As of the first quarter of 2020, the total market size of auto loan was \$1.35 trillion – that placed it as the third largest category of consumer debt in the US, only slightly below the size of student debt at \$1.53 trillion.¹ However, more car buyers have recently shown signs of struggling to make auto loan payments.² If the upward trend in auto loan delinquency rates continues or jumps unexpectedly, auto lenders could experience significant losses in a downturn.³ Furthermore, since only a small proportion of auto loans are securitized,⁴ any risk unaccounted for might have a direct impact on lenders' books in the next few years.

¹ For total consumer debt balances, see Federal Reserve Bank of New York and Equifax: <https://www.newyorkfed.org/microeconomics/hhdc.html>.² See, for example, reports like <http://www.cnbc.com/id/101931381#>, and <http://www.wsj.com/articles/subprime-flashback-early-defaults-are-a-warning-sign-for-auto-sales-1457862187>.³ Based on information from Experian AutoCount, the average origination LTV increased from 120 percent in 2013 to roughly 125 percent in 2016. Therefore, the recoveries on auto loans might be low if the loans default in the first few years after origination. LTVs can be higher than 100 percent with the addition of warranties, taxes, and especially the carry-over amount from the old loan, upon refinancing or purchase of a new vehicle.⁴ Most of the securitized auto loans are subprime auto loans from finance companies.⁵ See, for example, “Introducing the 97-month car loan,” Wall Street Journal, April 8, 2013, by Mike Ramsey, and the Wall Street Journal report at <http://blogs.wsj.com/totalreturn/2015/06/01/more-car-buyers-take-long-loans/>.

² See, for example, reports like <http://www.cnbc.com/id/101931381#>, and <http://www.wsj.com/articles/subprime-flashback-early-defaults-are-a-warning-sign-for-auto-sales-1457862187>.³ Based on information from Experian AutoCount, the average origination LTV increased from 120 percent in 2013 to roughly 125 percent in 2016. Therefore, the recoveries on auto loans might be low if the loans default in the first few years after origination. LTVs can be higher than 100 percent with the addition of warranties, taxes, and especially the carry-over amount from the old loan, upon refinancing or purchase of a new vehicle.⁴ Most of the securitized auto loans are subprime auto loans from finance companies.⁵ See, for example, “Introducing the 97-month car loan,” Wall Street Journal, April 8, 2013, by Mike Ramsey, and the Wall Street Journal report at <http://blogs.wsj.com/totalreturn/2015/06/01/more-car-buyers-take-long-loans/>.

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The most striking feature among auto loans in recent years is the increasing loan terms (namely, years to maturity at origination).⁵ Loan term has been rising over time from an average of three years in the 1970s to five years by 2002. Figure 1 shows that the proportion of new auto loans with terms beyond five years in the US has increased steadily from about 55 percent in the first quarter of 2013 to approximately 65 percent in the fourth quarter of 2016. Such a phenomenon is mainly driven by the increasing origination of seven-plus year loans, which is consistently more than 20 percent of auto loans originated after 2015. Furthermore, the fraction of newly originated five-year loans has been shrinking, and the six-year loan is currently the most common type. This phenomenon of lengthening terms is widespread and happens among all types of auto loan lenders.⁶

Does the sharp rise in auto loan terms in recent years make auto loans riskier? What is the relation between a loan's pricing and loan term? There is scant literature on the risks and pricing of long-term auto loans,⁷ and this study aims to provide some insights into the two questions above. We focus on delinquency probabilities as a measure of risk as we do not have data on loss recovery.⁸ We use the annual percentage rate (APR) when investigating pricing. The data do not report interest rate, so we calculate APR based on other available loan information.

Our study is based on a sample of auto loans from a credit bureau over a span of 11 years from 2005–2015. After accounting for the risk factors available in this sample, we find that auto

⁵ See, for example, "Introducing the 97-month car loan," Wall Street Journal, April 8, 2013, by Mike Ramsey, and the Wall Street Journal report at <http://blogs.wsj.com/totalreturn/2015/06/01/more-car-buyers-take-long-loans/>.

⁶ We have such results from Experian AutoCount data. These results are not reported because of space limitations and are available upon request.

⁷ For example, Heitfield and Sabarwal (2004); Agarwal, Ambrose, and Chomsisengphet (2008); Yeh and Lee (2013); and Wu and Zhao (2016).⁸ As a matter of fact, as far as we are aware of, there is no public data on loss given default on auto loans.⁹ We divide all balances by two if the account is a joint account and the credit score is of the primary account holder.

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loans with terms beyond five years have significantly higher delinquency rates than shorter ones during each year of their lifetimes. Furthermore, the yield curve among auto loans is inverted after we control for the loans' delinquency and prepayment risks. These patterns hold for both prime and subprime loans.

Therefore, the long-term auto loans have higher delinquency risk than what is indicated by the observables in our data, and yet the interest rates on the loans are lower than the rates one would expect given their higher delinquency risks. This finding poses a puzzle, and we discuss potential explanations for this puzzle. However, we also point out that the evidence, especially that on the APR, is rather preliminary because of data limitations. So, the exact reasons behind this puzzle will await future research.

The rest of the paper proceeds as follows: In Section 2, we discuss the data and present the summary statistics. We investigate the risks among long-term auto loans in Section 3 and examine the relation between APRs and loan terms in Section 4. We discuss potential explanations for the puzzle in Section 5 and draw a brief conclusion in Section 6.

2 Data description and summary statistics

2.1 Data construction

Our data come from a major credit bureau in the US. The dataset is longitudinal and contains a 0.7 percent random sample of all credit files of the credit bureau in the base year of 2005, after which new files are added each year to rebalance the sample due to attrition and new entrants.

The credit bureau data consist of both attribute and tradeline data. The attribute data are annual snapshots of borrower characteristics and account-level credit files as of June 30 of the file year from 2005 through 2015. The attributes include annual information on the geographic location

of an individual (such as city, state, and zip code), consumer credit risk score (i.e., credit bureau score), as well as 10 summary credit attributes that use tradeline data for each individual. The tradeline segment lists the details of a credit account, such as the consumer and tradeline identity key, account description (account ownership, type of creditor, type of account, loan purpose, etc.), credit limit or the highest balance, current balance, payment performance (for the past 48 months and current month), and account dates (e.g., open date, report date, and close date).⁹

The data do not have information on the loan-to-value (LTV) ratio of an auto loan, neither at origination nor after updating. There is no information on the vehicle transaction, such as value of the trade-in-vehicle, the back-end add-ons of the purchased vehicle, whether the collateral is a new or used car, or whether the loan is directly financed by a lender or indirectly financed through a dealership and so on.¹⁰ Additionally, there is no information on borrower income, job, or education.

We include in our analysis auto loans issued by banks, credit unions, and finance companies.¹¹ Our sample consists of auto loans originated and observable during the period from June 2005 to June 2015.

2.2 Summary statistics

Our data are at an annual frequency, but we can observe monthly loan performance status with the 48-month payment performance field. The delinquency event we focus on is 90 days past due (DPD). We choose 90 DPD because this is the most widely used default definition in the financial industry. In particular, the standard practice in the auto lending industry is to begin repossessions

⁹ We divide all balances by two if the account is a joint account and the credit score is of the primary account holder.

¹⁰ The overwhelming majority of auto loans are indirectly financed through a dealership, which we will discuss further in section V.

¹¹ “Buy here, pay here” auto loan lenders sell cars at inflated prices while cutting APRs (for example, see the paper by Melzer and Schroeder (2015)). These loans are made to deep subprime borrowers who do not have many financing options, and these loans are not included in our analysis.

at 90 DPD, and the collaterals are normally very quickly auctioned off afterwards.¹² This swift repossession and resolution is another reason that delinquency rates among auto loans are usually low, because borrowers can quickly lose their vehicles if they miss any payments. A loan is deemed to be prepaid if it is paid off more than one year before maturity. A loan-year drops out of our loan-year panel data once the loan is pre-paid or hits 90 DPD.

Panel A of Table 1 presents the summary statistics based on 2,363,261 loan-year observations, consisting of loans originated since 2005 and reported in our data starting from 2005. The numerator in the payment-to-income ratio (PTI) is the monthly payment of the auto loan in question, while the numerator in the outstanding loan-to-income ratio (LTI) is the total outstanding balance on all mortgages and auto loans of the borrower, except the auto loan in question.¹³ We exclude the auto loan in question from the LTI to avoid double counting because the auto loan in question is already included in the PTI. As a result, if a borrower has a mortgage and only one auto loan, the numerator of the LTI only includes the mortgage balance. For a borrower with only one auto loan and no mortgage, the LTI is equal to zero. The denominator in both the PTI and LTI is the annual average personal income at the county level and mapped to the consumer's zip code, as our data do not have income information at the individual level. Our PTI and LTI measures are far from ideal, but they are the best we could construct given the data. Our data do not have pricing

¹² Each state generally has a redemption period where the borrower can satisfy all arrears, but the redemption right does not lead to a protracted amount of time, as most auto lenders do not even pursue deficiency balances.

¹³ We have tried adding other types of consumer credit, such as credit cards, home equity lines, and student loans into the LTI calculation. We find the coefficient estimate of such alternative definitions of the LTI to be negative. This result means that higher consumer leverage is negatively related to the probability of 90 DPD on auto loans, which is counterintuitive. The coefficient estimate of the LTI is positive if only mortgages and auto loans are used to define it. Such results might be driven by the pecking order of delinquencies in consumer debts. Evidence from the academic literature and industry experience has been that consumers tend to be delinquent on other nonmortgage consumer debt before they become delinquent on auto loans (see, e.g., Jagtiani and Lang 2011; Lee, Mayer, and Tracy 2013). As a result, the amount of other types of nonmortgage consumer debt may not be particularly relevant to a consumer's decision to be delinquent on auto loans. The pecking order of delinquency in consumer debt is beyond the scope of this paper, and we only keep mortgages in this study to keep our side story simple. Note that the survival functions we uncover in this study hold regardless of how we define the LTI, or whether we include LTI in the regression specification.

information, and we calculate APRs based on the loan origination amount, monthly payment, and loan term.¹⁴ We define subprime as a credit bureau score being below 660.¹⁵ The macroeconomic variables incorporated in our study include unemployment rate at the county level (from Bureau of Labor Statistics), housing price index (HPI) at the 3-digit zip code level (from Federal Housing Finance Agency (FHFA)), household income at the county level (from US Census), and we merge them with our credit bureau data through zip code to county or state mapping. The used car prices are from Manheim Inc., the largest automobile auction company in the world by volume of trade. The Manheim used vehicle price index is the most widely used index in the industry.¹⁶

We report the summary statistics of the entire sample of 2,363,261 loan-years observations in Panel A of Table 1, and present in Panel B the origination loan and consumer characteristics on the cross-section of 875,516 unique loans by terms. Because of the limited number of observations in our sample among loans with terms above seven years and below two years, we group auto loans with terms seven years and above into one category and those with terms two years or less into another category. We also plot the kernel densities of some major variables by loan terms in Figure 2.

A pattern that clearly stands out in Panel B of Table 1 and Figure 2 is that the credit bureau scores at origination are the lowest among auto loans with terms less than or equal to two years

¹⁴ Auto loans typically have fixed rates. We use the `mort` (loan origination amount, monthly payment, term duration) function in SAS. We use the bureau variable `TRM_DURATION` for term information. We find that the calculated APRs overwhelmingly stay constant over time for the same loan, which gives us confidence in the data quality. The calculated APRs averaged over different subgroups are comparable to those reported in the Experian AutoCount data, which only report results at the aggregate level. We have also tried excluding from our study the few cases where APRs change from year to year for the same loan and results do not change. The calculated APR does not include the origination fee (typically 1-2% of the autocar loan amount, and a flat fee of \$450-\$700 for autocar leases) or other one-time fee or charges that are not amortized in the monthly payments.¹⁵ Throughout the paper, we use the up-to-date credit scores unless the credit scores are specifically noted as loan origination credit scores.

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¹⁶ County level unemployment is downloaded from Haver Analytics. The Manheim index is from <https://publish.manheim.com/content/dam/consulting/ManheimUsedVehicleValueIndex-WebTable.png>.

and six-year loans.¹⁷ Not surprisingly, the 90 DPD rates are much higher for these loans than for the remaining auto loans. Even though the seven-plus-year loans have comparable average credit bureau scores at origination as the three- to five-year loans in Panel B of Table 1, Panel A of Figure 2 shows that the mode of credit scores among seven-plus-year loans is noticeably lower than that for three- to five-year loans.

The deterioration in credit quality as the loan term rises from five to six years can also be clearly seen from credit card utilization rates at origination in Panel B of Table 1. In addition, the average LTI has a general upward trend as the term lengthens,¹⁸ and the loan amount at origination increases monotonically with terms. The average PTIs are flat from two to four years, and then increase monotonically as the terms lengthen.

The sixth column of Panel B of Table 1 shows that auto loan monthly payments are roughly \$50 to \$100 higher for five-year and up loans than for those with terms below five years. If borrowers shortened the terms of these long-term loans, the monthly payments would be much higher. For example, the monthly payment of a seven-year loan of \$30,000 with an APR at 8 percent is \$467.60. If the term is shortened to five years while keeping everything else the same, the monthly payment would increase by \$141.10 to \$608.70.

¹⁷ Note that the average credit bureau score of 676 among six-year loan borrowers is a high credit score and nearly 60% of the US population have credit scores higher than 675. Having low credit scores is most likely driven by their lower income (see, for instance, <https://www.valuepenguin.com/average-credit-score>), and county-level income might over-state these borrowers' income. In addition, even if the DTIs in Panel B of Table 1 reflect well these borrowers' actual DTIs, the same DTI value means very different things for a person making \$50K annually and a person making \$100K annually, as the first person does not have much discretionary income after taxes and necessities are paid for.

¹⁸ Even though the average LTI among six-year loans is slightly lower than those of five-year loans, this result could be explained by a lower proportion of borrowers of six-year loans with mortgages. However, a much larger fraction of those people who borrow six-year auto loans are subprime consumers. Together with their substantially higher credit card utilization rates, the slightly lower LTI among borrowers of six-year auto loans does not provide much assurance.

We have also broken out the analysis in Table 1 by each year and find robust results in which the choice of long-term loans is associated with a larger amount of auto loans and consumers who are more credit constrained in terms of credit scores and credit card utilization rates.¹⁹

3 Loan delinquency risk

In our formal regression analysis, we use the discrete hazard model and jointly estimate the probabilities of 90 DPD and prepayments. There are two equations in the multinomial logit: a delinquency equation and a prepayment equation. The dependent variable in the delinquency equation is equal to one if an auto loan hits 90 DPD during the period from July 1, year t , to June 30, year $t+1$, and zero for all other non-delinquency, non-prepayment loan-years. The dependent variable in the prepayment regression is equal to one if an auto loan is paid off during the period from July 1, year t , to June 30, year $t+1$, while the loan is scheduled to mature after June 30, year $t+1$, and zero for all other non-delinquency, non-prepayment loan-years. We define $P_{i,t+1} = 0$ if current, $P_{i,t+1} = 1$ if prepaid, and $P_{i,t+1} = 2$ if 90 DPD for an individual i at time $t+1$. The multinomial logit for $P_{i,t+1}$ can thus be written as:

$$\text{Pr } ob(P_{i,t+1} = j) = \frac{e^{\beta_j x_i}}{e^{\beta_0 x_i} + e^{\beta_1 x_i} + e^{\beta_2 x_i}} \quad (1)$$

where the independent variables include borrower- and loan-level variables, macroeconomic variables, the interaction terms between the age (namely, years since loan origination) and loan term, origination year dummies, and a lender-type fixed effect. We use the updated borrower- and loan-level variables if these variables are time-varying, for example, credit bureau scores, LTI,

¹⁹ The results are not reported for brevity.

PTI, and credit card utilization rates, to account for changes in the borrower's creditworthiness. We also include a few dummy variables to indicate whether the borrower has a mortgage(s) at the origination of the auto loan and whether the borrower has a mortgage(s) in the loan-year in question.

We measure the average regression residual after controlling for the observed risk factors via the interaction between age and loan term, which accounts for the possibility that the age survival functions may vary for different terms. Therefore, the coefficient estimates of the interaction terms in the delinquency equation in equation (1) are residual delinquency risks for that particular term-age group after controlling for the observed risk factors.

We only report the results from the delinquency equation in the paper because of space limitations, and prepayment regression results are available upon request. We report the coefficient estimates of loan and borrower characteristics in Panel A of Table 2. The first column of this panel shows the results for the full sample, while the second and third columns break down the analysis into subgroups of subprime (with credit bureau score <660) and prime (with credit bureau score ≥ 660) borrowers. The omitted credit bureau score range category is <560 in the first two columns of the panel and [660, 720) in the last column of the panel. Among the mortgage holder dummies, the omitted category consists of borrowers who did not have a mortgage at the origination of the auto loan and who remained non-mortgage holders.

Panel A of Table 2 shows that borrowers with higher credit scores are less likely to be delinquent on their auto loans,²⁰ and borrowers with higher PTIs and higher credit card utilization

²⁰ We use updated instead of origination credit bureau scores even though the updated credit bureau score might be endogenous. This is because we want to include all available up-to-date hard information that reflects borrowers' ability to pay and explore if there are still residual delinquency risks. For robustness tests, we also tried using the credit bureau scores at origination, and the results from such a specification are very close to those reported in Table 4. These results are not reported in the paper because of space limitations but they are available upon request.

rates are more likely to be delinquent on their auto loans. Among non-mortgage holders, those with higher LTIs are more likely to be delinquent on their auto loans. The relation between LTI and 90 DPD probability is not clear-cut among mortgage holders. In addition, large auto loans are less likely to be delinquent, and a borrower is less likely to be delinquent on the auto loan if the loan is the only auto loan he or she has. This panel also indicates that non-mortgage holders in general have higher auto loan delinquency rates.

In Table 2, we include macroeconomic variables realized from year t to year $t+1$. We have tried other local macroeconomic variables in addition to those reported in Table 2, such as the maximum unemployment rate during the one-year ahead forecast interval and percentage change in the number of new unemployment insurance claims,²¹ as well as one-year lagged local macro variables, macro variables at the origination date, and the change in the macro-variables from the origination year to the current year. These additional results are not reported because of space limitations. However, regardless of which macro-variables we incorporate or which functional form we use, the coefficient estimates for the age-term interaction terms (the key results of the paper as reported in Panel B of Table 2) do not change qualitatively.

We report the coefficient estimates for the interaction terms for the full sample (i.e., column 1 of Panel A of Table 2) in Panel B of Table 2. The base category in equation (1) is the first year of a four-year auto loan. Panel B of Table 2 shows that the coefficient estimate for the interaction between the first-year and the six-year term is 0.10, which is significantly different from zero. Therefore, during the first year after loan origination, the residual 90 DPD rates of six-year auto loans are 10.5 (the difference between $\exp(0.10)$ and 1) percent higher than those of four-year

²¹ New unemployment claims are at the state level and downloaded from Department of Labor Unemployment Insurance Program.²² The prime rates are downloaded from the St. Louis Fed: <https://www.federalreserve.gov/datadownload/Choose.aspx?rel=H15>

auto loans. In addition, Table 2 shows that the coefficient estimate of the interactive term of year 1 and the seven-plus-year term is statistically significant at 0.52, which suggests that the residual 90 DPD rates of seven-plus-year auto loans are 68.5 (the difference between $\exp(0.52)$ and 1) percent higher than that of four-year auto loans in the first year after loan origination. Similarly, we can see that the residual 90 DPD rates of the five-year auto loans are significantly lower than those of the four-year auto loans in the first year after origination.

Panel B of Table 2 shows a clear pattern in which during the first four years after loan origination, the coefficient estimates of the interaction terms for six- and seven-plus-year auto loans are overwhelmingly positive with large economic significances, while those for shorter auto loans are largely non-statistically significant or negative.

Panels A and B of Figure 3 depict the coefficients for the age-term interaction terms from the delinquency equation of equation (1) among the subprime and prime borrowers, separately, corresponding to the results in the second and third columns of Panel A of Table 2. Panel A of Figure 3 clearly shows that among subprime auto loans, the lines for the six- and seven-plus-year loans are above those for the shorter ones most of the time. Unreported test statistics show that after controlling for observed risk factors, seven-plus-year loans are always significantly riskier than those with terms below five years among subprime auto loans. Furthermore, other than their first and fifth years, six-year subprime auto loans are also significantly riskier than shorter subprime auto loans.

The riskiness of six-plus-year auto loans is the most obvious among the prime auto loans. Panel B of Figure 3 shows that the lines for the six- and seven-plus-year auto loans are substantially above all other lines for each loan age. Unreported test statistics confirm that all coefficient estimates for the age-term interaction terms are significantly higher among six-plus-year loans,

except for the seventh year for seven-plus-year loans. Such results indicate that among prime auto loans and after controlling for the observed risk factors available from the credit bureau data, six-plus-year auto loans have substantially higher 90 DPD rates than shorter-term auto loans during each year in their lifetimes.

We have also run equation (1) during the subperiods before 2009 and after 2009. In both subperiods, we find rather robust results in which after controlling for observed risk factors available from the credit bureau data, six- and seven-plus-year auto loans have higher residual delinquency rates than shorter ones in almost each year since origination.

4 Relation between APR and loan terms

We turn to APR analysis in this section. We illustrate in Figure 4 the average APRs along with prime rates by credit bureau score buckets and loan terms over time.²² This figure indicates that in all credit score buckets and across different terms, the relations between APRs and prime rates are not very close, and this lack of association is particularly notable among loans to borrowers with low credit scores.

For borrowers with credit bureau scores below 660 in Figure 4, the APR lines of the seven-plus-year loans are always at the bottom of the graph, while the APR lines of the six-year loans are either mingled with the APR lines for three- and four-year loans or below those lines. For borrowers with credit bureau scores above 660, the APR lines of the six- and seven-plus-year loans are largely in the middle. This is the first piece of evidence that the term structure of the APRs on auto loans might not be upward-sloping as is the case for most financial products, for example,

²² The prime rates are downloaded from the St. Louis Fed:
<https://www.federalreserve.gov/datadownload/Choose.aspx?rel=H15>

mortgages or corporate loans, mainly because of the liquidity premium and the higher funding cost among longer-term loans.²³

We next turn to a regression analysis to examine the relation between APRs and loan terms while controlling for delinquency and prepayment risks. Intuitively, APRs should be positively associated with delinquency risks, and maybe to a lesser extent, positively related to prepayment risks as well. We first calculate loan-year 90 DPD and prepayment probabilities following the estimated equation (1) for each sample separately in Table 2, and then we convert these probabilities into loan-level delinquency and prepayment probabilities. In this conversion, we account for the timing of a loan's 90 DPD and prepayment probabilities. To illustrate the importance of timing, consider two two-year loans with the same lifetime 90 DPD probabilities. The first loan's delinquency risk concentrates in the second year, but the second loan has a higher delinquency risk in the first year, and thus, the APRs should be different for these two loans because of the time value of money. The same logic applies to the difference in the timing of prepayment probabilities.

We construct the annualized lifetime delinquency and prepayment probabilities at the loan level by taking the weighted average of the full sets of annual, conditional 90 DPD and prepayment probabilities for the full life-time of the loan. The weights are set up such that 1) the weights for the previous year should be higher than the weights for the subsequent year, and 2) the weights should add up to one. The first condition assumes that lenders are more concerned with 90 DPD probabilities in the nearer horizons than longer horizons because the time-value-adjusted losses will be higher. Likewise, lenders should also be more concerned with prepayment in the nearer

²³ This counterintuitive inverted yield curve is likely not driven by investors' thirst for yield in recent years because the overwhelming majority of auto loans are not securitized. Further, investors could flock to shorter-term auto loans to obtain higher yields.

horizons because they need to re-invest the prepaid funds more frequently, which increases transaction costs. The second condition is to normalize the annualized lifetime delinquency probabilities, so they are at the same order as the annual delinquency probabilities from each year. For the results reported in Table 3, the weight for the previous year is twice the weight for the subsequent year. In robustness tests, we have also tried 1.5 and 2.5 times as well as equal weighting of the full sets of annual, conditional 90 DPD and prepayment probabilities. The results from such additional analysis are qualitatively similar to those reported in Table 3, and they are available upon request.

We have also tried an alternative measure of delinquency (prepayment) probability based on the observed 90 DPD (prepayment) events in the data. We define this measure as equal to one if the auto loan has hit 90 DPD (prepayment) in our sample, and zero otherwise. This alternative measure does not account for right censoring, as a loan may only have two years in the data since origination; even though the loan has not yet hit 90 DPD (prepayment) during the sample period, it may be delinquent (prepaid) in the future. However, the alternative measure will assign a value of zero to this loan. The results from either measure are consistent. We report the results from the estimated annualized lifetime delinquency and prepayment probabilities because of space limitations and because these measures are more accurate than the alternative by accounting for right censoring. The results using the alternative measures are available upon request.

Because Figure 4 shows that the APRs do not demonstrate a close relation with the prime rates, and the APRs of different credit bureau score buckets behave quite differently over time, we incorporate in the regression the origination year fixed effect and the interaction between the loan origination year and credit score bucket instead of including the prime rates among the right-hand-

side variables. The APR regression is estimated by using the ordinary least squares (OLS) with the model specification as follows:

$$\begin{aligned}
 APR_i = & \alpha + \beta_1' \times \text{Loan Lifetime Delinquency Risk}_i \\
 & + \beta_2' \times \text{Loan Lifetime Prepayment Risk}_i + \gamma' \times \text{Loan Term Dummies} \\
 & + \theta' \times \text{Lender Type Dummies} + \lambda' \times (\text{Credit Score Bucket} * \text{Origination Year}) \\
 & + \psi' \times \text{Origination Year Dummy} \tag{2}
 \end{aligned}$$

In all columns of Table 3, we use the four-year loans as the base category. If there is no association between APRs and loan terms, after controlling for the credit and prepayment risks, the coefficient of the term dummies should be statistically nonsignificant. A positive (negative) coefficient for a term dummy indicates that controlling for the same credit risk and prepayment risk, lenders charge higher (lower) APRs to that group of loans.

We report the results on the full sample as well as the subprime and prime samples in Table 3. We find that loans with higher predicted annualized lifetime delinquency probabilities are charged higher APRs and loans with higher prepayment rates are also charged higher APRs. The coefficient estimates for the 90 DPD probabilities are multiple times higher than those of prepayment probabilities, suggesting that lenders are more concerned with delinquency risks than with prepayment risks, which is reasonable. This table also indicates that delinquency risks are priced quite differently between borrowers with different credit profiles, but prepayment risks are priced similarly.

In all columns of Table 3, the coefficients for the two-minus-year loan dummy are significantly positive, while those for the five-, six-, and seven-plus-year loan dummies are significantly negative. These results show that after controlling for credit and prepayment risks and relative to four-year auto loans, lenders typically charge higher APRs to auto loans with terms

less than or equal to two years, and lower APRs to five-, six-, and seven-plus-year auto loans. In the second and third columns of Table 3, the coefficient estimates for a six-year loan are less negative than those for five-year loans, while the coefficient estimates are the most negative for the seven-plus-year loans. Among subprime loans, and relative to four-year loans with similar levels of credit risks, the APRs on seven-plus-year loans are nearly 2.5 percentage points lower, and six-year auto loans are charged APRs that are 0.84 percentage points lower. Among prime auto loans and compared with four-year loans with similar levels of credit risks, seven-plus-year loans are charged APRs roughly 0.7 percentage points too low and six-year auto loans are charged APRs that are 0.25 percentage points too low. Comparing these numbers with the APRs reported in Table 1 or those in Figure 4, the differences in APR clearly are far from trivial.

Therefore, after accounting for credit and prepayment risks, the yield curve among auto loans is generally downward sloping. However, we do not have sufficient data to fully explore the pricing of auto loans. One important risk factor that is missing from equation (2) is the LTV. However, we learn from practitioners that the LTVs are typically higher among long-term auto loans than among short-term auto loans, and higher LTVs are generally associated with lower loss recoveries. As such, the relatively lower APRs among long-term auto loans might be even more severe than what was documented in Table 3.

5 Possible explanations for the puzzle

The finding that the long-term auto loans are far riskier than the observable predictors of delinquency would indicate but the interest rates on the loans are lower than those congruent with their delinquency risks, poses a puzzle. There are several reasons that might explain this puzzle.

First, this puzzle might be driven by the spread and back-end add-ons. Most auto loans are indirect; that is, dealers obtain financing from lenders and then offer auto loans to customers. Therefore, the APRs are largely set by dealers not lenders.

Dealers are compensated through both the spread and the back-end add-ons. The spread is the difference between 1) the buy rate a dealer obtains from a lender and 2) the rate offered to a customer; the spread may be split between the dealer and the lender or retained entirely by the dealer. For example, a dealer may be offered a buy rate of 4% by the bank buying the loan. The dealer may sign the customer to a 5.5% loan. In this case, the spread is 1.5%. The APRs we have in the paper are the rates to the customer, since we calculated the rates based on scheduled loan payments. The APRs could be lowered if dealers are willing to earn lower spreads. The back-end add-ons (i.e., the markups) are the costs beyond the purchase prices of the vehicles, such as extended warranties, maintenance contracts, paint and fabric protection. The cost of back-end add-ons may range from just \$100 (like “undercoating” on a vehicle) to several thousand dollars (for an extended warranty).

Over the past few years, the industry has seen a compression of spreads in general, while sales of back-end add-ons have become more widespread. However, earning less spread (charging a lower APR) on more expensive cars (which tend to have longer terms, as can be seen from Panel B of Table 1), while selling the car and the back-end add-ons might actually boost, instead of dampening, the dealers’ profitability.

Second, other aspects of the vehicle sales transaction might also help to explain the APR, but we do not have such information in our data. For instance, we do not have the value of the trade-in-vehicle, the markup of the purchased vehicle, model and make of the underlying collateral, whether the collateral is a new car or a used car, or whether the loan is a direct loan

obtained from a bank or an indirect loan purchased through a dealer. Such missing information can potentially add more explanations to the APR variations and thus help us better understand the relation between APRs and loan terms. Because of such data limitations, the puzzle of why APRs are lower among longer-term auto loans even though these loans are riskier demands further investigation in the future when more transaction level data are available.

6 Conclusion

We examine the riskiness of long-term auto loans by using data from a credit bureau over an 11-year span from 2005–2015. We find that auto loans with six- plus-year terms have higher 90 DPD rates than shorter-term loans during each year of their lifetimes, after controlling for borrower and loan-level risk factors available from the credit bureau data and macroeconomic conditions. However, the yield curve among auto loans is inverted; that is, the APRs on six- and seven-plus-year auto loans are significantly lower than those on shorter-term auto loans with similar levels of delinquency and prepayment risks. The finding that APRs are lower among longer-term auto loans even though these loans are riskier poses a puzzle. We cannot fully decode this puzzle in this study because of our data limitations. The reasons behind this puzzle remain unknown and call for additional investigation in the future.

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Table 1 Summary statistics

Panel A Loan and borrower characteristics variables

These summary statistics are calculated based on the survival panel data with a total of 2,363,261 loan-years observations

	Mean	p5	p50	p95	Standard Deviation
90 DPD rate	1.45%				
Prepayment rate	9.80%				
Loan origination amount (\$)	20,448	7,005	19,177	38,367	9,515
Annual percentage rate (APR)	7.30%	1.88%	6.29%	18.01%	4.38%
Monthly auto loan payment	397	171	368	714	173
Credit bureau score	702	514	723	821	97
Payment-to-income ratio (PTI)	0.12	0.05	0.11	0.23	0.06
Liability-to-income ratio (LTI)	1.63	0.00	0.81	6.00	2.20
Credit card utilization rate	0.32	0.00	0.16	1.00	0.39
Proportion of mortgage holder	0.55				
Proportion of mortgage holder remaining mortgage holder	0.51				
Proportion of non-mortgage holder remaining non-mortgage holder	0.42				
Proportion of mortgage holder becoming non-mortgage holder	0.03				
Proportion of non-mortgage holder becoming mortgage holder	0.04				
Proportion of borrower with only one auto loan	0.65				
Proportion of subprime borrower	0.29				
Unemployment rate at county level - 1 year forward change (%)	0.01	-1.67	-0.43	2.93	1.44
House price appreciation index at zip3 level - 1 year forward percentage change	0.00	-0.11	0.00	0.10	0.06
Manheim used vehicle price index - 1 year forward percentage change	0.01	-0.04	0.01	0.11	0.04

Panel B Loan and borrower characteristics by loan term

These summary statistics are calculated based on loan and borrower characteristics at origination with a total of 875,516 unique loan observations.

Loan term	N	90 DPD rate	Origination Amount (\$)	APR	Monthly payment	Credit bureau scores	PTI	LTI	Credit card utilization rate	Proportion of mortgage holder	Proportion of subprime borrowers
2-	29,353	2.26%	7,243	9.73%	343	678	0.11	1.13	0.39	0.44	0.40
3	73,643	1.18%	12,109	7.06%	368	720	0.11	1.42	0.26	0.50	0.23
4	98,776	1.16%	14,191	7.52%	341	711	0.11	1.47	0.28	0.52	0.26
5	361,597	0.93%	19,888	6.41%	384	717	0.12	1.71	0.26	0.55	0.23
6	289,341	1.95%	24,981	7.72%	433	677	0.13	1.53	0.37	0.51	0.40
7+	22,806	1.09%	31,631	6.45%	476	712	0.15	2.05	0.30	0.61	0.21

Table 2 Auto loan delinquency risk—coefficient estimates from the delinquency equation of equation (1)

The loan-year panel data contain auto loans originated from January 2005 to June 2014 for the sample period from 2005 to 2015, and we jointly estimate delinquency and prepayment using a multinomial logit model—equation (1). We only report results from the delinquency equation of the multinomial logit model because of space limitations. The explanatory variables are observed in year t . The dependent variable in the delinquency equation is a dummy variable that equals 1 if a loan is 90 days past due or worse over the 12-month period from year t to year $t+1$ and 0 for all non-delinquency, non-prepayment loan-years. Panel A presents the coefficient estimates of the loan, consumer, and macro variables, and Panel B presents the coefficient estimates for the interaction between the age and loan term for the full sample regression. The *, **, and *** indicate statistical significance at the 10, 5, and 1 percent levels, respectively. Standard errors are reported in the parentheses in both panels.

Panel A Loan, consumer, and macro variables from the delinquency equation of equation (1)

	Full Sample	Subprime	Prime
Origination Amount (in \$1,000)	-0.02*** (0.00)	-0.02*** (0.00)	-0.03*** (0.00)
Credit bureau score [560, 620)	-1.14*** (0.01)	-1.14*** (0.01)	
Credit bureau score [620, 660)	-2.02*** (0.02)	-2.02*** (0.02)	
Credit bureau score [660, 720)	-2.90*** (0.02)		
Credit bureau score [720, 780)	-4.00*** (0.04)		-1.05*** (0.05)
Credit bureau score ≥ 780	-5.10*** (0.07)		-2.07*** (0.08)
LTI	0.13*** (0.03)	0.14*** (0.03)	0.18** (0.09)
PTI	3.62*** (0.13)	3.48*** (0.13)	5.08*** (0.44)
Credit card utilization rate	0.20*** (0.01)	0.21*** (0.01)	0.15** (0.08)
One auto loan	-0.03** (0.01)	-0.03* (0.01)	-0.09** (0.04)

Table 2 Panel A continued

	Full Sample	Subprime	Prime
Mortgage non-holder becoming mortgage holder	-0.30*** (0.04)	-0.26*** (0.04)	-0.67*** (0.11)
Mortgage holder remaining mortgage holder	-0.49*** (0.02)	-0.48*** (0.02)	-0.53*** (0.06)
Mortgage holder becoming non-mortgage holder	-0.16*** (0.03)	-0.16*** (0.04)	-0.16 (0.11)
Interaction of LTI and mortgage holder	-0.12*** (0.03)	-0.13*** (0.03)	-0.15* (0.09)
House price appreciation index at zip3 level - 1 year forward percentage change	-0.84*** (0.12)	-0.81*** (0.13)	-0.96** (0.47)
Interaction of house price appreciation index at zip3 level - 1 year forward percentage change and mortgage holder	-1.10*** (0.19)	-0.73*** (0.20)	-2.43*** (0.58)
Unemployment rate at county level - 1 year forward change	0.04*** (0.01)	0.03*** (0.01)	0.09*** (0.02)
Manheim used vehicle price index - 1 year forward percentage change	-1.19*** (0.12)	-1.28*** (0.13)	-0.60 (0.39)
Constant	-2.43*** (0.04)	-2.36*** (0.04)	-6.01*** (0.15)
Lender type fixed effect	Yes	Yes	Yes
Origination year fixed effect	Yes	Yes	Yes
<i>N</i>	2,363,261	690,197	1,673,064
pseudo <i>R</i> ²	0.156	0.119	0.136

Table 2

Panel B Interaction between the age and loan term for the full sample from the delinquency equation of equation (1), corresponding to the first column of Panel A

	Term =2-	Term=3	Term=4	Term=5	Term=6	Term=7+
First Year	0.06 (0.05)	0.12** (0.05)	base	-0.09** (0.04)	0.10*** (0.03)	0.52*** (0.07)
Second year	-0.26*** (0.07)	0.03 (0.05)	0.07 (0.05)	0.02 (0.04)	0.23*** (0.04)	0.61*** (0.08)
Third Year		-0.10 (0.06)	-0.01 (0.05)	-0.04 (0.04)	0.20*** (0.04)	0.52*** (0.09)
Fourth Year			-0.1 (0.07)	-0.16*** (0.04)	0.11*** (0.04)	0.44*** (0.11)
Fifth Year				-0.09** (0.05)	-0.09* (0.05)	0.44*** (0.13)
Sixth Year					0.12** (0.05)	-0.06 (0.19)
Seventh Year						-0.41 (0.27)

Table 3 APR regression

The sample period is from 2005 to 2015 for loans originated from January 2005 to June 2014. The dependent variable is APR in percentage. We construct the annualized lifetime delinquency and prepayment probabilities at the loan level by taking the weighted average of the full sets of annual, conditional 90 DPD and prepayment probabilities from equation (1) for the full term of the loan. The weights are set up such that 1) the weights for the previous year are twice the weight for the subsequent year, and 2) the weights should add up to one. For each column in this table, the annualized lifetime delinquency and prepayment probabilities are calculated using prepayment and delinquency regressions built specifically for the sample as reported in Table 2. The *, **, and *** indicate statistical significance at the 10, 5, and 1 percent levels, respectively. Standard errors are reported in the parentheses.

	Full Sample	Subprime	Prime
Lifetime delinquency probability	60.78*** (0.42)	39.93*** (0.44)	342.50*** (4.42)
Lifetime prepayment probability	15.71*** (0.19)	14.63*** (0.40)	13.16*** (0.19)
Two-minus-year loan	1.10*** (0.03)	1.10*** (0.06)	1.13*** (0.04)
Three-year loan	-0.64*** (0.02)	-0.46*** (0.06)	-0.48*** (0.02)
Five-year loan	-0.50*** (0.01)	-1.00*** (0.04)	-0.43*** (0.01)
Six-year loan	-0.02 (0.02)	-0.84*** (0.04)	-0.25*** (0.02)
Seven-plus-year loan	-0.34*** (0.02)	-2.46*** (0.06)	-0.68*** (0.03)
Constant	6.22*** (0.08)	7.20*** (0.11)	4.58*** (0.05)
Lender type fixed effect	Yes	Yes	Yes
Origination year fixed effect	Yes	Yes	Yes
Interaction of origination year and credit score bucket	Yes	Yes	Yes
<i>N</i>	875,516	257,923	617,593
<i>R</i> ²	0.428	0.211	0.263

Figure 1 Breakdown of auto loans by term and origination year (Source: Experian AutoCount data – the full population of newly originated auto loans in the US)

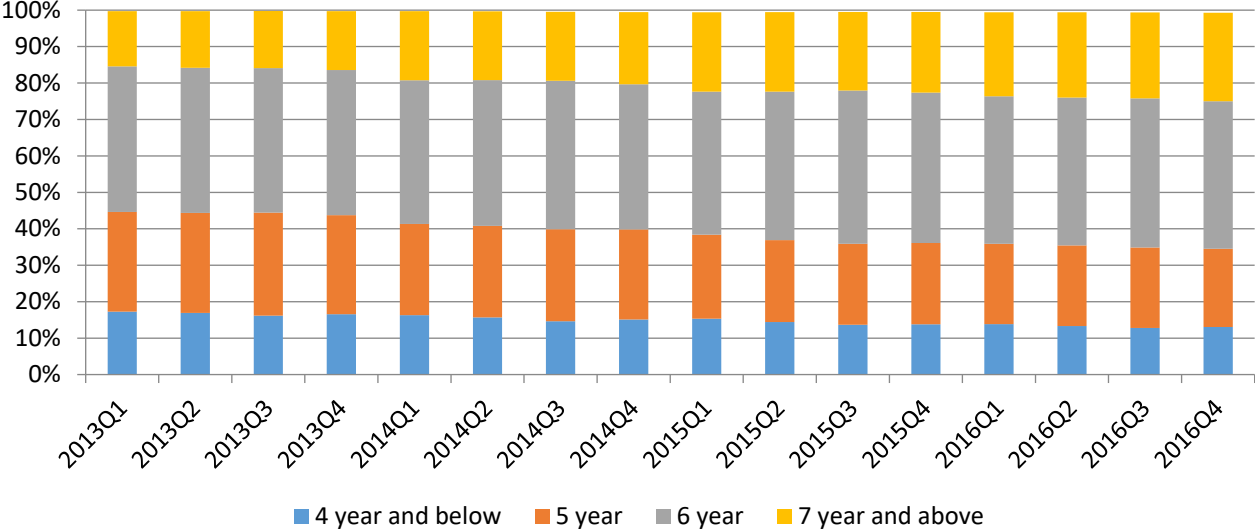
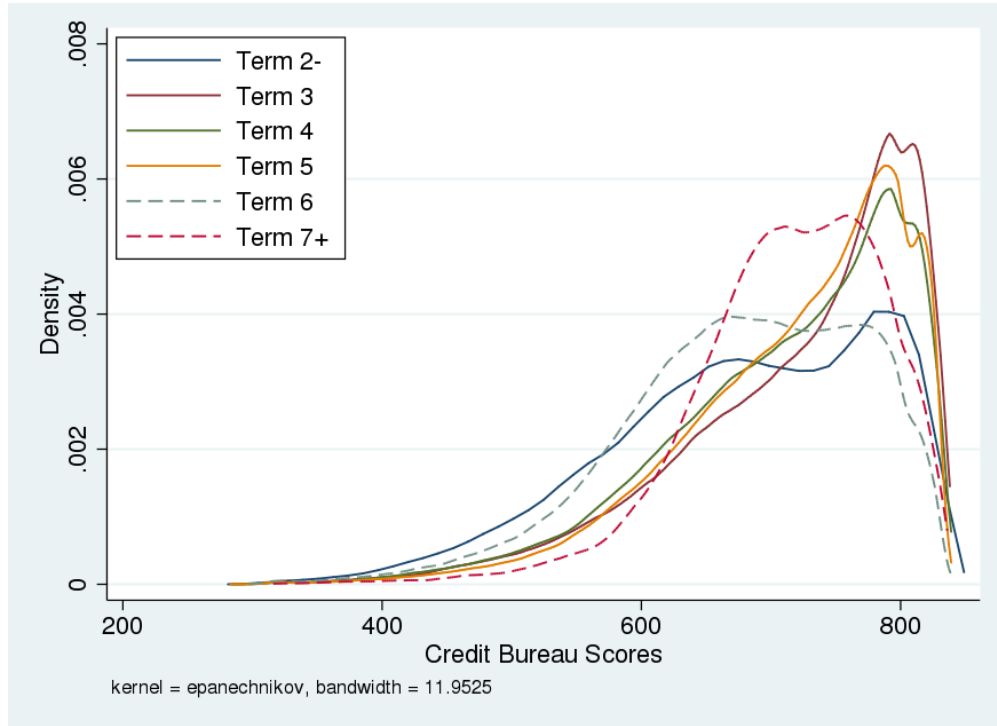
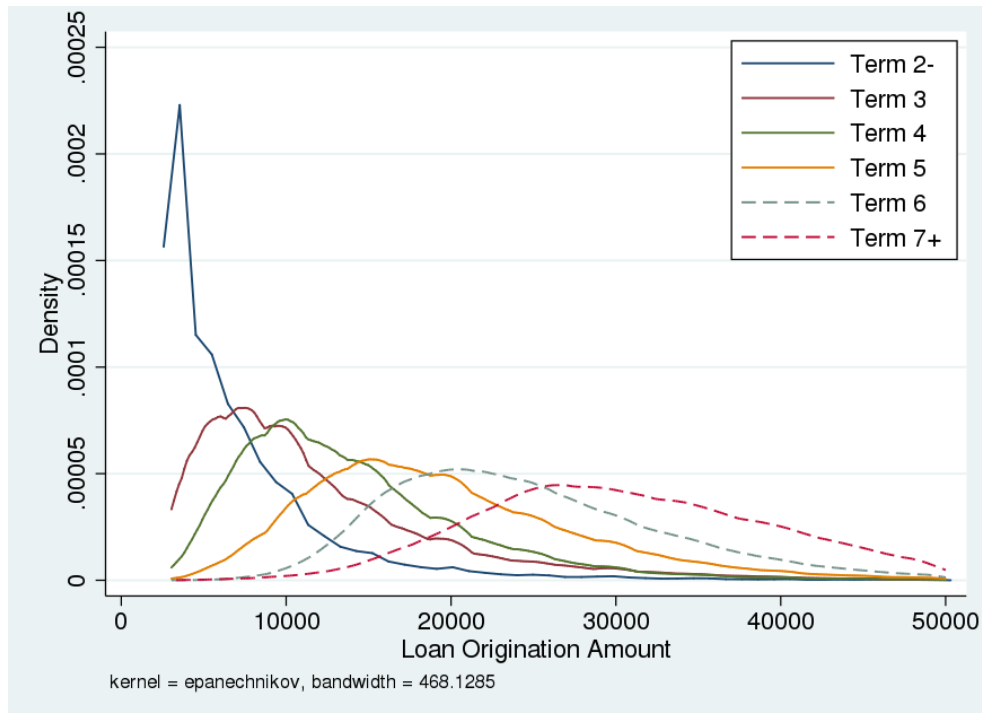


Figure 2 Distribution of credit bureau scores, origination loan amount, and payment-to-income ratio by loan term

Panel A Distribution of credit bureau scores by loan term



Panel B Distribution of loan origination amount by loan term



Panel C Distribution of payment-to-income ratio by loan term

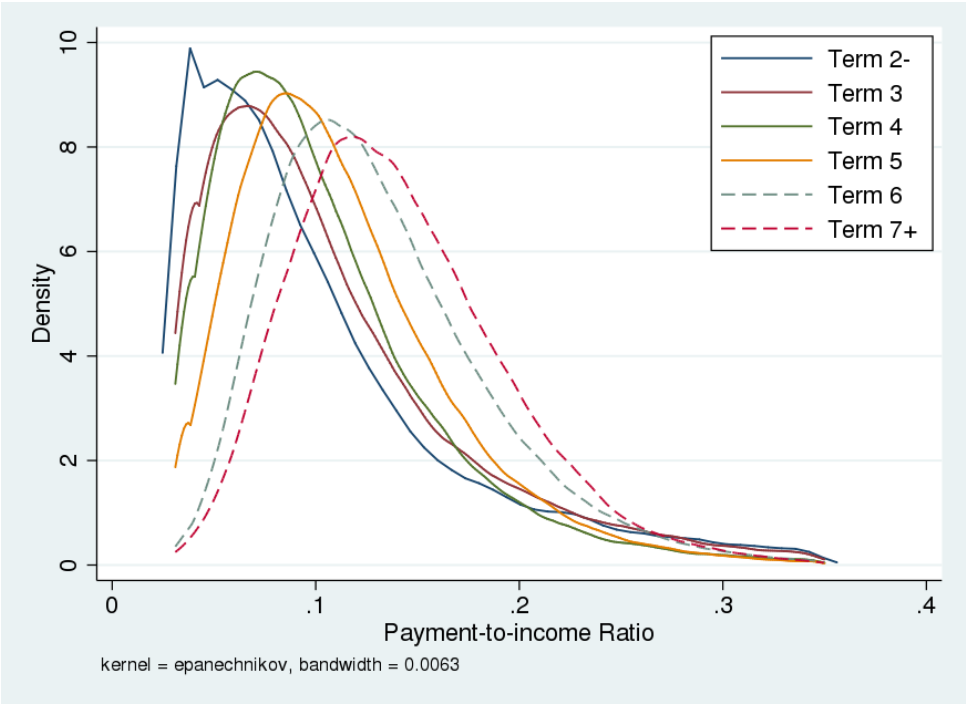
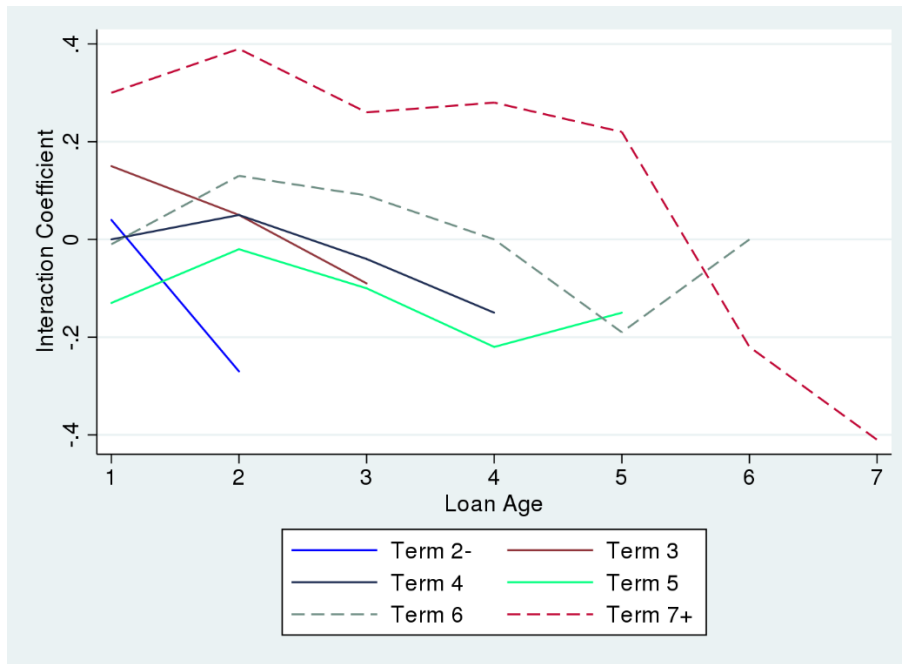


Figure 3 Coefficients of interaction term from the delinquency equation in Table 2

Panel A Subprime sample



Panel B Prime sample

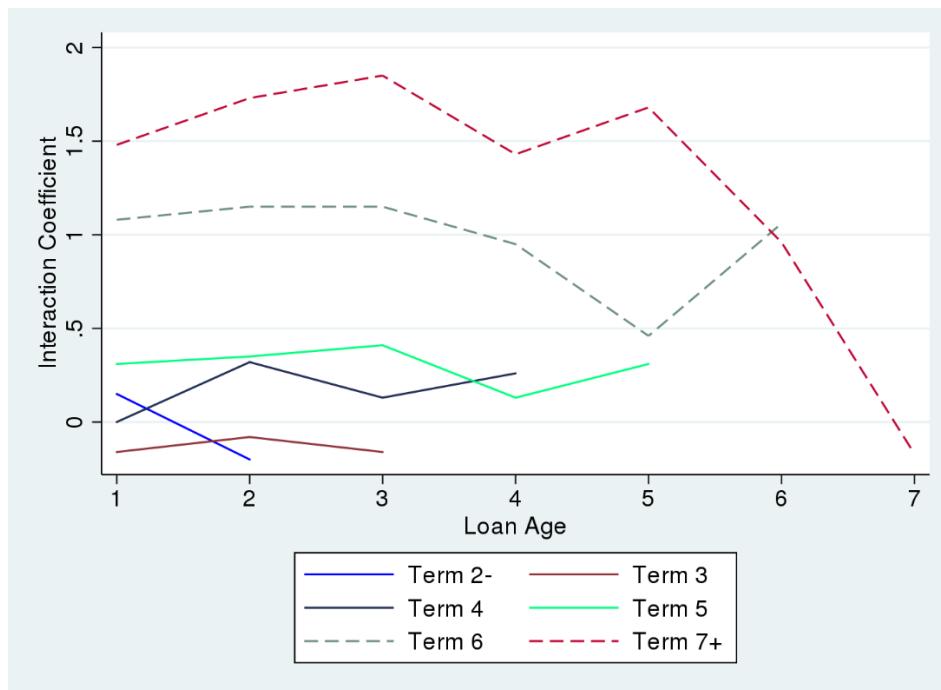
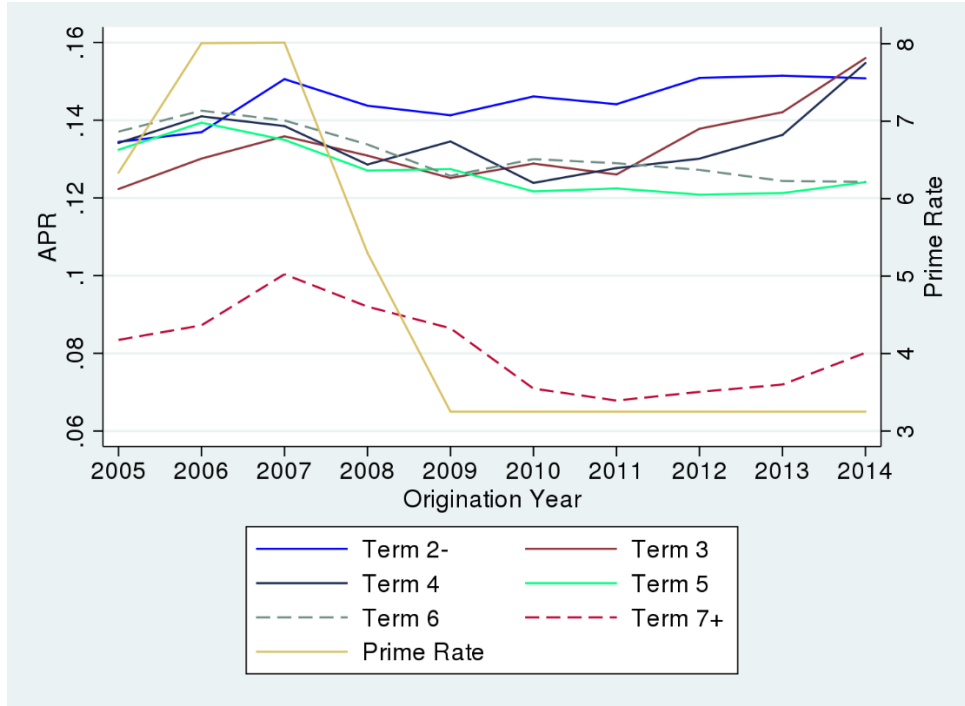
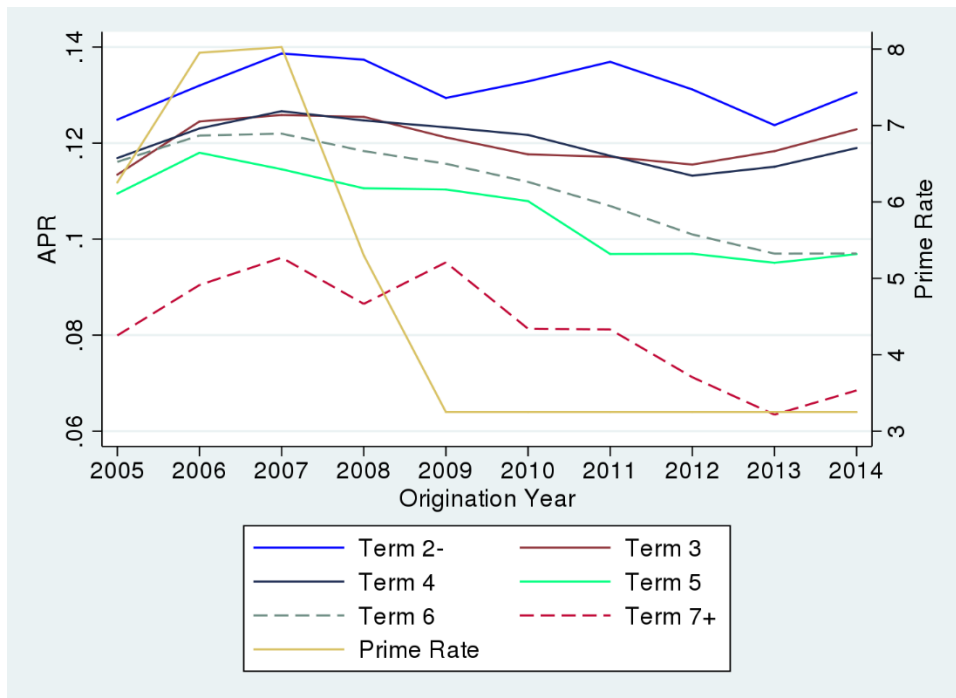


Figure 4 APRs by loan term and credit bureau score buckets

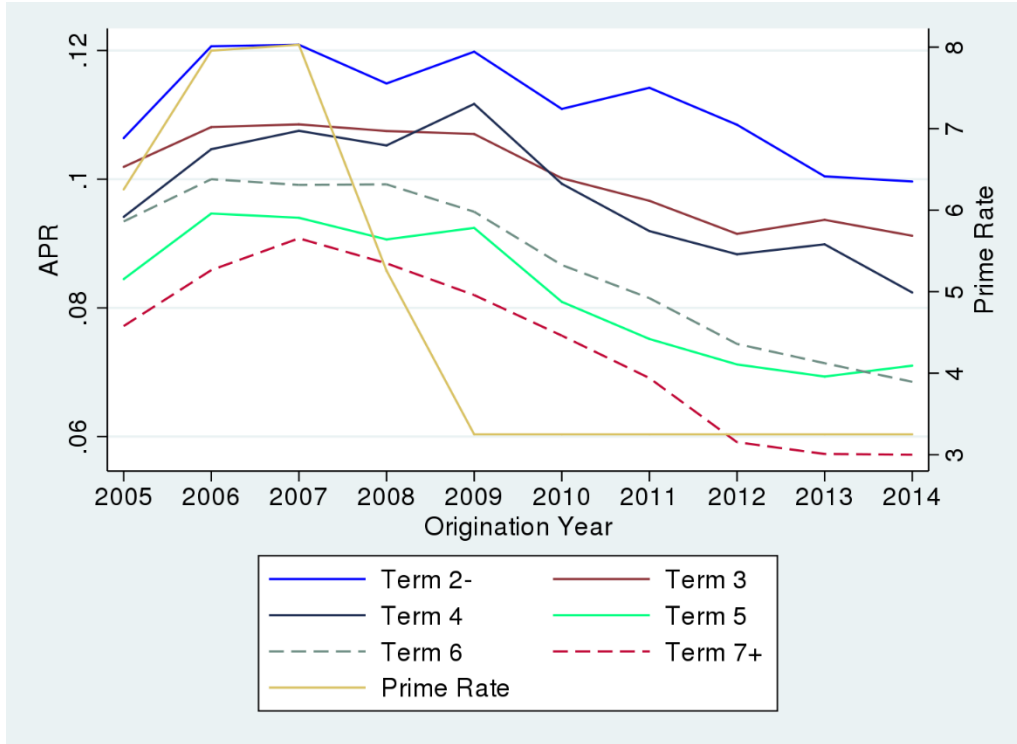
Panel A Credit bureau score <560



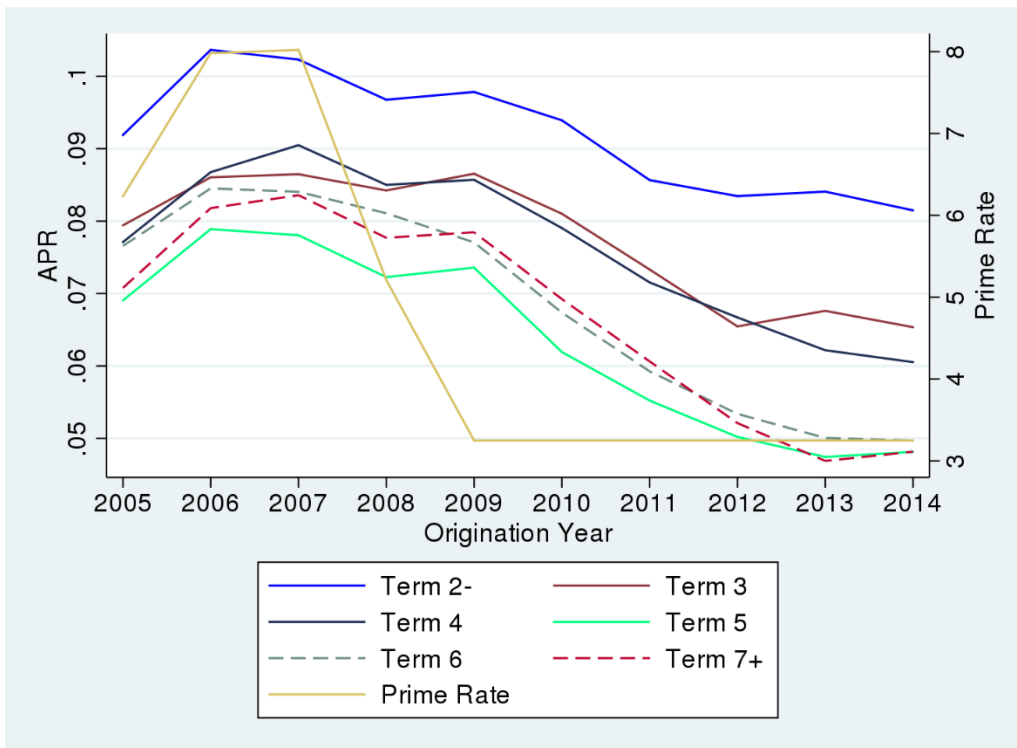
Panel B Credit bureau score [560, 620)



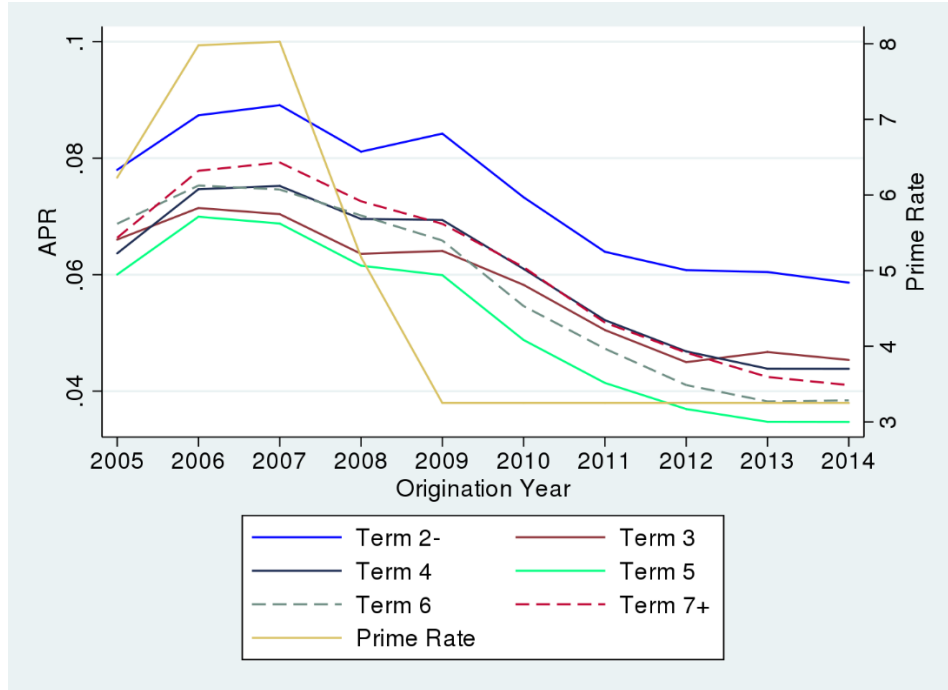
Panel C Credit bureau score [620, 660)



Panel D Credit bureau score [660, 720)



Panel E Credit bureau score [720, 780)



Panel F Credit bureau score ≥ 780

