Product Market Decisions and Subprime Lending by Captive Finance Companies

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Abstract

I study whether companies strategically utilize captive financing, a form of providing funding to consumers, to manage product demand. Using detailed data on auto loans, I show that captive lenders alter the financing terms and lending standards throughout the product life cycle. They reduce interest rates, allow longer maturity, charge lower down payments, and relax loan standards (1) when the underlying car models become outdated; (2) when competitors release new models; and (3) when they experience exogenous shocks such as recalls. While the lower interest rates offered by captive lenders reduce the likelihood of consumer default in the short term, the average default rate eventually increases in the long horizon because captive lenders' willingness to dispense higher-risk loans allows more subprime borrowers to access credit. For consumers who cannot find a loan from non-captive lenders, borrowing from captive lenders help them in purchasing a car, but they could potentially be approved for a loan they cannot afford. These findings collectively suggest that captive financing is a tool manufacturers use to boost car sales throughout the product life cycle, while this tool could induce overleveraging by consumers.

Keywords: Auto loan, Captive financing, Subprime lending, Product life cycle

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1 Introduction

Firms respond to the rapid changes in product demand in various ways. Besides operating decisions, such as changing prices and adjusting inventories, firms can also use financial tools, such as trade credit, to influence product demand (Emery, 1987). In the past few decades, numerous companies have formed wholly-owned subsidiaries, known as “captive finance companies” or “captive lenders,” with the primary function of providing financing for the sales of their parent companies’ products. As one of the fastest-growing financial intermediations, captive lenders took 58.5% of the new-vehicle financing market in 2020 (Pizzolato, 2020). Aside from profiting from the financial transactions, captive lenders and their affiliated business groups also profit from selling the products they finance. Hence, firms could strategically change loan terms according to product market conditions via captive lending.

Using detailed data on auto loans, this paper studies whether companies strategically utilize captive financing, a form of providing funding to consumers, to manage product demand. I hypothesize that automobile manufacturers lower interest rate and relax loan standards of captive finance over the life cycle of a car model. In a typical product life cycle, a new product moves through four stages: introduction, growth, maturity, and decline (e.g., Levitt et al., 1965, Rink and Swan, 1979). At the maturing and declining stages, captive lenders may offer incentives on financing terms, such as lowering the interest rate and relaxing the lending standard, to boost sales. Several arguments can justify this hypothesis: On the one hand, reducing the interest rate makes the product more price competitive (Carbary, 2018). Additionally, relaxing the loan standard can help expand the customer base (Staten et al., 2004). On the other hand, captive lenders and their affiliated business groups may have a lower breakeven point compared to traditional lenders because they also profit from product sales.

The automobile industry is an ideal laboratory for studying the relationship between product market considerations and captive financing for the following reasons. First, auto loans compose the third largest consumer credit market in the United States, with over $1.4 trillion worth of loans outstanding, double the amount from 10 years ago and expected to grow further (Kelly et al., 2022). Second, while both traditional lenders, such as banks and credit unions, and captive lenders offer auto loans, only captive lenders have the incentives aligned with manufacturers’. Thus, auto loans provided by traditional lenders can serve as a counterfactual to captive lenders' loan contracting decisions. Third, unlike real estate properties that are highly heterogeneous in terms of locations and individual property features, cars can be considered homogeneous products within the same make-model-year-trim. This feature allows me to control for the confounding effect of product characteristics by comparing loans offered by different lenders for the same car model. In addition, car manufacturers typically release a new generation of each car model every year. Hence, there is a relatively clear timeline of the product life cycle for cars. Finally, and most importantly, rich data in the auto loan sector support my analysis. Issuers of public auto loan asset-backed securities (ABS) have been required to report loan-level information monthly since November 2016. These data contain information on loan and borrower characteristics at origination and monthly payment records for both captive lenders and traditional lenders. Such rich data allow researchers to account for various factors, such as borrowers' credit score and loan performance, in their analysis (Momeni and Sovich, 2021).

I begin my analysis by comparing the terms of loans issued by captive lenders to those issued by non-captive lenders over the life cycle of the same car model. I find that captive lenders on average reduce the interest rate by 3.25 basis points (bps) for every one-month increase in car model age compared to that offered by non-captive lenders over the life of a car model. Besides lowering the interest rate, captive lenders also adjust other loan terms and loosen the loan standard throughout the life cycle of a car model. Compared to banks and credit unions, captive lenders provide loans with a longer maturity, charge lower down payments, and are less likely to verify a borrower's income and employment information as the car model becomes older.

Next, I use a difference-in-differences (diff-in-diff) research design to evaluate three main events during the life cycle of a car model to establish the relationship between captive financing decisions and product market considerations. The first event is the release of the next model generation, which cannibalizes the sales of the current model. I find that captive lenders reduce the interest rate for a car model when the next model generation is released. This evidence is consistent with car manufacturers trying to clear the inventory of the car model when they expect sales cannibalization from the next model generation. However, since the release of the next model generation is scheduled by the manufacturers, they can adjust the loan terms of the old generation ahead of the release, leading to a pre-trend in the interest rate reduction. Consistent with this conjecture, I indeed observe a pre-trend in the interest rate reduction for captive lending prior to the release of the next model generation instead of a sharp rate reduction around the release. The second event is the release of a new model generation by competitors. I also find that captive lenders reduce the interest rate for their cars after rivals release a new car model generation. In contrast to the interest rate pattern around the first event, the rate reduction by captive lenders occurs sharply after the release of a rival new model without a noticeable pre-trend. This is consistent with the rival new model release being an unpredictable event that captive lenders cannot respond to in anticipation. The third event is product recalls. A car recall is issued when the manufacturer or the National Highway Traffic Safety Administration (NHTSA) determines that a vehicle, equipment, car seat, or tire creates an unreasonable safety risk or fails to meet minimum safety standards. Recalls are deemed crises in some cases (Piotrowski and Guyette Jr, 2010) and often negatively impact the car's selling price (NADA used car guide, 2014). If captive lenders have the incentives to adjust loan terms in response to declines in product demand, one would expect these adjustments to occur during the recall period. The empirical results support my hypothesis: The interest rate offered by captive lenders reduces by 26.2 bps compared to loans for the same car offered by non-captive lenders following a recall announcement.

I perform further cross-sectional analysis to understand manufacturers' strategic motives behind captive financing decisions. Specifically, I identify the following situations in which car manufacturers face greater pressure to sell a car model and, thus, are more likely to use favorable loan terms to promote sales: (1) The current model has a lower reliability score; (2) the next model generation is a redesign; (3) the next model generation has a higher reliability score than the current one. Consistent with manufacturers' incentives to promote sales, I indeed find stronger decreasing trends in the interest rate and loan standards over the life of a car in these situations. As a placebo test, I also analyze loans on used cars, the sales of which do not directly affect manufacturers' revenue. I do not find similar life cycle patterns of the loan terms and standards observed for captive financing on used cars. This finding further supports my hypothesis that captive financing terms are shaped by manufacturers' operational considerations.

Building on the evidence above, I examine the effect of the aforementioned loan term adjustments on loan performance. As a car model approaches the maturing and declining stages, customers who finance the purchase through captive lenders are less likely to default in the first 12 months but are more likely to default eventually compared to those who finance through banks and credit unions. A plausible interpretation for this result is that a lower interest rate reduces customer default rate in the short term, while captive lenders' willingness to dispense higher-risk loans increases the customer default rate in the long run by including more subprime borrowers as customers. The empirical results support this interpretation: (1) The relationship between short-term default and model age reduces by 20.99% when I eliminate the influence of interest rate changes; (2) captive lenders lend to more subprime borrowers as the car model becomes older; (3) on average, the long-term default rates of subprime borrowers from captive lenders increase by 17 bps for every one-month increase in car model age compared to that of non-captive lenders. As a comparison, the number for the prime borrowers is 2.42 bps.

My study contributes to the literature on captive finance. For example, previous studies have shown that owning a captive finance subsidiary allows firms to tolerate higher default rates (Carey et al., 1998), profit from lending to low-quality borrowers (Mian and Smith Jr, 1992, Petersen and Rajan, 1997), and increase the resale value of its products (Murfin and Pratt, 2019). My study contributes to this literature by studying captive financing decisions from a product life cycle perspective. My findings provide further support to the theoretical prediction by Emery (1987) that firms can smooth production over time by adjusting trade credit policies, and the empirical findings by Bodnaruk et al. (2016) that firms with a captive finance subsidiary have lower sales volatility.

My study also contributes to the literature on product life cycle (e.g., see the theoretical works of Klepper, 1996, Shleifer, 1986). Previous studies investigate the evolution of product pricing over a product's life cycle (e.g., Adam and Weber, 2019, Bils, 2009, Broda and Weinstein, 2010, Nakamura and Steinsson, 2008). A recent study by Hoberg and Maksimovic (2022) discusses the role of product life cycle in corporate investment policies. My paper complements Hoberg and Maksimovic (2022) by showing the effect of product life cycle on firm policies in captive finance businesses.

Finally, my study is related to the literature on auto loan markets. While most of the previous studies focus on demand-side factors of auto loan markets (e.g., Adams et al., 2009, Argyle et al., 2020, Chah et al., 1995), more studies on supply-side factors have emerged recently. For example, recent studies have examined how dealer markups (Brown and Jansen, 2019), cash rebates (Busse et al., 2006), and reductions in non-bank lender credit supplies (Benmelech et al., 2017) affect the auto loan markets and consumer welfare. Pierce (2012) discusses the agency problem in car leasing. My study adds to this line of research by showing manufacturers' product market considerations as another supply-side determinant of the auto loan markets. My work also fits into the broader literature that studies the supply-side determinants of loan contracts (e.g., Benetton et al., 2021, Murfin, 2012).

Two concurrent studies also examine the sales incentive-related supply-side determinants of loan contracts. Ramcharan and Yao (2021) find that the loan rate declines and sales volume increases sharply on the last day of a calendar month; Jansen et al. (2021b) find evidence suggesting that customers switch from used to new cars as a result of the selling efforts by dealerships at the end of the month. My work differs from these studies in three ways. First, my study provides a holistic view of captive lenders' incentives over the entire product life cycle, whereas Ramcharan and Yao (2021) and Jansen et al. (2021b) focus on car dealers' sales motives around specific deadlines. Second, my study focuses on the incentives of car manufacturers who control captive lending policies instead of the incentives of dealerships. Third, while Ramcharan and Yao (2021) find a higher default rate for loans issued at the beginning of the month, and they attribute the higher default rate to the higher interest rate, Jansen et al. (2021b) instead find a higher default rate for loans issued at the end of the month, and they attribute their findings to changes in the credit quality of borrowers. My study helps resolve these contradictory findings. Specifically, I show that interest rate reductions can help reduce the default rate in the short term, while changes in the profiles of borrowers due to captive lenders' willingness to dispense higher-risk loans result in more defaults in the long run.

The rest of the paper is organized as follows. Section 2 describes the data and empirical strategy. Section 3 presents my main results on loan term changes across the product life cycle. In Section 4, I investigate how this product market consideration of captive lenders affects loan performance. Section 5 concludes the paper.

2 Data and empirical strategy

2.1 Data source and sample construction

Following Momeni and Sovich (2021), I collect loan-level data from the U.S. Securities and Exchange Commission's (SEC) EDGAR database. In November 2014, the SEC reformed the rules governing the asset-backed securities (ABS) market. The rules became effective in November 2016 after a two-year transition period. These rules, known as Reg AB II, require ABS issuers to disclose asset-level information monthly. In the cases of auto loans, these data contain loan and borrower characteristics at origination and monthly payment information for both captive and non-captive lenders. Specifically, the data include borrower information (e.g., credit score and income), loan information (e.g., interest rate and loan amount), and collateral information (e.g., model and invoice price).[1] Fourteen of the top-twenty auto lenders in the United States appear in these data. Momeni and Sovich (2021) validate these data and find that the Reg AB II data closely resemble the population of auto loans in the United States along most dimensions.

In addition to the main data, I gather vehicle information from Consumer Reports, a nonprofit organization dedicated to independent product testing .[2] Specifically, I obtain data on reliability scores, recall information, model redesign information, and cohort information for most of the car models.

I obtain all auto ABS filings with more than 300 million loan-month-level records from the SEC from November 2016 to September 2021. After dropping a few duplicate loans by asset number and aggregating these observations to the loan level, I am left with 14.5 million unique loans in the sample. Because of the data quality, the same car models might have different names in different filings. Next, I manually clean the make and model names and assign each of them unique identification keys. Reg AB II did not become effective until November 2016, when the filings began. However, some ABS can have loans originated before that date. Of the observations, 5.36 % are from 2015, and all observations before 2015 take only 5.72% of the share. Therefore, my sample period starts from 2015. Of the loans, 7.35 million are new car loans, and the rest (5.47 million) are used car loans. I limit the scope of this paper to new car loans since the sale of new

[1] See Momeni and Sovich (2021) table B.1 for a detailed filing requirement list.

[2] *Source*: https://www.consumerreports.org/cars/car-research/.

cars instead of used cars most contributes to the parent companies' revenue.[3] Of the 16 lenders in the sample, 9 are captive lenders, and the rest are non-captive lenders.[4] I drop observations with suspicious data points following Momeni and Sovich (2021).[5] More than 99% of new cars are sold within two years after introduction. Thus, I drop loans issued more than two years after the model's release. To ensure a sufficient number of observations for each model, I exclude models with fewer than 1,000 observations from the sample. The final sample comprises 5,176,405 loans covering 27 makes, 171 models, and 663 model-years.[6] Take year 2018 as an example, about 17 million new cars were sold in the United States, 1.12 million (6.6%) of which appear in the sample.

Since I am investigating the product life cycle of car models, identifying the release date of the models is an essential task. Even though the release dates for some models are publicly available, the actual date the model is on the market can be months before or after the advertised date. Therefore, I consult the data to identify the actual release of the models. I identify the earliest time a model is sold as the release of the model. To avoid special circumstances, as well as data errors, I must observe transactions of the same model in the data for two consecutive months after the identified release date.

2.2 Summary statistics

Table 1 summarizes the main variables used in the analyses. Panels A and B present the full sample statistics and statistics by lender type, respectively. A few facts are worth noticing in panel A. First, the average borrowers' credit score is 745, which is higher than the national average of 710. Considering the sample includes only new car loans and that consumers who purchase new cars usually have better financial conditions, this number is not a surprise. Second, in my sample, the lifetime default rate is 3.27%, and the 12-month default rate is 0.47%. These numbers are relatively

[3] In practice, manufacturers cannot sell cars directly to the consumers as required by franchise laws. Instead, they sell them to dealers, who do business with consumers. But dealers would not buy new cars from manufacturers if a large inventory of a model goes unsold. And the revenue will eventually be reflected on the parent firm's balance sheet.

[4] I drop observations from Santander Bank. See Section 3.7 for the reason. I will perform robustness tests based on an alternative classification of captive lenders in Section 3.7.

[5] Specifically, I require loans to have (1) a credit score between 300 and 850, (2) a payment-to-income ratio below 30%, (3) an amount below $250,000, (4) a loan-to-value ratio below 1.5, (5) an interest rate below 30%, (6) a vehicle value amount above $0, and (7) a scheduled monthly payment above $10. Income, vehicle value amounts, and maturity are winsorized at the 1% level.

[6] In this paper, car model refers to the model-year of cars. If the car model is a Ford Focus 2020, for example, then Ford is the make; Focus is the model; 2020 is the year.

low as seen in Momeni and Sovich (2021) (24-month default rate 6.0%), Jansen et al. (2021b) (24-month default rate 11%), and Ramcharan and Yao (2021) (12-month default rate 5.0%). However, the sample in Momeni and Sovich (2021) covers both new car loans and used car loans, and the average borrowers' credit score is 662. Jansen et al. (2021b) target subprime borrowers with an average credit score of 532. Ramcharan and Yao (2021)'s sample has the closest average borrowers' credit score (706) to my sample. One possible explanation for the difference in default rate from Ramcharan and Yao (2021) is that they use a more relaxed condition to define default.[7]

In panel B, I compare the summary statistics of loans from captive lenders and non-captive lenders. Compared to other lenders, captive lenders offer lower rates and are more likely to offer rate subventions. Captive lenders appear to be the more cautious lenders in terms of verifying income and employment status. In terms of borrower characteristics, the credit scores are similar between the two types of lenders (0.4% in difference), and the gap in borrower income is larger (borrowers of captive lenders are 8.6% higher than borrowers of non-captive lenders). The early default rate and lifetime default rate of loans issued by captive lenders are approximately two-thirds and half of the loans issued by non-captive lenders, respectively.

[Insert Table 1 near here]

2.3 Empirical strategy

My empirical strategy to examine the causal impact of product market considerations on financing terms is comparing loan terms of captive lenders and non-captive lenders through the product life cycle. In this section, I describe the research design from two aspects. First, I discuss the relationship between product life cycle and product market considerations. Second, I discuss the validity of using non-captive lenders as counterfactuals.

[7] They define default as a loan being 30 days delinquent. On the other hand, I allow for a 90-day delinquent period. If I use the same definition of default as theirs, the 12-month default rate is 1.6%.

2.3.1 Product life cycle and product market considerations

A typical life cycle of a new car model is around 18 months.[8] A common practice in the automobile industry is to release a new generation of each model series every year. For example, Chevrolet released Camaro 2020 in Fall 2019 and released the next model generation, Camaro 2021, in Fall 2020. Demuro (2021) documents that manufacturers often provide incentives on outgoing model year vehicles to clear them off dealer lots. Thus, I assume the product market considerations of manufacturers fluctuate across the product life cycle. Specifically, the willingness to sell would be stronger toward the end of the life cycle.

2.3.2 Non-captive lenders as counterfactuals

Captive lenders, as the wholly-owned subsidiaries of manufacturers, carry out the strategy of their parent firms.[9] Hence, firms could strategically change loan terms according to product market conditions via captive lending.

I use loans from non-captive lenders as the control group in my main analyses. As discussed in Section 2.2, borrowers of captive lenders and non-captive lenders are similar in credit score and slightly different in income. Although the average value of loan terms, such as interest rate, are different between captive and non-captive loans, the diff-in-diff design in Section 3 addresses this concern by including multiple fixed effects.

Another concern is that though product market considerations do not incentivize non-captive lenders to alter loan terms, these non-captive lenders may change the loan terms throughout the product life cycle. Previous literature suggests that the value of the collateral is closely tied to loan terms (e.g., Auh and Landoni, 2022). When car models become outdated, the values of the collaterals will decrease. Thus, the non-captive lenders may also alter loan terms throughout the product life cycle. However, captive lenders are subject to changes in collateral value as well. Thus, the change in the value of collateral should not affect differences in loan terms between captive and non-captive lenders. Overall, the loan strategy of non-captive lenders could serve as a

[8]New cars sold after the 18th month of the model's release account for less than 4% of the sample (see Table A1 in the appendix).

[9]Here, I assume that the interests of captive lenders and manufacturers are aligned and view the captive lender and its parent firm as a whole.

valid counterfactual to captive lenders when evaluating the impact of product market concerns on loan terms.

3 Loan terms and product life cycle

In this section, I present the empirical results on how captive lenders adjust loan terms and standards across the product life cycle.

3.1 Baseline results

3.1.1 Interest rates and product life cycle

To examine whether captive lenders adjust interest rates over the life cycle of a car model, I first estimate the following regression:

$$Y = \beta_1 captive_k \times model\, age_{t,j} + controls_i + \mu_t + \gamma_s + \delta_j + \eta_k + \epsilon, \tag{1}$$

where i, t, s, j, and k indicate the loan, the year-month when the loan originates, the state where the loan originates, the car model, and the lender, respectively. Y represents the interest rate at the time the loan originates. $Captive_k$ takes the value of 1 if the lender k is owned by an auto manufacturer (the lender is a captive lender), and 0 otherwise. $Model\, age_{t,j}$ is the length of time between the model j's release and loan issuance time t. The coefficient of interest is β_1 which captures the effect of model age on interest rate from captive lenders relative to other lenders. Control variables include the log-transformed borrowers' credit score ($ln(credit\, score)$), borrowers' income ($ln(income)$), vehicle value ($ln(vehicle\, value)$), loan amount ($ln(loan\, amount)$), and loan maturity ($ln(maturity)$).[10] μ_t, γ_s, δ_j, and η_k represent year-month fixed effects, state fixed effects, model fixed effects, and lender fixed effects, respectively. These fixed effects account for the macro economy trend that could affect interest rates, unobservable time-invariant characteristics at the state level, unobservable time-invariant features of car models, and unobservable time-invariant characteristics of the lenders, respectively. I cluster standard errors at the lender $\times$ state level

[10] In the data, I only observe the invoice price of a vehicle. I use it as a proxy for the vehicle's value to account for the differences in trim levels within a model-year.

since loans originated by the same lender at nearby places may be autocorrelated.

Table 2, column (1) presents the ordinary least squares (OLS) results for the analysis without control variables. The estimated β_1 is -0.0287 with a p-value<0.01. This value indicates that a one-month increase in the age of the model decreases the interest rate from captive lenders by 2.87 bps, 0.8% of the average loan rate, compared to non-captive lenders.[11] In column (2), I add borrower characteristics as control variables since borrowers' credit score and income are crucial factors in determining the interest rate. The estimated coefficient of interest remains significant and negative, and the magnitude is 0.0306, which is slightly greater than that in column (1). In column (3), I add the vehicle value, loan amount, and loan maturity as control variables in addition to borrower controls. The estimated β_1 is larger than those in columns (1) and (2). Instead of using the interest rate as the dependent variable, in column (4), I use a dummy variable, *rate subvention*, that takes the value of 1 if the loan receives a rate discount. The estimated coefficient suggests that captive lenders are more likely to offer rate discounts to models at their later stages of product lives. The results in Table 2 consistently suggest a negative relationship between interest rate offered by captive lenders and car model age.

[Insert Table 2 near here]

Next, I perform dynamic multivariate analysis to examine how captive lenders reduce interest rates over a product's life compared to non-captive lenders,

$$Y = \sum_{n=1}^{18} \beta_n captive_k \times model\, age_n + controls_i + \mu_t + \gamma_s + \delta_j + \eta_k + \epsilon, \tag{2}$$

where $model\, age_n$ are a set of dummy variables that equal to 1 if the number of month(s) between loan origination and the release of the model is n, and 0 otherwise.[12] All the subscripts, control variables, and fixed effects are the same as those in Model (1). Figure 1 plots the coefficient estimates of $model\, age_n$ with a 95% confidence interval. The figure suggests that captive lenders consistently reduce interest rates for about ten months, after which time the rates become relatively stable.

[11] 2.87/352.8=0.8%

[12] Fewer than 5% of the loans are issued after the 18^{th} month of the model's release. Thus, in this model, n=18 for all loans issued after the 18^{th} month of the model's release.

[Insert Figure 1 near here]

Overall, the evidence in this section supports the argument that captive lenders, compared to banks and credit unions, lower interest rates as a car model ages, holding all else constant. The evidence is consistent with my hypothesis that automobile manufacturers adjust the interest rate of captive finance over the life cycle of a car model.

3.1.2 Other loan characteristics and product life cycle

In addition to modifying interest rates, captive lenders can also adjust other loan terms and their loan standards to respond to changes in product market conditions (e.g., Benetton et al., 2021, Ramcharan and Yao, 2021). In this section, I examine whether captive lenders adjust other loan terms and their loan standards throughout the product life cycle. Specifically, I examine the change in loan maturity, loan amount in dollars, and whether verifying the borrowers' income and employment information throughout the product life cycle.

Like the analysis in Section 3.1.1, the specification in this section follows Model (1), where Y represents one of the loan characteristics mentioned above in each of the analyses. Table 3 displays the results. For each of the four loan characteristics, I perform two analyses. The first one includes no control variables, and the second one includes borrower- and loan-level controls. Columns (1) and (2) show the results of regressions with $ln(maturity)$ as the dependent variables. The positive and significant estimated coefficients of the interaction term in both columns indicate that loans from captive lenders, on average, have longer maturities as model age increases. The magnitude is about 0.1% per month, as reflected in column (2). Columns (3) and (4) display the results relating to loan amount. The results in column (4) indicate that for each additional month in product age increase, captive lenders provide a 0.09% higher amount relative to non-captive lenders. Next, I explore whether captive lenders loosen loan standards in terms of verifying borrower's income and employment information. $Income\,verification$ ($employment\,verification$) is a dummy variable that takes the value of 1 if borrowers' income (employment) information is verified during the lending process, and 0 otherwise. Results in columns (5)–(8) suggest that captive lenders are less likely to verify the income and employment of borrowers as product age increases. To evaluate the magnitudes, I focus on columns (6) and (8). -0.04 percentage points in column (6) and -0.02

percentage points in column (8) account for 0.8% and 0.4% of the sample average, respectively.[13]

[Insert Table 3 near here]

I plot the coefficients of a dynamic analysis of the regression according to Model (2). Figure 2 presents the results. Panels A, B, C, and D present the results on maturity, loan amount, income verification, and employment verification, respectively. All figures show trends as Table 3 suggests: When products age, captive lenders also adjust other loan terms and loosen loan standards compared to non-captive lenders. However, the patterns seem to break down into two parts around the middle of each figure. Breakdowns are likely due to the release of the next model generation. See Section 3.2.3 for a detailed discussion.

[Insert Figure 2 near here]

The evidence in this section suggests that captive lenders lower the barrier of purchasing and borrowing for borrowers throughout the product life cycle. Compared to banks and credit unions, captive lenders provide loans with a longer maturity, a larger loan amount, and are less likely to verify a borrower's income and employment information as the car model becomes older. Unlike the reduction in the interest rate that mainly takes place during the first half of the product life cycle, the loan terms and loan standards discussed in this section mainly change in the direction that makes getting loans easier during the second half of the product life. Putting the evidence in this section and that in Section 3.1.1 together, captive lenders reduce interest rates, allow longer maturity, charge lower down payment, and relax lending standards as car models become outdated. These findings collectively support the notion that manufacturers adjust loan terms through captive lenders to make loans cheaper and easier to access when products approach the end of their lives and are likely to experience decreases in demand.

3.2 The release of the next model generation

I examine the loan term changes around the main events during the product life cycle to establish the relationship between captive financing decisions and product market considerations. One crucial

[13] 0.04%/5.0%= 0.8%; 0.02%/4.5%= 0.4%

event during a car model's life cycle is the release of the next model generation, which cannibalizes the sales of the current model. Thus, manufacturers have the incentive to sell these outdated models to clear out inventories and may therefore adjust loan terms via captive lending. In this section, I evaluate how new model releases affect loan terms and hypothesize that the captive lenders would lower interest rates and loan standards for the current model after new model releases.

3.2.1 Interest rates and the next model generation

I first evaluate the new model release of the model series. For instance, if the loan is on Chevrolet Camaro 2020, the time when Camaro 2021 releases is the event time. I employ a diff-in-diff model by estimating the following regression:

$$Y = \beta_1 captive_k \times post\, new\, model\, release_{t,j} + controls_i + \mu_t + \gamma_s + \delta_j + \eta_k + \epsilon, \tag{3}$$

where $post\, new\, model\, release_{t,j}$ equals 1 if at time t, the next model generation of model j has released, and 0 otherwise. All else is the same as those in Model (1). The coefficient of interest is β_1, which captures the effect of the new model release on the interest rate of captive loans relative to non-captive loans. Table 4, column (1), presents the results. -0.193 indicates that captive lenders, on average, reduce interest rates by 0.193 percentage points after new model releases compared to non-captive lenders, which account for 5.4% of the sample average.[14]

[Insert Table 4 near here]

Next, I plot the coefficients of a dynamic diff-in-diff analysis of the regression according to the following model:

$$Y = \sum_{n=-12}^{6} \beta_n captive_k \times New\, model_n + controls_i + \mu_t + \gamma_s + \delta_j + \eta_k + \epsilon, \tag{4}$$

where $new\, model_n$ are a set of dummy variables that equal to 1 if the length of time between loan origination and the release of the next model generation is n, and 0 otherwise.[15] Figure 3, panel A, plots the estimated coefficients of $captive_k \times new\, model_n$ with a 95% confidence interval. Several

[14] 0.193%/3.528%=5.4%

[15] Fewer than 3% of loans are issued when n>6 and n<-12. Thus, I include n from -12 to 6 in this model.

patterns are worth noting. One can observe a drop in interest rate after the new model's release. However, since the release of the next model generation is scheduled by the manufacturers, they can adjust the loan terms of the old generation ahead of the release, leading to a pre-trend in the interest rate reduction. Consistent with this conjecture, I indeed observe a pre-trend in the interest rate reduction for captive lending prior to the release of the next model generation instead of a sharp rate reduction around the release.

[Insert Figure 3 near here]

The results in this section support the argument that captive lenders would lower interest rates for the old model after the new model releases. Since the next model generation is usually released at the later stage of the product life, the relationship between the new model release and interest rate is not surprising as it reconfirms the relationship between interest rate and product age mentioned in Section 3.1.

3.2.2 Interest rates and competitor's next model generation

Manufacturers make plans about when to release their new model. Knowing these plans allows them to adjust the interest rate for the old model before the release of the new model. However, the release date of the competitors' new model may not become publicly available until a few months before the actual release date, making the event unpredictable. Since the target customer may have overlaps, the introduction of the competitor's next model generation is also likely to affect demand for the underlying model. Therefore, I evaluate the release of the competitor's next model generation as the second identification strategy.

A competing model is identified based on the reliability score of each model. In the Consumer Reports database, most models have several comparing models within the same category, each with a reliability score.[16] I define the competing model as the model within the same category as the underlying model, not owned by the same company as the underlying model, and that has the closest reliability score to the underlying model.

I estimate Model (4) and change $new\,model_n$ to $competitor's\,new\,model_n$. Figure 3, panel

[16]Most categories have around ten models, which usually have similar prices, features, and target consumers.

B, plots the estimated coefficients of $competitor's\,new\,model_n$ with a 95% confidence interval. A downward trend starts from one month prior to competitors releasing their new model and continues for three months. This pattern suggests that manufacturers reduce interest rates for their own current model generation after competitors release their new models. In contrast to the interest rate pattern around the first event, the rate reduction by captive lenders occurs sharply after the release of a rival new model without a noticeable pre-trend. This is consistent with the rival new model release being an unpredictable event that captive lenders cannot respond to in anticipation.

3.2.3 Other loan characteristics and the next model generation

Recall Figure 2 in Section 3.1.2. Though the general trends favor my hypothesis, the patterns seem to break down into two parts around the middle of each figure. The middle of the product life cycle (10–14 months after the model introduction) is about the time when manufacturers release their next model generation. Thus, I hypothesize that the breakdown pattern is due to the new model release. I reestimate the model by changing $model\,age_n$ to $new\,model_n$ to test the loan terms around the new model releases. Figure 4 graphs the results. For maturity and loan amount, the upward trends do not exist until three months before the new model release and last about four months. For income and employment verification, the downward trend also appears near the time when a new model comes out but lasts until the end of the product life. Figure A1 in the appendix plots the figures with respect to the release of the competitor's new model and finds captive lenders adjust loan terms around the release of the competitor's new model in ways similar to Figure 2.

[Insert Figure 4 near here]

The diff-in-diff test results in Table 4, columns (2)–(5), confirm the patterns in Figure 4. The positive estimated coefficient of the interaction terms in columns (2) and (3) indicate captive lenders allow longer maturity and larger loan amount after new model releases. The negative estimated coefficient of the interaction terms in columns (4) and (5) indicate captive lenders are less likely to verify the income and employment information of borrowers after the new model releases. The evidence in this section suggests captive lenders also adjust other loan terms and relax loan standards after the new model releases.

3.3 Loan terms around product recalls

To further confirm the adjustments on loan terms are motivated by the product market consideration and establish a causal link, I evaluate the impact of product recalls on lender loan policies as my third identification strategy. A recall is issued when a manufacturer or The National Highway Traffic Safety Administration (NHTSA) determines that a vehicle, equipment, car seat, or tire creates an unreasonable safety risk or fails to meet minimum safety standards. Recalls are deemed crises in some cases (Piotrowski and Guyette Jr, 2010) and often negatively affect the selling price of the car (NADA used car guide, 2014). If captive lenders have the incentives to adjust loan terms in response to declines in product demand, one would expect these adjustments to occur during the recall period.

Several empirical challenges need to be addressed when dealing with recalls. First, more than one recall may occur throughout the life of a car model. Thus, the months before and after two recalls of the same model may have overlaps making it difficult to identify the relative time to a recall. To address this concern, I apply two methods. In one set of tests, I evaluate only the first recall. In another set of tests, I create a loan×recall level sample to include all recall information. Second, for how long the recall impacts the loan terms is also ambiguous. I consult NADA used car guide (2014), in which the author analyzes the relationship between vehicle price and recall. The figures in their paper suggest that the impact of recalls on a vehicle usually lasts three months. Thus, I expect the impact on loans to last for three months.

The regression results are estimated according to the model below:

$$Y = \beta_1 post\,recall_{j,t} \times captive_k + \beta_2 post\,recall_{j,t} + controls_i + \mu_t + \gamma_s + \delta_j + \eta_k + \epsilon \qquad (5)$$

Table 5, columns (1) and (2), show results based on the first-recall sample, and columns (3) and (4) show results based on the recall×loan sample. In columns (1) and (3), *post recall* equals 1 if the loan origination date is within three months after the recall, and 0 if it originates within three months before the recall. In these cases, only car models that have at least one recall are in the sample. In columns (2) and (4), *post recall* equals 1 if the loan origination date is within three months after the recall, and 0 otherwise. In these cases, I also include car models without a recall as a control group. Regardless of which sample I use and the definition of *post recall*, the coefficients of the interaction term are negatively significant. Take the result in column (1) as an example: The coefficient estimate of the interaction term indicates that the interest rate offered by captive lenders reduces by 26.2 bps compared to loans for the same car offered by non-captive lenders following a recall announcement. The positive coefficients for *post recall* indicate that banks and credit unions increase the interest rate after a recall. These results support the argument that when the value of collateral decreases, lenders increase the corresponding rates to price in the increasing risk. In Table A2 in the appendix, I check the changes in other loan terms around recalls under the setting of that in Table 5, column (1). I find that captive lenders offer longer maturities and a higher loan amount after recalls, but the effects on verifying borrower information are not significant.

[Insert Table 5 near here]

Figure 5 plots the coefficients based on the following model:

$$\begin{aligned} Y = & \sum_{m=-3}^{3} \theta_m captive_k \times Months\,to\,recall_m + \beta captive_k \times model\,age \\ & + controls_i + \mu_t + \gamma_s + \delta_j + \eta_k + \epsilon, \end{aligned} \tag{6}$$

where all the subscripts have the same meanings as Model (1). $Months\,to\,recall_m$ is the length of time between loan origination and the first recall of the model. And the sample used in this analysis is the same as that in Table 5, column (2). Note that I also include $captive_k \times model\,age$ to control for the effect of model age on interest rates. The figure confirms the findings in Table 5. After the recall, captive lenders reduce interest rates compared to non-captive lenders. The results are consistent with the argument that captive lenders adjust interest rates to support sales during the difficult times for these recall models.

[Insert Figure 5 near here]

3.4 Further cross-sectional analysis

In this section, I perform further cross-sectional analysis to understand manufacturers' strategic motives behind captive financing decisions. Specifically, I identify situations in which car manufacturers face greater pressure to sell a car model and, thus, are more likely to use favorable loan terms to promote sales: (1) The current model has a lower reliability score; (2) the next model generation is a redesign; (3) the next model generation has a higher reliability score than the current one.

Conditioning on price, products with lower quality should have lower demand on the market. If manufacturers adjust loan terms to support car sales, these low-quality cars should be the main targets. I use the reliability score as a proxy of product quality. Consumer Reports surveys its members about their car reliability experiences. The reliability ratings show how well vehicles have held up and the odds that an owner could be inconvenienced by problems and repairs. These scores come out after the model releases and reflect what the consumers think of the quality of the models.[17]

I estimate a triple-difference model according to Model (1) and let $captive_k \times model\ age_{t,j}$ further interact with the *reliability score*. Table 6, column (1), displays the results. The positive coefficient before the triple interaction term indicates that the negative relationship between interest rate and product age is weaker for high-quality products. Since the relationship between model quality and reliability score may not be linear, I use *low reliability* instead of *reliability score* as an alternative measure and display the results in column (2).[18] The results suggest that captive loans associated with low-reliability car models experienced an average decrease in interest rates of 4.5 (1.99+2.51) bps per month, whereas captive loans associated with high-reliability car models experienced an average decrease in interest rates of 2.51 bps. The difference is about 79.3% of the decrease in high-reliability car models.[19]

I provide another piece of evidence by examining the interest rate change around new model releases. In Section 3.2, I document that captive lenders charge lower interest rates and loosen loan standards for the current model generation after the release of the next model generation. If these results are driven by the product market consideration of manufacturers, I expect to observe stronger effects when the new model makes a large improvement compared to the old model. In general, new cars are fully redesigned about every five to seven years (Demuro, 2021). A redesign would make the old model even more difficult to sell. Thus, I hypothesize that captive lenders

[17] I do not observe historical changes in these scores. The scores and models are one-to-one mappings.

[18] *Low reliability* equals 1 if the reliability score is below 4 (the median of the sample), and 0 otherwise.

[19] 1.99/2.51=79.3%

reduce rates in a larger magnitude after the new model release when the new model is a redesigned model. I test this hypothesis by estimating another triple-difference model according to Model (3) and let $captive_k \times post\, new\, model\, release_{t,j}$ interact with *redesign*. *Redesign* equals 1 if the new model is a redesigned model, and 0 otherwise. Table 6, column (3), displays the results. The negative estimated coefficient of the triple interaction term confirms my hypothesis. The effect of the new model release on interest rate reduction is 2.82 times stronger when the new model is a redesigned model.[20]

I further show that when the new model improves in quality, the effect of the new model release on interest rate would be stronger. *Reliability difference* is calculated as $Reliability\, score\, (new\, model) - Reliability\, score\, (old\, model)$. A positive number indicates that the new model is better than the old model. The results in Table 6, column (4), suggest that when the new model is better than the old model in terms of reliability score, the effect of the new model release on interest rate is stronger. And the results are robust when I change *reliability difference* to *high reliability difference*, a dummy variable equals 1 if the reliability difference is above or equals to 0 (the median of the sample), and 0 otherwise.

[Insert Table 6 near here]

The evidence in this section supports the argument that the loan term fluctuations of captive lenders throughout the product life cycle is likely due to product market consideration and the effect is stonger when the car manufacturers face greater pressure to sell a car model.

3.5 Placebo test

In the main analyses, I focus only on new cars instead of used cars since new car sales are directly tied to the profits of manufacturers.[21] Though the used car market could also influence the manufacturers' revenue in multiple ways, such as brand reputation and the sale of car supplies and other services, this incentive also applies to the new cars. Thus, captive lenders would not have different

[20] (-0.2863%-0.1569%)/-0.1569%=2.82

[21] Manufacturers cannot sell cars directly to the consumers as required by franchise laws. Instead, they sell them to dealers, and dealers will do business with consumers. But dealers would not buy new cars from manufacturers if a large inventory of the model goes unsold.

credit strategies when dealing with used car sales compared to non-captive lenders. As a placebo test, I redo the main analyses in Section 3.1 with the used car loan sample.

Results in Table 7 are based on estimation from Model (1). Results in columns (1)–(5) are estimated in the same way as Table 2, column (3), Table 3, columns (2), (4), (6), and (8), respectively. The estimated coefficients of the interaction terms are insignificant and close to 0 for all other loan terms but interest rate. If I replicate Figure 1 with the used car loan sample, there are no consistent patterns in Figure A2. These results indicate that captive and non-captive lenders tend to have similar loan strategies when dealing with *used* cars. And these results further confirm that my main findings are unlikely to be due to random chance.

[Insert Table 7 near here]

3.6 Alternative explanations

Since both the product life cycle and loan terms are endogenous decisions made by manufacturers, my results have several alternative explanations. In this section, I examine these alternative explanations and find that none explains my results.

3.6.1 Vehicle price and interest rate

Previous literature documents the product price changes through the product life cycle (e.g., Adam and Weber, 2019, Bils, 2009, Broda and Weinstein, 2010, Nakamura and Steinsson, 2008). Then what is the difference between price and interest rate since both ultimately affect consumer wealth? Is interest rate only a substitution for vehicle price?

First, because of the special feature of the automobile industry, manufacturers cannot directly sell to consumers. Instead, they have to sell the cars to dealers at a price A (invoice price). Then the dealers will sell the car to consumers later at another price B (purchase price). Thus, how much the consumer pays to the dealer does not directly contribute to the manufacturer's revenue. In this paper, I provide evidence supporting the argument that captive lenders adjust interest rates to boost the sales of certain car models. A manufacturer has limited incentive and ability to influence the vehicle price since its interest is not closely tied to the purchase price.[22]

One way the manufacturer can influence the purchase price is by providing cash rebates. A cash rebate is an offer given to consumers for a cash discount when they purchase certain models during a certain period. If the interest rate is only a substitution for the vehicle price, then when manufacturers offer cash rebates, the effect of model age on loan terms should be weaker. I reestimate my baseline regression and control for *cash rebate*, a dummy variable equals 1 if the loan is associated with a purchase that receives a cash rebate, and 0 otherwise. Table A3, column (1), displays the results. The coefficient of the interaction term becomes larger in magnitude when controlling for cash rebate. The numbers in columns (2) and (3) confirm that with or without cash rebate, the magnitudes of the interaction terms are similar. The evidence does not support the argument that the interest rate is a substitution for the vehicle price.

3.6.2 Product life cycle coincides with the calendar (fiscal) month

If all new model releases take place during the same period in the year, studying how loan terms change throughout the product life cycle is purely studying how loan terms change in a year. To alleviate this concern, I first present the number of loans by model release month in Table A4. Around 80% of the models are released between June and November. August and September are the peaks of the new model releases. The data suggests that new models do not come at the same time of the year. Next, I plot the interest rate change with respect to the calendar month or the fiscal month (Figure A3) following the spirit of Figure 1. If it were the operation cycle of the manufacturer instead of the product life cycle driving the results, the highest interest rate from captive lenders should appear during August and September in Figure A3, panel A, since Figure 1 suggests captive lenders offer the highest interest rate at the start of product life. However, the month with the highest interest rate is December which only has a limited number of new model releases. In addition to that, Montoya (2021) documents that there is no unified new model season these days. If I change calendar month to fiscal month, Table A4 suggests the new model releases are equally distributed among the fiscal months. Therefore, studying how the new model release affects loan terms is not the same as studying how loan terms change in a year.

[22] I control for the invoice price in most of my analyses.

3.6.3 Dealer's ability to adjust rates

Even though lenders are the ones to issue loans and set the interest rates and other loan terms, the dealership is one crucial party in the lending process. The dealers can add a markup to the rate quote they get from lenders after submitting the consumer's credit application (Jansen et al., 2021a). Since dealerships also have the incentive to move specific car models off their lots, a natural question arises, are the differences in lending terms resulting from the lenders' incentives or the dealerships' incentives?

I leverage the legal penalty on Toyota Motor Credit Corporation (TMC), the financing subsidiary of Toyota, by the Consumer Financial Protection Bureau (CFPB) and the Department of Justice (DOJ) in February 2016, which reduced the interest rate markups that dealers can add onto the quote from lenders from 2.5 to 1.25 percentage points.[23] This penalty limited dealers' potential ability to markup less on car models they are more willing to sell and was later removed in May 2018. This event allows me to test whether the ability of dealers to adjust the interest rate affects fluctuations in interest rate throughout the product life cycle.

I use a diff-in-diff research design by estimating the model below:

$$\begin{aligned} Y =& \beta_1 Toyota \times post\,CFPB\,settlement \times model\,age + \beta_2 Toyota \times model\,age \\ &+ \beta_3 post\,CFPB\,settlement \times model\,age + controls_i + \mu_t + \gamma_s + \delta_j + \eta_k + \epsilon, \end{aligned} \tag{7}$$

where $Toyota$ equals 1 if the lender is TMC, $post\,CFPB\,settlement$ equals 1 if the loan is issued during the period when TMC is under penalization. I present the results in Table A5, the insignificant coefficient estimate of the triple interaction term in column (1) suggests this penalization has little impact on how captive lenders adjust interest rates through the product life cycle.

Though I cannot completely rule out the possibility that dealership incentive is contributing to the main results, the evidence in this section is likely to support that manufacturer is the main driving force of the main results. Conceptually, manufacturers (captive lenders) are the ones with greater power in deciding the terms of the loan. Additionally, dealerships are sometimes the carrier of manufacturer incentives, so it is difficult to separate the two parties apart completely.

[23] According to Ramcharan and Yao (2021), three other lenders were also penalized, but only the penalization to TMC occurred during my sample period and created enough pre- and post-observations.

3.6.4 The influence of COVID-19

One momentous event took place during my sample period, which is the rise of COVID-19 starting in 2020. COVID-19 affects auto loan originations (Canals-Cerdá and Lee (2021)) and automobile supplies. To make sure the findings between the loan term and product life cycle in this paper are not driven by this event, I reestimate Model (1) with subsamples that only contain loans before the COVID-19 period. Table A6 presents the results. All the estimated coefficients of the interaction terms have the same sign as those in Table 2 and Table 3, and are statistically significant. Therefore, COVID-19 cannot explain the results.

3.6.5 Self-selection of borrowers

Consumers can choose not only when to make purchases but also which lender to borrow from. Thus, it is possible that some borrowers self-select into the captive lender group at the end of the product life cycle because of the low rates and therefore bias the results. For the most part, the lenders can choose whether to accept or deny loan applications regardless of how the prospective borrower group changes. Even if the lenders have no such decision power and more borrowers choose to borrow from captive lenders as product age increases, one should observe an increase in the number of loans from captive lenders.

To formally test the difference in the number of loans offered by captive and non-captive lenders, I aggregate the data at the lender-model year-year month level and run a simple model based on Model (1). Table A7 presents the results. The negatively significant coefficients for the interaction term in both columns suggest that the relative numbers of loans from captive lenders decrease as model age increases. Figure A4 depicts the estimated coefficients of $mode\,age_n$ with a 95% confidence interval based on Model (2) but without time fixed effect. Instead of estimating the difference between captive and non-captive lenders, I plot a separate line for each of them. The trends of captive and non-captive lenders are similar for about 10 months. Then the captive lender line starts to decrease at a faster pace compared to non-captive lenders. Holding all else constant, a lender should have tightened loan policies if it only accepts a certain amount of loan applications. However, the findings in this paper show that captive lenders have weaker loan policies toward the end of the product life. Thus, no observable evidence supports the argument that more borrowers choose captive lenders as captive lenders lower interest rates and loosen loan standards. Though I cannot completely rule out the potential bias resulting from the selection issue, my findings suggest the effect of the selection bias is limited.

3.7 Robustness checks

I perform several robustness tests to alleviate concerns about my main findings. First, I show the results in Table 2, column (3), is robust with different fixed effects and clustering schemes (See Table A8). Specifically, I include model fixed effect and state × lender × year-month fixed effect in column (1), lender fixed effect and state × model × year-month fixed effect in column (2), and mode-year fixed effect, state × year-month fixed effect, make × year-month fixed effect, and lender × year-month fixed effect in column (3). By including these high-dimensional fixed effects, I control for unobservable characteristics at more specific levels. In columns (4)–(7), I use different clustering schemes, including lender, state, year-month, and model. And the estimated coefficients of $captive_k \times model\, age_{t,j}$ are significantly negative in similar magnitudes in all columns.

Second, the classification of captive lenders is crucial to the analyses in this paper. Two lenders in the data are neither typical captive lenders nor banks. World Omni provides financing for Toyota via Southeast Toyota Financial. In the sample, almost all loans from World Omni are for Toyota purchases. Though classified as a captive lender in some places, World Omni is owned by JM Family Enterprises instead of Toyota Motor Corporation. Therefore, in this paper's setting, World Omni should not have the same incentives to treat specific models differently as other captive lenders do. Instead, it is closer to being defined as a bank. In the main tests, I classify World Omni as a non-captive lender. As a robustness check, I drop loan observations from World Omni from the sample and redo the analyses in Table 2 and 3. Table A9, panel A, reports the results, which are robust. Additionally, Santander bank provides financing for Chrysler Group vehicles via Chrysler Capital, and it also has other non-captive loans, which potentially makes the bank's incentive complicated. In the main tests, I drop observations from Santander to avoid this potential uncertainty. In Table A9, panel B, I show that the results are robust after adding these Santander observations.[24]

Third, though the determination of interest rates heavily relies on the credit score of borrowers,

[24] If the loan from Santander is associated with a car from the Chrysler Group, I classify it as a captive lender. The rest of the Santander loans are deemed to be from a non-captive lender, and, thus, *captive* is not absorbed.

the relationship between the two is neither linear nor log-linear. Instead, lenders often classify borrowers into credit score bins and decide the interest rate according to the bins. For example, if two borrowers with all else the same, one has a credit score of 701, the other has a credit score of 720, they may get the exact same interest rate offer because both their credit scores fall into the 700–720 bin. As a robustness test of Tables 2 and 3, I classify the borrowers into 24 bins based on their credit score and include credit bins fixed effect to control for credit scores. Table A10 displays the results. The estimated coefficients for interest, maturity, and loan amount are similar to those reported in Tables 2 and 3. Similarly, the relationship between interest rate and maturity may not be linear. To alleviate this concern, I conduct another robustness test of Tables 2 and 3 with the same maturity.[25] Table A11 displays the results. The estimated coefficients for interest, loan amount, income verification, and employment verification remain the same sign as those reported in Tables 2 and 3.

Fourth, it is a common practice for banks and financial institutions to offer teaser rates to market their products to consumers. For example, lenders may offer low rates for a limited time and then charge higher rates. Since I only observe the interest rates at loan origination, it is possible that the results are driven by captive lenders issuing more loans with teaser rates than non-captive lenders at the late stages of the product life cycle. It turns out that all the loans in the sample have fixed interest rates. In case this self-report data point contains errors, I conduct robustness tests with a sample excluding loans with loan interest rates. Table A12 displays the results. In columns (1), (2), and (3), I drop loans with interest rates less than 1%, 2%, and 3%, respectively, from the sample. The estimated coefficients of the interaction terms remain negative and significant in all columns. Thus, the results are robust when possible loans with teaser rates are removed from the sample.

4 Loan performance

In this section, I first examine the effect of the aforementioned loan term adjustments on loan performance. Next, I evaluate how this strategy affects the loan performance of subprime borrowers.

[25] Loans with 72-month maturity take 24.24% of the main sample. Therefore, I include only loans with 72-month maturity.

4.1 Early default and lifetime default

In previous sections, I provide evidence supporting the argument that captive lenders offer lower rates and weaker credit policies to move specific car models off the lots. How does this behavior affect the loan performance? On the one hand, reduced interest rates should make the borrower less financially stressed when making repayments, thus lowering the default rate (intensive margin). On the other hand, captive lenders lend to borrowers who are less qualified, which leads to higher default rates (extensive margin).

To answer this question, I estimate Model (1) with $default$ as the dependent variable. The definition of $default$ follows Momeni and Sovich (2021), $default$ equals 1 if the loan has been charged-off, has been repossessed, or is 90 or more days past due, and 0 otherwise.[26] I first use default within 12 months after loan origination, also known as early default, as my dependent variable.[27] Table 8, panel A, column (1), shows the results without control variables. The estimated coefficient of the interaction term is negative and significant at the 1% level. 2.44 bps account for 5.2% of the sample average.[28] For a one-month increase in product age, the short-term default rate of borrowers from captive lenders reduces by 5.2% as compared to borrowers from non-captive lenders. Then I gradually add borrower-level controls, loan level controls except for interest rate, and interest rate in columns (2)–(4), respectively. In previous sections, I find that captive lenders reduce interest rates as product age increases. Controlling for interest rate allows me to estimate the effect on the default rate without the influence of interest rate changes. When I control for interest rate, the coefficient is still negative but is reduced by 20.99% compared to that in column (3).[29] This finding supports the idea that reduced interest rates lighten the repayment burden and thus lower the default rate. However, the low interest rate cannot fully explain the low early default rate since the coefficient is still negative and significant when controlling for interest rate.

The low interest rate could help borrowers with repayment in the short term. What if I extend

[26]In Table A13, I present results with a different measure of default. $Default$ equals 1 if the loan has been charged-off, has been repossessed, or is 30 or more days past due, and 0 otherwise. The results with this alternative definition of default are similar to those in this section.

[27]To avoid the truncation issue, I drop loans originated after August 2020, which is 12 months before the end of the sample. I also look into default within 24 months (see Table A14). The results are similar to those in Table 8.

[28]2.44/46.8=5.2%

[29](1.92-2.43)/2.43=-20.99%

the horizon? In panel B of Table 8, I change the dependent variable to loan lifetime default.[30] The results are different from those in panel A. The coefficient of the interaction term in column (1) is positive and significant. For a one-month increase in product age, the long-run default rate of borrowers from captive lenders increases by 3.23 bps (0.99% of the sample average) as compared to borrowers from non-captive lenders.[31] This result is robust after adding control variables. After I add interest rate as control variable in column (4), the coefficient of interest rises by 2.3 bps (74.7%) as compared to that in column (3).[32] This result suggests that the low interest rate also helps borrowers with repayment in the long run. However, the lifetime default rate increases when the incentive from the captive lender is stronger, even with the low interest rate. The weak loan policy channel, captive lenders loosen their lending standards and lend to borrowers who otherwise find it difficult to get loans, is one possible explanation for this result. And I will discuss this in detail in the next section.

[Insert Table 8 near here]

Next, Figure 6 plots the dynamics of the interaction term in Table 8, column (4). For both early default (panel A) and lifetime default (panel B), changes in general trends mainly take place during the second half of the product life cycle. In Figure 1, one can observe that the interest rate reduction mainly takes place during the first half of the product life cycle, a pattern that is different than that in Figure 6, panel A. Thus, the low interest rate cannot fully explain the low early default rate, which is consistent with the results in Table 8. Figures A5 and A6 plot similar information as that in Figure 6, but change model age to the time relative to the next model generation release and competitor's next model generation release, respectively. The patterns in these two figures consistently suggest borrowers who borrow from captive lenders are less likely to default in the short term but more likely to default in the long run after the new model releases.

[Insert Figure 6 near here]

Overall, in this section, I show that as car models approach the end of their product lives as new cars, borrowers who get loans from captive lenders default less in the first 12 months after

[30] To keep the sample consistent, I exclude from the sample loans originated after August 2020.

[31] 3.23/326.5=0.99%

[32] (5.38-3.08)/3.08=74.7%

loan originations (early default) but more during the lifetime of the loan compared to those who borrow from banks and credit unions. I further show that one of the reasons for less early default is the low interest rate.

4.2 Subprime lending

In the last section, I show that the lifetime default rate increases when the incentive to sell is strong. In this section, I provide evidence suggesting that it is because of the captive lenders' willingness to dispense higher-risk loans, which results in some subprime borrowers getting the loan. The results in Table 8 suggest that borrowers' credit score and income cannot fully explain the increase in lifetime default since lenders have various ways to decide the target borrowers besides what one can observe. However, investigating how borrowers' credit scores change over time can provide some insights into how lenders adjust their lending strategies.

I start by estimating regressions based on Model (1) with borrowers' credit score as the dependent variable. Table 9 displays the results. Column (1) presents the unconditional results. Without any control variables, captive lenders are more likely to lend to borrowers with lower credit scores when product age increases relative to non-captive lenders. After I add control variables, the magnitude becomes larger. The results in column (2) suggest that for a one-month increase in product age, the average borrowers' credit score of captive lenders reduces by 0.05% as compared to non-captive lenders. Though the economic magnitude is small, we can get some sense of captive lenders' financing policy change in borrower credit scores through the product life cycle.

[Insert Table 9 near here]

Borrowers with lower credit scores are on average more likely to default. I examine whether captive lenders and non-captive lenders are different in the relationship between credit score and default. The histograms in Figure 7 present the sample distribution and early default distribution over borrowers' credit scores.[33] For captive lenders, though the distribution of the full sample is left-skewed, the distribution of the default sample skews to the right, which indicates a lot of captive borrowers with low credit scores (subprime borrowers) default frequently. As a comparison, for

[33] For the histogram of lifetime default, see Figure A7.

banks and credit unions, borrowers with credit scores between 660-700 contribute most to default. The evidence suggests that lending to subprime borrowers is the main source of default for captive lenders. This is consistent with the notion that captive lenders intentionally lend to subprime borrowers to help these borrowers complete their purchases at the cost of more default. Therefore, I turn my attention to subprime borrowers. Mian and Sufi (2009) document that both credit and house prices rose disproportionately in ZIP codes with a higher percentage of subprime borrowers. Justiniano et al. (2016) provide theoretical evidence suggesting that the underlying mechanism of the stylized fact documented by Mian and Sufi (2009) is that more credit supply allows subprime borrowers to access credit. A recent paper by Schmidt (2019) documents that auto loan borrowers become less qualified since the recovery from the 2008 crisis, as reflected by a twenty-point decrease in credit score from 2010 to 2015.

[Insert Figure 7 near here]

I start by plotting the change in the proportion of default over the product life cycle. Figure 8, panel A, shows that captive lenders lend to more subprime lenders as product age increases, but non-captive lenders do not. Next, I find that no matter for early default or lifetime default, the proportions of default in subprime borrowers increase for captive lenders when product age increases. But for non-captive lenders, these proportions decrease over time (Figure 8, panels B and C). These findings are consistent with captive lenders issuing more high-risk loans to subprime borrowers during the late stages of the product life cycle.

[Insert Figure 8 near here]

To formally test the impacts on subprime borrowers' loan performance, I estimate a triple-difference model:

$$\begin{aligned} Y =& \beta_1 captive \times subprime \times model\,age + \beta_2 captive \times model\,age \\ &+ \beta_3 subprime \times model\,age + \beta_4 captive \times subprime + \beta_5 subprime \\ &+ controls_i + \mu_t + \gamma_s + \delta_j + \eta_k + \epsilon, \end{aligned} \tag{8}$$

where *subprime* is a dummy variable that takes the value of 1 if a borrower's credit score is lower than 660, and 0 otherwise.[34] I present the results in Table 10. I first discuss the results on early default in panel A. All columns with different control variables show similar results. If I add β_1 and β_2 together, the sum is positive, which indicates that subprime borrowers are more likely to commit early default when captive lenders loosen loan standards. Specifically, the short-term default rate of subprime borrowers from captive lenders increases by approximately 6 bps (12.8% of the sample average) for every one-month increase in car model age compared to that of non-captive lenders.[35] β_2 remains negative and statistically significant, which indicates that the short-run default rate of prime borrowers decreases as car models approach the end of their product lives. In panel B, I examine the lifetime default case. The magnitudes of the estimated coefficients of interest are similar in all columns. To interpret the results, I focus on column (3). On average, the long-term default rates of subprime borrowers from captive lenders increase by 17 bps (5.2% of the sample average) for every one-month increase in car model age compared to that of non-captive lenders.[36] As a comparison, the number for the prime borrowers is 2.42 bps. Subprime borrowers also commit more default during the lifetime of the loan when manufacturers have a strong incentive to sell these cars.

[Insert Table 10 near here]

The analyses in this section provide direct evidence supporting the notion that captive lenders lend to more subprime borrowers when they have stronger incentives to sell. While prime borrowers usually benefit from the low interest rate and default less, a great proportion of subprime borrowers still cannot afford the loan, even with the reduction in interest rates. However, captive lenders and their parent companies may not lose because they also profit from selling the car.

5 Conclusion

This paper studies whether companies strategically utilize captive financing in response to changes in product demand. Using detailed data on auto loans, I find captive lenders make loans cheaper

[34] I use an alternative definition for subprime that takes the value of 1 if a borrower's credit score is lower than 600. Table A15. contains the results.

[35] 6/46.8=12.8%

[36] 14.58+2.42=17; 17/326.5=5.2%

and easier to access in response to (or in anticipation of) declining demand for a car model. While the lower interest rates offered by captive lenders reduce the likelihood of consumer default in the short term, the average default rate eventually increases in the long horizon because captive lenders' willingness to dispense higher-risk loans allows more subprime borrowers to access credit.

The findings above suggest a few implications. First, my findings help us understand how manufacturers strategically utilize their financial arms to manage their product market portfolio. Second, for most consumers, knowing that captive lenders adjust loan terms on specific car models provides insights on negotiating the loan terms while making purchases. However, for consumers who cannot find a loan from non-captive lenders, borrowing from captive lenders help them in purchasing a car, but they could potentially be approved for a loan they cannot afford because of the lenders' willingness to dispense higher-risk loans.

This paper has some limitations and suggests a few possible directions for future research. First, it is unclear whether getting an unaffordable loan to complete the purchase benefits or hurts the subprime borrowers' interests. It is possible that the utility gain from purchasing new cars can compensate for the utility loss from defaulting. Second, I find that captive lenders reduce the number of loans at the end of the product life cycle. Therefore, it is possible that when captive lenders issue one high-risk loan, they have to reduce more than one ordinary loan, which suggests a spillover effect between products. Last, it is also unclear why borrowers choose to borrow from banks or credit unions when captive lenders offer better loan terms. Several explanations are possible. One is that some borrowers are unaware of the potential benefit they can get from borrowing from captive lenders. Another is that sometimes banks offer loan bundles that contain unobservable benefits.

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Figure 1: Interest rate and the product life cycle

This figure plots the coefficient estimates with a 95% confidence interval of the β_ns from Model (2), which is a linear regression model with year-month, state, model, and lender fixed effects that regresses "interest rate" on month(s) relative to the car model's release. The x-axis corresponds to the length of time between loan origination and the model's release. ">18" refers to all loans originated during or after the 18^{th} month since the model's release. The coefficient estimates on these interaction terms measure the differences in interest rate between captive and non-captive lenders from the model's release to 18 months after the release. Standard errors are clustered at the lender × state level.

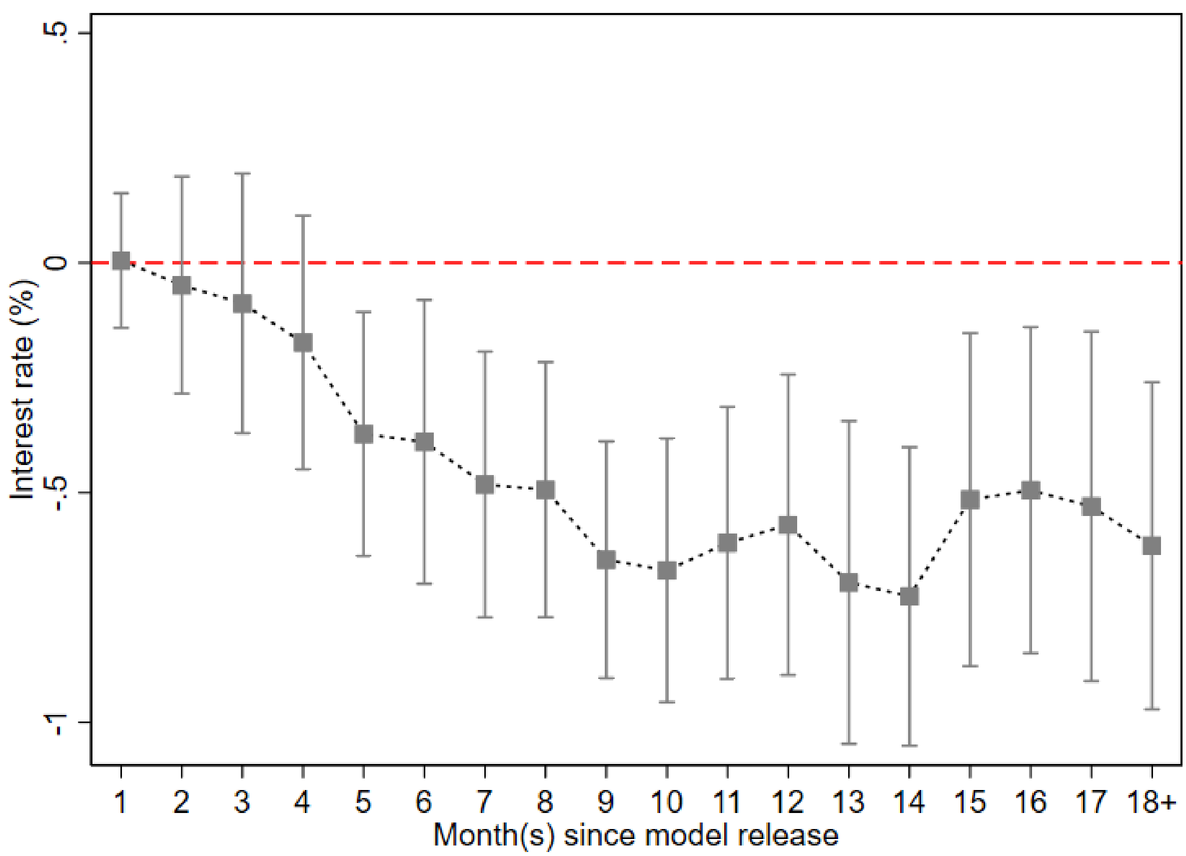
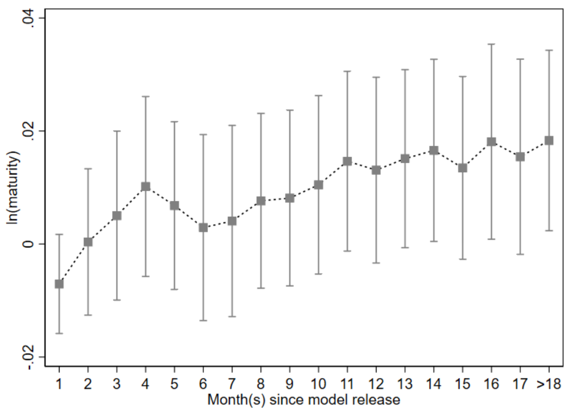
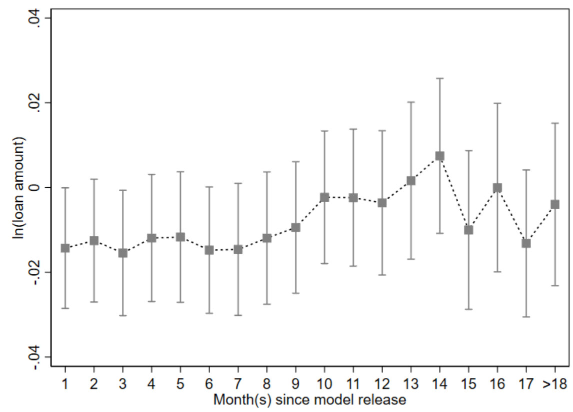


Figure 2: Other loan characteristics and the product life cycle

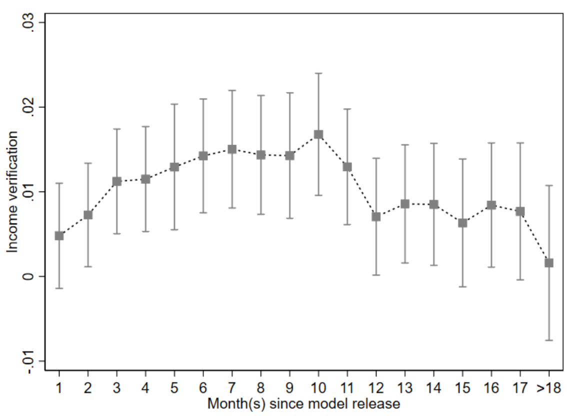
Similar to Figure 1, this figure plots the coefficient estimates with a 95% confidence interval of β_ns from Model (2). The dependent variables are the natural logarithm of maturity (panel A), the natural logarithm of loan amount (panel B), a dummy variable that measures whether the lender verifies borrower income (panel C), and a dummy variable that measures whether the lender verifies borrower employment (panel D). All else is the same as in Figure 1.



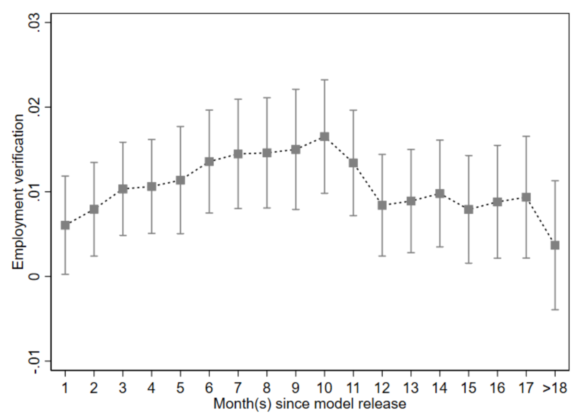
(a) Maturity



(b) Loan amount



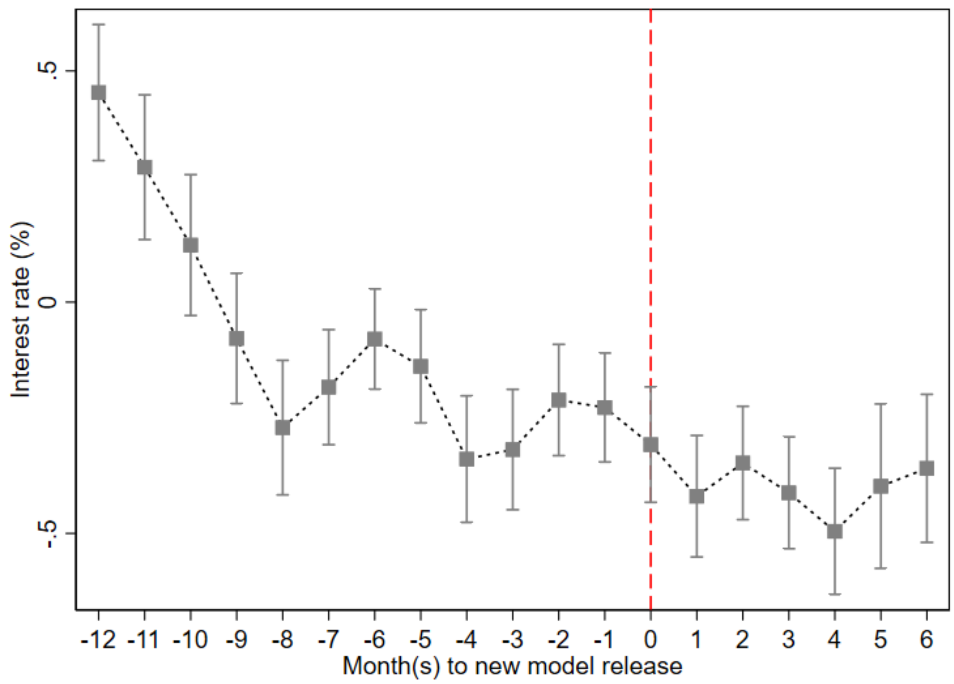
(c) Income verification



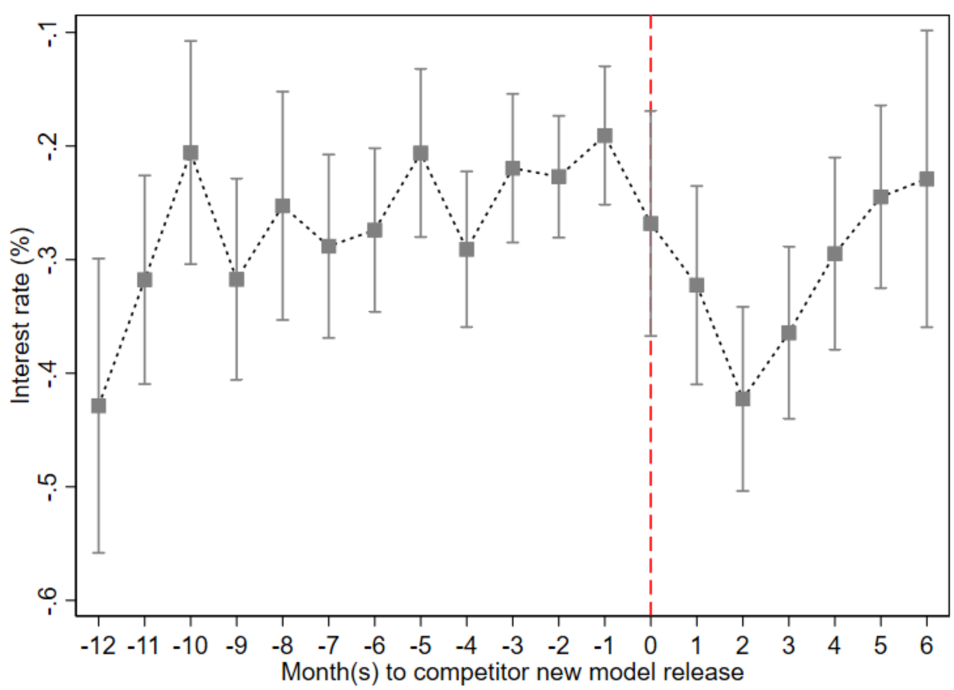
(d) Employment verification

Figure 3: Interest rate and new model release

This figure plots the coefficient estimates with a 95% confidence interval of β_ns from Model (4), which is a linear regression model with year-month, state, model, and lender fixed effects that regresses the "interest rate" on months relative to the next model generation's release. The x-axis corresponds to the length of time between loan origination and the release of the next model generation. β_ns measure the differences in interest rate between captive and non-captive lenders from 12 months before the underlying model's own (competitor's) new model release to 6 months after the release. Panel A plots β_ns according to own new model release, and panel B plots β_ns according to competitor's new model release. The vertical dashed line represents the time of the new model release. Standard errors are clustered at the lender $\times$ state level.



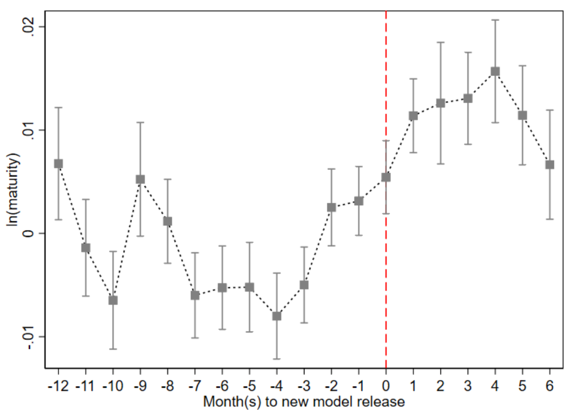
(a) Own next model generation



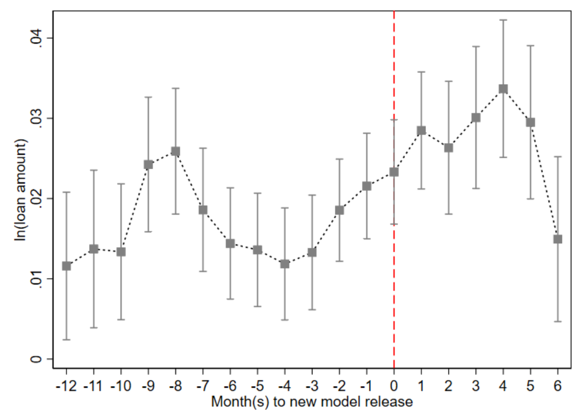
(b) Competitor's next model generation

Figure 4: Other loan characteristics and new model release

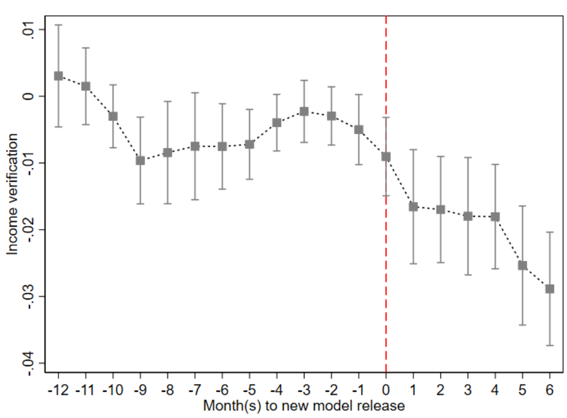
All are similar to Figure 2. The only difference is that the horizontal axis is months to the release of the next model generation instead of months since the release of the underlying model. The vertical dashed line represents the new model's release.



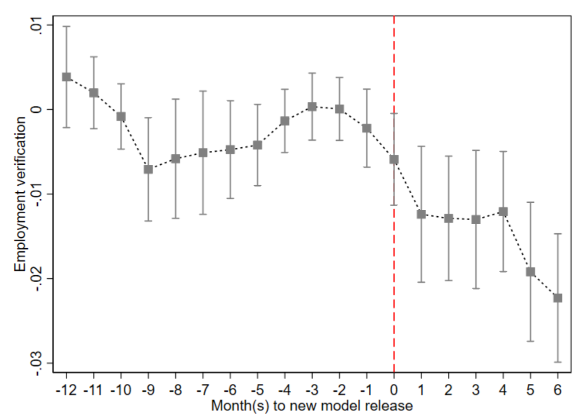
(a) Maturity



(b) Loan amount



(c) Income verification



(d) Employment verification

Figure 5: Interest rate and recall

This figure plots the coefficient estimates with a 95% confidence interval of θ_ms from Model (6). The coefficient estimates on these interaction variables measure the differences in interest rate between captive and non-captive lenders from 3 months before the first recall of the model to 3 months afterward. The x-axis corresponds to the length of time between loan origination and the first recall of the model. The vertical dashed line represents the time of the first recall. Standard errors are clustered at the lender $\times$ state level.

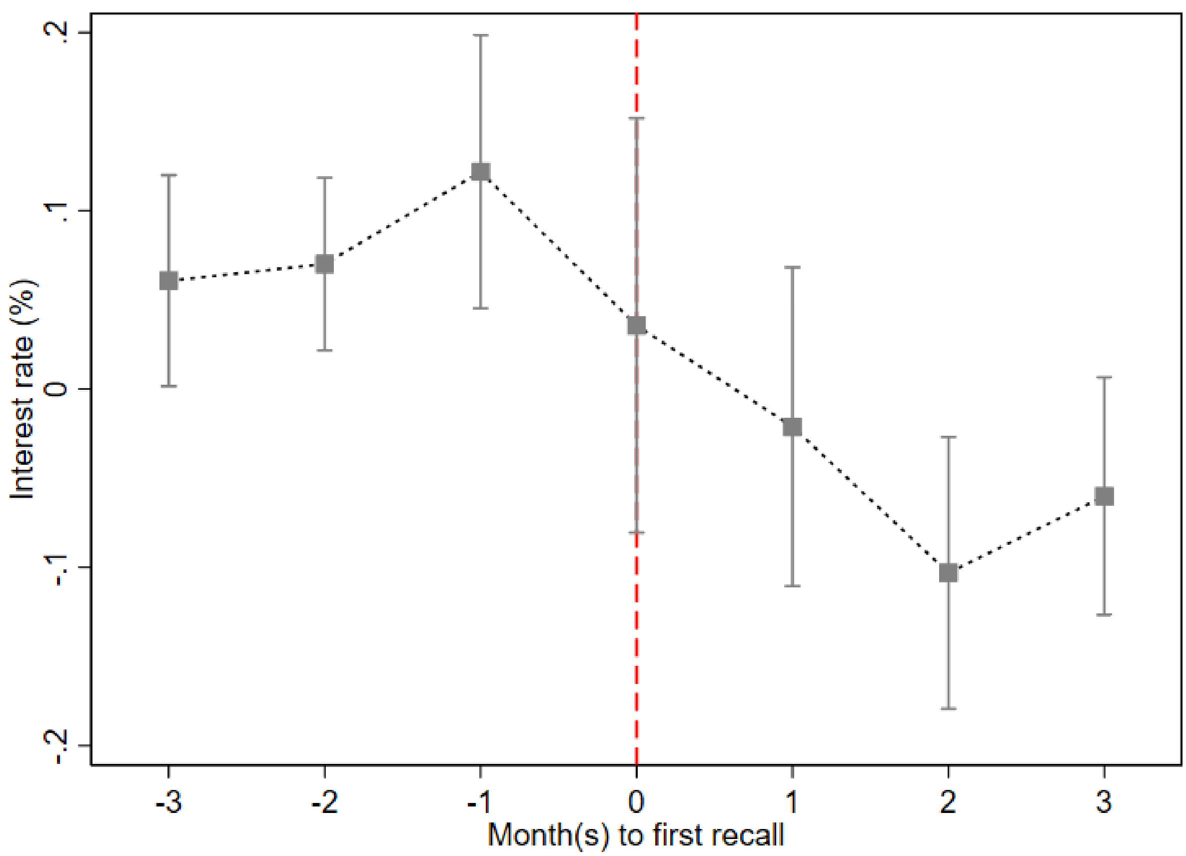
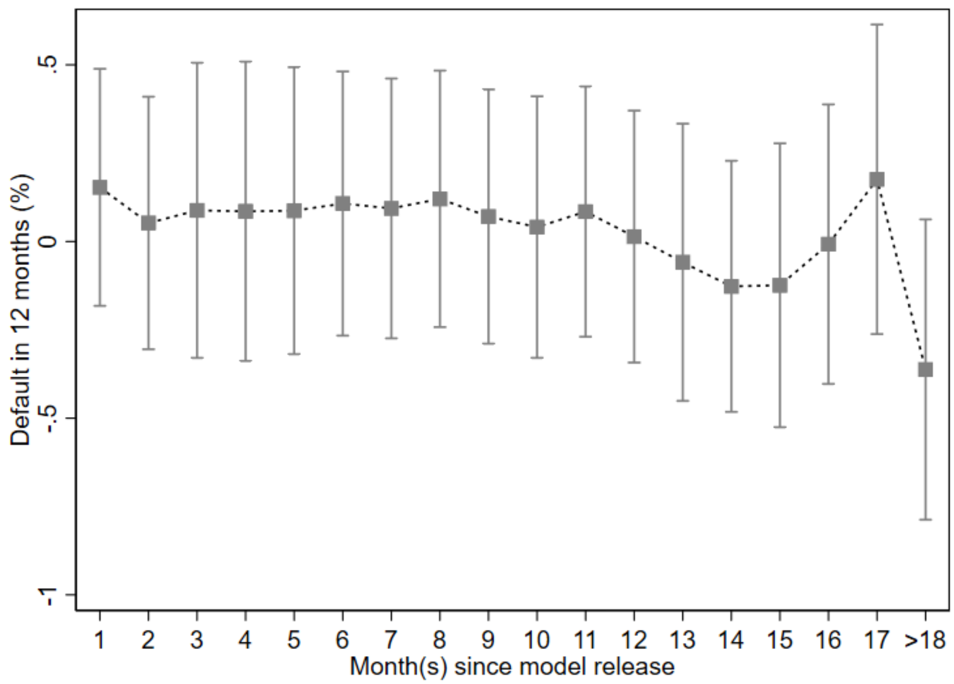
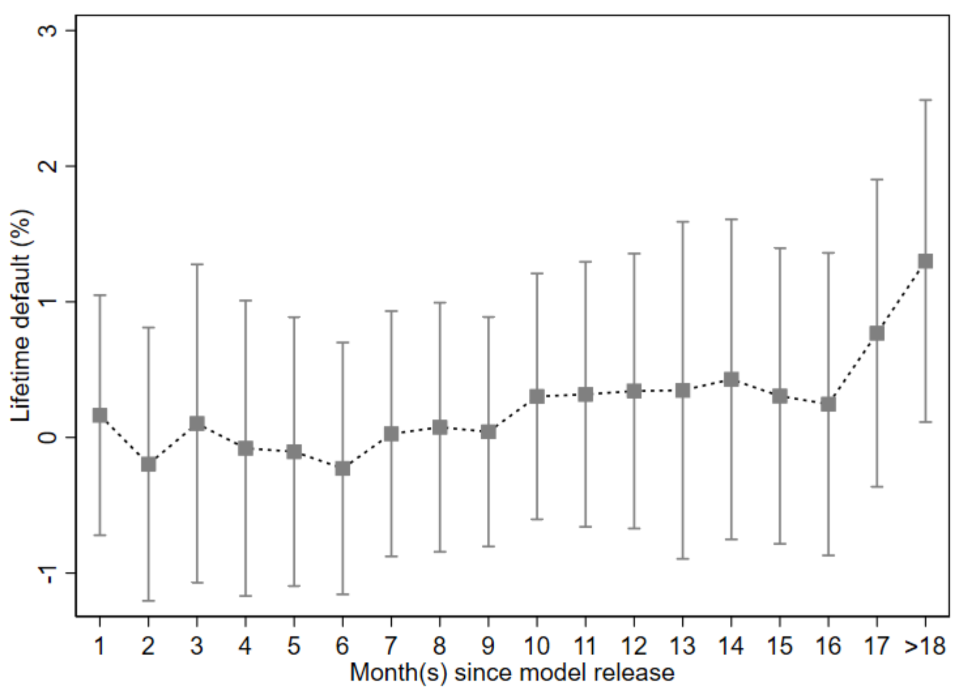


Figure 6: Default and the product life cycle

This figure plots the coefficient estimates with a 95% confidence interval of β_ns from Model (2), which is a linear regression model with year-month, state, model, and lender fixed effects that regresses "default" on months relative to the car model's release. The x-axis corresponds to the length of time between loan origination and the model's release. ">18" refers to all loans originated during or after the 18^{th} month since the model's release. The coefficient estimates on these interaction terms measure the differences in default rate between captive and non-captive lenders from the model's release to 18 months after the release. The dependent variable is early default (panel A) and lifetime default (panel B). The sample is restricted to auto loans originated between January 2015 and August 2020. Standard errors are clustered at the lender $\times$ state level.



(a) Early default

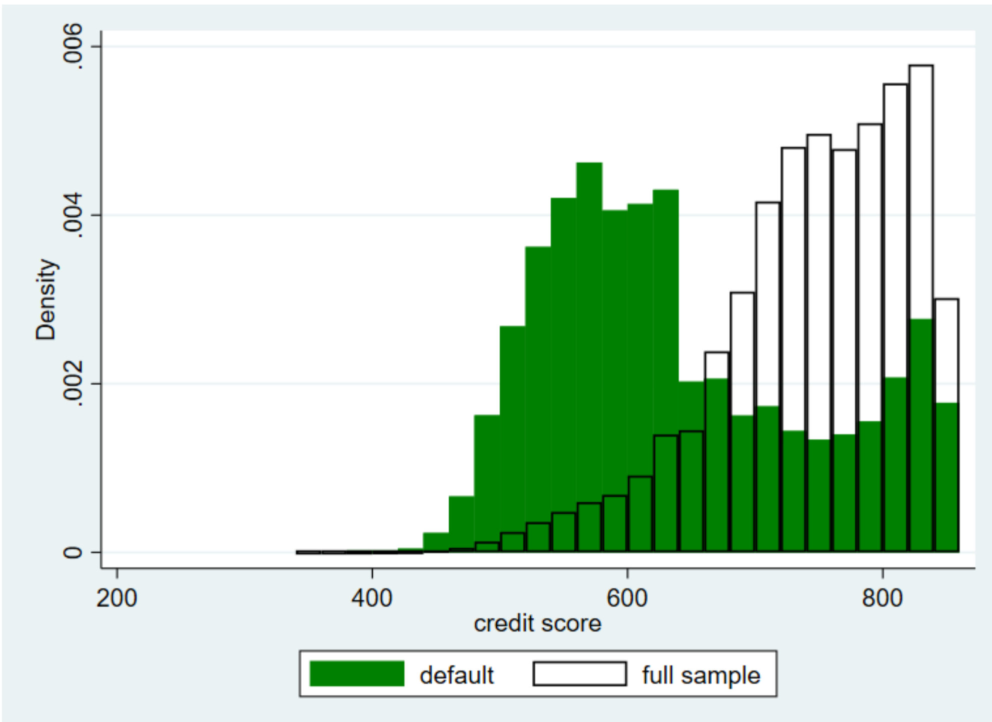


(b) Lifetime default

Figure 7: Borrowers' credit score distribution on default (12 months)

This figure presents the sample distribution and early default distribution by borrowers' credit score. Panel A plots the credit score distribution of borrowers from captive lenders. Panel B plots the credit score distribution of borrowers from banks and credit unions. In each panel, I present two distributions. One is the distribution of the full sample; the other is the distribution of borrowers who default in 12 months after loan issuance.

(a) Captive lenders



(b) Banks and credit unions

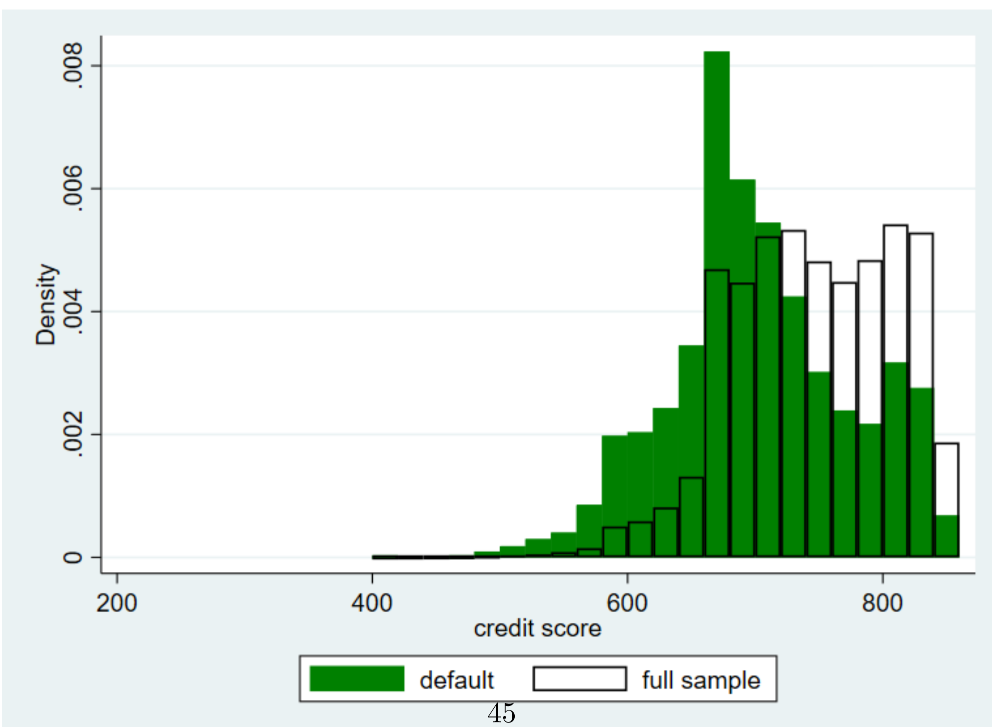
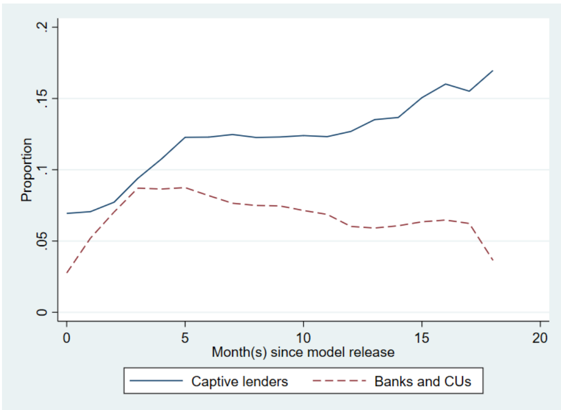
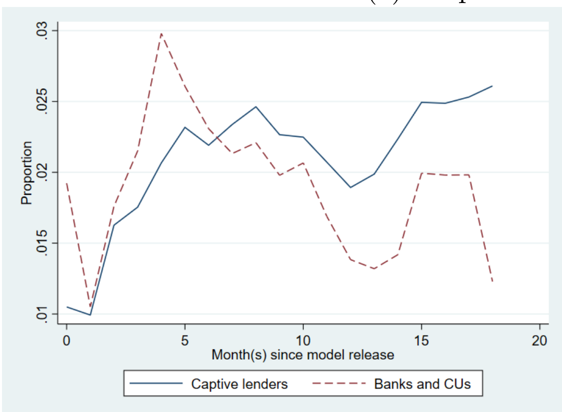


Figure 8: Proportion of subprime borrowers and the product life cycle

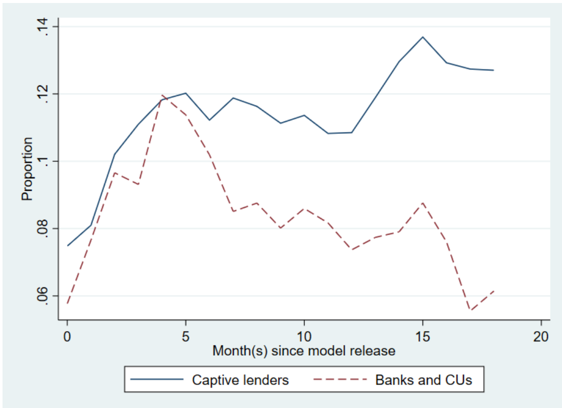
This figure presents the change in the proportion of subprime borrowers and the proportion of default through product life. In all panels, I plot one line with the captive lender sample and another line with the bank and credit union (CU) sample. Panel A plots the proportion of subprime borrowers among all borrowers from the month of the model's release to 18 months after the release. Panel B plots the proportion of subprime borrowers who default within 12 months after the model's release among all subprime borrowers from the month of the model's release to 18 months after the release. Panel C plots the proportion of subprime borrowers who default during the lifetime of the loan among all subprime borrowers from the month of the model's release to 18 months after the release. The sample is restricted to auto loans that originated between January 2015 and August 2020.



(a) Proportion of subprime borrowers



(b) Proportion of early default in subprime borrowers



(c) Proportion of lifetime default in subprime borrowers

Table 1: Summary statistics

This table reports the summary statistics of the data used in the analyses. Panel A reports the summary statistics for the full sample. Panel B reports the summary statistics by lender type. Note that I intentionally leave the median for dummy variables blank.

Panel A: Full sample

	Mean	Median	SD	Obs.
captive	0.821		0.383	5,176,405
credit score	744.728	754.000	73.915	5,176,405
rate (%)	3.528	2.900	3.358	5,176,405
rate subvention	0.591		0.492	5,176,405
income (monthly, in thousands)	8.555	6.504	7.075	5,176,405
vehicle value (in thousands)	32.337	29.033	11.376	5,176,405
maturity	66.452	72.000	8.852	5,176,405
loan amount (in thousands)	29.541	27.552	11.937	5,176,405
income verification	0.050		0.217	5,176,405
employment verification	0.045		0.207	5,176,405
default (12 months) (%)	0.468		6.827	4,906,943
default (%)	3.265		17.773	4,906,943
subprime	0.117		0.322	4,906,943

Panel B: By lender type

	Captive lenders			Banks and credit unions		
	Mean	SD	Obs.	Mean	SD	Obs.
credit score	745.137	75.664	4,248,932	742.851	65.272	927,473
rate (%)	3.276	3.370	4,248,932	4.682	3.046	927,473
rate subvention	0.660	0.474	4,248,932	0.271	0.444	927,473
income (monthly, in thousands)	8.679	7.130	4,248,932	7.990	6.791	927,473
vehicle value (in thousands)	32.272	11.620	4,248,932	32.636	10.179	927,473
maturity	65.879	8.767	4,248,932	69.080	8.762	927,473
loan amount (in thousands)	29.611	12.291	4,248,932	29.217	10.150	927,473
income verification	0.059	0.236	4,248,932	0.005	0.073	927,473
employment verification	0.054	0.226	4,248,932	0.004	0.062	927,473
default (12 months) (%)	0.437	6.598	4,065,138	0.618	7.840	841,805
default (%)	2.750	16.353	4,065,138	5.755	23.289	841,805
subprime	0.127	0.333	4,065,138	0.071	0.257	841,805

Table 2: Interest rate and the product life cycle

This table reports the results from OLS regressions of loan interest rate on model age, measuring the length of time between the model's release and loan issuance. The dependent variable is the interest rate of the loan at origination (columns 1–3). Column 4 has *rate subvention* (takes the value of 1 if the loan receives rate subvention, and 0 otherwise) as the dependent variable. *Captive* takes the value of 1 if the loan comes from a captive lender, and 0 otherwise. The main explanatory variable is $captive \times model\, age$, which measures the effect of model age on interest rate from captive lenders relative to other lenders. Column 1 shows the results of the regression without control variables. I gradually add borrower (credit score and income) and loan controls (vehicle value, loan amount, and maturity) in columns 2 and 3. Column 4 has the same control variables as column 3. I include year-month, state, model, and lender fixed effects. Standard errors are clustered at the lender$\times$state level, and t-statistics are shown in parentheses below the coefficient estimates. $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

	(1)	(2)	(3)	(4)
	rate(%)	rate(%)	rate(%)	rate subvention
captive × model age (months)	-0.0287***	-0.0306***	-0.0325***	0.0069***
	(-5.16)	(-6.17)	(-7.31)	(5.06)
ln(credit score)		-12.8438***	-12.6538***	0.2564***
		(-18.55)	(-18.67)	(5.99)
ln(income)		-0.1081***	0.0479***	-0.0187***
		(-10.58)	(4.93)	(-8.64)
ln(vehicle value)			-0.2294***	-0.1850***
			(-2.90)	(-12.39)
ln(loan amount)			-1.2138***	0.3149***
			(-16.83)	(16.98)
ln(maturity)			3.1924***	-0.5085***
			(16.32)	(-9.50)
Year-month FE	Y	Y	Y	Y
State FE	Y	Y	Y	Y
Model FE	Y	Y	Y	Y
Lender FE	Y	Y	Y	Y
Observations	5,176,405	5,176,405	5,176,405	5,176,405
Adjusted R-squared	0.473	0.592	0.609	0.417
SE cluster	Y	Y	Y	Y

Table 3: Other loan characteristics and the product life cycle

This table reports the results from OLS regressions of various loan terms on model age, measuring the length of time between the model's release and loan issuance. The dependent variables are the natural logarithm of maturity (columns 1 and 2), the natural logarithm of loan amount (columns 3 and 4), income verification (columns 5 and 6), and employment verification (columns 7 and 8). $Income\,verification$ ($employment\,verification$) takes the value of 1 if the lender verifies the borrower's income (employment) information during the lending process, and 0 otherwise. *Captive* takes the value of 1 if the loan comes from a captive lender, and 0 otherwise. Similar to that in Table 2, the main explanatory variable is $captive \times model\,age$. Columns 1, 3, 5, and 7 show the results of regressions without control variables. Other columns include borrower (credit score and income) and loan controls (vehicle value, loan amount, and maturity). I include year-month, state, model, and lender fixed effects. Standard errors are clustered at the lender×state level, and t-statistics are shown in parentheses below the coefficient estimates. $^{*}p$ <0.1; $^{**}p$ <0.05; $^{***}p$ <0.01.

	(1) ln(maturity)	(2) ln(maturity)	(3) ln(loan amount)	(4) ln(loan amount)	(5) income verification	(6) income verification	(7) employment verification	(8) employment verification
captive × model age (months)	0.0010***	0.0010***	0.0011**	0.0009***	-0.0003*	-0.0004**	-0.0002	-0.0002**
	(7.00)	(7.55)	(2.56)	(3.10)	(-1.80)	(-2.50)	(-1.17)	(-1.96)
ln(credit score)		-0.3170***		-0.8059***		-0.5972***		-0.5509***
		(-30.08)		(-29.45)		(-7.24)		(-7.16)
ln(income)		-0.0157***		0.0506***		-0.0019*		-0.0021**
		(-23.89)		(21.53)		(-1.84)		(-2.25)
ln(vehicle value)		-0.0234***		0.7769***		-0.0270***		-0.0251***
		(-7.86)		(82.12)		(-5.87)		(-5.84)
Year-month FE	Y	Y	Y	Y	Y	Y	Y	Y
State FE	Y	Y	Y	Y	Y	Y	Y	Y
Model FE	Y	Y	Y	Y	Y	Y	Y	Y
Lender FE	Y	Y	Y	Y	Y	Y	Y	Y
Observations	5,176,405	5,176,405	5,176,405	5,176,405	5,176,405	5,176,405	5,176,405	5,176,405
Adjusted R-squared	0.185	0.226	0.392	0.468	0.331	0.393	0.304	0.362
SE cluster	Y	Y	Y	Y	Y	Y	Y	Y

Table 4: Loan terms and new model release

This table reports the results from OLS regressions of various loan terms on new model releases. The dependent variables are the interest rate of the loan at origination (column 1), the natural logarithm of maturity (column 2), the natural logarithm of the loan amount (column 3), income verification (column 4), and employment verification (column 5). *Captive* takes the value of 1 if the loan comes from a captive lender, and 0 otherwise. *Post new model release* takes the value of 1 if the loan is issued after the release of the next model generation, and 0 otherwise. The main explanatory variable is *captive* $\times$ *post new model release*. Standard errors are clustered at the lender$\times$state level, and t-statistics are shown in parentheses below the coefficient estimates. *p <0.1; **p <0.05; ***p <0.01.

	(1) rate(%)	(2) ln(maturity)	(3) ln(loan amount)	(4) income verification	(5) employment verification
captive × post new model release	-0.1929***	0.0109***	0.0060**	-0.0087***	-0.0078***
	(-4.32)	(10.81)	(2.49)	(-4.35)	(-4.91)
post new model release	0.1203***	-0.0046***	-0.0025	0.0053***	0.0045***
	(2.71)	(-5.24)	(-1.22)	(3.53)	(3.72)
ln(credit score)	-12.6528***	-0.3171***	-0.8060***	-0.5972***	-0.5509***
	(-18.66)	(-30.10)	(-29.45)	(-7.24)	(-7.16)
ln(income)	0.0479***	-0.0157***	0.0506***	-0.0019*	-0.0021**
	(4.94)	(-23.89)	(21.54)	(-1.85)	(-2.26)
ln(vehicle value)	-0.2288***	-0.0234***	0.7769***	-0.0269***	-0.0250***
	(-2.87)	(-7.86)	(82.02)	(-5.87)	(-5.84)
ln(loan amount)	-1.2141***				
	(-16.85)				
ln(maturity)	3.1922***				
	(16.38)				
Year-month FE	Y	Y	Y	Y	Y
State FE	Y	Y	Y	Y	Y
Model FE	Y	Y	Y	Y	Y
Lender FE	Y	Y	Y	Y	Y
Observations	5,176,405	5,176,405	5,176,405	5,176,405	5,176,405
Adjusted R-squared	0.609	0.226	0.468	0.393	0.362
SE cluster	Y	Y	Y	Y	Y

Table 5: Interest rate and recall

This table reports the results from OLS regressions of loan interest rate on model recalls. The dependent variable is the interest rate of the loan at origination. *Captive* takes the value of 1 if the loan comes from a captive lender, and 0 otherwise. In columns 1 and 3, *post recall* takes the value of 1 if the loan origination date is within 3 months after the recall, and takes the value of 0 if the loan origination date is within 3 months before the recall. In columns 2 and 4, *Post recall* takes the value of 1 if the loan origination date is within 3 months after the recall, and 0 otherwise. In columns 1 and 2, I report the results from the loan-level sample and only investigate the first recall of car models. In columns 3 and 4, I report the results from the recall × loan-level sample and investigate all recalls in the sample period. Control variables include borrower (credit score and income) and loan controls (vehicle value, loan amount, and maturity). In columns 1 and 3, the sample is restricted to auto loans originated 3 months before and after recalls. I include year-month, state, model, and lender fixed effects. Standard errors are clustered at the lender×state level, and t-statistics are shown in parentheses below the coefficient estimates. *p <0.1; **p <0.05; ***p <0.01.

	only first recall		allow multiple recalls	
	(1)	(2)	(3)	(4)
	rate(%)	rate(%)	rate(%)	rate(%)
post recall × captive	-0.2624***	-0.0917***	-0.1941***	-0.0840***
	(-5.34)	(-2.66)	(-12.88)	(-4.89)
post recall	0.3826***	0.0156	0.1621***	0.0513***
	(9.95)	(0.51)	(11.30)	(3.55)
ln(credit score)	-11.3427***	-12.6536***	-11.5602***	-11.6627***
	(-13.68)	(-18.66)	(-14.53)	(-16.17)
ln(income)	0.0440***	0.0479***	0.0529***	0.0560***
	(3.67)	(4.94)	(5.42)	(5.74)
ln(vehicle value)	-0.1663*	-0.2302***	-0.1667*	-0.1583**
	(-1.81)	(-2.88)	(-1.75)	(-2.07)
ln(loan amount)	-0.9381***	-1.2138***	-1.1902***	-1.2569***
	(-11.66)	(-16.85)	(-14.88)	(-16.14)
ln(maturity)	3.2026***	3.1894***	3.1510***	3.0419***
	(16.88)	(16.38)	(15.93)	(16.37)
Year-month FE	Y	Y	Y	Y
State FE	Y	Y	Y	Y
Model FE	Y	Y	Y	Y
Lender FE	Y	Y	Y	Y
Observations	1,208,990	5,176,405	3,199,559	17,954,722
Adjusted R-squared	0.624	0.609	0.584	0.573
SE cluster	Y	Y	Y	Y

Table 6: Product heterogeneity

This table reports the results from OLS regressions of loan interest rate on model age (columns 1 and 2) and new model release (columns 3–5). The dependent variable is the interest rate of the loan at origination. *Captive* takes the value of 1 if the loan comes from a captive lender, and 0 otherwise. *Reliability score* is the car model reliability score from Consumer Reports, which surveys its members about their car reliability experiences. Possible values range from 1 to 5, where a larger score indicates a more reliable vehicle. *Low reliability* takes the value of 1 if the reliability score of the vehicle is below 4 (median of the sample), and 0 otherwise. *Redesign* takes the value of 1 if the next model generation is a redesign model, and 0 otherwise. $Reliability\, difference$ is calculated as $Reliability\, score\,(newmodel) - Reliability\, score\,(oldmodel)$. A positive number indicates that the new model is better than the old model. *High reliability difference* equals 1 if the reliability difference is above or equals to 0 (the median of the sample), and 0 otherwise. The main explanatory variables are the triple interaction terms in each column. Standard errors are clustered at the lender×state level, and t-statistics are shown in parentheses below the coefficient estimates. *p <0.1; **p <0.05; ***p <0.01.

	(1) rate(%)	(2) rate(%)	(3) rate(%)	(4) rate(%)	(5) rate(%)
captive × model age (months) × reliability score	0.0155*** (6.43)				
captive × model age (months) × low reliability		-0.0199*** (-3.40)			
captive × model age (months)	-0.0856*** (-8.53)	-0.0251*** (-5.56)			
captive × post new model release × redesign			-0.2863*** (-4.04)		
captive × post new model release × reliability difference				-0.0800*** (-4.49)	
captive × post new model release × high reliability difference					-0.3571*** (-6.89)
captive × post new model release			-0.1569*** (-3.06)	-0.2231*** (-4.85)	0.0290 (0.64)
Control variables	Y	Y	Y	Y	Y
Year-month FE	Y	Y	Y	Y	Y
State FE	Y	Y	Y	Y	Y
Model FE	Y	Y	Y	Y	Y
Lender FE	Y	Y	Y	Y	Y
Observations	4,719,160	4,719,160	5,176,405	4,331,124	4,331,124
Adjusted R-squared	0.579	0.579	0.609	0.560	0.560
SE cluster	Y	Y	Y	Y	Y

Table 7: Interest rate and the product life cycle (used cars)

This table reports the results of placebo tests on the used car loan sample. Column 1 reports results similar to Table 2, column 3. Columns 2–5 report results similar to Table 3, columns 2, 4, 6, and 8, respectively. All else is the same as the corresponding columns, except this table uses the used car loan sample instead of the new car loan sample. Standard errors are clustered at the lender×state level, and t-statistics are shown in parentheses below the coefficient estimates. *p <0.1; **p <0.05; ***p <0.01.

	(1) rate(%)	(2) ln(maturity)	(3) ln(loan amount)	(4) income verification	(5) employment verification
captive × model age (months)	-0.0075***	-0.0001	-0.0000	0.0001	0.0000
	(-4.38)	(-1.22)	(-0.48)	(1.01)	(0.71)
ln(credit score)	-20.1276***	-0.2620***	-0.4029***	-0.5546***	-0.5114***
	(-73.35)	(-35.31)	(-15.36)	(-5.77)	(-5.71)
ln(income)	-0.5178***	-0.0241***	0.0266***	0.0028***	0.0018*
	(-15.41)	(-39.70)	(15.26)	(3.13)	(1.77)
ln(vehicle value)	-3.6193***	0.0708***	0.7397***	-0.0677***	-0.0537***
	(-20.33)	(21.34)	(80.53)	(-8.64)	(-9.04)
ln(loan amount)	1.8447***				
	(10.20)				
ln(maturity)	2.4880***				
	(14.74)				
Year-month FE	Y	Y	Y	Y	Y
State FE	Y	Y	Y	Y	Y
Model FE	Y	Y	Y	Y	Y
Lender FE	Y	Y	Y	Y	Y
Observations	3,299,114	3,299,114	3,299,114	3,299,114	3,299,114
Adjusted R-squared	0.794	0.177	0.632	0.627	0.559
SE cluster	Y	Y	Y	Y	Y

Table 8: Loan performance

This table reports the results from OLS regressions of loan default on model age, measuring the length of time between the model's release and loan issuance. The dependent variable is $default$. A loan is considered in default if the loan has been charged-off, has been repossessed, or is 90 or more days past due. In panel A, default equals 1 if the loan defaults in the first 12 months after origination, and 0 otherwise. In panel B, default equals 1 if the loan defaults during its lifetime in the sample period, and 0 otherwise. *Captive* takes the value of 1 if the loan comes from a captive lender, and 0 otherwise. To avoid a truncation issue, I drop loans originated after August 2020, which is 12 months before the end of the sample. Column 1 shows the results of the regression without control variables. I gradually add borrower controls (credit score and income), loan controls (vehicle value, loan amount, and maturity), and interest rate in columns 2–4. I include year-month, state, model, and lender fixed effects. Standard errors are clustered at the lender×state level, and t-statistics are shown in parentheses below the coefficient estimates. *p <0.1; **p <0.05; ***p <0.01.

Panel A: Early default (12 months)

	(1) default (%)	(2) default (%)	(3) default (%)	(4) default (%)
captive × model age (months)	-0.0244***	-0.0249***	-0.0243***	-0.0192**
	(-3.06)	(-3.16)	(-3.12)	(-2.54)
ln(credit score)		-3.0873***	-3.3370***	-1.3157***
		(-9.43)	(-9.86)	(-8.50)
ln(income)		-0.0892***	-0.0826***	-0.0905***
		(-6.31)	(-5.66)	(-5.89)
ln(vehicle value)			-0.0291	0.0049
			(-0.42)	(0.06)
ln(loan amount)			-0.1609*	0.0411
			(-1.93)	(0.50)
ln(maturity)			-0.4259***	-0.9420***
			(-5.73)	(-8.72)
rate(%)				0.1632***
				(13.94)
Year-month FE	Y	Y	Y	Y
State FE	Y	Y	Y	Y
Model FE	Y	Y	Y	Y
Lender FE	Y	Y	Y	Y
Observations	4,906,942	4,906,942	4,906,942	4,906,942
Adjusted R-squared	0.017	0.019	0.019	0.021
SE cluster	Y	Y	Y	Y

Panel B: Lifetime default

	(1) default (%)	(2) default (%)	(3) default (%)	(4) default (%)
captive × model age (months)	0.0323*	0.0293*	0.0308*	0.0538***
	(1.80)	(1.67)	(1.76)	(3.04)
ln(credit score)		-18.1632***	-17.8217***	-8.7054***
		(-18.79)	(-18.39)	(-20.31)
ln(income)		-0.3185***	-0.3793***	-0.4152***
		(-7.52)	(-8.43)	(-8.83)
ln(vehicle value)			-2.3346***	-2.1811***
			(-11.36)	(-9.47)
ln(loan amount)			1.2798***	2.1907***
			(5.33)	(9.06)
ln(maturity)			-2.6794***	-5.0072***
			(-7.30)	(-11.20)
rate(%)				0.7362***
				(21.42)
Year-month FE	Y	Y	Y	Y
State FE	Y	Y	Y	Y
Model FE	Y	Y	Y	Y
Lender FE	Y	Y	Y	Y
Observations	4,906,942	4,906,942	4,906,942	4,906,942
Adjusted R-squared	0.076	0.085	0.086	0.093
SE cluster	Y	Y	Y	Y

Table 9: Borrowers' credit score

This table reports the results from OLS regressions of borrowers' credit score on model age, measuring the length of time between the model's release and loan issuance. The dependent variable is the log-transformed borrowers' credit score ($ln(credit\,score)$). *Captive* takes the value of 1 if the loan comes from a captive lender, and 0 otherwise. Column 1 shows the results of the regression without control variables. Column 2 shows the results of the regression with borrower (credit score and income) and loan controls (vehicle value, loan amount, maturity, and interest rate). I include year-month, state, model, and lender fixed effects. Standard errors are clustered at the lender×state level, and t-statistics are shown in parentheses below the coefficient estimates. *p <0.1; **p <0.05; ***p <0.01.

	(1) ln(credit score)	(2) ln(credit score)
captive × model age (months)	-0.0001*	-0.0005***
	(-1.69)	(-8.48)
ln(income)		0.0140***
		(24.07)
ln(vehicle value)		0.0894***
		(29.10)
ln(loan amount)		-0.0621***
		(-37.87)
ln(maturity)		-0.0096**
		(-2.47)
rate(%)		-0.0165***
		(-36.21)
Year-month FE	Y	Y
State FE	Y	Y
Model FE	Y	Y
Lender FE	Y	Y
Observations	5,176,405	5,176,405
Adjusted R-squared	0.278	0.481
SE cluster	Y	Y

Table 10: Loan performance (subprime borrower)

This table reports the results from OLS regressions of loan default on model age, measuring the length of time between the model's release and loan issuance, and further interacts with *subprime*, which takes the value of 1 if the credit score of the borrower is less than 660, and 0 otherwise. The dependent variable is $default$. A loan is considered in default if the loan has been charged-off, has been repossessed, or is 90 or more days past due. In panel A, default equals 1 if the loan defaults in first 12 months after origination, and 0 otherwise. In panel B, default equals 1 if the loan defaults during its lifetime in the sample period, and 0 otherwise. $Captive$ takes the value of 1 if the loan comes from a captive lender, and 0 otherwise. The main explanatory variable is $captive \times model\,age \times subprime$. Column 1 shows the results of regression without control variables. I gradually add borrower controls (credit score and income), loan controls (vehicle value, loan amount, and maturity), and interest rate in columns 2–4. I include year-month, state, model, and lender fixed effects. The sample is restricted to auto loans originated between January 2015 and August 2020. Standard errors are clustered at the lender×state level, and t-statistics are shown in parentheses below the coefficient estimates. *p <0.1; **p <0.05; ***p <0.01.

Panel A: Early default (12 months)

	(1) default (%)	(2) default (%)	(3) default (%)	(4) default (%)
captive × model age (months) × subprime	0.0959***	0.0943***	0.0937***	0.0957***
	(9.08)	(9.02)	(8.94)	(9.66)
captive × model age (months)	-0.0318***	-0.0318***	-0.0312***	-0.0266***
	(-4.40)	(-4.45)	(-4.40)	(-3.98)
subprime × model age (months)	-0.0819***	-0.0810***	-0.0809***	-0.0816***
	(-8.92)	(-8.90)	(-8.84)	(-9.52)
captive × subprime	-1.3756***	-1.4152***	-1.4157***	-1.1975***
	(-8.94)	(-9.94)	(-9.92)	(-8.87)
subprime	2.2240***	1.8727***	1.8575***	1.3042***
	(25.57)	(17.64)	(17.39)	(12.34)
ln(credit score)		-1.7682***	-2.0404***	-0.8184***
		(-7.30)	(-8.52)	(-5.87)
ln(income)		-0.0912***	-0.0857***	-0.0913***
		(-6.60)	(-6.02)	(-6.03)
ln(vehicle value)			-0.0220	0.0059
			(-0.30)	(0.07)
ln(loan amount)			-0.1450*	0.0386
			(-1.71)	(0.47)
ln(maturity)			-0.4050***	-0.9070***
			(-5.67)	(-8.50)
rate(%)				0.1555***
				(13.04)
Year-month FE	Y	Y	Y	Y
State FE	Y	Y	Y	Y
Model FE	Y	Y	Y	Y
Lender FE	Y	Y	Y	Y
Observations	4,906,942	4,906,942	4,906,942	4,906,942
Adjusted R-squared	0.019	0.019	0.019	0.022
SE Cluster	Y	Y	Y	Y

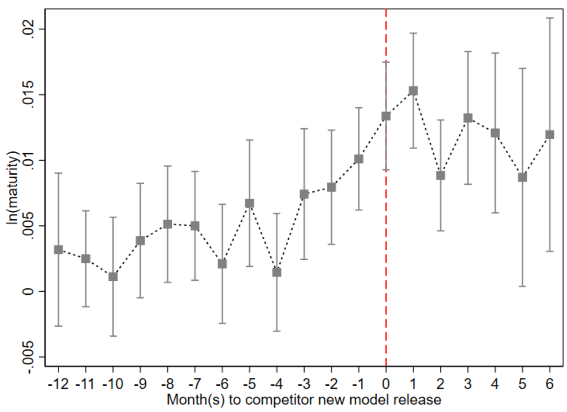
Panel B: Lifetime default

	(1) default (%)	(2) default (%)	(3) default (%)	(4) default (%)
captive × model age (months) × subprime	0.1603***	0.1496***	0.1458***	0.1551***
	(4.59)	(4.24)	(4.15)	(3.77)
captive × model age (months)	0.0227	0.0224	0.0242	0.0449**
	(1.16)	(1.13)	(1.23)	(2.14)
subprime × model age (months)	-0.1796***	-0.1734***	-0.1729***	-0.1764***
	(-5.84)	(-5.50)	(-5.54)	(-4.59)
captive × subprime	-2.6454***	-2.9489***	-2.9442***	-1.9531***
	(-5.68)	(-6.73)	(-6.66)	(-4.73)
subprime	8.2425***	5.8173***	5.8516***	3.3390***
	(26.92)	(19.76)	(19.41)	(10.09)
ln(credit score)		-12.5533***	-12.1217***	-6.5726***
		(-15.01)	(-15.62)	(-14.31)
ln(income)		-0.3286***	-0.3951***	-0.4208***
		(-8.08)	(-9.16)	(-9.17)
ln(vehicle value)			-2.2953***	-2.1687***
			(-10.46)	(-9.22)
ln(loan amount)			1.3518***	2.1854***
			(5.49)	(9.01)
ln(maturity)			-2.5974***	-4.8771***
			(-7.24)	(-10.81)
rate(%)				0.7062***
				(19.41)
Year-month FE	Y	Y	Y	Y
State FE	Y	Y	Y	Y
Model FE	Y	Y	Y	Y
Lender FE	Y	Y	Y	Y
Observations	4,906,942	4,906,942	4,906,942	4,906,942
Adjusted R-squared	0.084	0.086	0.087	0.093
SE Cluster	Y	Y	Y	Y

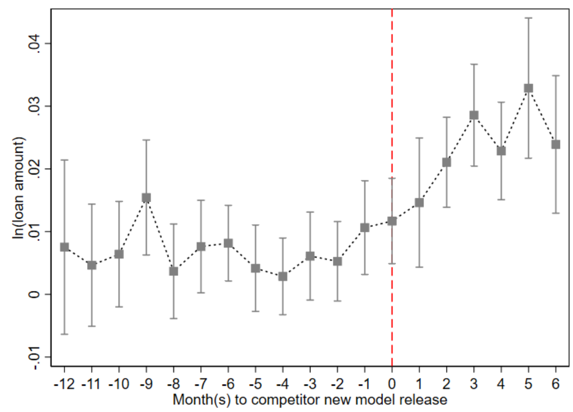
Appendix

Figure A1: Other loan characteristics and competitor's new model release

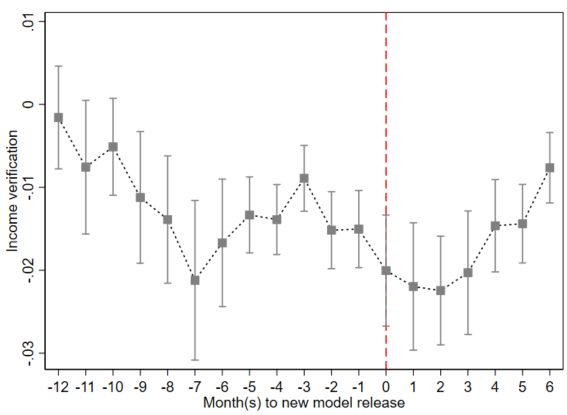
All else is similar to Figure 2. The only difference is that the horizontal axis is months to the competitor's release of the next model generation instead of months since the release of the underlying model. The vertical dashed line represents the time of the competitor's new model release.



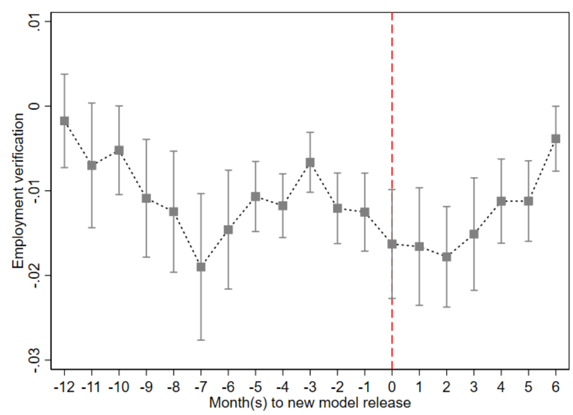
(a) Maturity



(b) Loan amount



(c) Income verification



(d) Employment verification

Figure A2: Interest rate and the product life cycle (used cars)

This figure plots information similar to Figure 1 but with the used car sample. The horizon is from 13 months after the model's release to 72 months after the release.

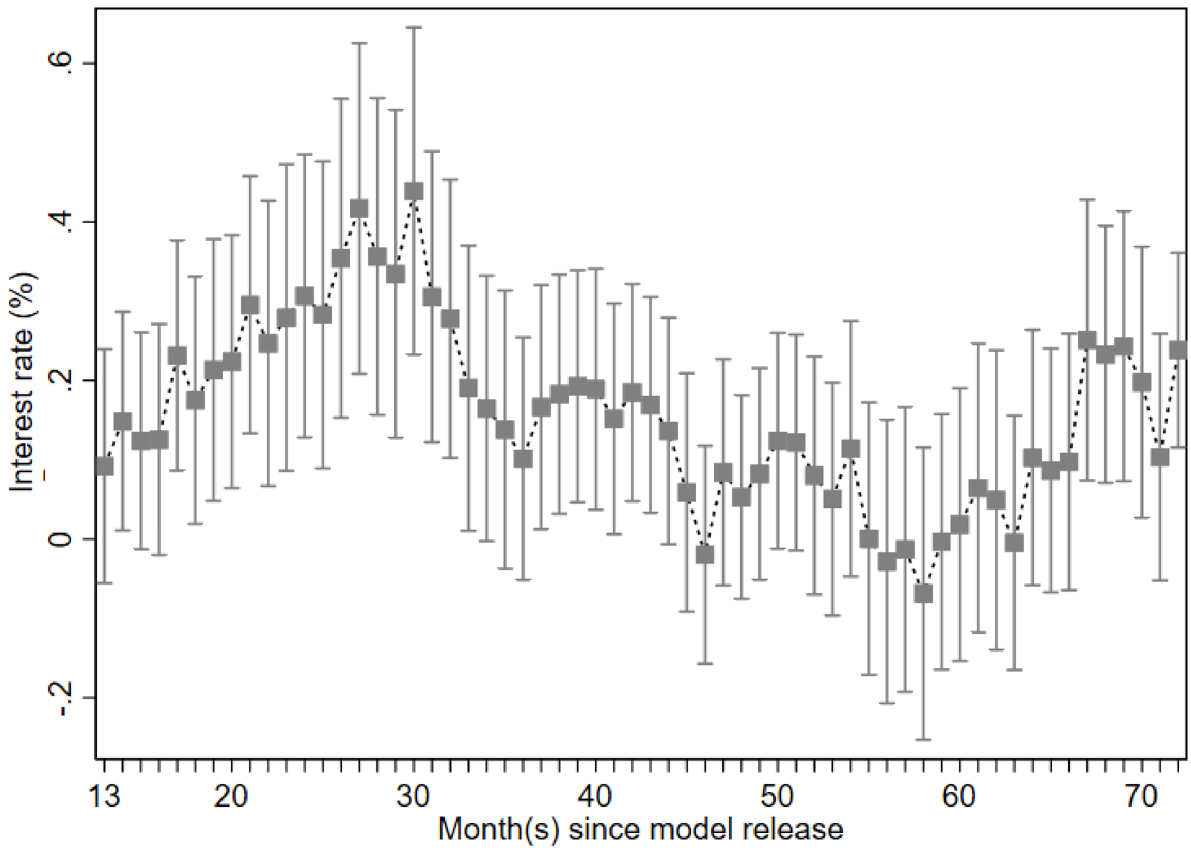
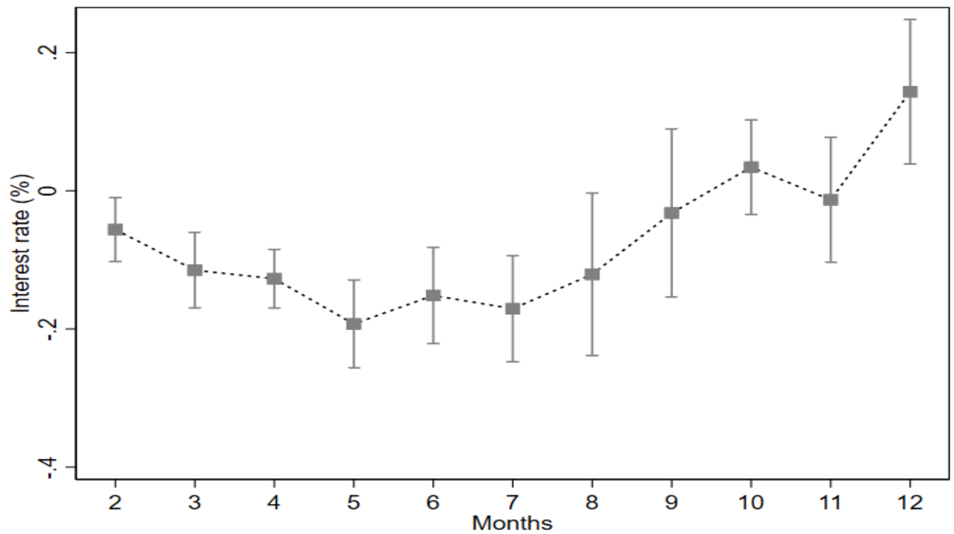


Figure A3: Interest rate and calendar (fiscal) month

This figure plots information similar to Figure 1. However, instead of regressing the interest rate on product age, in this figure, I regress the interest rate on the calendar and fiscal months. Panel A presents the coefficient estimates on the calendar month. Panel B presents the coefficient estimates on the fiscal month.

(a) Calendar month



(b) Fiscal month

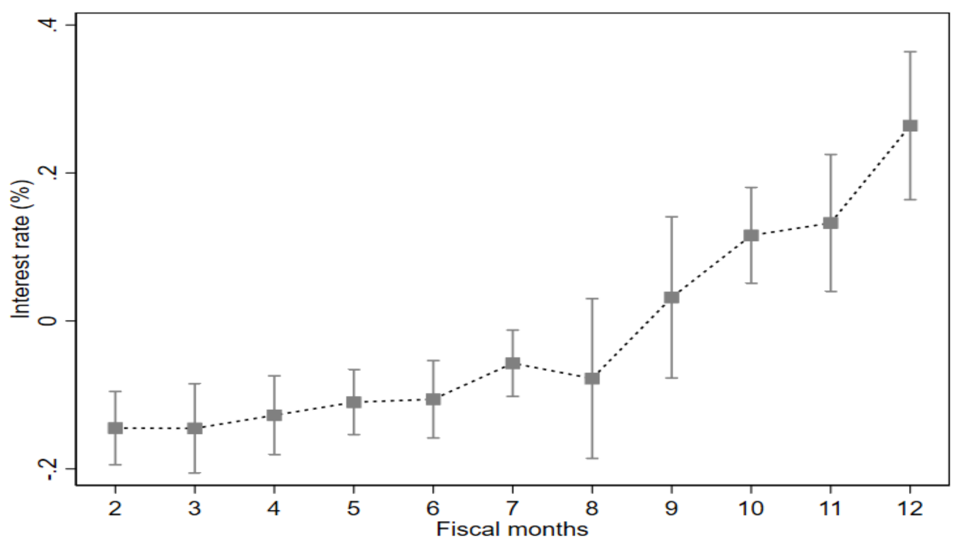


Figure A4: Number of loans and the product life cycle

This figure plots the coefficient estimates with a 95% confidence interval of β_ns from Model (2) that regresses the log-transformed number of loans on months relative to the model's age. However, instead of estimating $captive_k \times model\,age_n$, the model for this figure estimates $model\,age_n$. The coefficient estimates on these indicator variables measure the changes in the number of loans from the model's release to 18 months after the release. The sample is aggregated at the lender-model year-year-month level. Hence, the regression has no loan-level control variables. The analyses use two subsamples from the main sample that contains new car loans from 2015 to 2021. The first subsample contains only loans from captive lenders, and the second subsample contains only loans from banks and credit unions. Standard errors are clustered at the lender $\times$ state level.

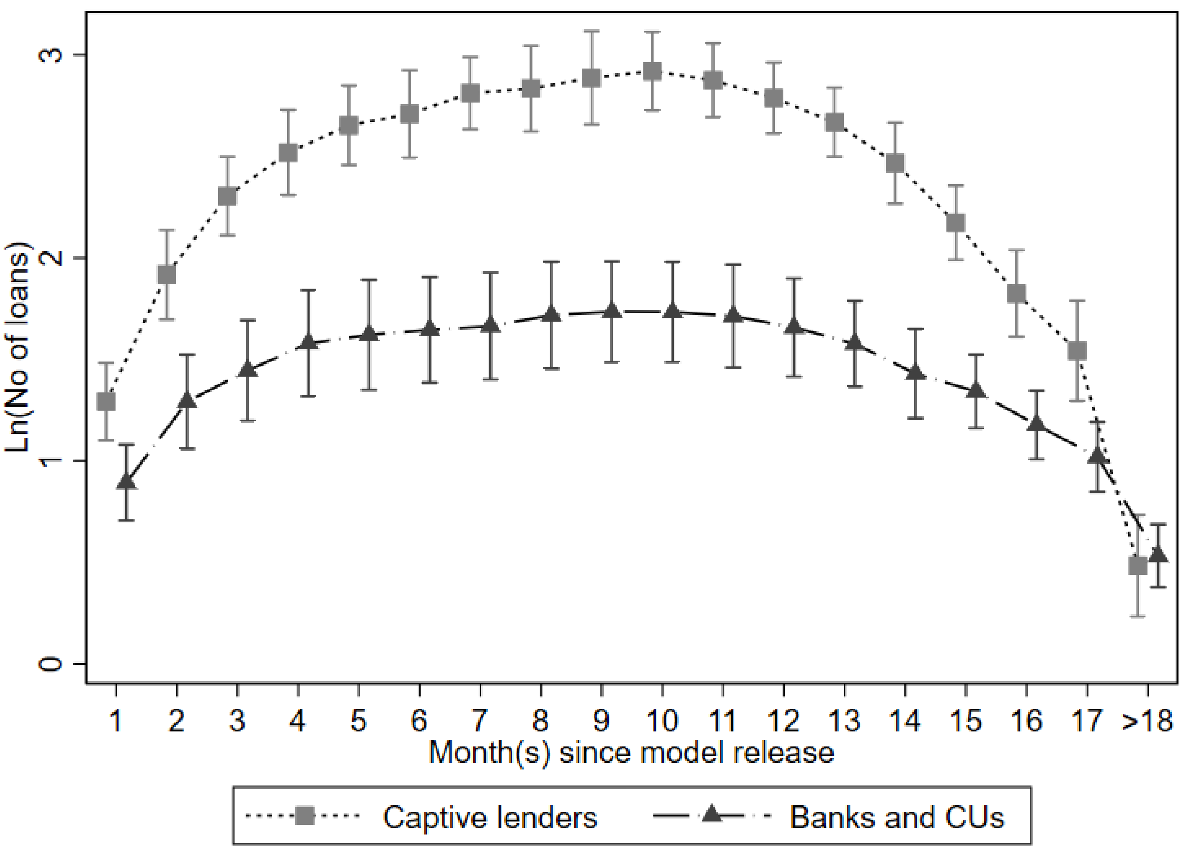
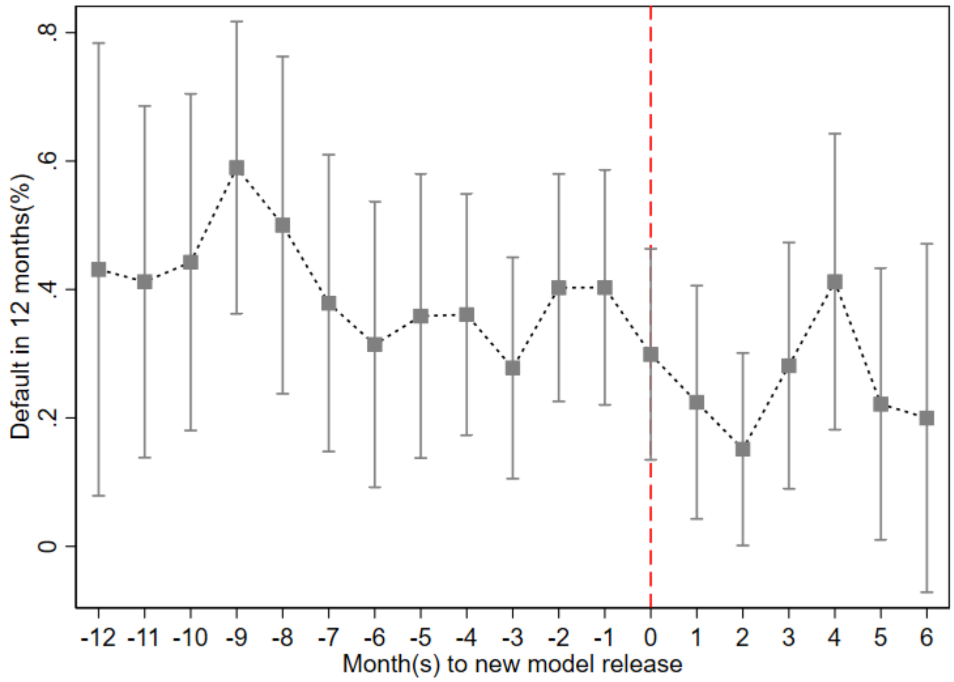
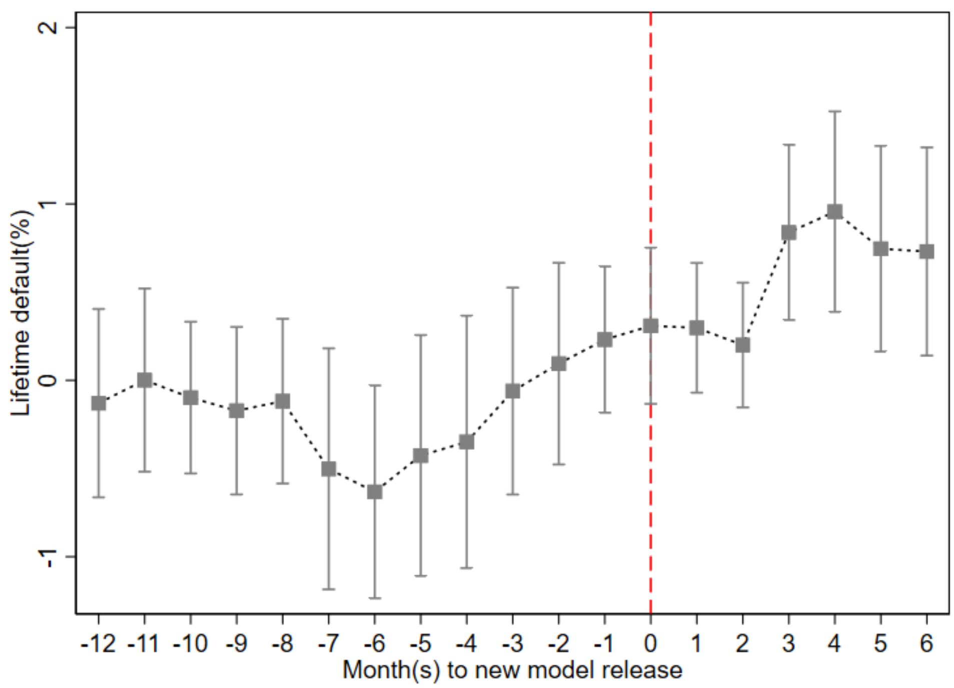


Figure A5: Default and own new model release

This figure plots the coefficient estimates with a 95% confidence interval of β_ns from Model (4), which is a linear regression model with year-month, state, model, and lender fixed effects that regresses "default" on the months relative to the release of the next model generation. The x-axis corresponds to the length of time between loan origination and the release of the underlying model's next model generation. β_ns measure the differences in the default rate between captive and non-captive lenders from 12 months before the underlying model's own new model release to 6 months after the release. The dependent variable is early default (panel A) and lifetime default (panel B). The vertical dashed line represents the time of the new model release. The sample is restricted to auto loans originated between January 2015 and August 2020. Standard errors are clustered at the lender $\times$ state level.



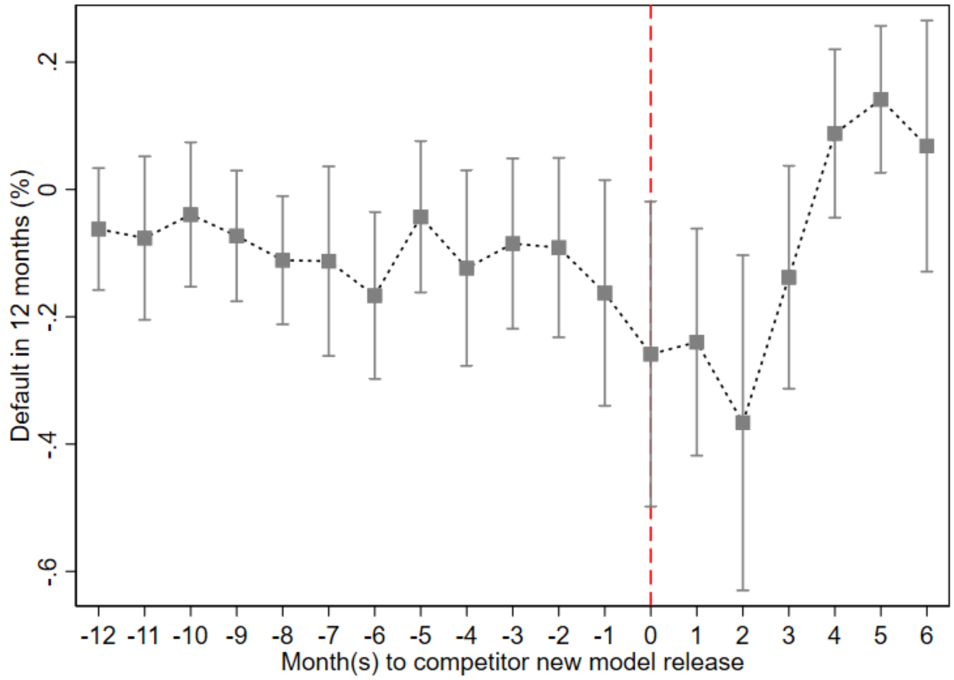
(a) Early default



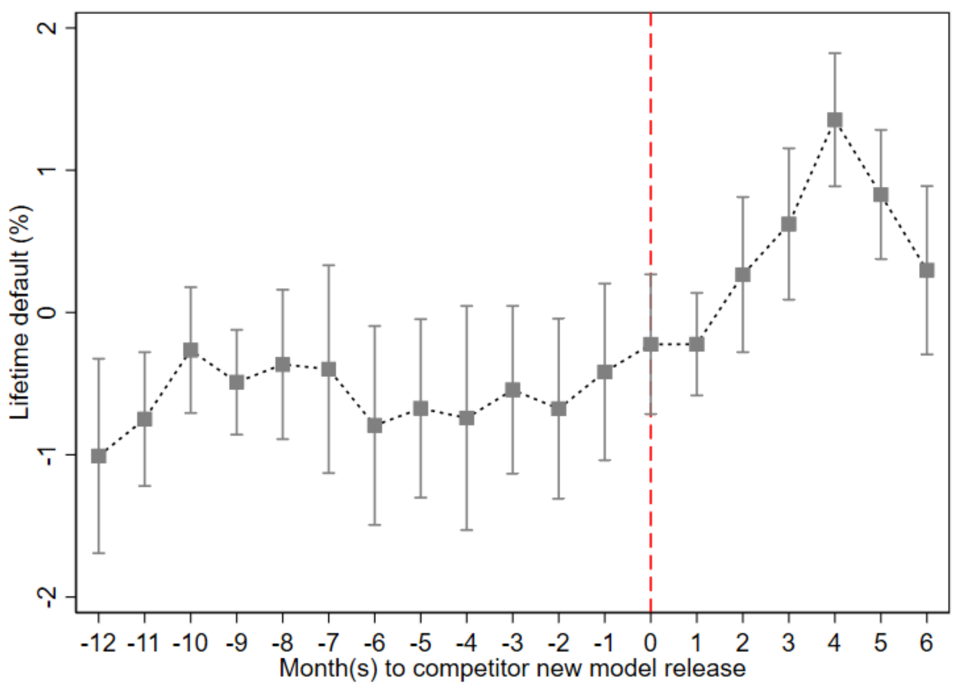
(b) Lifetime default

Figure A6: Default and competitor's new model release

This figure plots the coefficient estimates with a 95% confidence interval of β_ns from Model (4), which is a linear regression model with year-month, state, model, and lender fixed effects that regresses "default" on the months relative to the release of the next model generation. The x-axis corresponds to the length of time between loan origination and the release of the competitor's next model generation. β_ns measure the differences in default rate between captive and non-captive lenders from 12 months before the competitor's new model release to 6 months after the release. The dependent variable is early default (panel A) and lifetime default (panel B). The vertical dashed line represents the new model's release. The sample is restricted to auto loans originated between January 2015 and August 2020. Standard errors are clustered at the lender $\times$ state level.



(a) Early default

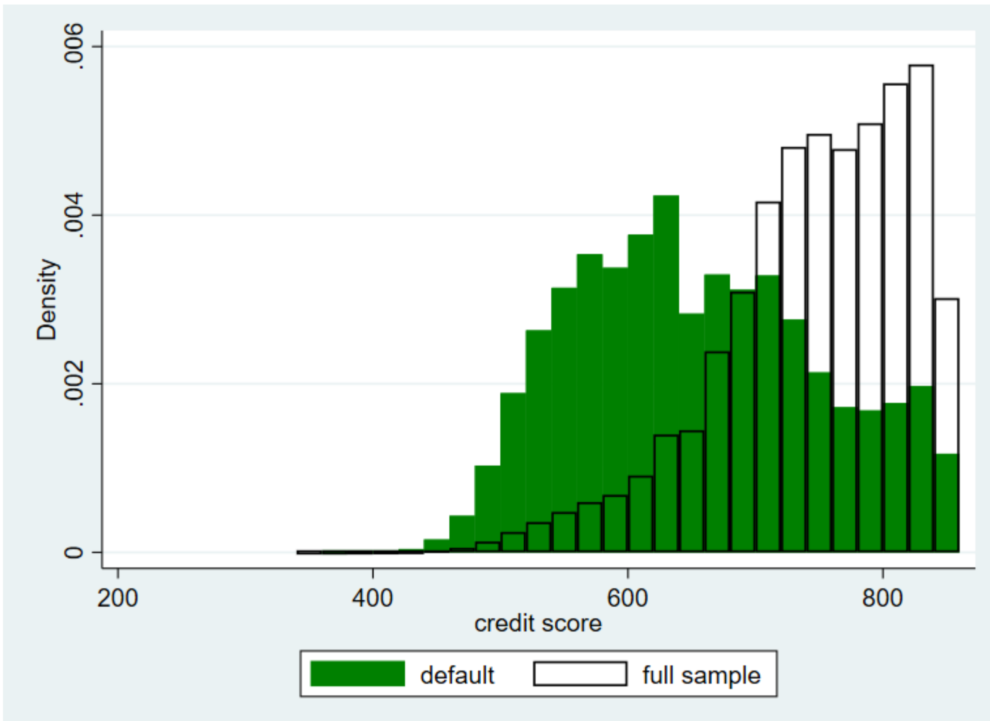


(b) Lifetime default

Figure A7: Borrowers' credit score distribution on default (lifetime)

This figure presents the sample distribution and lifetime default distribution over borrowers' credit scores. Panel A plots the credit score distribution of borrowers from captive lenders. Panel B plots the credit score distribution of borrowers from banks and credit unions. In each panel, I present two distributions. One is the distribution of the full sample; the other is the distribution of borrowers who default during the lifetime of the loan.

(a) Captive lenders



(b) Banks and credit unions

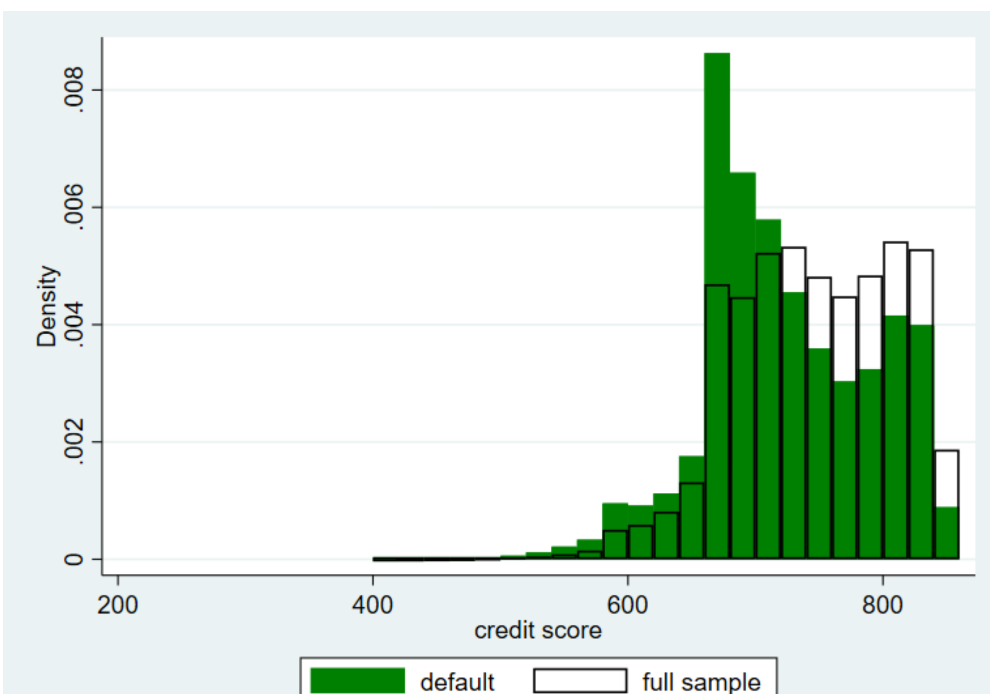


Table A1: Number of loans by model age

Age (month)	Frequency	Proportion (%)	Cumulative proportion (%)
0	13,990	0.27	0.27
1	74,200	1.43	1.70
2	152,212	2.94	4.64
3	221,801	4.28	8.93
4	275,070	5.31	14.24
5	314,694	6.08	20.32
6	354,520	6.85	27.17
7	379,518	7.33	34.50
8	390,558	7.54	42.05
9	417,075	8.06	50.11
10	416,532	8.05	58.15
11	414,360	8.00	66.16
12	374,046	7.23	73.38
13	331,338	6.40	79.78
14	286,537	5.54	85.32
15	215,582	4.16	89.48
16	168,641	3.26	92.74
17	124,208	2.40	95.14
18	83,582	1.61	96.76
19	59,743	1.15	97.91
20	41,994	0.81	98.72
21	28,135	0.54	99.26
22	19,241	0.37	99.64
23	11,611	0.22	99.86
24	7,217	0.14	100.00

Table A2: Other loan characteristics and recall

This table is similar to Table 5, column 1, except with different dependent variables. The dependent variables are the natural logarithm of maturity (column 1), the natural logarithm of the loan amount (column 2), income verification (column 3), and employment verification (column 4). *Income verification* (*employment verification*) takes the value of 1 if the lender verifies the borrower's income (employment) information during the lending process, and 0 otherwise. *Captive* takes the value of 1 if the loan comes from a captive lender, and 0 otherwise. *Post recall* takes the value of 1 if the loan origination date is within 3 months after the recall and takes the value of 0 if the loan origination date is within 3 months before the recall. Standard errors are clustered at the lender×state level, and t-statistics are shown in parentheses below the coefficient estimates. *p <0.1; **p <0.05; ***p <0.01.

	(1) ln(maturity)	(2) ln(loan amount)	(3) income verification	(4) employment verification
post recall × captive	0.0059***	0.0057***	0.0006	0.0003
	(4.74)	(3.45)	(0.67)	(0.39)
post recall	-0.0033**	-0.0041	-0.0004	-0.0006
	(-2.17)	(-1.48)	(-0.36)	(-0.52)
ln(credit score)	-0.3207***	-0.7922***	-0.3811***	-0.3478***
	(-35.22)	(-31.45)	(-6.20)	(-6.04)
ln(income)	-0.0157***	0.0484***	-0.0007	-0.0013**
	(-19.41)	(20.03)	(-1.03)	(-2.10)
ln(vehicle value)	-0.0249***	0.7742***	-0.0228***	-0.0206***
	(-5.95)	(63.23)	(-5.66)	(-5.36)
Year-month FE	Y	Y	Y	Y
State FE	Y	Y	Y	Y
Model FE	Y	Y	Y	Y
Lender FE	Y	Y	Y	Y
Observations	1,208,990	1,208,990	1,208,990	1,208,990
Adjusted R-squared	0.259	0.447	0.390	0.370
SE Cluster	Y	Y	Y	Y

Table A3: Alternative explanation: Substitutions between vehicle price and interest rate

This table reports results similar to Table 2, column 3. In column 1, I add *cash rebate* as control variable, a dummy variable equals to 1 if the loan is associated with a purchase that receives a cash rebate, and 0 otherwise. In column 2, I perform the same analysis with loans that receive cash rebates. In column 3, I include only loans that do not receive cash rebates in the sample. Standard errors are clustered at the lender×state level, and t-statistics are shown in parentheses below the coefficient estimates. *p <0.1; **p <0.05; ***p <0.01.

	(1) rate(%)	(2) rate(%) (with cash rebate)	(3) rate(%) (without cash rebate)
captive × model age (months)	-0.0364***	-0.0320***	-0.0336***
	(-7.25)	(-3.86)	(-6.96)
ln(credit score)	-12.6148***	-13.0469***	-11.3131***
	(-18.32)	(-22.01)	(-9.38)
ln(income)	0.0453***	0.0415***	0.0187
	(4.45)	(3.12)	(1.44)
ln(vehicle value)	-0.2473***	-0.5437***	-0.0416
	(-2.94)	(-7.19)	(-0.59)
ln(loan amount)	-1.1423***	-1.2183***	-0.6444***
	(-13.46)	(-17.66)	(-7.73)
ln(maturity)	3.1931***	3.1192***	2.9203***
	(15.12)	(23.34)	(14.65)
cash rebate	0.6869***		
	(3.15)		
Year-month FE	Y	Y	Y
State FE	Y	Y	Y
Model FE	Y	Y	Y
Lender FE	Y	Y	Y
Observations	5,176,405	2,418,567	2,757,820
Adjusted R-squared	0.614	0.646	0.586
SE cluster	Y	Y	Y

Table A4: Number of loans by model release calendar (fiscal) month

This table reports the number of loans by the model's release calendar month and fiscal month.

Calendar month	Frequency	Proportion (%)
1	182,572	3.53
2	105,944	2.05
3	74,719	1.44
4	135,982	2.63
5	210,313	4.06
6	603,162	11.65
7	610,266	11.79
8	973,287	18.80
9	886,864	17.13
10	659,543	12.74
11	528,332	10.21
12	205,421	3.97
Fiscal month	Frequency	Proportion (%)
1	383,846	7.42
2	435,887	8.42
3	435,518	8.41
4	426,079	8.23
5	463,903	8.96
6	429,645	8.30
7	444,579	8.59
8	470,783	9.09
9	449,322	8.68
10	388,422	7.50
11	382,972	7.40
12	465,449	8.99

Table A5: Alternative explanation: Dealer's ability to adjust the interest rate

This table reports the results from OLS regressions of loan interest rate on model age during the changes in government legal actions. The dependent variable is the interest rate of the loan at origination. The main explanatory variable is $Toyota \times post\,CFPB\,settlement \times model\,age$. $Toyota$ takes the value of 1 if the loan comes from the Toyota Motor Credit Corporation (TMC), the financing subsidiary of Toyota, and 0 otherwise. $Model\,age$ measures the length of time between the model's release and loan issuance. $Post\,CFPB\,settlement$ takes the value of 1 if the loan origination date is between February 2016 and May 2018, when the TMC was penalized by the CFPB/DOJ, and 0 otherwise. Control variables include borrower (credit score and income) and loan controls (vehicle value, loan amount, and maturity). I include year-month, state, model, and lender fixed effects. Standard errors are clustered at the lender×state level, and t-statistics are shown in parentheses below the coefficient estimates. *p <0.1; **p <0.05; ***p <0.01.

	(1) rate(%)
Toyota × post CFPB settlement × model age (months)	0.0009
	(0.14)
Toyota × model age (months)	-0.0246***
	(-3.23)
post CFPB settlement × model age (months)	-0.0163***
	(-3.29)
Toyota × post CFPB settlement	-0.6463***
	(-8.66)
Control variables	Y
Year-month FE	Y
State FE	Y
Model FE	Y
Lender FE	Y
Observations	5,176,405
Adjusted R-squared	0.610
SE cluster	Y

Table A6: Alternative explanation: COVID-19

This table reports the results from OLS regressions of various loan terms on model age but with a different sample than the results from the main analyses. Column 1 reports results similar to Table 2, column 3. Columns 2–5 report results similar to Table 3, columns 2, 4, 6, and 8, respectively. The sample is restricted to auto loans originated between January 2015 and December 2019. Standard errors are clustered at the lender×state level, and t-statistics are shown in parentheses below the coefficient estimates. *p <0.1; **p <0.05; ***p <0.01.

	(1) rate(%)	(2) ln(maturity)	(3) ln(loan amount)	(4) income verification	(5) employment verification
captive × model age (months)	-0.0323***	0.0007***	0.0011***	-0.0006***	-0.0004***
	(-7.14)	(5.24)	(3.89)	(-3.29)	(-3.03)
ln(credit score)	-12.2486***	-0.3263***	-0.8246***	-0.5908***	-0.5451***
	(-20.17)	(-33.86)	(-33.20)	(-7.40)	(-7.31)
ln(income)	0.0463***	-0.0156***	0.0502***	-0.0019*	-0.0019**
	(4.53)	(-22.53)	(21.83)	(-1.92)	(-2.29)
ln(vehicle value)	-0.2131***	-0.0229***	0.7801***	-0.0261***	-0.0235***
	(-2.84)	(-7.97)	(84.95)	(-5.93)	(-6.05)
ln(loan amount)	-1.2246***				
	(-16.33)				
ln(maturity)	3.1168***				
	(19.73)				
Year-month FE	Y	Y	Y	Y	Y
State FE	Y	Y	Y	Y	Y
Model FE	Y	Y	Y	Y	Y
Lender FE	Y	Y	Y	Y	Y
Observations	4,464,430	4,464,430	4,464,430	4,464,430	4,464,430
Adjusted R-squared	0.603	0.219	0.465	0.397	0.366
SE cluster	Y	Y	Y	Y	Y

Table A7: Alternative explanation: Number of loans

This table reports the results from OLS regressions of the number of loans on model age, measuring the length of time between the model's release and loan issuance. The sample is aggregated at the lender-model-year-month level. Hence, the regression has no loan-level control variables. The dependent variable is the number of loans in (column 1) and the log-transformed number of loans (column 2). *Captive* takes the value of 1 if the loan comes from a captive lender, and 0 otherwise. I include year-month, state, model, and lender fixed effects. Standard errors are clustered at the lender×state level, and t-statistics are shown in parentheses below the coefficient estimates. *p <0.1; **p <0.05; ***p <0.01.

	(1) No. of loans	(2) ln(No. of loans)
captive × model age (months)	-5.0793***	-0.0249**
	(-2.79)	(-2.34)
Year-month FE	Y	Y
State FE	Y	Y
Model FE	Y	Y
Lender FE	Y	Y
Observations	37,438	37,438
Adjusted R-squared	0.275	0.528
SE cluster	Y	Y

Table A8: Robustness: Alternative fixed effects and standard error clustering

This table reports results similar to Table 2, column 3, except with alternative fixed effects or different levels of clustering. In column 1, I include model and state × lender × year-month fixed effect. In column 2, I include lender and state × model × year-month fixed effect. In column 3, I include model, state × year-month, make × year-month, and lender × year-month fixed effects. In columns 4–7, I include the same fixed effects as in Table 2, column 3, but with different levels of clustering. In column 4, I cluster the standard errors at the lender level. In column 5, I cluster the standard errors at the state level. In column 6, I cluster the standard errors at the year-month level. In column 7, I cluster the standard errors at the car-model level.

	(1) rate(%)	(2) rate(%)	(3) rate(%)	(4) rate(%)	(5) rate(%)	(6) rate(%)	(7) rate(%)
captive × model age (months)	-0.0388***	-0.0546***	-0.0467***	-0.0325**	-0.0325***	-0.0325***	-0.0325***
	(-8.93)	(-12.33)	(-13.70)	(-2.45)	(-9.56)	(-6.88)	(-3.77)
ln(credit score)	-12.3213***	-11.7215***	-12.2461***	-12.6538***	-12.6538***	-12.6538***	-12.6538***
	(-17.75)	(-15.54)	(-17.81)	(-5.80)	(-27.07)	(-72.96)	(-30.97)
ln(income)	0.0414***	0.0269***	0.0379***	0.0479	0.0479***	0.0479***	0.0479***
	(4.46)	(2.78)	(4.06)	(1.51)	(5.41)	(8.69)	(5.96)
ln(vehicle value)	-0.2716***	-0.3830***	-0.3100***	-0.2294	-0.2294***	-0.2294***	-0.2294**
	(-3.54)	(-4.68)	(-3.84)	(-1.05)	(-5.06)	(-4.38)	(-2.51)
ln(loan amount)	-1.1310***	-0.9634***	-1.1146***	-1.2138***	-1.2138***	-1.2138***	-1.2138***
	(-16.09)	(-13.49)	(-15.97)	(-4.08)	(-29.09)	(-23.83)	(-16.10)
ln(maturity)	3.2393***	3.3235***	3.2515***	3.1924***	3.1924***	3.1924***	3.1924***
	(16.45)	(15.39)	(16.64)	(6.20)	(18.12)	(27.33)	(21.28)
Year-month FE	N	N	N	Y	Y	Y	Y
State FE	N	N	N	Y	Y	Y	Y
Model FE	Y	N	Y	Y	Y	Y	Y
Lender FE	N	Y	N	Y	Y	Y	Y
State × Lender × Year-month FE	Y	N	N	N	N	N	N
State × Model × Year-month FE	N	Y	N	N	N	N	N
State × Year-month FE	N	N	Y	N	N	N	N
Make × Year-month FE	N	N	Y	N	N	N	N
Lender × Year-month FE	N	N	Y	N	N	N	N
Observations	5,172,854	5,080,493	5,176,367	5,176,405	5,176,405	5,176,405	5,176,405
Adjusted R-squared	0.632	0.673	0.633	0.609	0.609	0.609	0.609
SE cluster	Lender × State	Lender × State	Lender × State	Lender	State	Year-month	Model

Table A9: Robustness: Captive classification

This table reports results similar to Table 2, column 3, and Table 3, columns 2, 4, 6, and 8, with alternative samples. In panel A, I drop from the main sample loans from World Omni. In panel B, I add into the sample loans from Santander. For loans from Santander, if the loan is associated with a car from the Chrysler Group, I classify it as a captive lender, and the rest of the Santander loans are deemed to be from a non-captive lender. Standard errors are clustered at the lender×state level, and t-statistics are shown in parentheses below the coefficient estimates. *p <0.1; **p <0.05; ***p <0.01.

Panel A: Drop World Omni

	(1)	(2)	(3)	(4)	(5)
	rate(%)	ln(maturity)	ln(loan amount)	income verification	employment verification
captive × model age (months)	-0.0404***	0.0009***	0.0017***	-0.0005**	-0.0004**
	(-8.69)	(5.50)	(6.58)	(-2.33)	(-2.23)
ln(credit score)	-11.8461***	-0.3111***	-0.7905***	-0.6598***	-0.6082***
	(-19.58)	(-29.32)	(-26.51)	(-8.26)	(-8.14)
ln(income)	0.0380***	-0.0154***	0.0526***	-0.0028***	-0.0030***
	(3.85)	(-23.99)	(22.53)	(-2.62)	(-3.11)
ln(vehicle value)	-0.3282***	-0.0204***	0.7852***	-0.0292***	-0.0273***
	(-4.69)	(-7.90)	(96.28)	(-6.02)	(-5.96)
ln(loan amount)	-1.1164***				
	(-16.40)				
ln(maturity)	2.7777***				
	(28.77)				
Year-month FE	Y	Y	Y	Y	Y
State FE	Y	Y	Y	Y	Y
Model FE	Y	Y	Y	Y	Y
Lender FE	Y	Y	Y	Y	Y
Observations	4,916,686	4,916,686	4,916,686	4,916,686	4,916,686
Adjusted R-squared	0.629	0.223	0.494	0.401	0.370
SE cluster	Y	Y	Y	Y	Y

Panel B: Add Santander

	(1) rate(%)	(2) ln(maturity)	(3) ln(loan amount)	(4) income verification	(5) employment verification
captive × model age (months)	-0.0264***	0.0011***	0.0010***	-0.0005***	-0.0004***
	(-6.63)	(10.19)	(4.08)	(-4.08)	(-4.05)
captive	-2.7661***	0.0192***	0.0405***	0.0198***	0.0144**
	(-12.09)	(6.29)	(4.70)	(3.07)	(2.48)
ln(credit score)	-13.2710***	-0.2990***	-0.7072***	-0.5735***	-0.5170***
	(-22.39)	(-29.12)	(-22.13)	(-7.71)	(-7.43)
ln(income)	0.0573***	-0.0155***	0.0521***	-0.0016	-0.0019**
	(5.84)	(-24.50)	(21.72)	(-1.64)	(-2.14)
ln(vehicle value)	-0.7364***	-0.0239***	0.7614***	-0.0340***	-0.0296***
	(-4.99)	(-8.84)	(79.03)	(-7.05)	(-6.61)
ln(loan amount)	-1.1093***				
	(-15.85)				
ln(maturity)	3.1271***				
	(16.75)				
Year-month FE	Y	Y	Y	Y	Y
State FE	Y	Y	Y	Y	Y
Model FE	Y	Y	Y	Y	Y
Lender FE	Y	Y	Y	Y	Y
Observations	5,897,811	5,897,811	5,897,811	5,897,811	5,897,811
Adjusted R-squared	0.770	0.247	0.489	0.349	0.337
SE cluster	Y	Y	Y	Y	Y

Table A10: Robustness: Credit bins

This table reports results similar to Tables 2 and 3, columns 2, 4, 6, and 8, with alternative control variables and fixed effects. Specifically, I classify borrowers' credit scores into bins and include this information as a fixed effect. Standard errors are clustered at the lender$\times$state level, and t-statistics are shown in parentheses below the coefficient estimates. *p <0.1; **p <0.05; ***p <0.01.

	(1) rate(%)	(2) ln(maturity)	(3) ln(loan amount)	(4) income verification	(5) employment verification
captive $\times$ model age (months)	-0.0317***	0.0009***	0.0008**	-0.0001	0.0000
	(-6.91)	(7.41)	(2.52)	(-1.30)	(0.00)
ln(income)	0.0157	-0.0150***	0.0524***	-0.0055***	-0.0053***
	(1.58)	(-23.12)	(21.97)	(-4.71)	(-5.18)
ln(vehicle value)	-0.1967**	-0.0241***	0.7757***	-0.0234***	-0.0217***
	(-2.52)	(-8.49)	(85.89)	(-5.63)	(-5.48)
ln(loan amount)	-1.1093***				
	(-15.85)				
ln(maturity)	3.3410***				
	(17.18)				
Credit bins	Y	Y	Y	Y	Y
Year-month FE	Y	Y	Y	Y	Y
State FE	Y	Y	Y	Y	Y
Model FE	Y	Y	Y	Y	Y
Lender FE	Y	Y	Y	Y	Y
Observations	5,176,405	5,176,405	5,176,405	5,176,405	5,176,405
Adjusted R-squared	0.639	0.232	0.475	0.469	0.429
SE cluster	Y	Y	Y	Y	Y

Table A11: Robustness: Same maturity (72 months)

This table reports results similar to Tables 2 and 3, columns 4, 6, and 8, with alternative sample. Specifically, I include only loans with 72-month maturity in the sample. Standard errors are clustered at the lender×state level, and t-statistics are shown in parentheses below the coefficient estimates. *p <0.1; **p <0.05; ***p <0.01.

	(1) rate(%)	(2) ln(loan amount)	(3) income verification	(4) employment verification
captive × model age (months)	-0.0371***	0.0004	-0.0015***	-0.0011***
	(-4.47)	(0.91)	(-6.70)	(-6.54)
ln(credit score)	-13.7256***	-0.4950***	-0.8338***	-0.7701***
	(-23.99)	(-15.84)	(-9.28)	(-9.18)
ln(income)	0.0585***	0.0476***	-0.0070***	-0.0069***
	(4.93)	(17.18)	(-3.10)	(-3.61)
ln(vehicle value)	-0.1988**	0.7974***	-0.0436***	-0.0394***
	(-1.98)	(120.53)	(-5.68)	(-5.72)
ln(loan amount)	-1.3980***			
	(-16.27)			
Year-month FE	Y	Y	Y	Y
State FE	Y	Y	Y	Y
Model-Year FE	Y	Y	Y	Y
Lender FE	Y	Y	Y	Y
Observations	1,254,555	1,254,555	1,254,555	1,254,555
Adjusted R-squared	0.644	0.632	0.482	0.441
SE Cluster	Y	Y	Y	Y

Table A12: Robustness: Teaser Rate

This table reports results similar to Table 2, column 3. In columns 1, 2, and 3, I drop loans with interest rates less than 1%, 2%, and 3%, respectively, from the sample. Standard errors are clustered at the lender×state level, and t-statistics are shown in parentheses below the coefficient estimates. *p <0.1; **p <0.05; ***p <0.01.

	rate(%)		
	(1)	(2)	(3)
	$\geq$ 1%	$\geq$ 2%	$\geq$ 3%
captive × model age (months)	-0.0165***	-0.0146***	-0.0177***
	(-4.43)	(-4.15)	(-5.05)
ln(credit score)	-11.7867***	-12.6347***	-12.9147***
	(-19.44)	(-25.36)	(-30.77)
ln(income)	0.0035	-0.0218	-0.0411**
	(0.26)	(-1.30)	(-2.13)
ln(vehicle value)	-0.5674***	-0.7421***	-0.8885***
	(-6.23)	(-7.72)	(-9.16)
ln(loan amount)	-0.4232***	-0.1526*	0.0211
	(-5.72)	(-1.91)	(0.27)
ln(maturity)	1.7358***	1.3856***	0.9804***
	(16.24)	(13.85)	(9.68)
Year-month FE	Y	Y	Y
State FE	Y	Y	Y
Model FE	Y	Y	Y
Lender FE	Y	Y	Y
Observations	3,687,159	2,946,005	2,336,154
Adjusted R-squared	0.635	0.639	0.628
SE Cluster	Y	Y	Y

Table A13: Loan performance (an alternative measure of default (30 days past due))

This table reports results similar to Table 8 with an alternative measure of default. The dependent variable is $default$. A loan is considered in default if the loan has been charged-off, has been repossessed, or is 30 or more days past due. In panel A, default equals 1 if the loan defaults in first 12 months after origination, and 0 otherwise. In panel B, default equals 1 if the loan defaults during its lifetime in the sample period, and 0 otherwise. Standard errors are clustered at the lender×state level, and t-statistics are shown in parentheses below the coefficient estimates. *p <0.1; **p <0.05; ***p <0.01.

Panel A: Early default (12 months)

	(1) default (%)	(2) default (%)	(3) default (%)	(4) default (%)
captive× model age (months)	-0.0397***	-0.0426***	-0.0411***	-0.0250**
	(-3.24)	(-3.71)	(-3.66)	(-2.47)
ln(credit score)		-18.3149***	-18.6392***	-12.2294***
		(-10.05)	(-9.81)	(-9.65)
ln(income)		-0.0033	-0.0037	-0.0290*
		(-0.19)	(-0.21)	(-1.73)
ln(vehicle value)			-0.7133***	-0.6054***
			(-6.07)	(-4.41)
ln(loan amount)			0.0429	0.6834***
			(0.35)	(5.54)
ln(maturity)			-1.3714***	-3.0081***
			(-6.37)	(-9.49)
rate(%)				0.5176***
				(13.66)
Year-month FE	Y	Y	Y	Y
State FE	Y	Y	Y	Y
Model FE	Y	Y	Y	Y
Lender FE	Y	Y	Y	Y
Observations	4,906,942	4,906,942	4,906,942	4,906,942
Adjusted R-squared	0.068	0.085	0.085	0.093
SE cluster	Y	Y	Y	Y

Panel B: Lifetime default

	(1) default (%)	(2) default (%)	(3) default (%)	(4) default (%)
captive × model age (months)	0.0257	0.0173	0.0171	0.0575***
	(1.10)	(0.82)	(0.82)	(2.78)
ln(credit score)		-54.1331***	-52.2335***	-36.2200***
		(-24.80)	(-22.67)	(-27.18)
ln(income)		-0.0732	-0.1576**	-0.2207***
		(-1.13)	(-2.46)	(-3.58)
ln(vehicle value)			-5.1523***	-4.8827***
			(-18.65)	(-16.43)
ln(loan amount)			2.8989***	4.4990***
			(9.93)	(15.28)
ln(maturity)			-2.5405***	-6.6294***
			(-5.69)	(-12.42)
rate(%)				1.2932***
				(25.93)
Year-month FE	Y	Y	Y	Y
State FE	Y	Y	Y	Y
Model FE	Y	Y	Y	Y
Lender FE	Y	Y	Y	Y
Observations	4,906,942	4,906,942	4,906,942	4,906,942
Adjusted R-squared	0.106	0.143	0.144	0.156
SE cluster	Y	Y	Y	Y

Table A14: Loan performance (an alternative measure of early default (within 24 months after loan issuance))

This table reports results similar to Table 8, panel A, except with the alternative measure of default. The dependent variable is $default$, which takes the value of 1 if the loan has been charged-off, has been repossessed, or is 90 or more days past due in first 24 months after loan origination, and 0 otherwise. To avoid a truncation issue, I drop loans originated after August 2019, which is 24 months before the end of the sample. Standard errors are clustered at the lender×state level, and t-statistics are shown in parentheses below the coefficient estimates. *p <0.1; **p <0.05; ***p <0.01.

	(1) default (%)	(2) default (%)	(3) default (%)	(4) default (%)
captive × model age (months)	-0.0379***	-0.0398***	-0.0390***	-0.0203**
	(-3.67)	(-3.88)	(-3.88)	(-2.03)
ln(credit score)		-11.8484***	-11.9087***	-5.7250***
		(-11.57)	(-11.51)	(-11.49)
ln(income)		-0.2366***	-0.2493***	-0.2713***
		(-6.94)	(-6.80)	(-7.04)
ln(vehicle value)			-1.0218***	-0.8939***
			(-5.33)	(-4.12)
ln(loan amount)			0.3493*	0.9610***
			(1.68)	(4.48)
ln(maturity)			-1.3380***	-2.9009***
			(-6.30)	(-9.42)
rate(%)				0.5087***
				(15.73)
Year-month FE	Y	Y	Y	Y
State FE	Y	Y	Y	Y
Model FE	Y	Y	Y	Y
Lender FE	Y	Y	Y	Y
Observations	4,183,203	4,183,203	4,183,203	4,183,203
Adjusted R-squared	0.047	0.053	0.054	0.060
SE cluster	Y	Y	Y	Y

Table A15: Loan performance (an alternative cutoff of subprime borrower)

This table reports results similar to Table 10 with an alternative measure of *subprime*, which takes the value of 1 if the credit score of the borrower is less than 600, and 0 otherwise. Standard errors are clustered at the lender×state level, and t-statistics are shown in parentheses below the coefficient estimates. *p <0.1; **p <0.05; ***p <0.01.

Panel A: Early default (12 months)

	(1) default (%)	(2) default (%)	(3) default (%)	(4) default (%)
captive × model age (months) × subprime	0.0893***	0.0885***	0.0881***	0.0915***
	(3.83)	(3.81)	(3.78)	(4.07)
captive × model age (months)	-0.0251***	-0.0256***	-0.0251***	-0.0205***
	(-3.20)	(-3.31)	(-3.28)	(-2.76)
subprime × model age (months)	-0.0822***	-0.0811***	-0.0810***	-0.0840***
	(-3.81)	(-3.77)	(-3.77)	(-4.06)
captive × subprime	-0.9354***	-0.9428***	-0.9526***	-0.7006**
	(-2.89)	(-2.96)	(-2.97)	(-2.46)
subprime	2.7776***	2.3664***	2.3373***	1.8825***
	(9.93)	(7.65)	(7.63)	(7.14)
ln(credit score)		-1.6209***	-1.8438***	-0.1621
		(-5.64)	(-7.10)	(-1.20)
ln(income)		-0.0998***	-0.0949***	-0.1008***
		(-7.06)	(-6.53)	(-6.60)
ln(vehicle value)			-0.0642	-0.0262
			(-0.93)	(-0.35)
ln(loan amount)			-0.1048	0.0769
			(-1.30)	(0.95)
ln(maturity)			-0.3580***	-0.8535***
			(-5.31)	(-8.34)
rate(%)				0.1538***
				(13.90)
Year-month FE	Y	Y	Y	Y
State FE	Y	Y	Y	Y
Model FE	Y	Y	Y	Y
Lender FE	Y	Y	Y	Y
Observations	4,906,942	4,906,942	4,906,942	4,906,942
Adjusted R-squared	0.019	0.020	0.020	0.022
SE cluster	Y	Y	Y	Y

Panel B: Lifetime default

	(1) default (%)	(2) default (%)	(3) default (%)	(4) default (%)
captive × model age (months) × subprime	0.3073***	0.3004***	0.2938***	0.3094***
	(4.53)	(4.43)	(4.37)	(4.22)
captive × model age (months)	0.0333*	0.0292	0.0305	0.0519***
	(1.79)	(1.55)	(1.63)	(2.72)
subprime × model age (months)	-0.3412***	-0.3323***	-0.3287***	-0.3424***
	(-5.72)	(-5.56)	(-5.55)	(-5.13)
captive× subprime	-4.0806***	-4.2103***	-4.2063***	-3.0428***
	(-4.67)	(-4.88)	(-4.87)	(-3.84)
subprime	12.1184***	8.6871***	8.7983***	6.6984***
	(16.84)	(12.00)	(12.16)	(10.53)
ln(credit score)		-14.0277***	-13.4052***	-5.6391***
		(-14.72)	(-16.58)	(-11.38)
ln(income)		-0.3471***	-0.4147***	-0.4420***
		(-8.20)	(-9.25)	(-9.40)
ln(vehicle value)			-2.4398***	-2.2641***
			(-11.74)	(-9.90)
ln(loan amount)			1.4472***	2.2866***
			(6.15)	(9.40)
ln(maturity)			-2.4867***	-4.7750***
			(-7.25)	(-11.18)
rate(%)				0.7104***
				(22.07)
Year-month FE	Y	Y	Y	Y
State FE	Y	Y	Y	Y
Model FE	Y	Y	Y	Y
Lender FE	Y	Y	Y	Y
Observations	4,906,942	4,906,942	4,906,942	4,906,942
Adjusted R-squared	0.082	0.086	0.087	0.094
SE cluster	Y	Y	Y	Y