Internet Appendix for "Consumer Credit and the Incidence of Tariffs: Evidence from the Auto Industry"

Kristine Hankins, Morteza Momeni, and David Sovich[1]

1. Kristine Hankins (Kristine.Hankins@uky.edu) is at University of Kentucky, Gatton College of Business and Economics. Morteza Momeni (mortezamomeni@gmail.com) is at Tennessee Tech University. David Sovich (davidsovich@uky.edu) is at University of Kentucky, Gatton College of Business and Economics.

A Additional Sample Details and Supplemental Analyses

A.1 Additional Sample Details

A.1.1 Market Shares of Captive and Non-Captive Lenders

Our final sample consists of 1,973,639 auto loans from 8 captive lenders and 6 non-captive lenders. Loans from captive lenders make up around 60 percent of the sample, and loans from non-captive lenders making up the remaining 40 percent. Consistent with the population patterns described in Section 2, we find that captive lenders have greater market share for new vehicles (76 percent) than used vehicles (32 percent), and vice versa for non-captive lenders.[1]

Although captive lenders specialize in financing their manufacturer's brands of vehicles (e.g., Hondas and Honda Finance), non-captive lenders also manage to acquire significant market share in these brands. Specifically, for the 87 percent of vehicle brands that have an in-house captive lender in our sample, non-captive lenders have a 30 percent overall market share, which rises (falls) to 56 percent (20 percent) for used (new) versions of these vehicles. Non-captive lenders tend to dominate the market for brands of vehicles that do not have an in-house captive lender. Indeed, for the 13 percent of vehicle brands that do not have an in-house captive lender in our sample, non-captive lenders have a 96 percent overall market share, which is persistent across both new and used versions of these vehicles. Table IA.19 provides a full list of the vehicle brands in our sample. This table also reports in-sample captive market shares for each brand and whether each brand has an in-house captive lender in our sample.

Defining a vehicle at the make-model-condition level, we find that around 98 percent of the loans in our sample are for vehicles that have both captive and non-captive lending options.[2] These are

1. Note that these in-sample market shares are different than the population market shares reported in Section 2. This is because captive lenders are over-represented in the Regulation AB II data, as the data excludes numerous smaller non-captive lenders that do not access public securitization markets. See Section 3.1.1.

2. These are vehicles for which there are both captive and non-captive loans in our sample, regardless of whether the captive loan is from the vehicle's in-house captive lender or another captive. The difference between the 98 percent of vehicles that have both captive and non-captive lending options and the 87 percent of vehicles that have their own in-house captive lenders comes from the fact that some captive lenders (in particular, GM-AmeriCredit) sometimes finance vehicles from other manufacturers. We note that this phenomenon is much more pronounced in the used car market than the new car market, as franchised dealers sometimes acquire and resell off-brand used

the loans from which our main source of identifying variation comes from, as most of our regressions include various forms of vehicle make-model-condition fixed effects. Given the large degree of overlap between this subsample and our main sample, it is not surprising that the market shares of captive and non-captive lenders are similar between them (e.g., 39 percent versus 40 percent for non-captive lenders). Moreover, as shown in Table IA.20, average pre-treatment lending conditions are almost identical across these samples.

A.1.2 Loan Price Determinants

As shown in Table 2, captive interest rates tend to be lower than non-captive interest rates even after controlling for vehicle and borrower characteristics. One reason for this gap is that a much larger fraction of captive loans are subvented than non-captive loans. Indeed, if we remove subvented loans from the sample, then the conditional distributions of captive and non-interest rates are much closer to one another. See Figure IA.4 and IA.5, which plot the distributions of non-subvented captive and non-captive interest rates for used and new vehicles across borrower characteristics.[3]

A.2 Robustness Tests

A.2.1 Assumptions About Standard Errors

Table IA.21 examines whether our results are robust to different assumptions about our standard errors. We find that our main results are unchanged if we calculate our standard errors using other forms of clustering – such as state clustering, vehicle make-model-condition clustering, and ABS clustering – or using a wild bootstrap procedure with lender clustering (Cameron, Gelbach, and Miller 2008).

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vehicles and solicit captive financing for them.

3. This is especially the case for the prime segment of the market, which is the segment of the market that captive lenders typically focus on. In fact, while captive lenders do tend to offer significantly lower (non-subvented) interest rates than non-captive lenders in the subprime segment of the market, they are much less willing to lend to these types of borrowers in the first place.

A.2.2 Choice of Fixed Effects

Table IA.22 examines whether our results are robust to including more granular versions of our baseline fixed effects. The purpose of this test is to rule out more nuanced concerns about our identification, such as whether our results capture the heterogeneous impact of other contemporaneous tariffs across states with different manufacturer market shares (i.e,. a manufacturer $\times$ state $\times$ time omitted variable). Inconsistent with the presence of various correlated omitted variables driving our results, we find that the magnitudes of our estimates do not change much when we include more granular versions of our baseline fixed effects (Oster 2019).

A.2.3 Controlling for Other Loan Terms

Table IA.23 re-estimates our baseline interest rate model after controlling for other co-determined loan terms such as loan amounts, maturities, and loan-to-value ratios. We continue to find that captive interest rates increased in response to the tariffs. Among other things, this result helps reinforce that our baseline estimates capture tariff pass-through and not borrower-level adjustments to worse loan terms (Argyle, Nadauld, and Palmer 2020).

A.2.4 Choice of Treatment Date

As mentioned in Section 3.2, our choice of January 2018 as the treatment date is conservative as it reflects the date of the Department of Commerce's initial recommendation to impose the metal tariffs. We find similar results if we instead use February 2018 or March 2018 as the treatment date, as shown in Table IA.5. The fact that our results are robust to small changes in the treatment date is not surprising given that Figure 6 shows that interest rates rose more during the later parts of the sample period when the tariffs were more binding and metals prices had risen more.

A.2.5 Choice of Sample Period

Figure IA.6 plots the coefficient estimates from Equation 3 after extending the the sample period to 2019. There are two main takeaways from the figure. First, there was a temporary decline in the effect on interest rates in Q2-Q3 2019, which is when the U.S. temporarily exempted some countries from the steel and aluminum tariffs. This effect then reverted to its prior level in Q4 2019 after the President announced plans to reinstate the tariffs on some of these countries and increase them on others. Second, the terminal coefficient estimate for the fourth quarter of 2019 is 50 basis points, which is almost double our pooled coefficient estimate of 26 basis points in Table 3. Thus, although our 26 basis point estimate might be representative of the average effect of the tariffs during the sample period, it might significantly understate the long-run effects of the tariffs going forward.[4]

A.2.6 Choice of Sample Filters

Table IA.2 re-estimates our baseline interest rate model after adjusting several of the sample filters listed in Section 3.2. Specifically, columns 1 and 2 adjust the credit score filters, columns 3 and 4 adjust the level of winsorization, column 5 extends the sample period to 2019, column 6 restricts the sample period to before the retaliatory tariffs from China, and column 7 removes the loan-to-value ratio filters. For all these cases, we continue to find that captive interest rates increased relative to non-captive interest rates following the tariffs.[5]

Table IA.24 re-estimates our baseline interest model after including the five lenders that we previously excluded in Section 3.2. Similarly, Table IA.6 re-estimates the same model but after removing World Omni from the sample (see Footnote 28). In both cases, we find that our main results persist.

A.2.7 Placebo Analyses

To strengthen our claim that the metal tariffs primarily drove the differential increase in captive interest rates in 2018, we conduct two placebo analyses using only auto loans originated between

4. For reference, we find that captive interest rates increased by 29 basis points, on average, when we re-estimate Equation 2 on the extended sample period. This is similar to our baseline estimate of 26 basis points in Table 3.

5. The fact that captive interest rates remained elevated in 2019 is inconsistent with an alternative explanation that centers on wholesale vehicle prices being difficult to adjust in the short-run due to purchase contracts with dealers / MSRP price stickiness (and hence incapable of offsetting higher input costs).

2015 and 2017.[6] Table IA.25 reports the coefficient estimates from Equation 2 for this sample after we redefine Post_t to be equal to one for loans originated in 2017, and zero otherwise. Consistent with our main results capturing the causal effects of the 2018 tariffs, we find no differential changes in captive lending rates during the placebo periods. Moreover, while our baseline estimates in Table 3 are positive and economically significant, our placebo estimates in Table IA.25 are mostly negative and economically small.

A.2.8 Negative Sample Weights

Given that treatment occurs all at once in our setting (i.e., it is not rolled out in a staggered manner over time), there is no particular reason to be concerned about potential biases arising from time-heterogeneous treatment effects (de Chaisemartin and D'Haultfoeuille 2020). Nevertheless, to further assuage this concern, we follow de Chaisemartin and D'Haultfoeuille 2020 and calculate the group-time weights used to construct our baseline difference-in-differences estimates. As shown in Figure IA.7, we find that over 95 percent of the group-time weights are positive, and that the sum of the negative group-time weights is only -0.007. This small number of (and size of) negative group-time weights helps rule out the principal concern raised in de Chaisemartin and D'Haultfoeuille 2020, which centers around the interaction of large negative weights and heterogeneous treatment effects.

A.3 Loan Originations and Vehicle Choices

To document some of the costs that captive lenders face when raising their interest rates, we start by examining how the tariffs impacted captive loan origination volumes. The model is:

$$y_{f,s,v,t} = \alpha + \Gamma \cdot \text{Treated}_f \cdot \text{Post}_t + \delta_f + \delta_{s,t} + \delta_{v,t} + \varepsilon_{f,s,v,t}, \tag{1}$$

6. Our data contains significantly fewer loans originated in 2015 than 2016. This is because the Regulation AB II reporting requirements only apply to public auto loan ABS issued after November 2016 and it is uncommon for ABS issuers to include very seasoned loans (e.g., older than 18 months) in their ABS offerings.

where the outcome variable is the logged number of loans that captive lenders ($f = 1$) or non-captive lenders ($f = 0$) originated in quarter t in state s for vehicle make-model-condition v.[7] Table IA.1 reports the coefficient estimates from the model. Relative to non-captive lenders, captive lenders experienced a 6.7 percent decline in loan originations following the tariffs. Given that captive interest rates rose 10 percent in response to the tariffs (= 26 basis points / 252 basis points), the implied interest rate elasticity of extensive margin loan demand is -0.67 (-6.7 / 10.0). This estimate of the interest rate elasticity is consistent with other estimates in the auto loan literature, which range from -0.00 in Attanasio, Goldberg, and Kyriazidou 2008 to -0.10 in Argyle, Nadauld, and Palmer 2020 and -0.94 in Argyle, Nadauld, and Palmer 2023.

Before we proceed, we highlight three important aspects of the above results. First, while our level of aggregation in Equation 1 follows Benneton, Mayordomo, and Paravisini 2022, Table IA.1 shows that our results are robust to other levels of aggregation, such as at the captive × state × income bin × credit score bin × quarter level. Second, although data limitations prevent us from discerning the extent to which the decline in captive loan originations comes from fewer vehicle sales versus lower loan penetration rates, the findings in Gavazza and Lanteri 2021 and Argyle, Nadauld, and Palmer 2023 suggest that both margins are likely active. Third, the decline in captive loan originations does not contradict the absence of borrower composition effects in Table 5. Indeed, both Argyle, Nadauld, and Palmer 2020 and Argyle, Nadauld, and Palmer 2023 find that loan originations decline in response to higher offered interest rates, and that the decline in originations is not correlated with observable borrower characteristics or future default rates.

Another potential cost that captive lenders face when raising their interest rates is that borrowers might substitute towards less profitable vehicles (Gulati, McAuslan, and Sallee 2017; Argyle et al. 2021; Argyle, Nadauld, and Palmer 2023). To examine the effect of the tariffs on vehicle choices, we re-estimate Equation 2 after making two changes. First, we use vehicle values as our outcome

7. To better account for the count-data structure of the number of loan originations, column 2 in Table IA.1 re-estimates Equation 1 using a Poisson model (Cohn, Liu, and Wardlaw 2022). For both our linear and Poisson models, we use hetroskedasticity-robust standard errors to conduct statistical inference. We do so because we cannot cluster our standard errors at the captive level, as there are just two clusters along this dimension. Our results are robust to alternative methods of computing the standard errors, including clustering at the captive × state × vehicle level ($t = -15.17$) and using a bootstrap procedure ($t = -10.45$).

variable instead of interest rates or other loan terms. Second, we relax our vehicle fixed effects so that we no longer control for demand-side purchasing responses to the tariffs. If substitution is present in our setting, then we should expect that average vehicle values will decline for captive loans relative to non-captive loans. However, as shown in Table IA.26, we find no differential changes in average vehicle values for captive loans following the tariffs. Although this test is imperfect because we do not observe the sales price, it suggests that captive borrowers did not fully offset the effects of the tariffs through their vehicle choices.

B Calculations for Tariff Pass-Through

This appendix provides more details about our pass-through calculations in Section 4.6. First, we elaborate on how we estimate ΔP, M, N, and ΔV. Afterwards, we present a range of estimates for ΔC.

B.1 Financing Costs

To estimate ΔP, we follow the approach used in Argyle, Nadauld, and Palmer 2023. Discounting at 5 percent, for a pre-treatment average captive loan with a principal of \$26,914 and a maturity of 66 months, a 26 basis point increase in captive interest rates from 2.52 percent to 2.78 percent corresponds to a present value increase in total loan payments of \$179. If we also incorporate a 7 basis point spillover effect, then this estimate rises to \$227 per captive loan

B.2 Captive Loan Penetration Rate

To estimate M, we first rewrite it as follows:

$$M = \frac{F_n + F_u}{N_n \cdot 0.9^{-1}} = 0.90 \cdot \left(\frac{F_n}{N_n} + \frac{F_u}{N_n} \right),$$

where F_n is the number of captive loan originations for new cars, F_u is the number of captive loan originations for used cars, N_n is the number of new cars that are financed, and 0.90 is the fraction of new cars that are financed relative to the number of new cars sold in the population (Butler, Mayer, and Weston 2023). Next, we rewrite the ratio of F_u to N_n as follows:

$$\frac{F_u}{N_n} = \frac{F_u}{N_u} \cdot \frac{N_u}{N_n},$$

where N_u is the number of used cars that are financed. From Experian 2021, we know that $F_n/N_n = 0.55$, $F_u/N_u = 0.07$, and $N_u/N_n = 1.50$. Therefore, we have that the captive loan penetration rate is $M = 0.90 \cdot (0.55 + 0.07 \cdot 1.50) = 0.59$.

B.3 Number of Vehicles Sold

From the U.S. Department of Transportation 2021, there are around $N = 17$ million new vehicles sold in the U.S. each year. For reference, there are around 50 million new and used vehicles sold per year.

B.4 Vehicle Prices

As shown in Table 6, we estimate that new vehicle sales prices rose 0.7 percent in response to the tariffs. Multiplying this by the pre-treatment mean sales price of \$32,206 for the sample, we estimate that $\Delta V = \$225$.

B.5 Production Costs

Estimating ΔC is highly difficult because granular data on auto manufacturers' costs is generally not available. Dawson and Colias 2018 illustrate the challenges involved with estimating ΔC by writing, "Tariff-related costs are raising expenses and squeezing profits for big and small auto-industry players, and driving some companies to fight their partners over who pays...A typical vehicle is made up of roughly 30,000 individual parts, and car companies on average work with hundreds of suppliers at once for each model line, either buying components directly or contracting them out further down the chain...Sorting out the cost of tariffs is difficult because some parts cross the U.S. border multiple times before being installed in a car, blurring the lines of what is 'domestic' content. And although much of the steel used in car manufacturing is American-made, the auto industry is still paying more because a new 25% tariff imposed in June on imports prompted domestic steelmakers to increase prices by an equivalent amount."

Given the difficulty of this problem, estimating ΔC requires us to make several assumptions that cannot be easily verified in the data, such as that the entire increase in steel prices (and, subsequently, manufacturers' costs) was due to the tariffs. Below, we present three methods for estimating ΔC which suggest that average production costs per new vehicle rose between \$200 and

\$700 following the tariffs.[8] However, we caution that these estimates are fairly speculative, which is one reason why we primarily focus on comparing the relative importance of interest rate and vehicle price pass-through in Section 4.6.

B.5.1 Ford Method

Ford's 2018 10-K cites \$750 million in additional tariff-related costs in North America. Given that Ford sold 2,540,000 new vehicles at wholesale to North American dealerships in 2018, this implies an average cost increase of \$295 per vehicle.

B.5.2 Media Mentions Method

1. Lobosco 2019 states, "Automakers, for example, have said the tariffs have driven up the cost of production in the United States by \$400 per vehicle. "

2. Center for Automotive Research 2019 states, "The price of the average vehicle sold in the United States could rise...by slightly more than USD 350, depending on which policies are enacted."

3. Panzino 2019 states, "Mike Manley, CEO of Fiat Chrysler Automobiles NV, said on Jan. 14 that U.S. metal tariffs are projected to raise the company's 2019 costs by \$300 million to \$350 million, Reuters reported. The automaker confirmed the numbers to S&P Global Market Intelligence, which translate to a price increase of about \$135 or \$160 per vehicle."

4. Tax Foundation 2019 states, "Ford and General Motors estimated that the tariffs cost them about \$1 billion each the first year they were in effect—roughly \$700 per vehicle produced."

8. We note that there are some estimates in the popular press of potential tariff costs to vehicle manufacturing which are much larger than ours (e.g., Higgins 2018). However, these larger estimates refer to a hypothetical vehicle import tariff that was never enacted, and not the steel and aluminum tariffs that we examine.

B.5.3 Weight-Based Method

Another method of estimating the average cost increase from steel and aluminum inputs per vehicle is to look at their contributions to vehicle weight. This is similar to the method used in Flaaen, Hortacsu, and Tintelnot 2020 to select ranges as their control group for washing machines.

The first step in this process is to figure how much steel and aluminum (in tons) goes into the average vehicle. According to Experian 2021, around 40 percent of vehicles are sedans and the rest are non-sedans, such as trucks and SUVs. The average weight of a sedan is around 1.5 tons, and the average weight of a non-sedan is around 2.5 tons. Thus, the average vehicle weighs around 2.1 tons. Steel accounts for around 55 percent of the average vehicle's weight and aluminum accounts for around 15 percent. Therefore, the average vehicle is comprised of around 1.16 tons of steel and 0.32 tons of aluminum.

The second step in this process is figuring out the cost of 1.16 tons of steel and 0.32 tons of aluminum in 2017 (i.e., prior to the tariffs). According to the Department of Commerce 2018, the average cost of steel was \$684 per ton in 2017, and the average cost of aluminum was \$2,200. This implies that the average cost of steel per vehicle was around \$790 in 2017, and the average cost of aluminum per vehicle was \$693 (for a total combined cost of \$1,483).

The third and final step is to then calculate how much these input costs change in response to the tariffs. Suppose that steel prices rose 20 percent in response to the tariffs and aluminum prices rose 10 percent. Then the increase in steel costs per vehicle would have been \$158, and the increase in aluminum costs per vehicle would have been \$69. Thus, our estimate of ΔC using this weight-based method is \$227 per vehicle. We note this is likely an underestimate given that it does not account for a variety of inputs in the manufacturing process that also use steel and aluminum, such as outsourced auto parts.

C Spillover Effects

This first part of this appendix introduces an imperfect competition model of the auto loan market in the spirit of Salop 1979 and Berg et al. 2021. There are two main insights from the model:

1. In response to a cost shock to captive lenders, both captive and non-captive lenders raise their loan prices. This effect arises due to competitive interactions between captive and non-captive lenders and the particular form of consumer demand assumed in the model. The main implication of this finding is that researchers must take into account the responses of both captive and non-captive lenders when measuring the aggregate effects of the cost shock.

2. The total effect of a cost shock on captive loan prices can be deconstructed into a direct effect p^d that is specific to captive lenders and a spillover effect p^s that is common to both captive and non-captive lenders. While the direct effect can be estimated using a difference-in-differences model that compares the loan prices of captive and non-captive lenders before-and-after the cost shock, the spillover effect cannot as it is absorbed into the common time trend. The model predicts that the spillover effect will be equal $p^s = p^d \cdot \bar{d}$, where $\bar{d}$ is the market share of captive lenders. The total effect on captive loan prices is $p^t = p^d + p^s = p^d \cdot (1 + \bar{d})$.

The second part of this appendix uses both the above model and a separate data-driven procedure to estimate the average spillover effect on non-captive lenders. We estimate an average spillover effect of 6.26 basis points using our data-driven procedure, which is almost identical to our model-based estimate of 7 basis points.

C.1 Model Setup

There are $i = 1, \ldots, n$ lenders located equidistant around a unit circle offering auto loans at prices p_i. There is also a unit mass of consumers uniformly distributed around the circle. The location of the lenders represents various non-price aspects of their loan offers – e.g., the convenience of doing business with the lender, the willingness of the lender to underwrite high LTV loans, etc. The location of the consumers represents their preferences for these non-price loan characteristics.[9]

C.1.1 Consumers

If a consumer is located at z and selects a loan from lender i located at z_i, then their net utility is $v - p_i - t \cdot |z - z_i|$, where v is the private value of the loan to the consumer and t is a cost of deviating from the ideal non-price loan features. We assume that v is large so that all consumers select an auto loan instead of purchasing the vehicle using cash.

C.1.2 Lenders

There are n_1 captive lenders with marginal costs of loan production $c > 0$. There are also n_2 non-captive lenders with marginal costs of loan production $c+\alpha$, where $n_1 + n_2 = n$ and $\alpha > 0$. Let $\bar{d} = n_1 \cdot n^{-1}$ denote the fraction of captive lenders. Lenders choose their prices to maximize profits $(p_i - c_i) \cdot q_i$, where q_i is the demand for lender i. Following Raith 2003 and Aghion and Shankerman 2004, we assume that lenders do not know the marginal costs of their neighboring lenders on the circle, and thus base their pricing decisions on the expected costs of their neighbors.

C.1.3 Cost Shock

We consider a cost shock to captive lenders that increases their marginal cost of loan production from c to $c + \gamma$. Our goal is to understand how the cost shock affects equilibrium prices.

C.1.4 Equilibrium Notation

Let $p(1)$ denote the equilibrium loan price for captive lenders prior to the cost shock, and let $\tilde{p}(1)$ denote the price after. Let $p(0)$ and $\tilde{p}(0)$ denote the same quantities but for non-captive lenders.

9. The model can also be re-framed as one where dealers represent consumers and have preferences over the amount of incentives offered from different lenders.

C.2 Equilibrium Prior to the Cost Shock

The solution to the model in the absence of the cost shock is well-known and is derived for a similar setting in Berg et al. 2021. The equilibrium loan price for captive lenders is:

$$p(1) = c + \frac{t}{n} + \alpha \left(\frac{n(1-\bar{d})}{2n-1} \right),$$

and their market share per firm is:

$$m(1) = \frac{1}{n} + \alpha \left(\frac{n(1-\bar{d})}{t(2n-1)} \right).$$

Similarly, the equilibrium loan price for non-captive lenders is:

$$p(0) = p(1) + \alpha \left(\frac{n-1}{2n-1} \right).$$

and their market share per firm is:

$$m(0) = \frac{1}{n} - \alpha \left(\frac{n\bar{d}}{t(2n-1)} \right).$$

Consistent with the data, the model predicts that non-captives charge higher loan prices than captives prior to the cost shock. Despite this gap, captives do not raise their loan prices because it will result in a loss of market share and total profits.

C.3 Equilibrium After the Cost Shock

The model with the cost shock is equivalent to the model without the cost shock but with the difference in marginal costs reversed. The equilibrium loan price for non-captive lenders after the cost shock is:

$$\tilde{p}(0) = (c + \alpha) + \frac{t}{n} + (\gamma - \alpha) \left(\frac{n\bar{d}}{2n-1} \right),$$

and the equilibrium loan price for captive lenders after the cost shock is:

$$\tilde{p}(1) = \tilde{p}(0) + (\gamma - \alpha)\left(\frac{n-1}{2n-1}\right).$$

There are two main findings from the model. First, non-captive lenders find it optimal to raise their loan prices in response to a cost shock to captive lenders:[10]

$$\tilde{p}(0) - p(0) = \underbrace{\gamma\left(\frac{n\bar{d}}{2n-1}\right)}_{:=p^s}.$$

We call the term p^s the spillover effect of the cost shock on non-captive lenders. Second, the total effect p^t of the cost shock on captive loan prices is equal to the spillover effect p^s plus an additional direct effect p^d that is specific to captive lenders:

$$\underbrace{\tilde{p}(1) - p(1)}_{:=p^t} = \underbrace{\gamma\left(\frac{n\bar{d}}{2n-1}\right)}_{:=p^s} + \underbrace{\gamma\left(\frac{n-1}{2n-1}\right)}_{:=p^d}.$$

C.3.1 The Size of the Spillover Effect in Relation to the Direct Dffect

As discussed further in Section C.4, the spillover effect p^s cannot be empirically identified in a difference-in-differences setting. This is problematic because it implies that our difference-in-differences estimates will only capture the direct effect of the cost shock p^d on captive lenders, which is an underestimate of the total effect p^t (which also includes the common spillover p^s).

An alternative approach for estimating the total effect is to leverage the implied relationship between p^d and p^s from the model. Notice that the ratio of the spillover effect to the direct effect is equal to:

$$\frac{p^s}{p^d} = \bar{d}\left(\frac{n}{n-1}\right).$$

10. Given that captives will raise their loan prices in response to the cost shock, non-captives can raise prices a little to increase their profits per loan without sacrificing market share. This model is not well-suited to examining effects on total quantities (as opposed to market shares) because no consumers exit the market (i.e., purchase the vehicle using cash) in response to higher loan prices.

If we hold $\bar{d}$ fixed, then the above ratio converges to $\bar{d}$ as the number of lenders n grows large. That is, the model predicts that the ratio of the spillover effect to the direct effect will be equal to the market share of captive lenders. Therefore, given an estimate of p^d from our difference-in-differences model and an estimate of the market share of captive lenders from population data, we can then estimate the spillover effect as:

$$p^s = p^d \cdot \bar{d},$$

and the total effect as:

$$p^t = p^d \cdot (1 + \bar{d}).$$

C.4 What Do We Recover From Difference-in-Differences?

We now demonstrate that empirical identification of the spillover effect is infeasible in a difference-in-differences setting without imposing strict assumptions on the data-generating process.

C.4.1 Setup

Suppose there are two periods, one before the cost shock ($t = 0$) and the other after ($t = 1$). Let P_t be a post-period indicator that is equal to one if $t = 1$, and zero otherwise. Suppose there are $i = 1, \ldots, N$ lenders in the sample. Let T_i be a treatment indicator equal to one if lender i is a captive lender, and zero otherwise.

C.4.2 Model

Suppose we estimate the following simplified difference-in-differences model:

$$p_{i,t} = \alpha + \beta_1 \cdot T_i \cdot P_t + \beta_2 \cdot T_i + \beta_3 \cdot P_t + \varepsilon_{i,t},$$

where $p_{i,t}$ is the loan price of lender i in period t. If the parallel trends assumption holds, then β_1 identifies the direct effect of the cost shock on captive loan prices:

$$\beta_1 = [\tilde{p}(1) - p(1)] - [\tilde{p}(0) - p(0)] = p^s + p^d - p^s = p^d.$$

Note that the above identification holds regardless of auto loan prices would have changed in the absence of treatment. For example, if we added a market-wide cost shock that affected both captive and non-captive lenders to our theoretical model, then we would still recover the direct effect of the original captive-specific cost shock from our difference-in-differences model.

C.4.3 Spillover Effect

If we assume that auto loan prices would not have changed in the absence of treatment, then β_3 identifies the spillover effect of the cost shock and $\beta_1 + \beta_3$ identifies the total effect. However, because changes in funding rates, loan demand, and other macroeconomic factors can cause auto loan prices to change over time, there is little reason to believe this assumption will be satisfied. Given this, we use both our model and an alternative data-driven procedure to estimate the average spillover effect, as discussed further below.

C.5 Estimating the Average Spillover Effect

As shown in Figure IA.8, the time-series of average captive and non-captive interest rates is consistent with the existence of spillover effects on non-captive lenders. However, extracting a reliable estimate of the average spillover effect from these time-series averages is difficult because other time-varying factors may have also affected non-captive interest rates during our sample period. Below, we use both our theoretical model and a data-driven procedure to estimate the average spillover effect on non-captive lenders.

C.5.1 Model-Based Estimate

Our model predicts that the average spillover effect on non-captive lenders should be equal to the product of our baseline difference-in-differences coefficient and the pre-treatment market share of captive lenders: $p^s = p^d \cdot \bar{d}$. From Table 3, we have that $p^d = 26$ basis points. From population data, we have that $\bar{d} = 26$ percent. Therefore, our model-based estimate of the spillover effect is 7 basis points (= 26 basis points $\times$ 0.26), and the spillover-inclusive increase in captive interest rates is 33 (= 26 + 7) basis points, or \$227 per loan in present value terms.

C.5.2 Data-Driven Estimate

Our data-driven procedure for estimating the spillover effect proceeds in two main steps. In the first step, we predict how non-captive lenders' interest rates would have changed in the absence of the tariffs based on realized changes in market interest rates and historical non-captive interest rate pass-through rates. Specifically, we start by estimating the following model during the pre-treatment to estimate non-captive lenders' historical pass-through rates:

$$\Delta \text{Rate}_t = \alpha + \beta \cdot \Delta R_t^f + \varepsilon_t, \tag{2}$$

where $\Delta\text{Rate}_t = \text{Rate}_t - \text{Rate}_{t-1}$ is the month-over-month change in the average non-captive interest rate, $\Delta R_t^f = R_t^f - R_{t-1}^f$ is the month-over-month change in the 1-year Treasury yield, and β is the pass-through rate.[11] Then, we combine the estimated model parameters with realized month-over-month changes in 1-year Treasury yields during the post-treatment period to construct a sequence of predicted changes in non-captive interest rates: $\{\widehat{\Delta\text{Rate}}_t = \widehat{\alpha} + \widehat{\beta} \cdot \Delta R_t^f\}$.

In the second step of our data-driven process, we take the difference between our predicted changes in non-captive interest rates from above and their actual changes during the post-treatment period. This gives us a sequence of interest rate residuals following the tariffs, which we then sum

11. Our estimate of the spillover effect is robust to using other risk-free interest rates besides the 1-year Treasury yield, as well as an alternative data-driven method based on loan-level data.

up to arrive at our estimate of the spillover effect:

$$\widehat{\text{Spillover}} = \sum_{2018-01}^{2018-12} \Delta\text{Rate}_t - \widehat{\Delta\text{Rate}}_t. \tag{3}$$

Using the above procedure, we estimate an average spillover effect of 6.26 basis points, which is almost identical to our model-based estimate of 7 basis points. Although the consistency of our estimates is reassuring, it is important to acknowledge that neither our data-driven estimate nor our model-based estimate is perfect, as they both rely on various sets of assumptions that are difficult to verify in the data. For instance, our data-driven procedure implicitly assumes that no other time-varying factors besides the rise in Treasury yields would have systematically affected non-captive interest rates during the post-treatment period.

Table IA.1: Loan Originations

Panel A: Captive-Level Aggregations

	Number of Loans Originated			
	Linear Model	Poisson Model	Linear Model	Poisson Model
	(1)	(2)	(3)	(4)
Treated × Post	-0.067***	-0.117***	-0.048***	-0.125***
	(-9.44)	(-3.25)	(-8.40)	(-10.54)
Level of Aggregation	$f \times s \times v \times t$	$f \times s \times v \times t$	$f \times s \times w \times c \times t$	$f \times s \times w \times c \times t$
Captive FE	Y	Y	Y	Y
State × Quarter FE	Y	Y	Y	Y
Vehicle × Quarter FE	Y	Y		
Income × Quarter FE			Y	Y
Credit Score × Quarter FE			Y	Y
N	321,016	312,757	183,824	183,824
R^2	0.49	0.70	0.76	0.76

Panel B: Lender-Level Aggregations

	Number of Loans Originated			
	Linear Model	Poisson Model	Linear Model	Poisson Model
	(1)	(2)	(3)	(4)
Treated × Post	-0.031***	-0.05	-0.047***	-0.121***
	(-6.59)	(-1.30)	(-15.37)	(-12.24)
Level of Aggregation	$l \times s \times v \times t$	$l \times s \times v \times t$	$l \times s \times w \times c \times t$	$l \times s \times w \times c \times t$
Lender FE	Y	Y	Y	Y
State × Quarter FE	Y	Y	Y	Y
Vehicle × Quarter FE	Y	Y		
Income × Quarter FE			Y	Y
Credit Score × Quarter FE			Y	Y
N	596,568	587,512	795,360	795,360
R^2	0.42	0.73	0.43	0.53

NOTE.—This table reports coefficient estimates from Equation 1. The dependent variable in columns 1 and 3 is the log of one plus the number of loans originated. The dependent variable in columns 2 and 4 is the raw number of loan originations. We estimate a linear regression model in columns 1 and 3 and a Poisson regression model in columns 2 and 4. In Panel A, we calculate the number of loan originations at either (i) the captive (f) × state (s) × vehicle make-model-condition (v) × origination quarter (t) level in columns 1 and 2; or (ii) captive × state × vehicle make-model-condition × income bucket (ω) × credit score (c) × origination quarter level in columns 3 and 4. In Panel B, we perform the same aggregations but at the lender (l) level instead of the captive level. The sample is restricted to auto loans originated between January 2017 and December 2018. t-statistics, presented below the coefficient estimates, are calculated using hetroskedasticity-robust standard errors. Statistical significance at the 10%, 5%, and 1% levels is denoted by *, **, and ***, respectively.

Table IA.2: Adjusted Sample Filters

	Interest rate						
	Credit score		Winsorizing		Sample period		Loan-to-value
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Treated × Post	0.260***	0.236***	0.245***	0.257***	0.286***	0.282*	0.265***
	(3.06)	(3.26)	(2.76)	(3.38)	(2.94)	(1.94)	(2.65)
Sample filter	660+	500+	Winsor 2%	No winsor	2017-2019	Only Q1 & Q2	No filter
Lender FE	Y	Y	Y	Y	Y	Y	Y
Vehicle × Quarter FE	Y	Y	Y	Y	Y	Y	Y
State × Quarter FE	Y	Y	Y	Y	Y	Y	Y
Income × Quarter FE	Y	Y	Y	Y	Y	Y	Y
Credit Score × Quarter FE	Y	Y	Y	Y	Y	Y	Y
N	1,772,625	2,498,681	1,881,895	2,086,697	2,255,225	960,415	2,431,877
R^2	0.65	0.85	0.68	0.73	0.70	0.71	0.73

NOTE.—This table reports coefficient estimates from Equation 2. The dependent variable is the interest rate. Across the columns, we adjust our sample filters from Section 3. In Columns 1 and 2, we adjust our credit score filter. In Columns 3 and 4, we adjust our level of winsorization. In Column 5, we extend our sample period to 2019. In Column 6, we restrict our sample period to prior to the retaliatory tariffs from China. In Column 7, we remove our loan-to-value ratio filter. The row *Sample filter* lists the sample adjustment being applied. t-statistics, presented below the coefficient estimates, are calculated by clustering at the lender level. Statistical significance at the 10%, 5%, and 1% levels is denoted by *, **, and ***, respectively.

Table IA.3: Comparison of Loan Terms Across Data Sources

Panel A: All Lenders

	Mean (1)	SD (2)	P25 (3)	P50 (4)	P75 (5)
Originations	0.32	0.28	0.14	0.25	0.43
Loan Amount	1.01	0.07	0.98	1.02	1.04
Loan Maturity	1.00	0.03	0.99	1.00	1.02
Monthly Payment	0.99	0.05	0.96	0.99	1.02

Panel B: Restricted Sample of Lenders

	Mean (1)	SD (2)	P25 (3)	P50 (4)	P75 (5)
Originations	0.37	0.31	0.15	0.27	0.45
Loan Amount	1.00	0.08	0.98	1.00	1.04
Loan Maturity	1.01	0.03	1.00	1.01	1.03
Monthly Payment	1.00	0.05	0.98	1.01	1.03

NOTE.—This table compares the average loan terms in the Regulation AB II data to the average loan terms in the population credit bureau data. The comparisons are conducted at the lender level for loans that were originated between 2017 and 2018. Panel A reports descriptive statistics for the entire set of 19 lenders in the Regulation AB II data. Panel B reports descriptive statistics for the restricted sample of 14 lenders that we use to estimate our regression models throughout the paper. The rows in the table are defined as follows. *Originations* is the ratio of the number of loan originations in the Regulation AB II data (calculated at the lender level) to the number of loan originations in the credit bureau data. *Loan amount* is the ratio of the average loan amount for originated loans in the Regulation AB II data (calculated at the lender level) to the average loan amount of originated loans in the credit bureau data. *Loan maturity* and *Monthly payment* are the same ratios but for average loan maturities and monthly payments, respectively.

Table IA.4: Comparison of Large Non-Captive Lenders Across Data Sources

Panel A: Unweighted Models

	Interest Rate (1)	Loan Amount (2)	Maturity (3)	Interest rate (4)	Loan Amount (5)	Maturity (6)
Regulation AB Lender	0.1927	0.017	0.031	0.1128	0.0091	0.0246
	(0.28)	(0.27)	(1.13)	(0.14)	(0.12)	(0.78)
Month FE	Y	Y	Y	Y	Y	Y
Credit Score FE	Y	Y	Y	Y	Y	Y
Credit Score × Month FE				Y	Y	Y
N	624	624	624	624	624	624
R^2	0.94	0.77	0.64	0.95	0.8	0.71

Panel B: Weighted Models

	Interest Rate (1)	Loan Amount (2)	Maturity (3)	Interest rate (4)	Loan Amount (5)	Maturity (6)
Regulation AB Lender	0.0444	0.016	0.0287	0.0623	0.0035	0.0207
	(0.07)	(0.27)	(1.07)	(0.08)	(0.05)	(0.67)
Month FE	Y	Y	Y	Y	Y	Y
Credit Score FE	Y	Y	Y	Y	Y	Y
Credit Score × Month FE				Y	Y	Y
N	624	624	624	624	624	624
R^2	0.95	0.76	0.64	0.96	0.78	0.71

NOTE.—This table reports coefficient estimates from the following model: $y_{l,t} = \alpha + \beta \cdot \text{Regulation AB Lender}_l + \delta_t + \delta_c + \varepsilon_{l,t}$, where the outcome variable, $y_{l,t}$, is either the average interest rate, log loan amount, or log loan maturity for loans originated by non-captive lender l in month t. The indicator variable Regulation AB Lender$_l$ is equal to one if non-captive lender l is in the Regulation AB II data, and zero otherwise, δ_t are month fixed effects, and δ_c are 25-point average credit score bin fixed effects that are constructed at the lender level. The model is estimated using our population credit bureau data (see Section 3.1.1), and the sample is restricted to large non-captive lenders with at least 10,000 auto loan originations per quarter. The sample period runs from January 2017 to December 2018. Panel A reports coefficient estimates for unweighted models. Panel B reports coefficient estimates for weighted models that use lender-level loan origination volumes as population weights. t-statistics, presented below the coefficient estimates, are calculated by clustering at the lender level. *, **, and *** denote statistical significant at the 10%, 5%, and 1% levels, respectively.

Table IA.5: Alternative Choices of Treatment Date

	Interest Rate					
	All Loans			Excluding Subvented Loans		
	(1)	(2)	(3)	(4)	(5)	(6)
Treated × Post	0.245***	0.222**	0.229**	0.294***	0.298***	0.302***
	(2.69)	(2.53)	(2.50)	(2.96)	(2.97)	(3.04)
Treatment date	Jan-18	Feb-18	Mar-18	Jan-18	Feb-18	Mar-18
Lender FE	Y	Y	Y	Y	Y	Y
Vehicle × Month FE	Y	Y	Y	Y	Y	Y
State × Month FE	Y	Y	Y	Y	Y	Y
Income × Month FE	Y	Y	Y	Y	Y	Y
Credit Score × Month FE	Y	Y	Y	Y	Y	Y
N	1,971,643	1,971,643	1,971,643	789,583	789,583	789,583
R^2	0.71	0.71	0.71	0.68	0.68	0.68

NOTE.—This table reports coefficient estimates from Equation 2 when using either January 2018, February 2018, or March 2018 as the treatment date. The dependent variable is the interest rate. The sample is restricted to auto loans originated between January 2017 and December 2018. t-statistics, presented below the coefficient estimates, are calculated by clustering at the lender level. Statistical significance at the 10%, 5%, and 1% levels is denoted by *, **, and ***, respectively.

Table IA.6: Excluding World Omni

	Interest Rate (1)	Loan Amount (2)	Loan Maturity (3)	Loan-to-Value (4)
Treated × Post	0.315**	-0.008	-0.008***	-0.008*
	(2.49)	(-0.88)	(-2.76)	(-1.69)
Lender FE	Y	Y	Y	Y
Vehicle × Quarter FE	Y	Y	Y	Y
State × Quarter FE	Y	Y	Y	Y
Income × Quarter FE	Y	Y	Y	Y
Credit Score × Quarter FE	Y	Y	Y	Y
N	1,814,144	1,814,144	1,814,144	1,814,144
R^2	0.72	0.56	0.21	0.22

NOTE.—This table reports coefficient estimates from Equation 2 after excluding loans from World Omni from the sample. The dependent variable is either the interest rate, log loan amount, log loan maturity, or loan-to-value ratio. The sample is restricted to auto loans originated between January 2017 and December 2018. t-statistics, presented below the coefficient estimates, are calculated by clustering at the lender level. Statistical significance at the 10%, 5%, and 1% levels is denoted by *, **, and ***, respectively.

Table IA.7: Auto Loan Terms for New and Used Vehicles

Panel A: New Vehicles

	Interest rate	Loan Amount	Loan Maturity	Loan-to-Value
	(1)	(2)	(3)	(4)
Treated × Post	0.243***	-0.029***	-0.023***	-0.020***
	(3.20)	(-3.55)	(-5.75)	(-4.22)
Lender FE	Y	Y	Y	Y
Vehicle × Quarter FE	Y	Y	Y	Y
State × Quarter FE	Y	Y	Y	Y
Income × Quarter FE	Y	Y	Y	Y
Credit Score × Quarter FE	Y	Y	Y	Y
N	1,289,837	1,289,837	1,289,837	1,289,837
R^2	0.67	0.42	0.23	0.21

Panel B: Used Vehicles

	Interest Rate	Loan Amount	Loan Maturity	Loan-to-Value
	(1)	(2)	(3)	(4)
Treated × Post	0.297**	0.010	0.003	0.004
	(2.35)	(1.04)	(0.51)	(0.83)
Lender FE	Y	Y	Y	Y
Vehicle × Quarter FE	Y	Y	Y	Y
State × Quarter FE	Y	Y	Y	Y
Income × Quarter FE	Y	Y	Y	Y
Credit Score × Quarter FE	Y	Y	Y	Y
N	683,230	683,230	683,230	683,230
R^2	0.66	0.55	0.15	0.14

NOTE.—This table reports coefficient estimates from Equation 2. The dependent variable is either the interest rate, log loan amount, log loan maturity, or loan-to-value ratio. The sample is restricted to auto loans originated between January 2017 and December 2018. In Panel A, we restrict the sample to loans for new vehicles. In Panel B, we restrict the sample to loans for used vehicles. t-statistics, presented below the coefficient estimates, are calculated by clustering at the lender level. Statistical significance at the 10%, 5%, and 1% levels is denoted by *, **, and ***, respectively.

Table IA.8: Captive Auto Loan Terms for U.S. Made and Foreign Made Makes and Models

	Interest Rate (1)	Interest Rate (2)	Interest Rate (3)	Interest Rate (4)
US Made × Post	0.120	0.013	-0.043	-0.043
	(0.99)	(0.17)	(-0.46)	(-0.80)
Definition of US Made	Make	Make	Make-Model	Make-Model
Excluding Subvented Loans?		Y		Y
Lender FE	Y	Y	Y	Y
Vehicle FE	Y	Y	Y	Y
State × Quarter FE	Y	Y	Y	Y
Income × Quarter FE	Y	Y	Y	Y
Credit Score × Quarter FE	Y	Y	Y	Y
N	1,195,740	189,255	1,195,709	189,228
R^2	0.60	0.74	0.60	0.74

NOTE.—This table reports coefficient estimates from Equation 2 after we (i) restrict the sample to captive auto loans, (ii) replace *Treated* with *US Made*, and (iii) replace the vehicle × quarter fixed effects ($\delta_{v,t}$) with vehicle fixed effects (δ_v). The dependent variable is the interest rate. The sample consists of captive auto loans originated between January 2017 and December 2018. In columns 1 and 2, *US Made* is assigned at the vehicle make level, and it is equal to one if at least 50 percent of make m's vehicles are manufactured in the U.S, and zero otherwise (see Section 4.5). In columns 3 and 4, *US Made* is assigned at the vehicle make-model level, and it is equal to one if at least 50 percent of make-model $\tilde{m}$'s vehicles are manufactured in the U.S, and zero otherwise (see Section 4.5). t-statistics, presented below the coefficient estimates, are calculated by clustering at the lender level. Statistical significance at the 10%, 5%, and 1% levels is denoted by *, **, and ***, respectively.

Table IA.9: Controlling for Differential Pass-Through of Risk-Free Interest Rates

Panel A: All Loans

	Interest Rate					
	(1)	(2)	(3)	(4)	(5)	(6)
Treated × Post	0.255***	0.252***	0.256***	0.259***	0.264***	0.268***
	(2.75)	(2.72)	(2.78)	(2.80)	(2.82)	(2.78)
Treated ×Δ Fed Funds		Y				Y
Treated ×Δ 1Y Treasury			Y			Y
Treated ×Δ 5Y Treasury				Y		Y
Treated ×Δ 10Y Treasury					Y	Y
Lender FE	Y	Y	Y	Y	Y	Y
Vehicle × Time FE	Y	Y	Y	Y	Y	Y
State × Time FE	Y	Y	Y	Y	Y	Y
Income × Time FE	Y	Y	Y	Y	Y	Y
Credit Score × Time FE	Y	Y	Y	Y	Y	Y
N	1,973,067	1,973,067	1,973,067	1,973,067	1,973,067	1,973,067
R^2	0.70	0.70	0.70	0.70	0.70	0.70

Panel B: Non-Subvented Loans

	Interest Rate					
	(1)	(2)	(3)	(4)	(5)	(6)
Treated × Post	0.288***	0.292***	0.288***	0.298***	0.306***	0.295***
	(2.85)	(2.87)	(2.84)	(2.92)	(2.95)	(2.75)
Treated ×Δ Fed Funds		Y				Y
Treated ×Δ 1Y Treasury			Y			Y
Treated ×Δ 5Y Treasury				Y		Y
Treated ×Δ 10Y Treasury					Y	Y
Lender FE	Y	Y	Y	Y	Y	Y
Vehicle × Time FE	Y	Y	Y	Y	Y	Y
State × Time FE	Y	Y	Y	Y	Y	Y
Income × Time FE	Y	Y	Y	Y	Y	Y
Credit Score × Time FE	Y	Y	Y	Y	Y	Y
N	791,300	791,300	791,300	791,300	791,300	791,300
R^2	0.67	0.67	0.67	0.67	0.67	0.67

NOTE.—This table reports coefficient estimates from Equation 2 after including an extensive set of controls for changes in risk-free interest rates. Specifically, we include interactions between our treatment indicator variable and monthly changes in the Fed Funds rate, 1-year Treasury rate, 5-year Treasury rate, and 10-year Treasury rate. The dependent variable is the interest rate. The sample is restricted to auto loans originated between January 2017 and December 2018. In Panel A, we report coefficient estimates for the full sample of auto loans. In Panel B, we restrict the sample to loans without subsidized financing. t-statistics, presented below the coefficient estimates, are calculated by clustering at the lender level. Statistical significance at the 10%, 5%, and 1% levels is denoted by *, **, and ***, respectively.

Table IA.10: Invoice Prices for Captive-Financed and Non-Captive-Financed Vehicles

	Invoice Price (1)	log Invoice Price (2)
Treated × Post	11.689	0.001
	(0.40)	(1.35)
Lender FE	Y	Y
Vehicle × Time FE	Y	Y
State × Time FE	Y	Y
Income × Time FE	Y	Y
Credit Score × Time FE	Y	Y
N	1,289,837	1,289,837
R^2	0.87	0.89

NOTE.—This table reports coefficient estimates from Equation 2 for the subsample of new vehicles. The dependent variable is either the invoice price in column 1 or the log invoice price in column 2. The sample is restricted to auto loans originated between January 2017 and December 2018. t-statistics, presented below the coefficient estimates, are calculated by clustering at the lender level. Statistical significance at the 10%, 5%, and 1% levels is denoted by *, **, and ***, respectively.

Table IA.11: More-Exposed Captive Lenders Versus Less-Exposed Captives

	Interest Rate	
	(1)	(2)
More Exposed × Post	0.271	0.234**
	(1.27)	(2.19)
Exclude Subvented Loans?		Y
Lender FE	Y	Y
Make × Model × Condition FE	Y	Y
State × Quarter FE	Y	Y
Income × Quarter FE	Y	Y
Credit Score × Quarter FE	Y	Y
N	1,185,234	181,246
R^2	0.58	0.73

NOTE.—This table reports coefficient estimates from Equation 2 after we replace the *Treated* variable with *More Exposed*, which is equal to one for more-exposed captive lenders (defined in Section 4.2, and zero otherwise. The sample is restricted to captive auto loans originated between January 2017 and December 2018. The dependent variable is the interest rate. In column 1, the model is estimated using all captive auto loans. In column 2, the model is estimated on the subsample of non-subvented captive auto loans. t-statistics, presented below the coefficient estimates, are calculated by clustering at the lender level. Statistical significance at the 10%, 5%, and 1% levels is denoted by *, **, and ***, respectively.

Table IA.12: Controlling for Differential Changes in Borrowing Costs

Panel A: All loans

	Interest Rate			
	(1)	(2)	(3)	(4)
Treated × Post	0.502**	0.423*	0.395**	0.305***
	(2.48)	(1.91)	(2.37)	(3.54)
Financing Cost Proxy	Cost of debt	Note rate	Bond rate	Credit rating
Lender FE	Y	Y	Y	Y
Vehicle × Quarter FE	Y	Y	Y	Y
State × Quarter FE	Y	Y	Y	Y
Income × Quarter FE	Y	Y	Y	Y
Credit score × Quarter FE	Y	Y	Y	Y
N	1,755,262	1,755,262	1,755,262	1,610,090
R^2	0.71	0.71	0.71	0.70

Panel B: Excluding subvented loans

	Interest Rate			
	(1)	(2)	(3)	(4)
Treated × Post	0.450***	0.479***	0.374***	0.299***
	(3.35)	(2.65)	(2.59)	(2.94)
Financing Cost Proxy	Cost of debt	Note rate	Bond rate	Credit rating
Lender FE	Y	Y	Y	Y
Vehicle × Quarter FE	Y	Y	Y	Y
State × Quarter FE	Y	Y	Y	Y
Income × Quarter FE	Y	Y	Y	Y
Credit score × Quarter FE	Y	Y	Y	Y
N	686,092	686,092	686,092	454,308
R^2	0.67	0.67	0.67	0.75

NOTE.—This table reports coefficient estimates from Equation 2 after including two additional control variables: (i) a linear financing cost proxy and (ii) the interaction between the linear financing cost proxy and the treatment indicator. The dependent variable is the interest rate. The sample is restricted to auto loans originated between January 2017 and December 2018. In Panel B, we remove subvented loans from the sample. The row *Financing Cost Proxy* lists the proxy variable for firm financing costs used in each model. These variables are sourced from Bloomberg and are available for most (but not all) of our lenders. Our financing cost proxies include estimates of the cost of debt, the short-term note (par) coupon rate, the long-term bond (par) coupon rate, and the credit rating. Vehicle fixed effects refer to vehicle make-model-condition combinations. t-statistics, presented below the coefficient estimates, are calculated by clustering at the lender level. Statistical significance at the 10%, 5%, and 1% levels is denoted by *, **, and ***, respectively.

Table IA.13: Controlling for Differential Exposures to Auto Loan Default Risk

	Interest Rate	
	All Loans	Non-Subvented Loans
	(1)	(2)
Treated × Post	0.226**	0.283***
	(2.48)	(2.78)
Treated ×Δ Default Rate	Y	Y
Lender FE	Y	Y
Vehicle × Quarter FE	Y	Y
State × Quarter FE	Y	Y
Income × Quarter FE	Y	Y
Credit Score × Quarter FE	Y	Y
N	1,973,067	791,300
R^2	0.70	0.67

NOTE.—This table reports coefficient estimates from Equation 2 after controlling for the interaction between the treatment indicator variable and quarterly changes in aggregate auto loan default rates reported by the New York Fed. The dependent variable is the interest rate. The sample is restricted to auto loans originated between January 2017 and December 2018. In column 1, we report coefficient estimates for the full sample of auto loans. In column 2, we restrict the sample to loans without subsidized financing. t-statistics, presented below the coefficient estimates, are calculated by clustering at the lender level. Statistical significance at the 10%, 5%, and 1% levels is denoted by *, **, and ***, respectively.

Table IA.14: Ruling Out Changes in Dealer Loan Markups

	Interest Rate (1)	Loan Amount (2)	Loan Maturity (3)	Loan-to-Value (4)
Treated × Post	0.273***	-0.017*	-0.018***	-0.015***
	(2.70)	(-1.88)	(-5.50)	(-3.93)
Lender FE	Y	Y	Y	Y
Vehicle × Quarter FE	Y	Y	Y	Y
State × Quarter FE	Y	Y	Y	Y
Income × Quarter FE	Y	Y	Y	Y
Credit Score × Quarter FE	Y	Y	Y	Y
N	1,783,813	1,783,813	1,783,813	1,783,813
R^2	0.72	0.56	0.22	0.22

NOTE.—This table reports coefficient estimates from Equation 2. The dependent variable is either the interest rate, log loan amount, log loan maturity, or loan-to-value ratio. The sample is restricted to captive auto loans with subsidized financing and non-captive auto loans with-or-without subsidized financing that are originated between January 2017 and December 2018. Vehicle fixed effects refer to vehicle make-model-condition combinations. t-statistics, presented below the coefficient estimates, are calculated by clustering at the lender level. Statistical significance at the 10%, 5%, and 1% levels is denoted by *, **, and ***, respectively.

Table IA.15: Prepayment Speed

	12-month paid-off		24-month paid-off	
	All loans	No subventions	All loans	No subventions
	(1)	(2)	(3)	(4)
Treated × Post	0.002	-0.004	0.007	0.002
	(0.26)	(-1.31)	(0.73)	(0.25)
Lender FE	Y	Y	Y	Y
Vehicle × Quarter FE	Y	Y	Y	Y
State × Quarter FE	Y	Y	Y	Y
Income × Quarter FE	Y	Y	Y	Y
Credit score × Quarter FE	Y	Y	Y	Y
N	1,973,067	791,300	1,361,478	557,380
R^2	0.05	0.04	0.06	0.04

NOTE.—This table reports coefficient estimates from Equation 2. The dependent variable is either an indicator for whether a loan is paid off within 12 months of its origination date or an indicator for whether a loan is paid off within 24 months of its origination date. The sample is restricted to auto loans originated between January 2017 and December 2018. In Columns (2) and (4), we further restrict the sample to loans without subsidized financing. Vehicle fixed effects refer to vehicle make-model-condition combinations. t-statistics, presented below the coefficient estimates, are calculated by clustering at the lender level.Statistical significance at the 10%, 5%, and 1% levels is denoted by *, **, and ***, respectively.

Table IA.16: Ruling Out Changes in Securitization Practices

Panel A: All Lenders

	Originations	Loan Amount	Loan Maturity	Monthly Payment
	(1)	(2)	(3)	(4)
Treated × Post	0.04	0.02	0.00	0.00
	(0.33)	(0.52)	(0.01)	(0.09)
Lender FE	Y	Y	Y	Y
Quarter FE	Y	Y	Y	Y
N	142	142	142	142
R^2	0.72	0.72	0.80	0.77

Panel B: Restricted Sample of Lenders

	Originations	Loan Amount	Loan Maturity	Monthly Payment
	(1)	(2)	(3)	(4)
Treated × Post	0.01	0.02	-0.01	0.00
	(0.06)	(0.44)	(-0.64)	(-0.21)
Lender FE	Y	Y	Y	Y
Quarter FE	Y	Y	Y	Y
N	112	112	112	112
R^2	0.71	0.72	0.82	0.75

NOTE.—This reports coefficient estimates from regressions of the form:

$$y_{l,t} = \alpha + \Gamma \times \text{Treated}_l \times \text{Post}_t + \delta_l + \delta_t + \varepsilon_{l,t},$$

where the unit of observation is at the lender-origination quarter level and the sample period runs from 2017 to 2018. Panel A reports coefficient estimates for all 19 lenders in the Regulation AB II data. Panel B reports coefficient estimates for the restricted sample of 14 lenders that we use to estimate our regression models throughout the paper. The outcome variables are defined as follows. *Originations* is the ratio of the number of loan originations in the Regulation AB II data (calculated at the lender-origination quarter level) to the number of loan originations in the credit bureau data. *Loan Amount* is the ratio of the average loan amount for originated loans in the Regulation AB II data (calculated at the lender-origination quarter level) to the average loan amount of originated loans in the credit bureau data. *Loan Maturity* and *Monthly Payment* are the same ratios but for average loan maturities, and monthly payments respectively. Statistical significance at the 10%, 5%, and 1% levels is denoted by *, **, and ***, respectively.

Table IA.17: Excluding Direct Non-Captive Loans

	Interest Rate (1)	Loan Amount (2)	Loan Maturity (3)	Loan-to-Value (4)
Treated × Post	0.250**	-0.000	-0.010**	-0.003
	(2.20)	(-0.04)	(-2.33)	(-0.76)
Lender FE	Y	Y	Y	Y
Vehicle × Quarter FE	Y	Y	Y	Y
State × Quarter FE	Y	Y	Y	Y
Income × Quarter FE	Y	Y	Y	Y
Credit Score × Quarter FE	Y	Y	Y	Y
Original Estimate	0.255***	-0.008	-0.011***	-0.008**
N	1,742,214	1,742,214	1,742,214	1,742,214
R^2	0.71	0.54	0.22	0.21

NOTE.—This table reports coefficient estimates from Equation 2 after restricting the control sample to auto loans originated by either CarMax, Santander, or World Omni. The dependent variable is either the interest rate, log loan amount, log loan maturity, or loan-to-value ratio. The sample consists of auto loans originated between January 2017 and December 2018. t-statistics, presented below the coefficient estimates, are calculated by clustering at the lender level. Statistical significance at the 10%, 5%, and 1% levels is denoted by *, **, and ***, respectively.

Table IA.18: Average Cost Increase Calculations

Vehicle Type (1)	Financing Source (2)	Percent of Population (3)	Δ Average Financing Cost (4)	Δ Average Vehicle Price (5)	Δ Average Total Cost (6)
New	Captive	17.70%	227	225	452
New	Non-Captive	12.30%	48	225	273
New	Cash	3.33%	0	225	225
Used	Captive	3.03%	227	0	227
Used	Non-Captive	40.30%	48	0	48
Used	Cash	23.33%	0	0	0
Weighted Average:			72	74	146
Percent of Average Loan Amount:			0.28%	0.29%	0.57%

NOTE.—This table calculates the average change in costs faced by consumers that purchase a vehicle in the U.S. The definitions of the columns are as follows. *Vehicle Type* describes whether the consumer purchases a new or used vehicle. *Financing Source* describes whether the vehicle was financed by a captive, a non-captive lender, or in cash. *Percent of Population* is the percent of consumers in the population that purchase a particular vehicle type and finance it in a particular way. Δ *Average Financing Cost* is the change in the average present value financing cost (inclusive of spillovers) for consumers in each group. Δ *Average Vehicle Price* is the change in the average vehicle price for consumers in each group. Δ *Average Total Cost* is the sum of Δ *Average Financing Cost* and Δ *Average Vehicle Price*. The weighted average increase in costs is calculated by summing the product of the average cost increase for each group and their population weights in column 3. Population data is from Experian 2021.

Table IA.19: List of Vehicle Brands and Captive Market Shares

Make (1)	Number of Loans (2)	In-House Captive (3)	In-House Captive in Sample? (4)	Captive Market Share (%) (5)
Acura	29,612	Honda	Yes	79
Alfa Romeo	16		No	0
Audi	21,090	Volkswagen	Yes	75
BMW	40,270	BMW	Yes	71
Buick	29,452	GM Financial	Yes	56
Cadillac	22,623	GM Financial	Yes	63
Chevrolet	262,025	GM Financial	Yes	64
Chrysler	11,337		No	4
Dodge	42,306		No	5
Fiat	1,713		No	1
Ford	217,340	Ford Credit	Yes	69
GMC	68,196	GM Financial	Yes	66
Honda	363,491	Honda	Yes	89
Hyundai	35,749	Hyundai	No	3
Infiniti	8,480	Nissan	No	2
Jaguar	872		No	2
Jeep	42,119		No	3
Kia	29,588	Hyundai	No	4
Land Rover	2,002		No	4
Lexus	35,870	Toyota	Yes	71
Lincoln	16,435	Ford Credit	Yes	84
Maserati	17		No	0
Mazda	11,305		No	2
Mercedes	40,114	Mercedes	Yes	72
Mercury	14		No	0
Mini	1,702	BMW	Yes	14
Mitsubishi	7,974		No	6
Nissan	60,387	Nissan	No	4
Porsche	877		No	3
Ram	13		No	0
Scion	802	Toyota	Yes	100
Sprinter	123		No	2
Subaru	11,057		No	3
Suzuki	13		No	8
Tesla	27	Tesla	No	7
Toyota	497,447	Toyota	Yes	57
Volkswagen	59,079	Volkswagen	Yes	83
Volvo	2,102	Volvo	No	2
All Makes	1,973,639	–	–	61

NOTE.—This table reports the complete list of vehicle makes (i.e., brands) in our sample. Columns 3 through 5 are defined as follows. *In-House Captive* is the name of the make's in-house captive lender, regardless of whether it is in the sample. (External lending partnerships are not considered in-house.) *In-House Captive in Sample?* is "Yes" if the make has an in-house captive lender and it is in our sample, and "No" otherwise. (Recall that Hyundai and Nissan are in the Regulation AB II data but we exclude them from our sample.) *Captive Market Share* is the percent of captive-financed loans in our sample for each make, regardless of whether the captive is the make's in-house captive or a different captive. The rows highlighted in light grey correspond to makes without an in-house captive lender. The rows highlighted in dark grey correspond to makes that have an in-house lender but it is not in our sample.

Table IA.20: Average Lending Conditions for Main Sample and Overlap Subsample

	Non-Captive Loans		Captive Loans	
	Main Sample	Overlap Subsample	Main Sample	Overlap Subsample
Variable	(1)	(2)	(3)	(4)
Loan Amount	22,256	22,196	26,914	26,612
Interest Rate	6.30	6.26	2.52	2.51
Monthly Payment	397	395	450	446
Loan Maturity	68	68	66	66
Loan-to-Value	0.92	0.92	0.89	0.90
Vehicle Value	25,044	24,979	30,862	30,361
New Vehicle?	0.39	0.39	0.81	0.81
Credit Score	730	730	756	756
Income	81,537	81,253	89,979	89,160
Co-Signed?	0.36	0.36	0.31	0.31
Subvented?	0.22	0.22	0.81	0.81
12-Month Default	0.01	0.01	0.00	0.00
24-Month Default	0.02	0.02	0.01	0.01
12-Month Paidoff	0.09	0.09	0.03	0.03
24-Month Paidoff	0.22	0.22	0.11	0.11

NOTE.—This table reports pre-treatment means for our main sample of 1,973,067 auto loans (called the *Main Sample*) and our 98 percent subsample of these loans for vehicles that have both a captive and a non-captive lending option (called the *Overlap Subsample*). For these comparisons, we restrict our attention to the subsample of auto loans that were originated prior to the treatment date. Columns 1 and 2 report pre-treatment means for non-captive loans. Columns 3 and 4 report pre-treatment means for captive loans.

Table IA.21: Alternative Forms of Clustering

	Interest Rate				
	(1)	(2)	(3)	(4)	(5)
Treated × Post	0.255***	0.255***	0.255***	0.255***	0.255***
	(2.75)	(5.67)	(3.90)	(2.68)	(2.76)
Lender FE	Y	Y	Y	Y	Y
Vehicle × Quarter FE	Y	Y	Y	Y	Y
State × Quarter FE	Y	Y	Y	Y	Y
Income × Quarter FE	Y	Y	Y	Y	Y
Credit Score × Quarter FE	Y	Y	Y	Y	Y
Lender Clustering	Y				
State Clustering		Y			
Vehicle Clustering			Y		
ABS Clustering				Y	
Lender Wild Cluster Bootstrap					Y
N	1,973,067	1,973,067	1,973,067	1,973,067	1,973,067
R^2	0.70	0.70	0.70	0.70	0.70

NOTE.—This table reports coefficient estimates from Equation 2 using different methods for computing the standard errors. The dependent variable is the interest rate. In Column (1), we cluster the standard errors at the lender level as we do throughout the paper. In Column (2), we cluster the standard errors at the state level. In Column (3), we cluster the standard errors at the vehicle make-model-condition level. In Column (4), we cluster the standard errors at the asset-backed security level. In Column (5), we compute the standard errors using the wild cluster robust bootstrap with lender clustering. The sample is restricted to auto loans originated between January 2017 and December 2018. Vehicle fixed effects refer to vehicle make-model-condition combinations. Statistical significance at the 10%, 5%, and 1% levels is denoted by *, **, and ***, respectively.

Table IA.22: More Granular Fixed Effects

	Interest Rate			
	(1)	(2)	(3)	(4)
Treated × Post	0.255**	0.324**	0.334***	0.347***
	(2.75)	(3.01)	(3.25)	(4.64)
Lender FE	Y	Y	Y	Y
State × Quarter FE	Y			
Vehicle × Quarter FE	Y			
Income × Quarter FE	Y	Y		
Credit Score × Quarter FE	Y	Y		
Vehicle × State × Quarter FE		Y	Y	
Income × Credit Score × State × Quarter FE			Y	
Vehicle × Income × Credit Score × State × Quarter FE				Y
N	1,973,067	1,935,616	1,924,144	1,031,917
R^2	0.70	0.73	0.75	0.85

NOTE.—This table reports coefficient estimates from Equation 2 after including more granular versions of our baseline fixed effects. The dependent variable is the interest rate. The sample is restricted to auto loans originated between January 2017 and December 2018. In Column (1), we re-estimate our baseline model used throughout the paper. In Column (2), we include separate origination quarter fixed effects for each vehicle and state combination. In Column (3), we include separate origination quarter fixed effects for each income and credit score bucket combination. In Column (4), we include separate origination quarter fixed effects for each vehicle-state-income bucket-credit score bucket combination. Vehicle fixed effects refer to vehicle make-model-condition combinations. t-statistics, presented below the coefficient estimates, are calculated by clustering at the lender level. Statistical significance at the 10%, 5%, and 1% levels is denoted by *, **, and ***, respectively.

Table IA.23: Fixed Effects for Other Loan Terms

	Interest Rate			
	(1)	(2)	(3)	(4)
Treated × Post	0.255***	0.249***	0.329***	0.322***
	(2.75)	(2.70)	(3.63)	(3.50)
Lender FE	Y	Y	Y	Y
State × Quarter FE	Y	Y	Y	Y
Vehicle × Quarter FE	Y	Y	Y	Y
Income × Quarter FE	Y	Y	Y	Y
Credit Score × Quarter FE	Y	Y	Y	Y
Loan Amount × Quarter FE		Y	Y	Y
Maturity × Quarter FE			Y	Y
LTV × Quarter FE				Y
N	1,973,067	1,973,067	1,973,067	1,973,067
R^2	0.70	0.71	0.72	0.73

NOTE.—This table reports coefficient estimates from Equation 2. The dependent variable is the interest rate. The sample is restricted to auto loans originated between January 2017 and December 2018. In Column (1), we re-estimate our baseline model used throughout the paper. In Column (2), we include separate origination quarter fixed effects for loan amount buckets. In Column (3), we include separate origination quarter fixed effects for loan maturity buckets. In Column (4), we include separate origination quarter fixed effects for LTV buckets. Vehicle fixed effects refer to vehicle make-model-condition combinations. Loan amount fixed effects refer to loan amount deciles. Maturity fixed effects refer to maturity deciles. LTV fixed effects refer to LTV deciles. t-statistics, presented below the coefficient estimates, are calculated by clustering at the lender level. Statistical significance at the 10%, 5%, and 1% levels is denoted by *, **, and ***, respectively.

Table IA.24: Reincluding Removed Lenders

Panel A: Reincluding all Removed Lenders Except for Hyundai

	Interest Rate (1)	Loan Amount (2)	Loan Maturity (3)	Loan-to-Value (4)
Treated × Post	0.267**	-0.005	-0.011***	-0.007*
	(2.31)	(-0.88)	(-5.13)	(-1.86)
Lender FE	Y	Y	Y	Y
Vehicle × Quarter FE	Y	Y	Y	Y
State × Quarter FE	Y	Y	Y	Y
Income × Quarter FE	Y	Y	Y	Y
Credit Score × Quarter FE	Y	Y	Y	Y
N	2,351,905	2,351,905	2,351,905	2,351,905
R^2	0.68	0.54	0.19	0.20

Panel B: Reincluding all Removed Lenders Including Hyundai

	Interest Rate (1)	Loan Amount (2)	Loan Maturity (3)	Loan-to-Value (4)
Treated × Post	0.206*	0.002	-0.009***	-0.002
	(1.81)	(0.63)	(-3.48)	(-0.59)
Lender FE	Y	Y	Y	Y
Vehicle × Quarter FE	Y	Y	Y	Y
State × Quarter FE	Y	Y	Y	Y
Income × Quarter FE	Y	Y	Y	Y
Credit Score × Quarter FE	Y	Y	Y	Y
N	2,351,905	2,351,905	2,351,905	2,351,905
R^2	0.68	0.54	0.19	0.20

NOTE.—This table reports coefficient estimates from Equation 2 after adjusting the sample of lenders. The dependent variable is either the interest rate, log loan amount, log loan maturity, or loan-to-value ratio. The sample is restricted to auto loans originated between January 2017 and December 2018. In Panel A, we reinclude all removed lenders from Section 3.2 except for Hyundai, which has its own integrated steel manufacturer. In Panel B, we also reinclude Hyundai in the sample. Among the five reincluded lenders, Harley Davidson, Hyundai, Nissan are classified as treated lenders. Capital One and California Republic are classified as control lenders. t-statistics, presented below the coefficient estimates, are calculated by clustering at the lender level. Statistical significance at the 10%, 5%, and 1% levels is denoted by *, **, and ***, respectively.

Table IA.25: Placebo Analyses Between 2015 and 2017

	Interest Rate (1)	Interest Rate (2)	Interest Rate (3)	Interest Rate (4)
Treated × Post 2017	-0.076	0.053	-0.201	-0.074
	(-0.56)	(0.70)	(-1.31)	(-0.86)
Placebo Period	2016-2017	2016-2017	2015-2017	2015-2017
Excluding Subvented Loans?		Y		Y
Lender FE	Y	Y	Y	Y
Vehicle × Quarter FE	Y	Y	Y	Y
State × Quarter FE	Y	Y	Y	Y
Income × Quarter FE	Y	Y	Y	Y
Credit Score × Quarter FE	Y	Y	Y	Y
N	1,689,948	663,615	2,054,008	805,627
R^2	0.71	0.68	0.7	0.68

NOTE.—This table reports coefficient estimates from Equation 2 for placebo samples of loans originated between 2016-2017 (columns 1 and 2) and 2015-2017 (columns 3 and 4). The Post 2017_t variable is equal to one for all quarters t after January 2017, and zero otherwise. Columns 1 and 3 report coefficient estimates for all loans. Columns 2 and 4 report coefficient estimates after excluding subvented loans from the sample. Vehicle fixed effects refer to vehicle make-model-condition combinations. t-statistics, presented below the coefficient estimates, are calculated by clustering at the lender level. Statistical significance at the 10%, 5%, and 1% levels is denoted by *, **, and ***, respectively.

Table IA.26: Vehicle Choices

Panel A: Dollar Vehicle Value

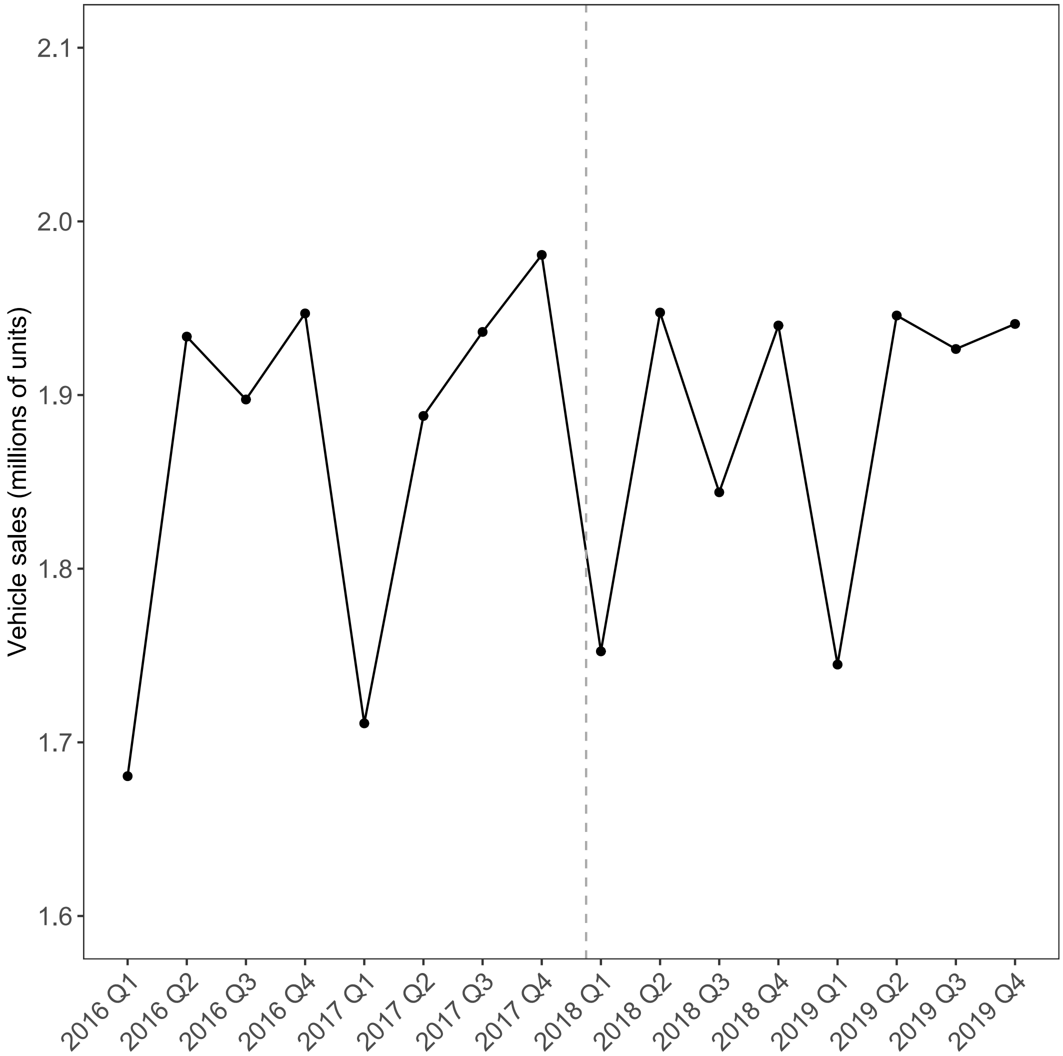
	All Vehicles		New Vehicles		Used Vehicles	
	(1)	(2)	(3)	(4)	(5)	(6)
Treated × Post	72.300	-359.562	549.868	-174.072	-98.380	-252.723
	(0.13)	(-1.13)	(0.73)	(-0.34)	(-0.27)	(-0.78)
Lender FE	Y	Y	Y	Y	Y	Y
Condition × Quarter FE	Y					
Condition × Type × Quarter FE		Y				
Type × Quarter FE				Y		Y
State × Quarter FE	Y	Y	Y	Y	Y	Y
Income × Quarter FE	Y	Y	Y	Y	Y	Y
Credit Score × Quarter FE	Y	Y	Y	Y	Y	Y
N	1,973,639	1,973,634	1,290,119	1,290,116	683,520	683,518
R^2	0.47	0.59	0.35	0.52	0.26	0.39

Panel B: Log Vehicle Value

	All Vehicles		New Vehicles		Used Vehicles	
	(1)	(2)	(3)	(4)	(5)	(6)
Treated × Post	0.005	-0.012	0.017	-0.007	-0.003	-0.011
	(0.26)	(-1.15)	(0.69)	(-0.41)	(-0.19)	(-0.75)
Lender FE	Y	Y	Y	Y	Y	Y
Condition × Quarter FE	Y					
Condition× Type × Quarter FE		Y				
Type × Quarter FE				Y		Y
State × Quarter FE	Y	Y	Y	Y	Y	Y
Income × Quarter FE	Y	Y	Y	Y	Y	Y
Credit Score × Quarter FE	Y	Y	Y	Y	Y	Y
N	1,973,639	1,973,634	1,290,119	1,290,116	683,520	683,518
R^2	0.49	0.63	0.34	0.54	0.24	0.41

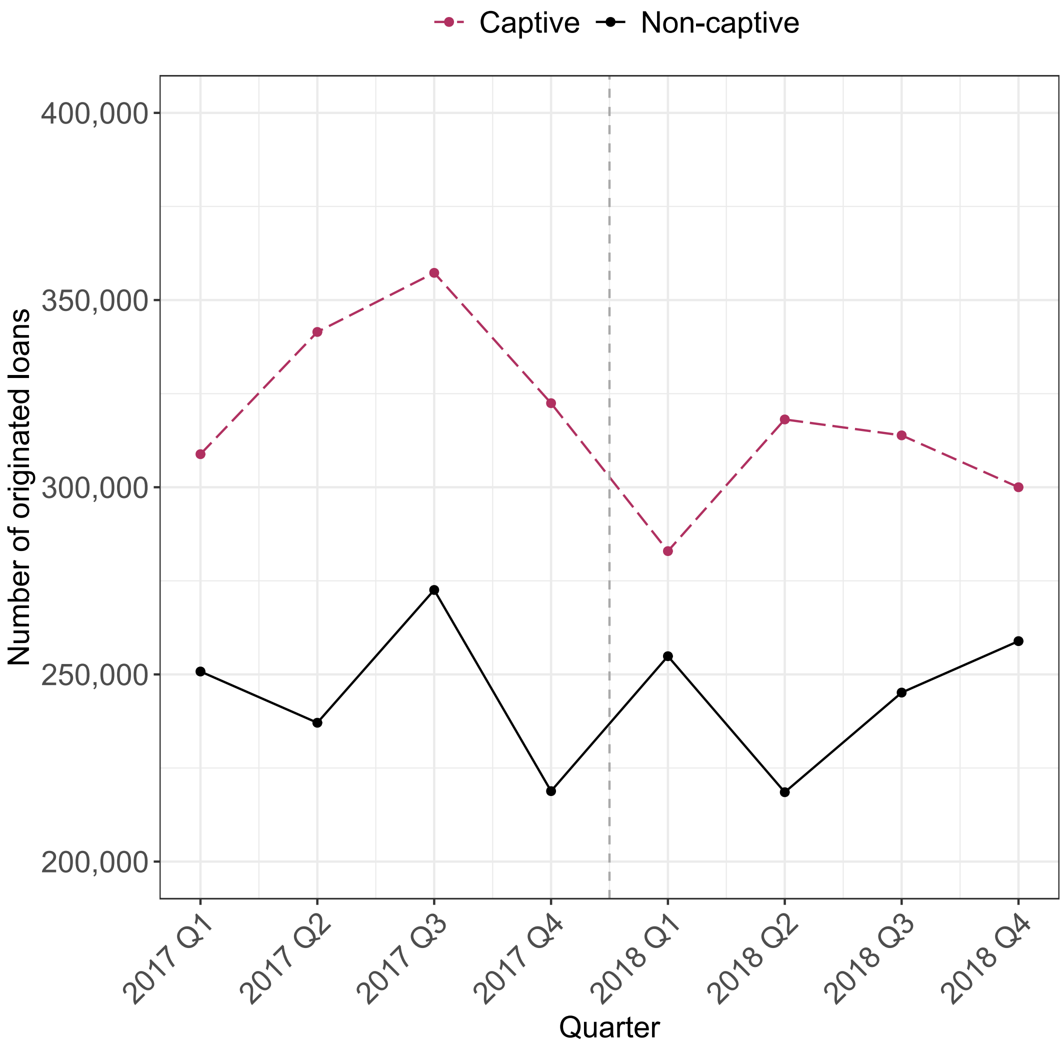
NOTE.—This table reports coefficient estimates from Equation 2 after removing the vehicle make-model-condition × origination quarter fixed effects. The dependent variable is either the assessed vehicle value in Panel A or the natural log of the assessed vehicle in Panel B. The sample is restricted to auto loans originated between January 2017 and December 2018. In columns 3 and 4, the sample is restricted to loans for new vehicles. In columns 5 and 6, the sample is restricted to loans for used vehicles. Column 1 includes vehicle condition × origination quarter fixed effects to examine substitution within new and used vehicles. Column 2 includes vehicle condition × type (i.e., truck, SUV, or sedan) × origination quarter fixed effects to examine substitution within new and used vehicles for a particular type. Column 4 and 6 includes type fixed effects to examine substitution within new vehicles and types and used vehicles and types, respectively. t-statistics, presented below the coefficient estimates, are calculated by clustering at the lender level. Statistical significance at the 10%, 5%, and 1% levels is denoted by *, **, and ***, respectively.

Figure IA.1: Time Series of Vehicle Sales



NOTE.——This figure plots the number of vehicles sold in the U.S. between January 2017 and December 2018 for BMW, Ford, General Motors, Honda, Mercedes-Benz, and Volkswagen. For each manufacturer, we include all its affiliated brands in its sales total (e.g., we include both Acura and Honda sales for Honda).

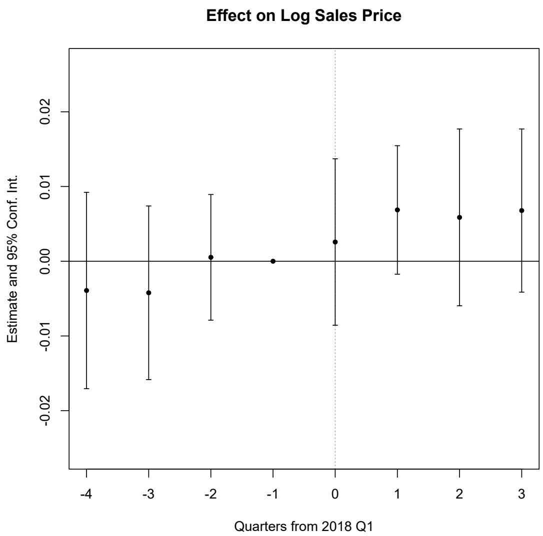
Figure IA.2: Securitization Volumes for Captive and Non-Captive Lenders



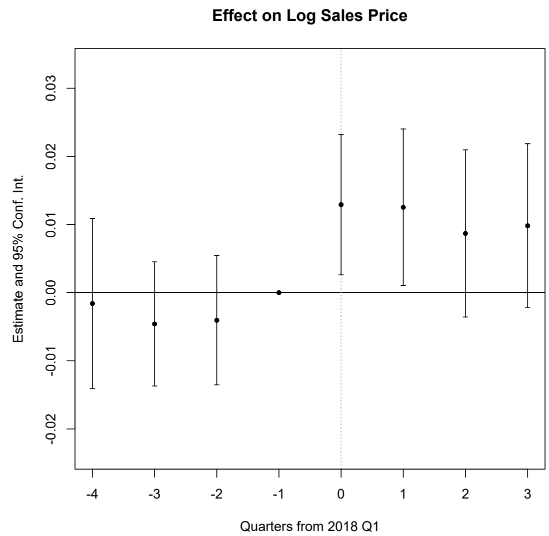
NOTE.——This figure plots securitization volumes, measured in terms of the number of loans originated each quarter that were later securitized, for captive lenders (red) and non-captive lenders (black).

Figure IA.3: Vehicle Invoice and Sales Prices

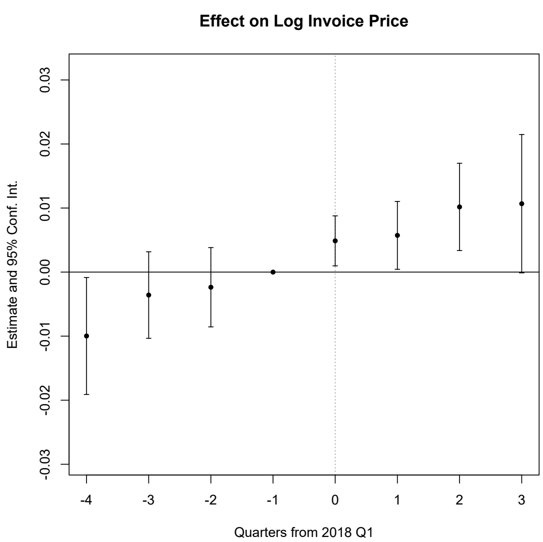
(a) Sales Price with Make Treatment



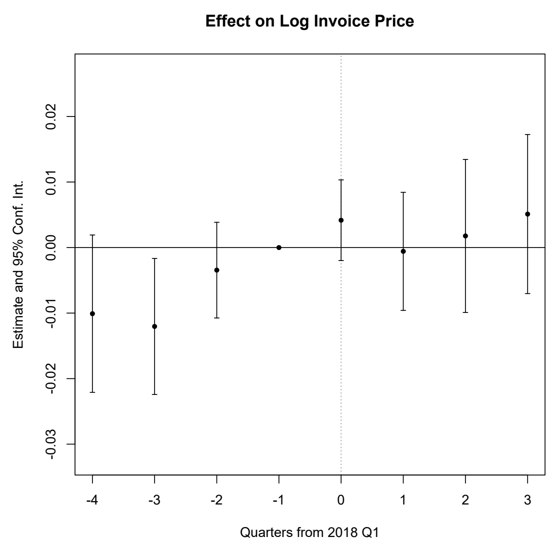
(b) Sales Price with Make-Model Treatment



(c) Invoice Price with Make Treatment



(d) Invoice Price with Make-Model Treatment

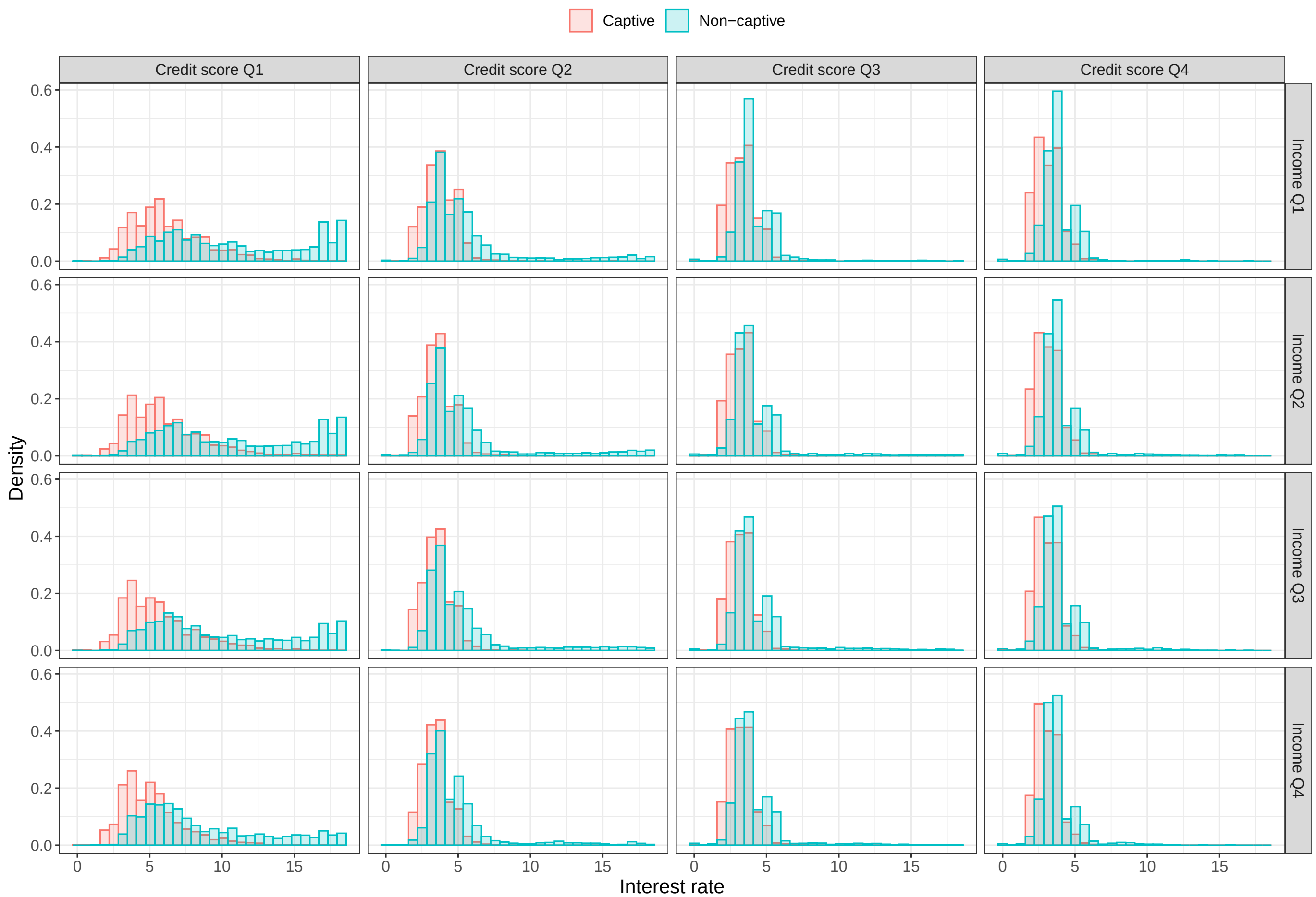


NOTE.——This figure plots coefficient estimates from Equation 6. The dependent variable is either the log sales price or log invoice price. The x-axis corresponds to the number of quarters from the treatment date. The quarter $\tau = -1$ is the reference quarter. The circles correspond to the coefficient estimates, and the vertical bars correspond to 95 percent confidence intervals. The sample and variable definitions are the same as in Table 6. Standard errors are clustered by either vehicle makes (Panels A and C) or make-models (Panels B and D).

Figure IA.4: Distribution of Non-Subvented Interest Rates for Used Vehicles

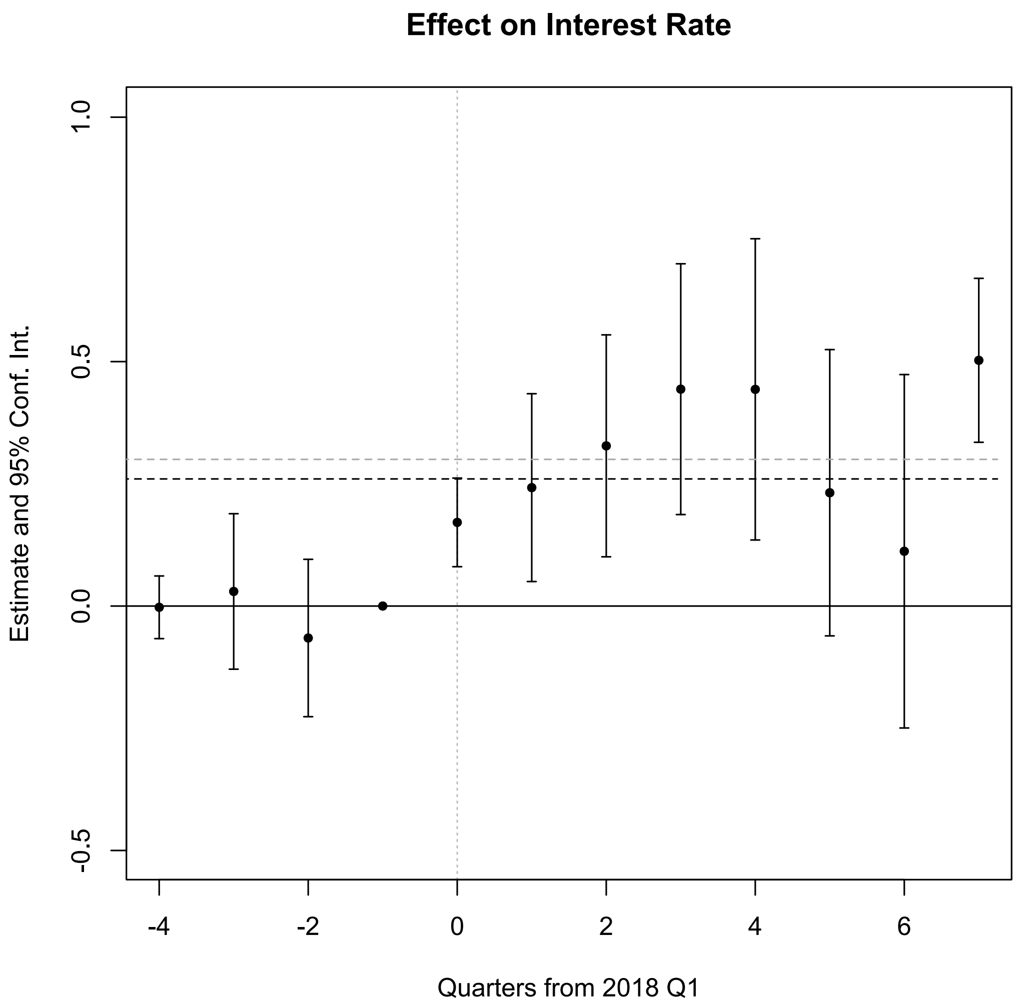
NOTE.——This figure plots the distribution of non-subvented captive interest rates (red) and non-captive interest rates (blue) for used vehicles. The sample is restricted to non-subvented used vehicle loans that were originated during the pre-treatment period of January 2017 to December 2017. The columns correspond to quartiles of the credit score distribution, and the rows correspond to quartiles of the income distribution. Each panel depicts the interest rate distribution for a particular credit score quartile × income quartile combination.

Figure IA.5: Distribution of Non-Subvented Interest Rates for New Vehicles



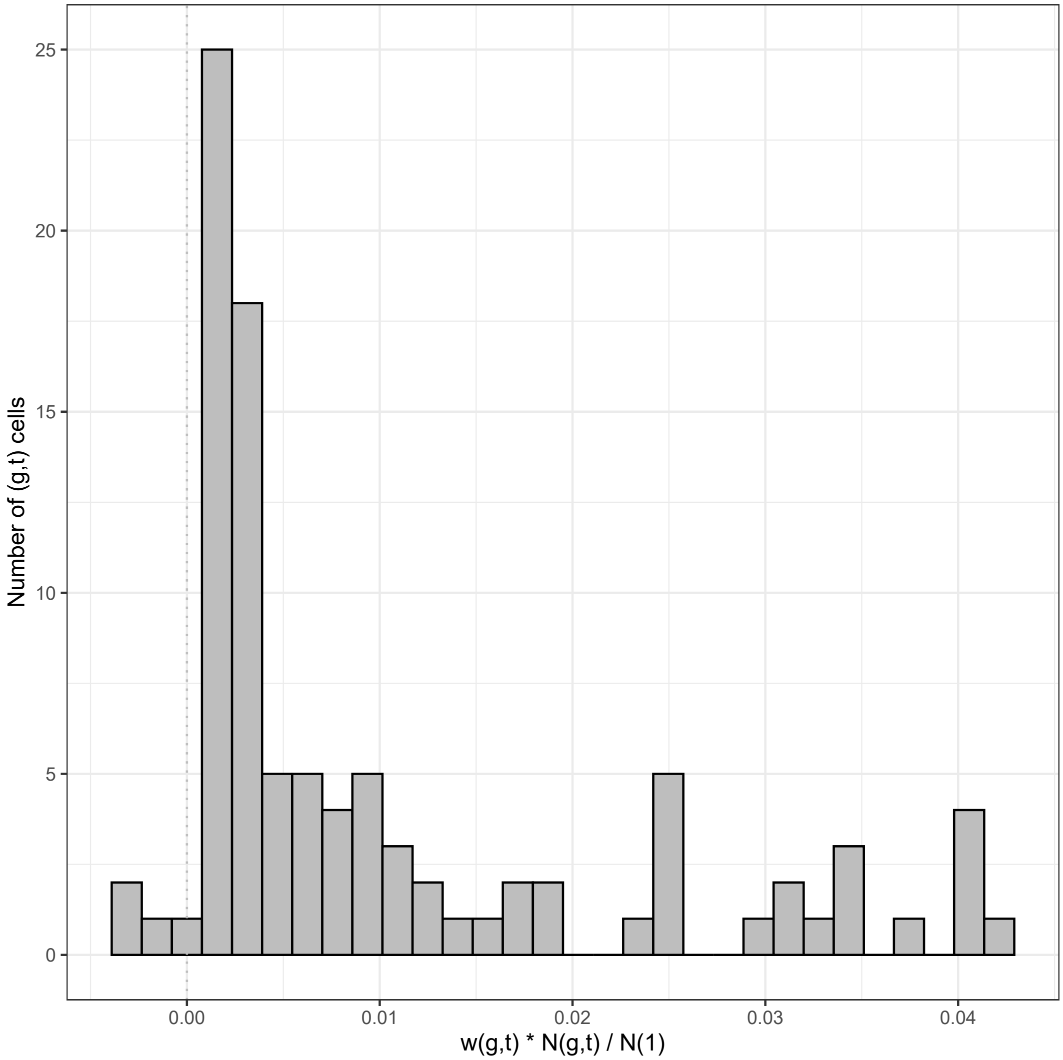
NOTE.——This figure plots the distribution of non-subvented captive interest rates (red) and non-captive interest rates (blue) for new vehicles. The sample is restricted to non-subvented new vehicle loans that were originated during the pre-treatment period of January 2017 to December 2017. The columns correspond to quartiles of the credit score distribution, and the rows correspond to quartiles of the income distribution. Each panel depicts the interest rate distribution for a particular credit score quartile × income quartile combination.

Figure IA.6: Long-Run Effect on Interest Rates



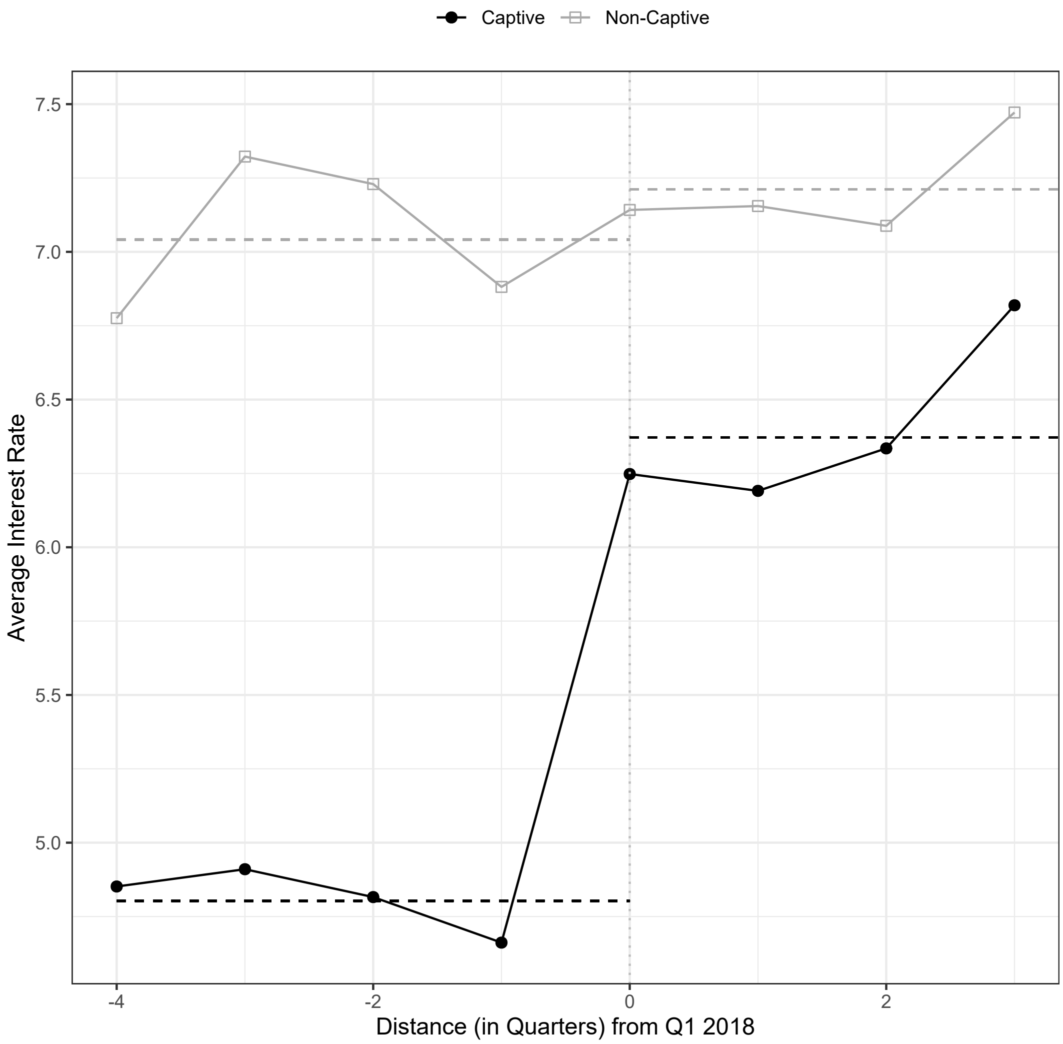
NOTE.——This figure plots coefficient estimates from Equation 3 after extending the sample period to Q4 2019. The dependent variable is the interest rate. The x-axis corresponds to the number of quarters from the treatment date. The quarter $\tau = -1$ is the reference quarter. The circles correspond to the coefficient estimates, and the vertical bars correspond to 95 percent confidence intervals. The dashed black line corresponds to our baseline difference-in-differences estimate of 26 basis points from Table 3. The gray dashed line corresponds to 30 basis points, which is the estimate we arrive at when we re-estimate our baseline difference-in-differences model on the extended sample period. The sample is restricted to auto loans originated between January 2017 and December 2019 that do not have subsidized financing. Standard errors are clustered at the lender level.

Figure IA.7: Weights Used to Construct Difference-in-Differences Estimate



NOTE.——This figure plots the histogram of group-time weights used to construct our baseline difference-in-differences estimates. Groups are defined in terms of lenders, and time is defined in terms of origination months. For more details on this procedure, see de Chaisemartin and D'Haultfoeuille 2020.

Figure IA.8: Average Captive and Non-Captive Interest Rates



NOTE.——This figure plots the average captive and non-captive interest rates during the sample period. The sample is restricted to non-subvented loans that were originated between January 2017 to December 2018. The dashed horizontal lines to the left of zero correspond to average captive and non-captive interest rates during 2017. The dashed horizontal lines to the right of zero correspond to average captive and non-captive interest rates during 2018.