Auto Finance, Credit Risk, and Electric Vehicles*

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Abstract

One-seventh of household expenditures are from transportation, mostly auto operating and financing commitments made at vehicle purchases. Choosing an EV implies better ongoing financial health from lower credit risk (positive selection) and lower risk of fuel costs shocks (operating treatment). EV loans default one-third less, and lenders price this lower credit risk with 0.87% lower interest rates. Twenty percent of the better financial health emerges from operating costs, both expected ex ante and arriving ex post as energy price shocks in a Borusyak-Hull-Jaravel (2021) 'shift-share'. Commitments from engine choice affect household financial health at a scale that impacts the macroeconomy.

Keywords: Credit risk, Consumer finance, Auto loans, Electric vehicles, Captive auto lenders, Total cost of vehicle ownership, Gasoline price shocks, Shift share

JEL: G51, G23, R41

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1 Introduction

Rarely discussed is the extent to which the financial health of U.S. households—and therefore the U.S. macroeconomy—is tied to transportation expenses. Transportation comprises 13.8% of monthly spending for a representative household according to Bertrand and Morse (2016). The lion's share of this spending comes from autos, given that 92% of households possess at least one personal vehicle.[1] Auto operating expenses (maintenance, insurance, and fuel) and auto financing costs (depreciation and interest) are material to most households' financial health. According to the American Automobile Association's (AAA) "Your Driving Costs" study, annual operating expenses not including financing and depreciation for a 2023 new car are projected to be $6,341; the total with the $5,791 in depreciation and financing costs is $12,132.[2] Over 80% of new vehicles use finance.[3] Cross-sectionally, as of 2025, the average outstanding auto loan balance is over $16,000, calculated from 100 million auto loans, totaling near $1.7 trillion.[4] Given how significant auto operating and auto financing expenses are, any shift in the financial exposures and credit risk surrounding auto ownership would be material to households and the broader economy.[5]

In this paper, we explore the implications of the electric vehicle (EV) transition on household's financial health and financial exposures. Most auto-related costs are both predictable and reflect long-term financial commitments set at the time of purchases. These costs vary with vehicle choice; as a result, households' auto decisions shape recurring auto-related expenses and, in turn, their long-term financial health and vulnerability to distress. Hence, if EV ownership has different implications for ongoing financial exposures, the transition might have material impacts on the financial health of households and the economy.

A starting point might be the possibility that the characteristics of EVs and their owners could differ in a way that matters for credit risk. For instance, the choice of an engine may proxy for household behavior, income risk, or home ownership. More directly, a household making an EV choice may be also making an different financial commitment in expected operating expenses reflective of his or her financial condition. This selection may lead to Stiglitz and Weiss (1981) revisions of credit risk and pricing. If lenders pass any positive price of credit risk back to households,

[1] https://www.experian.com/blogs/ask-experian/research/auto-loan-debt-study/

[2] https://newsroom.aaa.com/wp-content/uploads/2023/08/YDC-Fact-Sheet-FINAL-8.30.23-1.pdf

[3] Federal Reserve Bank of New York Household and Debt Report, Q3 2025. Retrieved Jan. 8, 2026, https://www.newyorkfed.org/medialibrary/interactives/householdcredit/data/pdf/HHDC_2025Q3.

[4] https://www.autoinsurance.com/research/car-ownership-statistics/

[5] See, for example, Eberly (1994), Attanasio, Goldberg, and Kyriazidou (2008); Adams, Einav, and Levin (2009); Einav, Jenkins, and Levin (2012); Hausman (1979); Benmelech, Meisenzahl, and Ramcharan (2016); Busse, Knittel, and Zettelmeyer (2013); Argyle, Palmer, and Nadauld (2020); and Dinerstein, Yannelis, and Chen (2024).

lower credit risk may have implications for transport consumption decisions, a topic of interest to industry and policymakers.[6]

The characteristics of vehicle engines may also affect the ongoing link between auto ownership and household distress avoidance, over and above any ex ante profiling and expected operating costs. Debt balances and their respective payment streams carry distress implications, a topic studied in, for instance, recent work by Benetton, Mayordomo, and Paravisini (2025). Depreciation risks (and the implications for car equity) are the topic of Bena, Bian, and Tang (2024) and Schloter (2022).

EV ownership may also imply different exposures to auto expense shocks. One of our main insights concerns the possibility that fuel cost exposures may be materially different for EV and ICEV owners, spilling over to financial distress and credit risk implications. On this front, credit risk realizations offer a window into understanding the characteristics of the 'treatment' of running an EV or ICEV.

To explore how EV ownership interacts with household finance, we gather data from ABS-EE filings with the Securities and Exchange Commission (SEC). Our main data covers 84 million monthly observations of auto loan performance in a panel covering over 4 million loans in the United States from 2017 to mid-2023.

After adjusting only for macroeconomic time, we find that EV borrowers default (experience 60-day delinquencies) by 0.149 percentage points less monthly relative to ICEV borrowers. This magnitude is material relative to the mean ICEV default rate of 0.201 percent. In dollar terms, we estimate that this -0.149 percentage points default difference is worth $2,776 in payments. These magnitudes of lower default by EV borrowers serve as our baseline. Off this baseline, our empirical analysis studies (i) immediate financial implications at the initial auto financing arising from positive selection on engine type and (ii) ongoing financial commitment implications for EV-versus-ICEV ownership.

To first study positive selection as the cause of default differentials, we introduce the standard variables used in underwriting auto loans: credit score, payment-to-income ratio, loan-to-value ratio, and income. Because of the speed in the auto loan process at the point of sale, these are likely close to the full set of profiling variables in loan approval and pricing, beyond the car model, origination date, and the loan term requested. These underwriting variables explain 53% of the -0.149 percentage points raw difference in monthly default. However, EV borrowers still default by

[6] In the total cost of ownership literature, the cost metrics typically cover EV versus ICEV distinctions related to tax credits, fuel cost, driving distances, maintenance, and the value of EVs for resale (Parker et al. (2021), Schloter (2022), and Danielis et al. (2020)), without reference to financing costs differentials.

-0.0695 percentage points less monthly than ICEVs. In percentage change, EVs default by a third less than ICEVs.

To explore positive selection by borrowers beyond the underwriting variables, we consider selection on operating costs. Borrowers may calibrate their vehicle choice on ex ante expected operating costs or the volatility of expected costs. Using U.S. Environmental Protection Agency (EPA) and Kelly Blue Book data, we calculate the time-varying expected cost of ownership, known at origination. We find that households act rationally, and take expected costs into account. This action accounts for an additional 9% of the variation of EV and ICEV defaults.

Importantly, lenders may recognize that engine choices reflect credit risk-relevant unobservables such as home ownership, tastes, driving patterns, and employment sources. Thus lenders may train algorithmic pricing models using historical default data that use engine as a proxy for unobservables. Thus, we create a price-implied measure of credit risk. This involves estimating the EV effect on interest rates, controlling for underwriting observables, time, car value, loan attributes, and macroeconomic time. In doing so, we find that conditional on observables, EV loans carry rates that are 2.3 percentage points lower than those on ICEV loans. Yet, many of the lenders are captive lenders (related to manufacturers), which may use different pricing incentives for EVs. For example, the EV sticker price could have a higher embedded margin, to be met with greater incentives in interest rate subsidies and cash back promotions.[7] Thus, for our calculation of price-implied credit risk, we focus on non-captive lenders. We find that non-captive lenders provide EV borrowers with interest rates that are 0.87 percentage points lower than ICEV rates, all else equal. In dollar terms, 0.87 percentage points is worth $981 in saved amortization streams for the mean EV loan.

Using the price-implied credit risk, calculated specifically at a point in time and within a credit worthiness bucket, we re-estimate our default specification. The inclusion of price-implied risk, which is a significant predictor of default, reduces the EV coefficient to -0.0531 percentage point and accounts for an additional 11 percent of the EV effect on default.

Despite chipping away at positive selection in our analysis, some residual unexplained credit risk favors EV ownership. In the second main agenda of the paper, we seek to ascribe this value difference from realized credit risk savings to treatment effects of owning an EV. Specifically, we study whether EVs may insulate borrowers from gasoline price shocks. We follow Acemoglu, Autor, and Lyle

[7]This strategy is analogous to the role of financing in other contexts: For example, Hankins, Momeni, and Sovich (2022) show how automakers pass through cost shocks from tariffs to consumers via auto financing terms. As we discuss in the text, U.S. automakers may have incentives to use the mechanism of interest rates to encourage volume tax credit legislation, fund the development and acceptance of a new technology, and remain sticker price adaptive.

(2004) and use a continuous variable version of a difference-in-difference, appealing to identification of a differential shock exposure by treatment (a shift-share style estimation) of Borusyak, Hull, and Jaravel (2021) and Bartik (1991). Following the literature on gasoline prices and demand for fuel-efficient cars, our differential shock is the gasoline price level, which exposes only the control group—ICEV owners—to a cost pressure on default.[8] We implement the shock both at the national gasoline price level and at the regional level. Importantly, for the regional specification, we control for year-month fixed effects and hence identify effects from regional differences in gasoline prices.

We find that the treatment effect of EV ownership insulates borrowers from energy price shocks, leading to lower delinquency rates. This result is robust to stringent specifications that exploit fine regional variation in gasoline prices. Quantitatively, our estimates imply that a $1.00 increase in regional gasoline prices is associated with a 0.02 percentage point reduction in 60-day delinquency rates for EV and hybrid loans, corresponding to roughly a 10 percent decline relative to the mean delinquency rate of 0.201 percent. These magnitudes suggest that reduced exposure to unexpected high levels of gasoline prices and volatility can meaningfully improve household financial health outcomes.

A potential concern for a causal interpretation is that engine type may be correlated with households' broader financial resilience through channels other than gasoline costs. To address this concern, we augment our baseline specification with interactions between EV ownership and alternative measures of household financial stress and examine whether these interactions materially affect our main estimates.

We consider four such stress variables: local median income, local unemployment, and two measures of local utility costs that capture weather-driven variation in heating and cooling needs. These variables are designed to proxy for household financial pressure that could plausibly interact with vehicle choice in the way a potential confounder might drive our shift-share results. Under our identification assumption, if EV choice does not proxy for other exposure or resilience attributes, we would expect the coefficient on the interaction on the financial stress variables with EV not to be significant.

We find this to be the case for employment and utilities costs. While we find that the interaction between EV ownership and local income is statistically significant, its opposite sign and magnitude, together with the stability of the EV–gasoline price interaction, suggest that our baseline estimates

[8]For instance, Li, Timmins, and Von Haefen (2009), Klier and Linn (2010), and Beresteanu and Li (2011) study how gasoline prices (and federal tax credit) lead to higher demand for fuel-efficient cars.

are conservative. Furthermore, the inclusion of these interactions does not attenuate the estimated effect of gasoline prices on EV borrowers. Overall, we find no evidence that EV ownership proxies for unobserved resilience unrelated to fuel costs, and the results remain consistent with a causal interpretation in which EV ownership mitigates exposure to gasoline price shocks and reduces credit risk. It is worth noting that this treatment effect—insulation from gasoline price shocks—points to a potentially novel dimension of credit risk heterogeneity that may not be fully captured by existing risk assessment frameworks, with possible implications for how lenders and policymakers evaluate household vulnerability to energy price volatility.

The final section of the paper addresses two additional layers of robustness. First, we reconcile our results with those of Bena, Bian, and Tang (2024) ("BBT").[9] We show that their finding of higher interest rates for EV loans is driven primarily by their inclusion of a subsidy dummy, the pooling of EVs with hybrids, and the use of car-body fixed effects. While the latter is appropriate for their question—isolating depreciation effects across engines—it imposes a counterfactual that EV buyers would otherwise purchase the same vehicle with a different engine, which is less suitable for our setting given systematic differences in borrower characteristics. Second, we seek validation in the auto asset-backed securities (ABS) market, where a large share of auto loans are securitized. If lenders pass through credit risk discounts to EV borrowers, these should also be reflected in ABS pricing. Mapping our loan-level data to auto ABS pools, we find no effect of EV share on ABS spreads, but we do find that credit support reserves are lower when pools have higher EV exposure, contributing to the growing literature on EV securitization alongside Latino, Pelizzon, and Riedel (2024).

The paper is largely focused on the household finance implications of engine type on credit risk. We make a contribution alongside that of Bena, Bian, and Tang (2024) and also to the total cost of vehicle ownership literature (Parker et al. (2021), Schloter (2022), and Danielis et al. (2020)). The question of the pricing pass-through additionally allows our research to contribute to the study of economic transitions, which create opportunities and disruptions where some parties gain, and others lose. Consider for example, the term 'robber baron' and its applications to the new railroad and electrification monopolies in the 19th century. The rents from these transitions were captured by a few disrupters. Yet, at other times, the distribution of rents can support the transition. This

[9]These authors study differing technological risk for EVs versus ICEVs, which affects financing costs via rates of depreciation. They find evidence of higher rates for EV borrowers, consistent with a story of technology risk arising from owning the first generation of new engines. Our paper differs from their specifications in that we level borrowers on credit risk profiles rather than on engines and find the opposite sign on pricing. Yet, the technology channel through depreciation risk is important, with depreciation evidence also documented by Schloter (2022).

was the case after the Bubonic Plague in the 14th century, where disruptions caused labor capture of rents and reinforced labor-saving innovations.[10] Finance is one of the channels through which reinforcing distributions of gains and losses can occur.

Another strand of literature to which our study contributes is the auto lending topic more generally. For example, Adams, Einav, and Levin (2009) and Einav, Jenkins, and Levin (2012) study adverse selection, risk-based pricing, and loan contracts in the subprime auto loan market. Butler, Mayer, and Weston (2022) document significant, unexplained racial biases in auto lending, that are mitigated by regulatory efforts and worsen when those efforts subside. Auto consumption has also been approached from the choice problem on durables. For example, Hausman (1979) and Busse, Knittel, and Zettelmeyer (2013) study consumer decision encompassing the up-front capital cost and the later operating costs of fuel-efficient household appliances. However, relatively less emphasis has been placed on the ability of auto lending to promote innovation, including technology related to the energy transition.

With regard to EVs, many researchers have focused on studying government actions including subsidies and taxation.[11] Muehlegger and Rapson (2022) find that price elasticity for EVs is high especially for middle- to low-income households and these households capture most of the subsidies. Knittel (2011) finds that U.S. automakers could have substantially improved fuel economy if they did not allocate as much resources to improve other vehicle attributes such as engine power from 1980 to 2006 amid a lack of government incentives. And while subsidies are critical, even taxation can promote innovation: Martinsson, Stromberg, and Thomann (2024) find that carbon taxes forced trucking fleet operators to be more efficient when fuel prices increased.

2 Data

Our primary data source is SEC form ABS-EE. It is the required disclosure form for public offerings of auto ABS under SEC Regulation AB II, effective November 23, 2016. These data comprise the population of auto loans which pool into publicly-placed auto ABS.[12] The data contains rich loan-level information including borrower, collateral, and loan characteristics as of loan origination. The data also track information on monthly loan performance through the life of the loan.

[10] See Jedwab, Johnson, and Koyama (2022) for related literature.

[11] See Hall and Lerner (2010) for a comprehensive review on the literature.

[12] These data have been used by recent studies including Klee and Shin (2020) to identify asymmetric information in auto ABS, Bakshi and Rose (2021) to explore the effect of forbearance on auto loan defaults during the pandemic, and Kontz (2023) to study pass-through of ESG convenience yield to consumers.

We apply several filters. We focus on loans for new cars to minimize potential unobserved information associated with used cars. We limit borrowers to those with a prime credit score above 620, due to the paucity of subprime EV borrowers in our data. We drop outlier observations for borrowers with reported monthly income below $1,500 or above $83,333, to remove individuals with extreme income, data errors or missing other income sources. Finally, we limit our sample to loans with terms greater than or equal to 6 years, the most common term (Katcher et al. (2024)), to reflect the common underwriting practice of implementing different credit risk models by loan term.[13] Our final sample covers over 85 million performance time observations on around 4 million auto loans on passenger cars, trucks, and SUVs, from January 2017 to July 2023.

2.1 Classification by Engine Type

We construct a make-model-year taxonomy to assign vehicles to one of three categories: EVs, hybrid vehicles, or ICEVs. We hand-construct engine type classifiers using information from the U.S. Department of Energy and the Environmental Protection Agency (EPA) on EVs and hybrids in various model years and then develop full attribution with manufacturer and model names found in Car and Driver magazine, Kelley Bluebook, and Google searches.[14] We condition our classification on the model year to accommodate cases in which a manufacturer introduces EV or hybrid technology without changing the model name. We also search for relevant strings that indicate for EVs or hybrids in model names, such as "HV," "PLUG-IN," "EV," and "E-." Together, we identify 113 hybrid models and 29 electric models among 4,734 model names in our final data set. Throughout our sample period, the share of vehicles flagged as hybrid or electric is around 5 percent of all loans and trends up over time (see Internet Appendix B Table B1 for more detailed summary statistics on the proportion of vehicles flagged as hybrid or electric.) Internet Appendix C provides details on the list of hybrid cars and EVs based on our classification.

2.2 Vehicle and Loan Characteristics

Based on engine type classification, we gather information on vehicle values and other loan characteristics. Table 1 Panel A reports summary statistics. Vehicle value averages around $35,000, in line

[13] Credit models typically differ by term to reflect consumers' targeting of monthly payments (Hertzberg, Liberman, and Paravisini (2018) and Argyle, Palmer, and Nadauld (2020)), planned down payment amount (Einav, Jenkins, and Levin (2012)) and monthly budget-minded constraints (Bertrand and Morse (2011)).

[14] See https://www.fueleconomy.gov/ for more information.

with the reported average of new car prices over our sample period.[15] The average hybrid vehicle is slightly more expensive than ICEVs, while EVs are materially more expensive than ICEVs, with a $6,000 difference at the mean.[16]

Turning to loan characteristics, loan amounts average $34,457 for ICEVs, $35,941 for hybrids, and $38,537 for EVs. EV loan terms are on average one month shorter than ICEV loans. Even so, EV monthly payments are lower than for ICEVs or hybrids, as EV loans generally carry lower interest rates and loan-to-value (LTV) ratios (i.e., higher down payments).

The majority of loans in our sample were originated by captive lenders. Captive financing is a mechanism for manufacturers to close auto sales, where salespeople seal deals by offering subsidies such as lower financing rates or cash discounts on the sticker price. Such subsidies are called subvents or "subventing the deal." Subvents are evident in loan terms, especially for EVs. EV loan interest rates are, on average, more than 2 percentage points lower than those for combustion engine loans (2.3 versus 4.9 percent).[17] In addition, cash back promotions are more frequent for EVs than for ICEVs (in 49.6 versus 37.8 percent of loans).[18]

2.3 Underwriting Variables

Auto loan underwriting is typically algorithmic, based on a standard, limited set of variables. The underwriting process is intentionally speedy, since the loan underwriting coincides with and holds up the completion of the car purchase. With speed as a priority, the lender pulls credit history and collects proof of income. The resulting standard underwriting variables include the borrower's credit score, income, LTV ratio, and payment-to-income (PTI) ratio.

Table 1 Panel B displays summary statistics for these underwriting variables. The average credit score for ICEV borrowers is 741, whereas that for EV borrowers is significantly higher, at 788. Average monthly income, derived from the reported payment-to-income ratio and monthly payment, is also materially higher for EV borrowers, $13,309 compared to $8,308 for ICEV borrowers. The average LTV at origination for EV loans is statistically lower on average (0.95) than

[15] See https://www.bts.gov/content/new-and-used-passenger-car-sales-and-leases-thousands-vehicles. The majority, 3.3 million, of our vehicle values are direct values. The residual are MSRP per detailed vehicle make.

[16] Tax credits may account for some of the differential. As of November 2024, federal tax credits up to $7,500 were available for both new and used EVs and plug-in hybrid electric vehicles under certain eligibility criteria.

[17] In other consumer finance products, lower interest rates might reflect "teaser rates" at loan origination to attract borrowers. However, this practice is not common in auto lending, and initial rates remain in place for the duration of the loan (Katcher et al., 2024). Consistent with this, the average loan interest rate at 13 months is almost identical to the average rate at origination.

[18] As with other credit dimensions, average rates on hybrid loans fall between EVs and ICEVs (3.7 percent). Interestingly, only 31% of hybrid vehicles receive cash back, possibly reflecting high demand for hybrid vehicles.

that for ICEV loans (1.01). Note that an LTV above 1.0 is not unusual, as vehicle purchases with financing can involve loan amounts being based on a price higher than sticker to include incidentals or to involve cash back incentives. We can also take into account the cash inflow from the tax credit to ensure robustness of results to a tax-adjusted LTV in underwriting. Thus, we report statistics for rebate-adjusted LTV, which makes the EV LTV higher than the LTV of ICEVs. PTI is lower for EV borrowers (0.062), compared to ICEV borrowers (0.087), driven by income differentials.

2.4 Operating Costs and Macroeconomic Variables

We collect data on the vehicle-specific expected cost of operating the vehicle, calculated at origination. These costs include expected retail gasoline price and electricity price, both calculated as the month-year price at origination and available by region from the U.S. Energy Information Administration (EIA).[19] Second, we gather costs arising from expected (at origination) other costs– depreciation, insurance, maintenance, repair, taxes, and fees—from Edmunds. These expectation values lead to our creating an Edmund-based projection of operating costs for the specific vehicle-month vintage.[20] All expected cost variables—other than the expected fuel cost which stays constant over vintage— dynamically vary over the life of the car but in a way that is still known ex ante.

As shown in Table 1 Panel C, the expected cost-to-income ratio for EV borrowers (7.7 percent) is significantly less than that for ICEV (15.7 percent) or hybrid borrowers (13.7 percent). Our sample ICEV mean is externally validated: data from the Bureau of Labor Statistics show that transportation expenses absorb around 16 percent of monthly income.[21] Table 2 Panel A shows the summary statistics of each component in these expected costs in the panel, reported in units of monthly dollars. The most important contributor to the EV-ICEV difference is the expected monthly fuel cost, which is twice as high for ICEVs ($133) than EVs ($63).[22] Expected monthly maintenance costs are also significantly higher for ICEVs ($87) than EVs ($51), driven by differing regular engine and transmission maintenance needs. Expected repair costs are higher for ICEVs

[19]For hybrid vehicles, we use the ratio of each model's gas to electricity usage from EPA. We match these data to our auto loan data based on state and year-month. Data from the EIA is grouped by seven regions including West Coast, Rocky Mountain, Midwest, New England, Central Atlantic, Lower Atlantic, and Gulf Coast.

[20]Because maintenance and depreciation costs are computed based on industry forecast models that only cover up to first five years of a car's life, we assume that all years thereafter have the same maintenance and depreciation costs as those of the fifth year.

[21]https://data.bts.gov/stories/s/Transportation-Economic-Trends-Transportation-Spen/ida7-k95k/. Transportation expenses are also highly inelastic to income shocks (Bertrand and Morse (2016)).

[22]We cannot construct a more granular estimate specific to a borrower's typical driving distance, as we do not observe the city or town in which borrower resides.

to a lesser extent. Conversely, expected depreciation cost, the largest component of total cost, is similar for ICEVs ($248) as to EVs ($247). As a proportion of car value, thus, EVs have lower expected depreciation, although realized depreciation could be different, in line with the technology risk evidence in Bena, Bian, and Tang (2024). Insurance cost, taxes, and fees are marginally higher for EVs than for ICEVs, due to generally higher EV prices.

Table 2 Panel B turns to summary statistics of various macroeconomic variables, including gasoline and electricity prices. Since our auto loan data indicate in which state the loan was originated, we match all macroeconomic variables based on state and year-month. In addition to fuel-related data sources mentioned above, we also use multiple sources to obtain other types of macroeconomic variables that have been shown to affect loan performance. Monthly unemployment rate data by state is from the Bureau of Labor Statistics and is seasonally adjusted. Data on annual median household income by state is from U.S. Census Bureau. Cooling degree days (HDD) and heating degree days (HDDs) are from the National Oceanic and Atmospheric Administration (NOAA) and these measure how much and for how many days the outside air temperature was above or below a certain base temperature. In our analysis, we use these measures to capture potentially significant income shocks for households through abrupt jumps in energy expenses.

3 Univariate Realized Credit Risk

Our key realized credit risk outcome is 60-day delinquency post the payment date, 90 days after invoice. We loosely refer to this as default. We use only the initiation into a delinquency to avoid double-counting during episodes of continuing delinquency. Thus, our estimation drops recurring default months until the borrower cures (if ever), at which point the borrower re-enters the dataset.

Table 2 Panel C shows the first univariate depiction of results. The 60-day delinquency likelihood at a monthly frequency is 0.201% for ICEVs, more than five times higher than 0.04% for EVs.[23] Figure 1 illustrates raw evidence of lower credit risk of EV borrowers relative to ICEV borrowers by plotting the realized cumulative delinquency rates for each month since origination by engine type. ICEVs and hybrids are shown up to 60 months and EVs are shown up to 48 months, to reflect the more recent origination density of observations. It is clear that there is a large and persistent difference in delinquency by engine type. Comparing results at the 24-month mark, the cumulative delinquency of loans on ICEV, hybrid vehicles, and EVs are 4.3%, 1.7%, and 1.0%, respectively.

[23] We also test for and confirm the robustness of all of our findings using 30-day delinquency. However, because this measure can contain noise from inattention, we use 60-day delinquency as our primary measure of credit risk.

At 48 months, these cumulative delinquencies further rise to 8.8%, 4.2%, and 1.7%, respectively.

As a second, monetized measure, we construct a missed payment ratio, defined as as the ratio of the difference between the monthly scheduled payment and the monthly realized payment to the monthly scheduled payment, cumulated to one observation per loan. The cumulative missed payment measure sidesteps the issue of repeat defaulters and episodes of default in an statistically clean way based on a few assumptions.[24] Table 1 Panel D provides payment ratio summary statistics. We consider two versions of this ratio—one calculated as principal only and the other with principal and interest, as the interest payment ratio proxies for the time value of money. The payment ratio results are consistent with those based on default incidence: EV borrowers are nearly 5 percentage points less likely to miss payments over the life of the loan, a statistically significant difference.

4 Empirical Analysis: Positive Selection

Our univariate results do not level borrowers on ex ante credit risk unrelated to engine choice. Engine choice may proxy for observable or unobservable positive selection. Our interest is not orthogonal to this positive selection and proceeds along three dimensions. First, we examine the extent to which standard underwriting captures the positive selection. Second, we analyze rational ex ante selection based on the expected costs of operating an EV versus ICEV. Third, we explore unobservable but known differential credit risk. In particular, lenders may know that EV buyers represent different credit risk than ICEV borrowers and price such risk differentials into loan contracts, even if the source of the differentials are unobserved. We call this price-implied risk.

4.1 Positive Selection on Underwriting Variables

Method. We begin by leveling loans on the risk characteristics used by underwriters to profile borrowers for credit risk. Consider an auto loan indexed by borrower i at loan aging of h months and calendar year-month of t. The underwriting variables model of credit risk analyzes realized

[24] First, we floor the ratio at zero if actual payments exceed scheduled payments. Some borrowers may be ahead on principal repayment, but will asymptote to zero. We include robustness in Internet Appendix B to exclude loans with no cumulative missed payment. Second, for purposes of economic magnitude, we assume that the missed payment ratio will reflect the final missed payment ratio achieved on average. This assumption will sometimes be aggressive in that some loans cure. This assumption will also sometimes be conservative in that some borrowers who are paying on time at the cumulation may later fall into distress. We have no reason to believe this assumption is biased, but caveat our inference accordingly. Third, note that we cannot limit our sample to loans for which we observe the entire payment history, since most EV loans are more recent than the six-year term.

credit risk, denoted with $default_{it}$ as follows:

$$default_{it} = \beta_0^{EV} EV_i + \Gamma_0^{Default} X_i + \mu_{t*h} + \mu_{state} + \mu_{term} + e_{it}. \quad (1)$$

The underwriting variables, denoted X_i, include credit score, LTV, log income, and PTI. We introduce these variables in linear form, as well as using piecewise linear splines to capture the possibility that credit risk may work on thresholds of risk with respect to the underwriter variables.[25] In addition, we control for the interaction of calendar year-month fixed effects with loan aging months in μ_{t*h}. Calendar time fixed effects for each origination year-month removes selection of engine type correlated with buying a car at certain points over the business cycle as well as overall macroeconomic conditions affecting all borrowers' ability to repay. Loan aging time refers to the number of months since loan origination and controls for "seasoning" patterns exhibited by auto loans (Kane, 2001). We also control for state fixed effects, μ_{state}, and loan term fixed effects (all terms are at least 72 months), μ_{term}.

Finally, the model includes an indicator for the engine type. We denote electric vehicles by EV_i. In the estimations, we also include a separate hybrid indicator. Our parameter of interest, β_0^{EV}, captures the differential default for an EV loan, holding constant underwriting profiles and macroeconomic time crossed with aging fixed effects.

Results. Table 3 Column (1) presents the raw results of default by engine type once the macroeconomy is taken into account, mimicking the univariate result displayed in Figure 1. Our dependent variable is the 60-day delinquency, and we report estimates in percentage points, multiplying by 100.[26] We find that EV loan borrowers default less than ICEV borrowers, with 0.149 percentage points lower probability. This means that EV borrowers default by 74 percent less compared to the mean default rate of ICEV borrowers from Table 2. Hybrid owners also default less, but to a lesser extent, with a coefficient of -0.105. As a result, we focus mainly on EVs in our results.

Table 3 Column (2) introduces the standard underwriting variables as well as loan term month and state fixed effects, without the engine type. Borrowers with high PTI, low credit scores, and high LTV default more. These variables have strong predictive power; for example, the t-statistic on credit score is nearly 200. The coefficient on the log of income is counterintuitively positive. Yet

[25] See 17 CFR S 246.18, for underwriting standards for qualifying automobile loans.

[26] We estimate a linear probability model rather than a logit model because of the difficulty in inverting matrices with our very large data set and the calendar crossed with aging fixed effects.

such an association is consistent with the strong role of conditioning on PTI in the estimation.[27]

Column (3) combines the indicator variables for engine type from Column (1) and the standard underwriting variables from Column (2). Our preferred model is Column (4), which introduces the underwriting variables in a spline/linear piecewise estimation, as we do not know the parametric form of the relationship between underwriting variables and realized credit risk (see, for example, Fuster et al. (2022)).[28] We find that EV borrowers enter into 60-day delinquency with a 0.0695 percent lower probability per month, relative to ICEVs. This means that EV borrowers default by 34.5 percent less compared to the mean default rate for ICEV borrowers, which is displayed in the bottom row of the table.[29]

Columns (5)-(6) consider the robustness of our results. In Column (5), we implement a Cox proportional hazard (exponential) model, allowing for repeat delinquencies. The hazard model analyzes the hazard of default over loans' aging, with the same macroeconomic time fixed effects and underwriter variables. The Column (5) coefficient on the EV indicator is 0.560. This coefficient is interpreted relative to unity. Thus, EVs exhibit a lower hazard of default, all else equal, by 44 percentage points (1.00 minus 0.56) each period. This is a larger economic magnitude, which we take as an upper bound rather than our primary result since hazard models are not the standard way risk modelers gauge risk from financial distress.

In Column (6), we use a propensity score matching model based on the underwriting variables and time of origination. Our objective is to align EVs with comparable ICEVs that reflect risk closer in proximate regions in the dimensions of the underwriting variables.[30] Because the average EV borrower is less risky than the average ICEV borrower, imposing a common support leads

[27]The intuition is as follows. Imagine two borrowers with the same loan term (6 years) and the same PTI, but one has higher income. By definition, the borrower with higher income must also have a larger loan (assuming similar maturities). Mechanically, a higher loan value might occur because the higher income borrower has made a lower down payment or has more expensive taste in cars. Presumably, controlling for LTV would absorb some of this effect, but not all. Thus, this significant positive coefficient on income likely reflects the higher income person's greater other debt and/or consumption, a higher risk proposition. As shown in Internet Appendix B Figure B3a, without this conditioning, higher income predicts lower predicted default since income is strongly negatively related to PTI.

[28]We plot the estimates from the spline in Internet Appendix B Figure B4. The piecewise linear spline is constructed as follows. Credit score is broken into 9 bins with width 30 covering the credit score range from 620 to 890. LTV is broken into 6 bins with width 0.2 and ranging from 0.1 to 1.3. PTI is broken into 5 bins with width 5% and ranging from 0% to 25%. The logarithm of income is broken into 8 bins of width 0.5 and ranging from 7 to 11. We include a slope and a bin node indicator for each of the 9 credit score, 6 LTV, 5 PTI, and 8 income intervals.

[29]An additional way to calculate the economic magnitude of our results is to express it in terms of credit score equivalence. Predicting the average change in delinquency across all loans as credit score increases using the credit score spline leads to an inference that borrowing against an EV has the same effect on delinquency as having 30.7 higher credit score points. We thank our discussant Jordan Nickerson for this suggestion.

[30]For each EV loan, we select up to 174 ICEV loans that have a propensity score (based on LTV, PTI, and income) within a caliper, belonging in the same credit score bucket, and have the same origination month. We then run weighted OLS on the panel of these sampled loans and give equal weighting to each EV loan and all its matches.

the average 60-day delinquency rate on ICEV loans in this sample to fall to 0.062 (from 0.201, previously). Thus our sample captures a lower risk segment of ICEV borrowers, with the number of observations dropping by half. Our model estimates indicate that the EV coefficient drops to -0.0148. However, because the sample has an overall lower default for ICEVs, the relative economic magnitude of the EV coefficient remains strong: EV borrowers still default by 24% less than ICEV borrowers. This result both lends confidence to our main result with the full sample and provides a lower bound to accompany the higher bound from the hazard model estimation. Finally, we consider robustness checks, reported in Internet Appendix B. These include considerations related to tax rebates. [31] We also consider a car body matched model to consider the possibility that the car body (and its depreciation) represents a way to level on credit risk.

In Table 4, we turn to our alternative measure of realized credit risk—the missed payment ratio. Using missed payments provides robustness to collapsing to a single observation per loan, provides a measure that incorporates the curing of delinquencies, and allows us to tackle economic magnitude in dollar values. The estimated metric can be easily converted into a notion of profitability. We consider both the principal-only components of payments in Columns (1)-(3) and the principal and interest payments together in Columns (4)-(6). The payment ratio ranges from zero to 1. We use tobit (columns 1 and 4) and fractional logit (all other columns) to cement the robustness of our results to the lower bound of zero. The fractional logit specification constrains our estimates so that the projected minimum loan payment ratio is not greater than zero.[32] Columns (3) and (6) used a matched sample, akin to columns (6) in the prior table. Our results are presented as marginal effects, as appropriate to each model.

In all columns of Table 4, we find a negative, significant coefficient on EV loans. The interpretation of the coefficients is that EV borrowers miss between 2 and 6 percentage points less of their scheduled principal payments compared to ICEV borrowers, with smaller marginal effects when

[31] We first explore the role of tax rebates. Tax rebates might affect our results through two channels. First, consider two households with the same cash on hand for a down payment on a new car, but one buying an EV and another an ICEV. The tax rebate may encourage the household buying an EV to purchase a more expensive car, knowing that they will be receiving a refund check from the government. This would affect the value ("V") part of the LTV and work in the opposite direction of our results on credit risk. Yet, from the underwriting perspective, the borrower still has a credit risk profile as if they were buying a car at the value of the car value minus the tax rebate. Hence, we can subtract out the tax rebate from value in the denominator to adjust for this credit risk profiling. Second, the tax rebate has a direct effect on the ability to pay in the tax rebate season in the year after origination. Thus, another robustness can involve excluding the months of February to June of the year after origination. In both robustness checks, we find that the coefficients on EV remain statistically significant at 1% level. Hence, we conclude that neither the credit risk profiling adjustment nor the tax rebate periods are driving our result.

[32] For robustness, Internet Appendix B Table B4 presents results with alternative measures of the payment ratio, including dropping loans, that, when cumulated, indicate prepayment.

considering the principal and interest payment ratio.

We translate our Column (1) result into a dollar amount to characterize how EV loans reduce lender credit losses. We rely on this column in part because the Tobit model adjusts for the possibility that our data are censored at 0. We multiply the estimate from Column (1) with the average EV loan amount of $38,537. We then multiply the result by one minus the average recovery ratio from collections. This recovery ratio (0.32) is calculated as the recovered amount divided by the outstanding amount at the time of collections for all defaulted loans in our dataset; i.e., the haircut on the value of the loans when turning the loan over for collection. Using this methodology, EV loans outperform comparable ICEV loans by $1,295 in credit risk value.

We can express this $1,295 lower credit risk as an equivalent loan interest rate effect. Using the average loan amount ($34,587), loan term (74 months), and interest rate (4.8%) from Table 1, we derive the interest rate equivalent for the estimated $1,295 dollar amount. We find that $1,295 in foregone default costs translates to a 1.1 percentage points lower interest rate. We continue to return to these calculations to understand the univariate engine default result.

4.2 Positive Selection beyond Underwriting Variables

4.2.1 Selection Based on Ex Ante Expected Costs

Method. Our first method to carve out positive selection unrelated to underwriting variables explores ex ante expected ownership costs. Operating costs such as fuel, maintenance, insurance, depreciation (through resale value effects), and interest (calculated as an expected value during the origination month, not at the borrower level) can be specific to the vehicle. The borrower knows these costs in expectation at the time of purchase and loan origination through many widely-used resources such as Edmunds, Kelley Blue Book, or AAA. Stated as a budget share of income, an expected cost variable that might account for positive EV selection is thus:

$$E[Costs : Income]_{it} = \frac{fuel_i + insurance_{it} + depreciation_{it} + maintenance_{it} + interest_{it}}{income_i}. \quad (2)$$

It may be that these expected costs induce consumers to self-select into a choice of an EV vs. an ICEV. Similarly, we also investigate whether ex ante expected volatility in fuel prices could prompt a similar self-section. Observing years of high volatility in gasoline prices, for example, can influence expectations about future price volatility and drive the choice into an EV. We create expected fuel volatility defined as a coefficient of variation of the average historical fuel price in borrower i's state,

based on the previous three years before i's loan was originated. The estimated coefficient on such volatility might be considered as an informal certainty equivalent metric in credit risk space.

Results. Table 5 presents results from a specification that incorporates ex ante costs to gauge which of these ownership costs explain positive selection. We focus on Column (2), using the splines of credit risk variables. Our ex ante costs variable has a strongly significant and economically meaningful coefficient of 0.980. A back-of-the-envelope calculation helps to put the economic magnitude in context. In our data, borrowers spend 15.6% of monthly income on direct and indirect costs of operating a car.[33] If this expense were to increase by 10% , our estimate of 0.980 would predict a 8% increase from the average 60-day delinquency rate. By contrast, we do not find statistical significance for the ex ante measure of fuel volatility.

4.3 Positive Selection Observed through Price-Implied Risk

Our second method for identifying positive selection unrelated to underwriting variables is to turn to pricing. Vehicle lenders may view engine selection as a proxy for homeownership, wealth, education, or behavioral variables. They may also develop algorithmic pricing models based on historical default data, in which the engine serves as a proxy for unobserved factors. These borrower characteristics could explain positive selection that further differentiates EV and ICEV borrower loan performance, and could be reflected in loan pricing.

To motivate our investigation of how positive selection by engine type is reflected in pricing, we plot histograms of interest rates by engine. As shown in Figure 2, the distribution of EV interest rates is markedly to the left of those for hybrids and ICEVs, with a significant mass at zero. Even for loans with nonzero rates, the distribution for EVs remains left of that for ICEVs.[34] In this section, we take steps to estimate rate differentials and then to use the rate differentials predictions as an implied price of default to take to the credit risk estimation.

[33]The budget share in our sample is higher than the transportation cost share of households reported in the introduction. Our time period differs from (is later than) that of Bertrand and Morse (2016), which could explain the difference. Also, our sample is not population income adjusted or reflective of the used car market.

[34]Because EV originations are weighted towards the latter part of our sample, we weight observations for ICEVs and hybrids to match the EVs' distribution of origination year and month.

4.3.1 Baseline: Loan Interest Rates

Method. We first model credit risk pricing in auto loan interest rates, $rate_i$ as:

$$rate_i = \alpha_0 EV_i + \Gamma_0^{rate} X_i + \mu_{date} + \mu_{state} + \mu_{term} + \epsilon_i, \tag{3}$$

where we employ the same set of underwriting variables X_i (credit score, LTV, income, and PTI), as well as the fixed effects for calendar year-month, state, and loan term.

Results. Table 6 reports the estimation of Equation (3). Column (1) reports estimated coefficients for a baseline credit risk pricing model with no EV or hybrid indicator variables; these coefficients have intuitive signs and magnitudes. As reported in Column (2), we find that an EV loan carries a 2.2 percentage points lower interest rate, all else equal with linear inclusion of the underwriting variables. Column (3) is our preferred specification that reproduces Column (2) but incorporates nonparametric relationships of credit score, PTI, LTV, and income with interest rate. We use a node-and-slope spline specification with six to nine breaks for each variable. With this specification, the R-squared increases to 0.48 and the economic magnitude of the EV's effect on the rate slightly increases to 2.3 percentage points. These estimations reveal that EV borrowers face a much lower interest rate relative to the overall sample mean rate of 4.8 percentage points.

The final two columns of Table 6 display results from robustness checks. In Column (4), we provide a within-lender analysis, adding lender fixed effects, to help isolate the effects of borrower variation. The EV coefficient slightly decreases to 1.5 percentage points with robust statistical significance. In Column (5), we address the possibility that lenders could be offering different incentives ('subvents', in auto finance vernacular) to EV versus ICEV car buyers, perhaps trading off lower interest rates and cash-back purchase incentives, in line with results from Beyene and Scopelliti (2024) who find that captive lenders and banks priced loans differently to consumers within the context of the Dieselgate episode. Thus, we explore if EV purchasers systemically receive lower cash back incentives, which might offset lower interest rates. We find the opposite. Column (5) reports that EV borrowers have a 20 percentage point higher likelihood of receiving cash back than ICEV borrowers. Related, to test the possibility of our results being driven by teaser rates, Appendix B Table B5 runs the same specification, with similar results, on a subsample of loans that are at their 13th month-mark since origination, because promotional rates are usually for a year. We continue to find sizable interest rate differentials.

A 2.3 percentage point spread is more than double that which would be expected if lenders were simply competitively pricing credit risk. One reason could be that the interest rate pricing was just wrong in over-predicting lower defaults, giving the EV buying household too much of a discount. This seems unlikely. A more likely answer is that the EV-to-ICEV interest rate spread is not just about credit risk, which we turn to next.

4.3.2 Price-Implied Risk

Method. A few plausible channels could affect lender pricing strategies for EV loans. First, during our sample period, auto manufacturers faced Corporate Average Fuel Economy (CAFE) standards from the National Highway Traffic Safety Administration (NHTSA) that set weighted average fuel economy standards at the manufacturer level, with sales volume of each vehicle model as weights.[35] Second, anecdotal evidence suggests that automakers may take lower profit margins in the short run to encourage EV production and, thereby, influence supply chain decisions. Favorable actions might include expanding charging infrastructure. The sales also influence the supply chain by inducing the suppliers to expand on production capacity and develop new relevant technologies. The suppliers can grow economies of scale from higher and more stable volumes of EV sales. Lastly, uncertainty around sales volume and production costs of EV may lead automakers to adopt different business and pricing strategies for EVs, including the use of subsidies in offered interest rates. Unlike ICEVs, consumers' price sensitivity and the overall demand function is less well known for EVs. Manufacturers may employ a pricing strategy that introduces a higher sticker price and then use subsidies (including lower interest rates) at the dealer to allow flexibility to price EVs according to overall demand, sales turnout, competitor actions, etc. Moreover, manufacturers may also extend more promotions to turn inventory, prevent significant depreciation, and make room for newer models because EV technologies are first generation and changing rapidly.

Rather than seeking to untangle these effects, we analyze the pricing of loans unrelated to captive incentives. We manually identify captive and non-captive lenders.[36] We then take care to align observations in apple-to-apple comparisons in that captive lenders may face a different credit risk profile pool of borrowers than non-captive. Thus, we place borrowers in ten credit worthiness buckets, indexed by n using two methods. The first method takes the first principal component of credit score, LTV, PTI, and $ln(Income)$ and constructs credit worthiness buckets as the deciles

[35] See Internet Appendix A for more background on related federal regulations.

[36] Non-captive lenders include banks, such as Santander, and nonbanks other than captives, such as Carmax.

of this variable. This first principal component has an eigenvalue of over 1.5 and explains half of the variance within these risk characteristics. The second method focuses on credit score only, and divides the credit score into ten buckets, separated by 30 credit score points.

Our estimating equation is as follows:

$$rate_i = \sum_n \{(\alpha_1^n EV_i + \kappa_1^n) \cdot Captive_i + (\alpha_2^n EV_i + \kappa_2^n) \cdot Non\text{-}Captive_i)\} \cdot Credit\ Bucket_i^n + \Gamma_1^{rate} X_i + \mu_{date} + \mu_{state} + \mu_{term} + \epsilon_i \quad (4)$$

where $Captive_i$ indicates a captive auto lender for loan i and $Non\text{-}Captive_i$ indicates a non-captive auto lender. $Credit\ Bucket_i^n$ indicates the credit worthiness bucket. We interact EV with captive and non-captive lenders (and control for level effect of captive) and estimate a coefficient for each of the credit buckets.

Results. Figures 3 shows the results by plotting the coefficients on EV interacted with captive (in orange) or non-captive (in blue) across the ten creditworthiness buckets (left panel) and credit score buckets (right panel).[37] Each dot represents an estimate of the EV-ICEV interest rate spreads (y-axis) by bucket (x-axis). We find a captive-to non-captive differential in these EV-to-ICEV rate spreads, with non-captive EV borrowers carrying lower interest rates than non-captive ICEV borrowers, but with a smaller differential compared to captive lenders. This is consistent with manufacturers' use of captive lending to incentivize automobile purchases. This captive to non-captive differential in the EV-to-ICEV rate spread expands for more creditworthy borrowers. (The blue set of dots diverges from the orange moving left to right.)

Honing in on non-captives and taking weighted averages by sample count in each bucket, we find a EV-to-ICEV spread for non-captive loans of -0.84 percentage points based on Panel A and -0.70 percentage points based on Panel B. This evidence from non-captive lenders suggests that (i) non-captive lenders pass the lower credit risk of EV borrowers to households in pricing, and (ii) captives also pass this risk, but supplement with additional rate incentives to promote EVs.

4.3.3 Credit Risk Results: Price-Implied Risk to Absorb Positive Selection

Method. With our understanding of the determinants of interest rates on auto loans, we return to our identification of the components of realized credit risk that explain the difference in defaults

[37] See Internet Appendix Table B6 for the results in table form.

between EVs and ICEVs. We construct $\widehat{PriceImpliedRisk_i}$ for each loan i in our dataset as the non-captive estimated coefficient $(\widehat{\alpha}_2^n EV_i + \widehat{\kappa}_2^n)$ from Figure 3 for each observation's credit worthiness bucket n and engine type EV_i . This variable removes the effect of dealer incentives, while incorporating lender understanding of credit risk by engine and credit worthiness buckets. Our estimation model of realized credit risk is thus:

$$default_{it} = \beta_2^{EV} * EV_i + \eta * \widehat{PriceImpliedRisk_i} + \gamma E[Cost\text{-}to\text{-}Income]_{it} + \zeta \sigma_i + \Gamma_2^{default} X_i + \mu_{t*h} + \mu_{state} + \mu_{term} + e_{it}. \quad (5)$$

We focus on the credit worthiness specifications, as they include the more inclusive list of credit risk variables. We include specifications with (even columns) and without (odd columns) the other credit risk variables (the underwriting variables plus the ex ante cost of ownership and volatility). The underwriting variables are already be reflected in the implied price of risk construction and may induce multi-collinearity concerns.

Results. Columns (1) and (2) of Table 7 present the results using creditworthiness, and Columns (3) and (4) using credit score.[38] We see that the price-implied credit risk is always positive and significant across the columns of Table 7. Likewise, the EV coefficients are always negative and significant. These results hold even with the full set of underwriting and ex ante cost variables. We interpret this as evidence that the lender uses the vehicle type as a proxy for unobserved credit risk, a positive selection effect in our terminology, since this is credit risk at origination.

5 Empirical Analysis: Treatment Effects of Engine Ownership

So far, we have examined the credit risk properties of EV borrowers compared to ICEV borrowers. We have rationalized some, but not all, of engine-specific credit risk differences through underwriting variables, ex ante calculated cost of ownership, and price-implied credit risk. In doing so, we investigated how lenders incorporate this differential credit risk into loan pricing, effectively passing the positive price of credit risk back to households. This risk-adjusted pricing, along with manufacturers' incentives to offer lower pricing, is sizable and hence considerably alleviates financial

[38] Because the estimation includes a generated regressor, we bootstrap the standard errors following Petrin and Train (2010). To implement this bootstrap, we create a subsample of all EVs and Hybrids plus a randomly drawn 1% of ICEV loans, applied to each period, and bootstrap the estimation 20 times, keeping the fixed effects parameter estimates fixed throughout the bootstrap. This subsampling is necessary to accommodate the computational complexity of the estimation and sample size.

distress of EV borrowers by reducing their monthly payment burdens.

Omitted from our analysis is the possibility that the residual credit risk differential results from unexpected exposure to differential costs of owning an EV. In this section, we ask whether characteristics of EVs cause differential (lower) exposures to cost of ownership shocks, reducing the distress risk of ongoing financial commitments. A critical cost of ownership differential between EVs and ICEVs is the fuel: EVs rely on electricity while ICEVs rely on gasoline. For instance, Knittel and Tanaka (2021), among others, show that fuel costs are a significant factor in automobile choice. We implement a formal test of the cost of ownership treatment (exposure to shocks) using a shift-share methodology.

5.1 Shocks to Gasoline Prices

Method. We use the variation of the gasoline price as a set of as-good-as-random shocks to the ongoing cost of owning an ICEV vehicle, applying a varying intensity of shock exposure. Using gasoline prices as a shock is based on the work of Busse, Knittel, and Zettelmeyer (2013) and Knittel and Tanaka (2021). Our primary implementation is akin to a Bartik (1991) or shift-share formulation, with exposure to shocks that differ regarding the intensity of treatment (Borusyak, Hull, and Jaravel (2021)). Specifically, we take a continuous form of difference-in-differences, similar to Acemoglu, Autor, and Lyle (2004), using loan-level shocks regional gasoline prices, P_{it}^{Oil}, as the exogenous shock. Regional gasoline prices may affect both the EV and the ICEV group indirectly, but regional gasoline prices only affect ICEV owners through a direct channel of vehicle expense.

Our regional gasoline price specification is:

$$default_{it} = \beta_{11}^{Oil} EV_i + \beta_{12}^{Oil} P_{it}^{Oil} + \beta_{13}^{Oil} EV_i P_{it}^{Oil} + \mu_i + \mu_{t*h} + e_{it}. \tag{6}$$

We compute P_{it}^{Oil} by subtracting the gasoline price at a loan i's origination from the current gasoline price at t. Loan-level fixed effects μ_i control for possible selection effects of consumers into EV versus ICEV, including any differences in expectations about future fuel prices or volatility. The year-month fixed effects absorb macroeconomic determinants of credit risk. Identification in this specification comes from variation in gasoline prices over time across regions. Under the assumptions of Borusyak, Hull, and Jaravel (2021), the coefficient on EV interacted with the gasoline price can be interpreted as a treatment effect in the default avoided by owning an EV.

Our methodology relies on the plausible assumptions that (i) the ex-post realizations of gasoline

prices involve uncertainty resolution (gasoline prices are, at least to a degree, unpredictable), and (ii) the correlation of engine choice and default through gasoline prices is a direct fuel cost channel, conditional on loan and macroeconomic time fixed effects. The second assumption requires some explanation. Gasoline price realizations may affect macroeconomic conditions, which in turn influence loan repayment. This indirect channel could happen through wage or expense (e.g., groceries) effects. The Borusyak, Hull, and Jaravel (2021) formulation allows for the coefficient on gasoline prices (un-interacted with the engine type) to be interpreted as correlational and potentially spurious to other causes, not a causal gasoline direct effect. However, these macroeconomic indirect channels should not vary in a way correlated with engine selection. We return to this assumption after showing our main treatment results.

Results. Table 8 shows results from estimating Equation (6) to determine the ex post impact of fuel costs exposure on the unexplained default difference between ICEVs and EVs. We combine EVs and hybrid vehicles for these tests to ensure sufficient observations in each shock period, even though it makes our estimates conservative. We also include monthly macroeconomic controls for median household income, house prices (HPI), and unemployment rate at the state level.

Columns (1)-(2) display the regional gasoline price results. In Column (1), we find that the interaction of the regional gasoline shock with the EV dummy has a significant and negative coefficient. A $1.00 increase in regional gasoline prices results in a 0.02 lower 60-day delinquency for EV/hybrid loans. In Column (2), we use a continuous version of the EV dummy, "MPG-Based Gasoline Cost." We construct this variable using EPA data that provides gallons per mile efficiency specific to each make and model of the car, as well as other factors, to produce an estimate of the extra gasoline cost burden in a month. For EVs, this variable is zero. We find that the results remain similar; this variable interacted with the regional gasoline price shock is positive and statistically significant at 1% level.

In Columns (3) and (4), we repeat these exercises using shocks in national gasoline prices instead of regional gasoline prices as our instrument. We adjust our calendar fixed effects to month-of-year to capture seasonality in gasoline prices, but drop year-month fixed effects to avoid collinearity with our instrument. With these adjustments, we identify the effect on delinquency from changes in national gasoline prices over time. The results are remarkably similar to Column (1). In particular, the coefficient of interest on the EVs and hybrids interacted with the national gasoline price is -0.0171, which is only slightly smaller than in that from the regional gasoline shock, -0.02.

5.2 Robustness of Shocks to Gasoline Prices

Method. As mentioned above, a concern with our treatment interpretation of EVs in the face of gas price shocks might exist if engine type is correlated with households' ability to weather distress shocks to income or expenses. To test for this possibility, we implement a series of specifications similar to equation (6) but also including non-gasoline shocks to household financial conditions at the local (state) level. In particular, we consider what happens to the interaction of EV with gasoline prices when we include other financial condition shock variables with EV. If engine type is uncorrelated with a household's ability to weather distress shocks, the interaction of EV with these other household financial condition shock variables should be zero.

We consider four financial condition variables – median state income, the state unemployment rate, and two proxies for utility bills. Median income and unemployment are natural financial conditions variables. To the extent that they do not move dynamically enough with expense side of shocks, we introduce heating degree days (HDDs) and cooling degree days (CDDs) as alternative financial conditioning variables. These variables, relevant in different months of the year, refer to how much and for how many days the outside air temperature was above or below a certain base temperature, thus triggering added utility costs.[39] These measures can capture potentially significant fluctuations in income shocks for households through sudden spikes in utility bills, such as increased cooling costs during heatwaves or heating expenses during severe cold snaps.

Results. Tables 9 and 10 present the results, using regional and national gas price shocks, respectively. The results are similar; thus, we focus on the regional version, Table 9. Column (1) reproduces our main gasoline shock result for comparison. Column (2) investigates the interaction of EV with state median income. We reject the assumption that the engine choice is unrelated to the households' ability to withstand distress. All households experience lower default when and where incomes are higher, but EV and hybrid borrowers experience even more distress relief. Nevertheless, despite rejecting our assertion that engine is unrelated to distress except through fuel effects in our specification, we find that the β^{Oil} on EV*gasoline variable increases in absolute value. If we were picking up spurious macroeconomic effects in our main shift share estimation, inclusion of EV*median income would diminish the β^{Oil} (EV*gasoline) effect.

In column (3), we include local unemployment interacted with EV. In this case, we find no

[39] These data are available from the National Oceanic and Atmospheric Administration (NOAA), https://www.ncei.noaa.gov/access/monitoring/climate-at-a-glance/statewide/time-series/28/tavg/ytd/4/1895-2023?base_prd=true&begbaseyear=1895&endbaseyear=2000.

significant effect of the test relationship, supporting the asserting that EV*gasoline identifies the fuel effect we have in mind.

Columns (4) and (5) of Table 9 address the energy expense channel. Column (4) uses controls for CDDs, and limits the sample to May through October, when cooling is in highest demand. Similarly, Column (5) uses controls for HDDs, and limits the sample to November through April. Even when interacting these factors with our EV/hybrid dummy, we find that, in both cases, the coefficients on β^{Oil} stay strongly significant, and of slightly larger economic importance relative to our Column (1) specification.

As a final check, Table 10 repeats the same exercises, using the national-level gas price shock, rather than the regional-level gas price shock. Again, we find that our main result remains both statistically and econonmically significant. Taken together, both sets of results confirm the relevance of our EV treatment channel for auto loan performance in the face of gasoline price shocks. Further, these results point to the broader role of finance in supporting the adoption of technology, and in the technology supporting loan performance.

6 Additional Robustness

6.1 Contrast to Bena, Bian, and Tang (2024)

Contemporaneous work by Bena, Bian, and Tang (2024) (BBT) find that EV/hybrid loans have higher interest rates than ICEV loans, seemingly in conflict with our results. BBT attribute their finding to a higher depreciation rate for EVs relative to ICEVs, leading to lower collateral value and, hence, relatively tighter lending standards for EV/hybrids than for ICEVs.[40] Their work makes a significant contribution to understanding the technology risk channel in auto lending. In this section, we demonstrate why their setup, which is fine-tuned to identify the technology channel, is not well suited for the credit risk channel, simply a different question than they ask.

Table 11 provides estimates from a series of exercises designed to pin down the key differences between our analysis and the BBT results.[41] On the far left of the table, in Column (1), we reproduce our main finding from Table 6, which demonstrates a 2.3 percentage point lower interest

[40] BBT's results primarily rely on European auto lending data, reflecting a difference in country-specific settings on a host of dimensions including pricing strategies of manufacturers, the role of lenders, tax credits, bankruptcy frameworks, and transportation infrastructure. However, in a series of exercises, BBT also use U.S. data to conduct similar analyses and find that interest rates are higher for EVs.

[41] We focus on the modeling choices that contribute to our differing conclusions. Other choices do not lead to different conclusions—for example, BBT have a shorter time period (July 2022 rather than July 2023)–and so we do not present analysis of those choices.

rate for EV loans compared to ICEV loans. On the far right of the table, in Column (6), we recreate the BBT result that EV/hybrids loans carry higher interest rates than ICEV loans. In the interim columns, we vary choices of sample and specification to investigate the drivers of the difference.

We start by considering sample differences. We limit our sample to loans with 6+ year terms, following the literature that shows lenders differentiate underwriting models by term (Hertzberg, Liberman, and Paravisini (2018) and Argyle, Palmer, and Nadauld (2020)). BBT pool all term lengths. In Column (2), we mimic BBT by including all loan terms, doubling the sample size from 4 million to 8 million loans. The coefficient on EV in Column (2) is similar to that of Column (1).

Our second sample difference considers the filters used by BBT. BBT evaluate a small set of auto dealers (Harley-Davidson, BMW, Carmax, Daimler, Hyundai, and Toyota) and limit the EV and hybrid models to those vehicles where they can isolate an exact car body match to an ICEV one.[42] The BBT filtering reduces the sample to 1.9 million loans. In Column (3), we continue to implement our estimation specification, but on the smaller sample of cars used by BBT. We find that coefficient on EV remains negative and significant, but is much smaller in economic magnitude. To unpack what is driving this shift, imagine a Toyota hybrid borrower. The Prius is not in the BBT dataset because there is no equivalent ICEV version; thus, we focus on a buyer of a Toyota Corolla Hybrid. The column (3) specification estimates the role of the credit risk parameters based on the manufacturers mentioned above. Note that the BBT sample excludes (except intermediated through Carmax) Ford, GM, Stellantis/Fiat-Chrysler, Honda, Kia, and others. This sample eliminates many moderately-priced car models. Consequently, a concern with using this Column (3) sample is that the credit risk calibration may compare the interest rate offered to the Corolla hybrid borrower based on a lower-risk sample of ICEVs borrowers.[43]

This leads us to considerations of specification differences between our work and BBT. Column (3) served as a stepping stone to trigger thoughts of how to level EVs or hybrids to appropriate risk characteristics of ICEVs. In Column (4), we start again with our sample but use the BBT independent variable specification. As in Column (3), the coefficient on EV stays negative and significant, but is diminished in magnitude. EV borrowers pay 81 basis points lower in interest rates relative to ICEV borrowers. What in the variable selection in BBT versus our models is

[42] BBT also have a shorter time period – July 2022 rather than July 2023, – but the time sampling is not driving the results.

[43] A study by the Arizona Republic newspaper from May 1, 2014 finds that the four lowest credit score vehicle models were from Dodge, Kia, Nissan, and Chrysler. https://www.azcentral.com/story/money/business/consumer/2014/05/01/can-you-tell-a-persons-credit-score-by-the-car-they-drive/8565251/

driving the diminished EV coefficient?

We first rule out those factors that do not lead to material differences in results.[44] What is material in understanding the differences are three choices made in specifications. One specification choice that we consider inappropriate to evaluate credit risk profiles is that BBT include a subvent dummy. Recall in our histograms of interest rates that EVs have a much larger mass of interest rates at zero percent APR. These are subvented loans. Thus, by including the subvent dummy, BBT are effectively eliminating the role of these observations and any other use of subventing to lower EV rates. It is not at all surprising that the negative EV coefficient is eliminated by the subvent dummy. In our view, this is a result, not a control. Auto lenders are choosing to subvent loans, conditional on engine type and underwriting variables.

The second specification choice that appears to drive differences and may not inform credit risk is that BBT include Make*Model (i.e, the car body matching of a Corolla hybrid and a Corolla ICEV) fixed effects for each hybrid or EV. (ICEVs with no match are also included for estimating the underwriting variable parameters.) For BBT's objective in estimating the role of the engine technology risk, this method is fine-tuned to isolate the collateral value channel. However, as we aim to level on credit risk, the model assumes that the borrower for the EV would have the same risk profile as the borrower for the ICEV version of the same car. This seems implausible in many circumstances; for example, the typical risk-profile of a Bolt borrower is likely different from that of a Trax borrower. Furthermore, the estimation is affected by the observation-level influence on the EV coefficient from the counts of car body observations and the proportion of EVs relative to ICEVs for a given car body.

The third specification choice that drives differences is combining EVs and hybrids. In Column (4), we find that the coefficient on hybrids is positive. Our paper focuses on EVs, and we generally separate hybrids from EVs. BBT, however, pool hybrids and EVs, and report that their sample is overwhelmingly hybrids. In Column (5), when we pool hybrids and EVs, we also find a positive coefficient on these engines, even with the negative coefficient on EV in Column (4).

Finally, in Column (6), we combine the specification from Column (5) with the BBT sample filter, which limits the car manufacturers. We find a slightly less positive coefficient than in Column

[44]Differences in the parametrics of the underwriting profile variables are not driving disparities. While we use a spline of the underwriting credit risk variables including the log of income, BBT use income (in levels), the log of vehicle price, an employment verification dummy, and linear inclusion of the underwriting variables. Also immaterial are the differences of absorbing time. We absorb the month-year of origination. BBT instead have state-year fixed effects and fixed effects for the ABS package in which the loan emerges securitized. This timing is a bit less precise than ours, but the difference is not material in the results.

(5). Thus, Column (4) remains our best estimate of reconciling our finding with BBT. We conclude that BBT's specification is intended to prioritize the isolation of technology risk, and we commend that work. Yet, when leveling borrower profiles on credit risk, we do not think the inclusion of subvents or the car body effects enables an apples-for-apples credit risk profiling for our agenda.

6.2 Validation: Auto ABS Market Pricing

Auto ABS is one of the largest segments of the broader ABS market, underscoring the widespread practice of securitizing auto loans to obtain funding from capital market participants.[45] A significant share of auto loans are packaged into auto ABS, which is a large and active market of nearly $300 billion as of 2023 Q4.[46] If credit risk varies by engine type and lenders pass that benefit to households, lenders may demand compensation from investors who purchase auto ABS pools. Such a result would serve as a validation of our ex ante positive selection.

The data source for our exploration is Bloomberg Finance LP, ABS Backoffice. It covers $361 billion in publicly-placed auto ABS issued from 2017 to 2023. We merge these data with the SEC ABS-EE data to obtain aggregates of loan-level attributes. The merged data covers 20 distinct issuers of which a little over half are captive auto lenders. Each auto ABS deal is comprised of tranches, rated by S&P and Moodys. We synthesize these ratings to the S&P scale, with AAA as the highest rating, BBB as the lowest investment-grade rating, and BB or lower as speculative-grade.

To understand whether and how auto lenders are compensated through the ABS market, we consider four gauges of auto ABS credit risk pricing. The first gauge is the coupon rate spread, which is the ABS's tranche coupon rate over a comparable-maturity Treasury security.[47] The second is the z-spread, which is the implied spread over the risk-free rate necessary for the discounted cash flows to match the market price for the security. [48] The third and fourth are gauges of credit

[45] Auto ABS was the first consumer ABS to come to market in the 1980s (Olegario, 2016). Despite a downturn in the 2007-2009 financial crisis, on net, auto ABS has generally weathered the post-crisis securitization market, in sharp contrast to other private-label securitizations, most notably, for mortgages (Campbell et al., 2011).

[46] Source: Inside MBS & ABS, Merrill Lynch, Bloomberg, JPMC.

[47] Because auto ABS are often issued within a few cents away from par (Faltin-Traeger, Johnson, and Mayer (2010), differentials in the price of credit risk by engine type appear in rate spreads or loss reserves.

[48] The z-spread is the solution for $ZSpread_{jk}$ for the ABS pool (j)-tranche (k) security in the below formula to discounting cash flows to match the issuance market price P_j for the security:

$$P_{jk} = \sum_{t=1}^{n} \frac{cashflow_{jkt}}{1 + r_t + ZSpread_{jk}}. \tag{7}$$

Time variation in this measure enters through r_t, the expected risk-free discount rate at tenor t, assumed to be the zero coupon Treasury yield. To model cash flows, we use the monthly principal and interest payment, with typical amortization and an industry-standard prepayment rule. Our results remain robust to including realized z-spreads, calculated using actual cash flows (adjusted for prepayments) instead of expected cash flows.

risk embedded in the intermediation. The intermediaries do not price ABS at the interest rate of the underlying household loans, but at a rate that accounts for intermediation costs and profits, unwinds subsidies (subvents) by auto manufacturers, and adjusts credit risk. They do this through two credit support mechanisms. One is the excess spread, our third measure, which is defined as the spread between weighted average household loan rate and ABS coupon rate. Because the auto loan rate is often higher than the ABS coupon rate, this "excess spread" offers a source of credit support for the deal. Another is the ABS loss reserve, our fourth measure, a credit support account escrowed as a percentage of the total dollar value of auto loans in pool. [49]

Table 12 summarizes the tranche-level summary statistics of the auto ABS in the data. Panel A describes the shares of loans by engine and issuer type. All the shares in this panel are computed based only on the dollar amount of 6-year loans in the deal. As shown, an average deal (or, tranche) has 0.3% and 3.8% of dollar value of loans collateralized by EVs and hybrid vehicles, respectively. Around 60 percent of the dollar value of 6-year loans were originated by a captive auto lender. Panel B provides summarizes the distribution of the ABS tranches by rating, focusing on the investment grade tranches. We report shares of dollar value for the deals. Nearly 60 percent of the tranches are rated AAA, while only 7% of tranches are BBB. Floating rate tranches can be of any rating, but are usually high quality.

Panel C provides information on credit support measures. We construct the coupon spread using a daily zero-coupon yield estimated from a smoothed yield curve sourced from Gürkaynak, Sack, and Wright (2007).[50,51] The mean spread is 60 basis points, and spreads widen in the later part of our sample, reflecting macroeconomic factors. Coupon spreads by rating are in line with expectations, with investment grade spreads relatively narrow and low, and the unrated tranche with higher mean and variance. Expected z-spreads have a slightly lower mean, but similar variability and range as the coupon spread, despite the difference in methodology.[52] Across all tranches, the excess spread averages 5.6 percentage points, with wide variation. In addition to the excess spread, the loan loss reserve is often a substantial part of the overall ABS deal, indicating the portion of the securitization intended to absorb losses. The mean loan loss reserve share (credit support) is

[49] For this fourth measure, it is helpful to consider the waterfall of cash flows in auto ABS. When a household defaults or is delinquent on a payment, a loss reserve account covers the payment to the tranched ABS payments. Only if the loss reserve account is fully spent will the waterfall imply that the lowest tranche receives a reduced payment.

[50] Data are available at https://www.federalreserve.gov/data/yield-curve-tables/feds200628_1.html.

[51] Internet Appendix B Figure B6 displays the distribution of coupons and spreads on tranches of auto ABS over time and across rating agency tranches AAA to BB or below.

[52] Internet Appendix B Figure B7 presents the distribution of expected z-spreads over our sample by year and rating.

22%. This also varies substantially, likely reflecting deals with an elevated share of risky loans.

Denoting one of our rate spreads or credit support measures by y_{jk}, we estimate whether the share of EVs in the overall ABS pool, EV_j, explains any variation in risk pricing as follows:

$$y_{jk} = \eta_0 EV_j + \Gamma_{ABS} CreditRisk_{jk} + \mu_{year} + \varepsilon_{jk}. \tag{8}$$

In this case $CreditRisk_{jk}$ is a whether the issuer is captive or not captive (i.e., whether the issuer is affiliated with a car manufacturer or not) and the security rating (AAA to nonrated). We also include year fixed effects to control for broad macroeconomic factors.

Table 13 presents the results from estimating Equation (8). Column (1) evaluates the pricing of the ABS pool as the coupon spread above the risk free rate as the dependent variable. Looking at Column (1), we see that the share of EVs in an ABS pool does not statistically significantly affect the coupon spread at issuance. By contrast, the share of hybrids does affect the coupon spread. The estimated coefficients suggest that for a one standard deviation increase in the share of hybrid vehicles in an ABS pool, the coupon spread declines by 15 basis points, an economically meaningful amount. Importantly, these effects are economically and statistically significant even after controlling for issuer type—spreads are 26 basis points narrower for captive issuers than for other issuers—and for tranche rating. The results reported in Column (2) using the z-spread as the pricing outcome of interest are economically and statistically similar to those in Column (1).

ABS issuers might incorporate differing credit risk pricing for engine types by adjusting the amount of loan loss reserves escrowed for absorbing delinquencies so that the waterfall of cash flow payments to the lowest tranches is not impacted until such credit support is depleted. Columns (3) and (4) look at two measures of loss reserve accounts established to buffer risk and ensure that ABS investors receive full payments under most scenarios.

We find that, all else equal, these buffers are smaller in deals with higher percentages of EVs, likely reflecting lower credit risk. Focusing on Column (3), the coefficient on the EV share variable is -0.185 and statistically significant. A one standard deviation increase in the EV share (an increase in the percent of EVs by 1.7 percentage points) results in a narrowing of the excess spread by 31 basis points. In Column (4), focusing on credit support defined as the loan loss reserve account as a percent of the overall ABS value, we find that the coefficient on EV share is -0.232 and significant.

To understand the economic magnitude, we focus on Column (4). A one standard deviation larger EV share would be an increase of the EV share by 1.7 percentage points. This larger share,

combined with the coefficient in Column (4), would imply 39 basis points less of the ABS face value to be held in reserve.

7 Conclusion

We set out to explore whether auto loan credit risk differs by engine type and then to disentangle the drivers of such differing credit risk. Toward that aim, we show that EVs have significantly lower credit risk. Even after controlling for underwriting risk variables, we find that EVs default by a third less than ICEVs. From the vantage of a household, lower credit risk leads to a materially lower cost of vehicle ownership. Our estimates suggest that EV borrowers' reduced defaults value at $1,295 in lower credit risk realizations. What is unique in our finding, and perhaps even surprising, is that these benefits are largely passed on to households. Of the $1,295, households enjoy $981 in the form of lower interest rate loans.

The question of credit risk and pricing pass-through allows our research to contribute to the study of economic transitions. In transition, opportunities and disruptions create situations where some parties gain, and others lose. Finance is one of the channels through which reinforcing distributions of gains and losses can occur. Our finding that households have incentives to buy EVs through lower costs of ownership is such a reinforcing effect. More research in the intersection between consumer finance and economic transitions should continue to shed light on the roles of each in technological innovation. Further, we think transparency in the face of technological change can have benefits. In this case, our evidence might suggest markets should begin to separate ABS pooling of EVs and ICEVs.

Finally, we spend much of the paper attributing these realized credit risk effects to ex post treatment effects of owning an EV and to positive selection mechanisms. Our main treatment effect is worthy of a final mention. We find that the ex post insulation of borrowers from gas price shocks is material in preventing default. This is a mechanism not yet explored in the literature, a form of assurity from shocks coming from technological advancement into less volatile fuels.

We end with the note that auto loan markets are large and auto servicing absorbs a substantial share of household's budgets each month. Yet, the role of auto finance for households and the implied tradeoffs in transportation and house location decisions are topics vastly understudied in the finance literature. On the flip side, auto manufacturing is also an important component of the U.S. economy. Auto financing supports a high level of durables consumption, and in our setting,

economic growth, productivity, and innovation.

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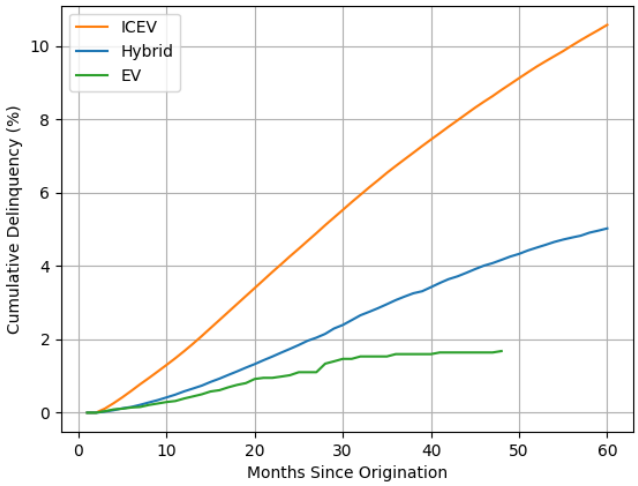
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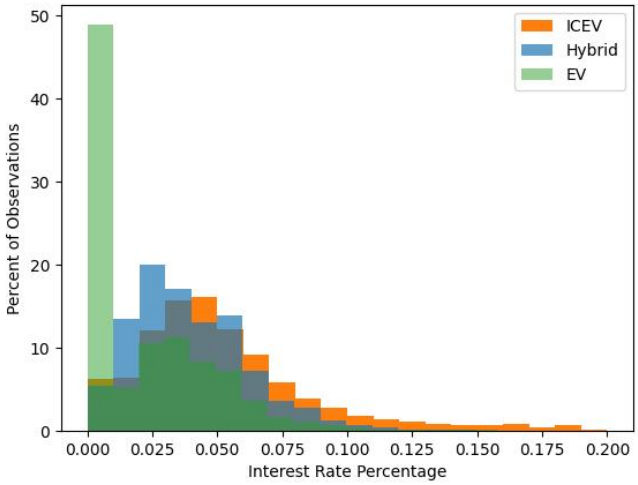
Figure 1: Cumulative 60-day Delinquency Rates by Engine Type



Note: This figure shows cumulative 60-day delinquency rates by months since origination and by engine type, based on our data sample consisting of 6-year new car auto loans originated in between January 2017 to July 2023. Engine types include internal combustion engine vehicle (ICEV), hybrid vehicle, and electric vehicle (EV). We define a loan to be 60-day delinquent when it newly enters the 60-day delinquency in that month. Denominators capture the entire set of loans that exist at each month mark after origination. Source: SEC form ABS-EE.

Alt Text: This line chart shows cumulative 60-day delinquency rates by months since origination and by engine type from January 2017 to July 2023. The x-axis measures months since origination (0-60 months), while the y-axis shows cumulative delinquency rates as a percentage (0-9%). Three lines represent internal combustion engine vehicles (ICEVs), hybrid vehicles, and electric vehicles (EVs). ICEVs show the highest delinquency rates, reaching 4.3% at 24 months and 8.8% at 48 months. Hybrid vehicles show moderate delinquency rates of 1.7% at 24 months and 4.2% at 48 months. Evs demonstrate the lowest delinquency rates at 1.0% at 24 months and 1.7% at 48 months. The chart clearly illustrates a persistent difference in delinquency by engine type throughout the loan lifetime.

Figure 2: Auto Loan Interest Rates by Engine Type

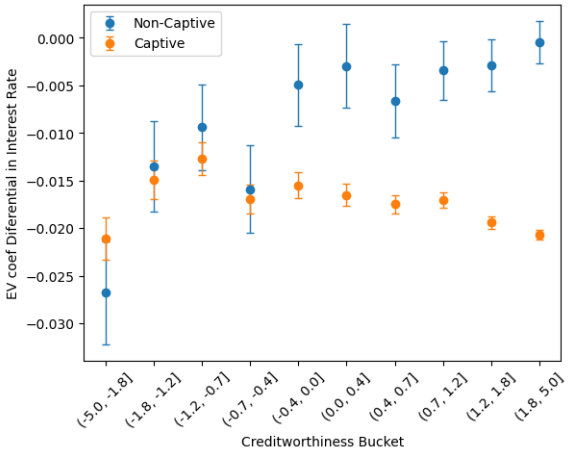


Note: This figure shows the density plot of original interest rates of auto loans in our data of 6-year new car auto loans originated in between January 2017 to July 2023, broken down by engine type. The classification is by internal combustion engine vehicle (ICEV), hybrid vehicle, and electric vehicle (EV). We weight observations within engine type to match the EVs' distribution of origination year and month to account for various macroeconomic factors that might affect origination patterns on ICEVs and EVs. Source: SEC form ABS-EE.

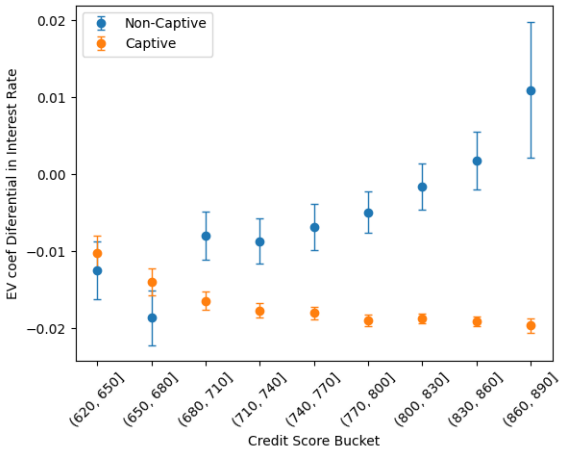
Alt Text: This density plot shows the distribution of original interest rates for auto loans by engine type from January 2017 to July 2023. The x-axis shows interest rates from 0-15%, and the y-axis represents density. Three distributions are shown for internal combustion engine vehicles (ICEVs), hybrid vehicles, and electric vehicles (Evs). The EV distribution (shown in green) is markedly to the left of those for hybrids and ICEVs, with a significant mass at zero percent interest rate. Even for loans with nonzero rates, the distribution for Evs remains to the left of that for ICEVs, indicating generally lower interest rates for EV loans. The hybrid vehicle interest rate distribution falls between Evs and ICEVs. The plot shows that Evs receive more favorable interest rates compared to the other vehicle types.

Figure 3: Loan Pricing Results by Captive vs Non-Captive Lender

(a) By Creditworthiness Bucket



(b) By Credit Score Bucket



Note: These figures show the coefficients of electric vehicle (EV) indicator variable interacted with an indicator variable for whether the lender is a captive auto lender or not, in interest rate regressions, based on our data of 6-year new car auto loans originated in between January 2017 to July 2023. In sub-figure (a), bucketing uses ten bins defined based on the first principal component of four underwriting variables, credit score, LTV, PTI, and $ln(Income)$. In sub-figure (b), bucket is based on the credit score. Source: SEC form ABS-EE.

Alt Text: This figure consists of two panels showing coefficients of electric vehicle (EV) indicators interacted with lender type across different credit risk buckets. Panel (a) By Creditworthiness Bucket: This scatter plot shows interest rate differences between Evs and ICEVs (y-axis, in percentage points) across ten creditworthiness buckets (x-axis, from lowest to highest). Two series are plotted: captive lenders (orange dots) and non-captive lenders (blue dots). For captive lenders, the EV-to-ICEV interest rate differential ranges from approximately -2.1 to -1.3 percentage points across all buckets. For non-captive lenders, the differential is negative but smaller in magnitude, ranging from about -2.7 to 0 percentage points, with the differential diminishing as creditworthiness increases. Panel (b) By Credit Score Bucket: This scatter plot shows similar data but organized by credit score buckets from 620-890. The captive lender series (orange dots) shows a consistently negative EV-to-ICEV rate differential of about -1.0 to -2.0 percentage points across all credit scores. The non-captive lender series (blue dots) shows a differential that starts at approximately -1.9 percentage points for lower credit scores but gradually reduces to near zero or slightly positive for the highest credit scores.

Table 1: Summary Statistics of Auto Loans (Cross-Section)

Engine Type:	All		ICEV		Hybrid		EV	
	Mean	Std	Mean	Std	Mean	Std	Mean	Std
Panel A: Vehicle and Loan Characteristics								
Vehicle Value Amount ($)	34,929	12,559	34,867	12,640	35,586***	10,498	40,881***	10,438
Loan Amount ($)	34,538	13,014	34,457	13,042	35,941***	12,112	38,537***	13,324
Loan Term (Months)	74.1	2.4	74.1	2.4	73.8***	1.4	73.3***	2.4
Scheduled Payment ($)	546	251	544	249	609***	277	530***	277
Captive	0.830	0.375	0.824	0.381	0.969***	0.173	0.935***	0.246
Interest Rate	0.048	0.038	0.049	0.038	0.037***	0.023	0.023***	0.027
Month 13 Interest Rate	0.047	0.035	0.048	0.036	0.038***	0.023	0.023***	0.027
Cash Back	0.377	0.485	0.378	0.485	0.314***	0.464	0.496***	0.500
Panel B: Standard Loan Underwriting Variables								
Credit Score	742	69	741	69	763***	62	788***	59
Monthly Income ($)	8,380	6,800	8,308	6,745	9,429***	7,517	13,309***	8,324
Loan-To-Value (LTV)	1.01	0.23	1.01	0.23	1.02***	0.23	0.95***	0.21
Rebate-Adjusted LTV	1.01	0.23	1.01	0.23	1.04***	0.24	1.15***	0.29
Payment-to-Income (PTI)	0.087	0.045	0.087	0.045	0.079***	0.045	0.062***	0.043
Panel C: Ex Ante Costs and Fuel Volatility at Origination								
Expected Cost-to-Income (Monthly)	0.156	0.090	0.157	0.090	0.137***	0.080	0.077***	0.065
Expected Fuel Volatility	0.105	0.055	0.105	0.054	0.127***	0.063	0.067***	0.042
Panel D: Loan Performance								
Prepay	0.255	0.436	0.258	0.438	0.198***	0.399	0.089***	0.284
Missed Principal Payment Ratio	0.069	0.224	0.070	0.227	0.035***	0.147	0.021***	0.119
Missed Principal+Interest Payment Ratio	0.064	0.220	0.065	0.223	0.031***	0.143	0.022***	0.120
N	4,096,083		3,910,601		163,038		22,444	

Note: This table presents cross-section summary statistics for the primary variables used in our empirical analyses, based on the sample of 6-year new car auto loans originated in between January 2017 and July 2023. Engine type classifies a car into internal combustion engine vehicle (ICEV), hybrid vehicle, or electric vehicle (EV). The asterisks on the hybrid and EV columns represent results from t-tests on differences in means compared to the ICEV column. In Panel A,"Vehicle Value Amount" and "Loan Amount" are in dollars; "Loan Term" is in months. "Scheduled payment" refers to monthly loan payment for the first observation of a loan. "Captive" is an indicator variable of 1 if the loan was originated by a captive auto lender and zero otherwise. "Interest rate," "Month 13 interest rate," and "Cash back" are in decimal form, not a percentage. "Month 13 interest rate" is the loan's interest rate at 13th month mark. "Cash back" is an indicator variable for whether the loan got a cash back subvent. In Panel B, "Credit Score" reflects the borrower's credit score according to the major credit bureaus. "Monthly Income" is the imputed borrower's monthly income. "LTV" is the loan-to-value ratio at origination. "Rebate-Adjusted LTV" incorporates the effect of any tax credits into the LTV. "Payment-to-Income" represents the scheduled monthly payment to borrower monthly income. In Panel C, all variables are in decimal form. "Expected Cost-to-Income" is as defined in Equation (2). "Expected Fuel Volatility" is a coefficient of variation of the average historical fuel price in borrower's state, based on the previous three years before loan origination. In Panel D, "Prepay" is an indicator variable for loans that prepaid; "Missed Payment Ratio" is the ratio of the difference between the scheduled payment and the monthly realized payment to the monthly scheduled payment, cumulated to one observation per loan. Source: SEC form ABS-EE, Edmunds, Bureau of Labor Statistics, Federal Housing Finance Agency, U.S. Census Bureau, FRED, and U.S. Energy Information Administration.

Table 2: Summary Statistics of Auto Loans (Panel)

Engine Type:	All		ICEV		Hybrid		EV	
	Mean	Std	Mean	Std	Mean	Std	Mean	Std
Panel A: Expected Operating Costs (Monthly)								
Fuel (Expected; $)	131	42	133	41	83***	27	63***	22
Maintenance (Expected; $)	87	47	87	47	90***	49	51***	35
Repairs (Expected; $)	35	23	35	23	28***	21	30***	17
Depreciation (Expected; $)	248	204	248	206	249***	148	247**	267
Insurance (Expected; $)	64	8	64	8	64***	7	70***	5
Taxes & Fees (Expected; $)	64	88	63	89	68***	86	66***	71
Total Cost (Expected; $)	628	284	630	285	582***	242	527***	317
N	78,815,894		75,787,426		2,846,481		181,987	
Panel B: Macroeconomic Variables								
Regional Gasoline Price ($)	3.02	0.77	3.01	0.76	3.29***	0.80	3.81***	0.70
National Gasoline Price ($)	2.97	0.70	2.96	0.70	3.09***	0.70	3.43***	0.51
Gasoline Shock Regional ($)	0.476	0.781	0.473	0.780	0.554***	0.798	0.588***	0.818
Gasoline Shock National ($)	0.466	0.765	0.465	0.765	0.500***	0.763	0.474***	0.752
Electricity Price ($)	14.6	4.4	14.5	4.3	16.6***	5.6	19.1***	7.2
MPG-Based Gasoline Cost ($100s)	0.517	0.141	0.527	0.134	0. ***	0.072	0.000***	0.000
Median Household Income ($)	74,239	11,391	74,082	11,353	78,279***	11,638	82,397***	9,893
Unemployment Rate	4.79	2.48	4.80	2.48	4.79***	2.50	4.15***	1.58
Cooling Degree Days	163	189	165	190	142***	176	107***	157
Heating Degree Days	267	328	267	328	278***	322	337***	349
N	84,675,532		81,420,320		3,058,310		196,902	
Panel C: Delinquency								
60-Day Delinquency (%)	0.197	4.430	0.201	4.478	0.092***	3.036	0.035***	1.874
30-Day Delinquency (%)	0.590	7.658	0.601	7.729	0.329***	5.725	0.130***	3.596
N	84,675,532		81,420,320		3,058,310		196,902	

Note: This table presents panel summary statistics for variables used in our empirical analyses, based on the sample of 6-year new car auto loans originated between January 2017 and July 2023. Engine type classifies a car into internal combustion engine vehicle (ICEV), hybrid vehicle, or electric vehicle (EV). The asterisks on the hybrid and EV columns represent results from t-tests on differences in means compared to the ICEV column. In Panel A, all variables are in monthly dollars; they are car-specific,"expected" costs because these costs are known ex ante at the time of loan origination. Other than the fuel variable (which is constant over the life of the loan), all other components of operating costs dynamically vary over the life of the car but in a way that is still known ex ante. Panel B reports macroeconomic controls, covering the same period as the auto loan data. The "Gasoline Shock" variables are calculated by subtracting the current gasoline price level from the gasoline price at a loan's origination. "MPG-based Gasoline Cost" is the monthly extra cost of gasoline from operating an ICEV or a hybrid vehicle if the gasoline price increases by one dollar, based on the assumption of driving an average mileage. This cost takes into account different miles per gallon of cars and is zero for EVs. "Unemployment" is monthly unemployment rate by state and is seasonally adjusted. "Cooling Degree Days" and "Heating Degree Days" are measures of how much and for how many days the outside air temperature was above or below a certain base temperature. In Panel C, "60/30-Day delinquency" measures the average percentage of loans that newly enter the 60- or 30-day delinquency in each year-month of the panel data. Source: SEC form ABS-EE, Edmunds, Bureau of Labor Statistics, Federal Housing Finance Agency, U.S. Census Bureau, FRED, U.S. Energy Information Administration, and NOAA.

Table 3: Results for Positive Selection on Underwriting Variables

Dependent variable:	60-Day Delinquency (Percent)					
Estimation:	Linear Probability				Hazard	Matched Sample
	(1)	(2)	(3)	(4)	(5)	(6)
EV	-0.149***		-0.0584***	**-0.0695*** **	0.560***	-0.0148***
	(-30.58)		(-10.78)	**(-13.06)**	(-4.411)	(-2.836)
Hybrid	-0.105***		-0.0251***	**-0.0196*** **	0.790***	
	(-43.38)		(-10.26)	**(-8.130)**	(-9.473)	
Credit Score		-0.00237***	-0.00236***	**[spline]**	0.985***	[bucket-match]
		(-193.5)	(-193.1)		(-205.6)	
Payment-to-Income (PTI)		1.14***	1.14***	**[spline]**	7.98***	[matched]
		(37.78)	(37.72)		(16.27)	
Loan-to-Value (LTV)		0.234***	0.234***	**[spline]**	7.49***	[matched]
		(67.50)	(67.54)		(109.9)	
ln(Income)		0.0150***	0.0152***	**[spline]**	0.877***	[matched]
		(8.388)	(8.506)		(-12.03)	
Aging*Calendar FE	YES	YES	YES	**YES**	Hazard	Propensity
Loan Term FE		YES	YES	**YES**	Estimation:	Estimation:
State FE		YES	YES	**YES**	YES	
Term Duration Month FE					YES	
OrigMonth FE					YES	[bucket-match]
Aging FE						YES
Observations	84,592,010	83,689,616	83,689,616	**84,047,036**	80,277,148	41,530,440
R-Squared	0.000	0.003	0.003	**0.004**		0.000
AUROC	0.549	0.676	0.676	**0.678**		0.532
$Mean(ICEVDepVar)$	**0.201**	**0.202**	**0.202**	**0.201**		**0.062**
$\widehat{EV}/Mean(DepVar)$	**-74.0%**		**-29.0%**	**-34.5%**	**-44.0%**	**-24.0%**

Note: This table reports the results from estimating the underwriter's model of realized credit risk based on our sample of 6-year new car auto loans originated in between January 2017 and July 2023, measuring default with 60-day delinquency. In Columns (1)-(4), we use linear probability model while in Columns (5) and (6), we use hazard model and propensity score matching, respectively. "EV" and "Hybrid" are indicator variables flagging if the loan was extended to an electric vehicle (EV) or a hybrid vehicle, respectively, as opposed to an internal combustion engine vehicle (ICEV). Dependent variable is defined as the empirical probability of a loan newly entering a 60-day delinquency in that month from a non-delinquency status in the previous month, and is in percent. $Mean(ICEVDepVar)$ shows the mean of the dependent variable for ICEVs in the corresponding estimation and $\widehat{EV}/Mean(ICEVDepVar)$, hence, the economic magnitude of coefficient of interest off this sample mean of ICEVs. Robust t-statistics are in parentheses. Significance levels are denoted by: *** p<0.01, ** p<0.05, * p<0.1. Source: SEC form ABS-EE.

Table 4: Results for Positive Selection on Underwriting Variables Using Missed Payment Ratio

Dependent variable:	Missed Principal Payment Ratio			Missed Principal+Interest Payment Ratio		
Estimation:	Tobit	Logit	Matched Sample	Tobit	Logit	Matched Sample
	(1)	(2)	(3)	(4)	(5)	(6)
EV	**-0.0494*** **	-0.0573***	-0.0259***	-0.0406***	-0.0477***	-0.0200***
	(-42.72)	(-25.27)	(-20.20)	(-28.94)	(-23.89)	(-17.10)
Hybrid	**-0.0100*** **	-0.0137***		-0.00686***	-0.0146***	
	(-25.82)	(-20.58)		(-15.86)	(-21.55)	
Credit Score	**-0.000421*** **	-0.000525***	[bucket-match]	-0.000416***	-0.000446***	[bucket-match]
	(-325.9)	(-279.3)		(-319.9)	(-247.9)	
Payment-to-Income (PTI)	**0.101*** **	0.184***	[matched]	0.122***	0.159***	[matched]
	(36.20)	(54.48)		(44.39)	(47.59)	
Loan-to-Value (LTV)	**0.0323*** **	0.0219***	[matched]	0.0346***	0.0211***	[matched]
	(82.17)	(40.07)		(86.40)	(39.05)	
ln(Income)	**-0.00127*** **	0.00810***	[matched]	0.00228***	0.00709***	[matched]
	(-6.105)	(29.41)		(10.81)	(26.16)	
OrigMonth FE	**YES**	YES	[bucket-match]	YES	YES	[bucket-match]
Loan Term FE	**YES**	YES		YES	YES	
State FE	**YES**	YES		YES	YES	
Observations	**4,067,640**	4,067,640	2,980,917	4,067,640	4,067,640	2,980,917
AUROC	**0.697**	0.878	0.703	0.544	0.828	0.673
$Mean(ICEVDepVar)$	**0.070**	**0.070**	**0.047**	**0.065**	**0.065**	**0.043**
$\widehat{EV}/Mean(DepVar)$	**-70.2%**	**-81.4%**	**-55.3%**	**-62.0%**	**-72.9%**	**-46.3%**

Note: This table reports the results on default based on our sample of 6-year new car auto loans originated in between January 2017 and July 2023, measuring default with missed payment ratio. All columns examine the cumulative actual-to-scheduled missed payment ratio that is computed over the observed lifetime of each loan in our sample. Further, we add principal payments equal to the starting loan balance when the ending loan balance and the matured indicator imply the loan is prepaid but the corresponding payment amount is listed as zero. In Columns (1) through (3), the missed payment ratio captures only missed principal payments while in Columns (4) and (6), the ratio captures missed interest payments as well. "EV" and "Hybrid" are indicator variables flagging if the loan was extended to an electric vehicle (EV) or a hybrid vehicle, respectively, as opposed to an internal combustion engine vehicle (ICEV). $Mean(ICEVDepVar)$ shows the mean of the dependent variable for ICEVs in the corresponding estimation and $\widehat{EV}/Mean(ICEVDepVar)$, hence, the economic magnitude of coefficient of interest off this sample mean of ICEVs. Robust t-statistics are in parentheses. Significance levels are denoted by: *** p<0.01, ** p<0.05, * p<0.1. Source: SEC form ABS-EE.

Table 5: Results for Positive Selection Beyond Underwriting Variables Using Ex Ante Costs

Dependent variable:	60-Day Delinquency (Percent)	
	(1)	(2)
EV	-0.0487***	**-0.0554*** **
	(-7.449)	**(-8.558)**
Hybrid	-0.0193***	**-0.0145*** **
	(-7.508)	**(-5.689)**
Credit Score	-0.00236***	**[spline]**
	(-182.2)	
Loan-to-Value (LTV)	0.317***	**[spline]**
	(100.6)	
ln(Income)	0.0615***	**[spline]**
	(31.25)	
Expected Cost-to-Income Ratio	1.12***	**0.980*** **
	(59.58)	**(42.32)**
Expected Fuel Volatility	-0.0479	**0.0340**
	(-0.7435)	**(0.5283)**
Aging*Calendar FE	YES	**YES**
Loan Term FE	YES	**YES**
State FE	YES	**YES**
Observations	74,536,332	**74,536,332**
R-Squared	0.003	**0.004**
AUROC	0.687	**0.689**
$Mean(ICEVDepVar)$	**0.203**	**0.203**
$\widehat{EV}/Mean(DepVar)$	**-23.9%**	**-27.2%**

Note: This table summarizes results from a selection model using ex ante expected costs. The dependent variable is defined as the empirical probability of a loan newly entering a 60-day delinquency in that period from a non-delinquency status in the previous period, in percent. "EV" and "Hybrid" are indicator variables flagging if the loan was extended to an electric vehicle (EV) or a hybrid vehicle, respectively, as opposed to an internal combustion engine vehicle (ICEV). Expected cost-to-income ratio is as defined in Equation (2) and expected fuel volatility is defined as a coefficient of variation of the average historical fuel price in borrower's state, based on the previous three years before loan origination. $Mean(ICEVDepVar)$ shows the mean of the dependent variable for ICEVs in the corresponding estimation and $\widehat{EV}/Mean(ICEVDepVar)$, hence, the economic magnitude of coefficient of interest off this sample mean of ICEVs. Robust t-statistics are in parentheses. Significance levels are denoted by: *** p<0.01, ** p<0.05, * p<0.1. Source: SEC form ABS-EE.

Table 6: Results on Loan Pricing

	Baseline			Robustness	
Dependent variable:	Interest Rate				Dummy: Cash Back
	(1)	(2)	(3)	(4)	(5)
EV		-0.0223***	**-0.0226*** **	-0.0152***	0.198***
		(-119.7)	**(-129.5)**	(-111.7)	(59.77)
Hybrid		-0.00252***	**-0.00199*** **	0.000898***	-0.0169***
		(-45.36)	**(-39.32)**	(19.51)	(-14.20)
Credit Score	-0.000230***	-0.000229***	[**spline**]	[spline]	0.000106***
	(-984.0)	(-979.3)			(28.86)
Payment-to-Income (PTI)	0.0816***	0.0823***	[**spline**]	[spline]	-0.207***
	(146.9)	(148.5)			(-24.26)
Loan-to-Value (LTV)	-0.0172***	-0.0173***	[**spline**]	[spline]	-0.215***
	(-258.1)	(-260.2)			(-185.5)
ln(Income)	0.000363***	0.000537***	[**spline**]	[spline]	-0.0108***
	(9.875)	(14.61)			(-17.15)
OrigMonth FE	YES	YES	**YES**	YES	YES
Loan Term FE	YES	YES	**YES**	YES	YES
State FE	YES	YES	**YES**	YES	YES
Lender FE				YES	
Observations	4,067,636	4,067,636	**4,067,636**	4,067,636	4,067,636
R-Squared	0.418	0.420	**0.480**	0.607	0.094

Note: This table reports the results from estimating Equation (3), based on our sample of 6-year new car auto loans originated in between January 2017 and July 2023. The dependent variable is interest rate in all columns except for Column (5) where subvention in the form of cash back takes the place as the dependent variable. "EV" and "Hybrid" are each indicator variables flagging if the loan was extended to an electric vehicle (EV) or a hybrid vehicle. Columns (3) and (4) use splines for credit score, payment-to-income, loan-to-value, and $ln(Income)$. Source: SEC form ABS-EE. Robust t-statistics in parentheses. Significance levels are denoted by: *** p<0.01, ** p<0.05, * p<0.1.

Table 7: Results for Positive Selection Beyond Underwriting Variables Using Price-Implied Risk

Dependent variable:	60-Day Delinquency (Percent)			
Measures of Price-Implied Risk:	Creditworthiness		Credit Score	
	(1)	(2)	(3)	(4)
EV	-0.0830***	**-0.0531*** **	-0.0725***	-0.0351***
	(-12.72)	**(-7.858)**	(-9.297)	(-4.344)
Price Implied Risk	6.43***	**2.92*** **	8.60***	8.61***
	(19.78)	**(4.981)**	(17.06)	(11.58)
Expected Cost-to-Income Ratio		**0.777*** **		0.916***
		(7.483)		(7.544)
Expected Fuel Volatility		**-0.0500**		0.0141
		(-0.8385)		(-0.1302)
Controls (X_i)		**YES**		YES
Aging*Calendar FE	YES	**YES**	YES	YES
Loan Term FE	YES	**YES**	YES	YES
State FE	YES	**YES**	YES	YES
Observations	80,663,564	**71,794,835**	81,155,250	71,487,576
R-Squared	0.002	**0.003**	0.003	0.004
AUROC	0.645	**0.691**	0.672	0.692
$Mean(ICEVDepVar)$	**0.201**	**0.203**	**0.199**	**0.201**
$\widehat{EV}/Mean(DepVar)$	**-41.2%**	**-26.1%**	**-36.5%**	**-17.4%**

Note: This table reports the results from estimating Equation (5), based on our sample of 6-year new car auto loans originated in between January 2017 and July 2023. The dependent variable is defined as the empirical probability of a loan newly entering a 60-day delinquency in that period from a non-delinquency status in the previous period, in percent. "EV" is an indicator variable flagging if the loan was extended to an electric vehicle (EV) (we drop hybrid vehicles from this sample). In Columns (1)-(2), the bucketing uses ten ($n = 1...10$) buckets of similar creditworthiness based on the first principal component of credit score, loan-to-value ratio, payment-to-income ratio, and $ln(Income)$. In Columns (3)-(4), we divides the credit score into ten buckets, separated by 30 credit score points. Standard errors are bootstrapped. Source: SEC form ABS-EE. Robust t-statistics in parentheses. Significance levels are denoted by: *** p<0.01, ** p<0.05, * p<0.1.

Table 8: Treatment Effects Using Gasoline Price Shift-Share Model

Dependent variable:	60-Day Delinquency (Percent)			
	(1)	(2)	(3)	(4)
Gasoline Shock Regional	**0.0085***	-0.0085		
	(1.87)	(-1.54)		
EV*Gasoline Shock Regional	**-0.0200*****			
	(-4.74)			
MPG-Based Gasoline Cost*Gasoline Shock Regional		0.0312***		
		(5.29)		
Gasoline Shock National			-0.0142***	-0.0328***
			(-9.38)	(-9.48)
EV*Gasoline Shock National			-0.0171***	
			(-3.89)	
MPG-Based Gasoline Cost*Gasoline Shock National				0.0355***
				(5.92)
ln(Median Household Income)	**-0.1156*****	-0.1302***	0.0561***	0.0257*
	(-7.19)	(-7.91)	(3.8)	(1.7)
Unemployment Rate	**0.0033*****	0.0037***	-0.0018***	-0.0022***
	(4.77)	(5.29)	(-5.49)	(-6.52)
Loan FE	**YES**	YES	YES	YES
Aging*Calendar FE	**YES**	YES		
Aging FE			YES	YES
Month FE			YES	YES
Observations	**83,866,799**	78,663,376	83,866,799	78,663,376
R-Squared	**0.096**	0.092	0.096	0.091

Note: This table summarizes results from evaluating equation (6), based on our sample of 6-year new car auto loans originated in between January 2017 and July 2023. "EV" is an indicator variable that equals one of the loan was originated on an electric vehicle (EV) or a hybrid vehicle, and zero if on an internal combustion engine vehicle (ICEV). The "Gasoline Shock" variables are calculated by subtracting the current gasoline price level from the gasoline price at a loan's origination, using either regional or national gasoline price. "MPG-based Gasoline Cost" is the monthly extra cost of gasoline from operating an ICEV or a hybrid vehicle if the gasoline price increases by one dollar, based on the assumption of driving an average mileage. This cost takes into account different miles per gallon of cars and is zero for EVs. "ln(Median household income)" is annual by state. "Unemployment" is monthly unemployment rate data by state and is seasonally adjusted. Robust t-statistics are in parentheses. "Month FE" captures seasonal fixed effects. Significance levels are denoted by: *** p<0.01, ** p<0.05, * p<0.1. Source: SEC form ABS-EE, Edmunds, Bureau of Labor Statistics, Federal Housing Finance Agency, U.S. Census Bureau, FRED, and U.S. Energy Information Administration.

Table 9: Robustness to Treatment Effects Using Regional Gas Price Shocks

Dependent variable:	60-Day Delinquency (Percent)				
	(1)	(2)	(3)	(4) May-Oct	(5) Nov-Apr
Gasoline Shock Regional	0.0084*	0.0088*	0.0084*	0.0195***	-0.0008
	(1.83)	(1.91)	(1.82)	(3.1)	(-0.1)
EV*Gasoline Shock Regional	-0.0200***	-0.0243***	-0.0190***	-0.0223***	-0.0236***
	(-4.74)	(-5.64)	(-3.71)	(-4.13)	(-3.17)
ln(Median Household Income)	-0.1165***	-0.1031***	-0.1165***	-0.0749***	-0.1636***
	(-7.18)	(-6.26)	(-7.18)	(-3.28)	(-7.04)
EV*ln(Median Household Income)		-0.3591***			
		(-4.74)			
Unemployment Rate	0.0033***	0.0033***	0.0032***	0.0047***	0.0012
	(4.69E+00)	(4.71E+00)	(4.63)	(5.15)	(1.13)
EV*Unemployment Rate			0.0005		
			(0.35)		
CDD	-0.000006	-0.000007	-0.000006	0.00003***	
	(-7.90E-01)	(-0.85)	(-0.78)	(2.65)	
EV*CDD				-0.00004	
				(-1.43)	
HDD	0.000002	0.000002	0.000002		0.00002***
	(0.59)	(0.64)	(0.58)		(2.66)
EV*HDD					-0.00007***
	(-3.3)				
Loan FE	YES	YES	YES	YES	YES
Aging*Calendar FE	YES	YES	YES	YES	YES
Observations	83,548,865	83,548,865	83,548,865	42,135,145	41,287,420
R-Squared	0.0957	0.0957	0.0957	0.1356	0.1385

Note: This table summarizes robustness results from evaluating equation (6), based on our sample of 6-year new car auto loans originated in between January 2017 and July 2023. "EV" is an indicator variable that equals one of the loan was originated on an electric vehicle (EV) or a hybrid vehicle, and zero if on an internal combustion engine vehicle (ICEV). The "Gasoline Shock" variables are calculated by subtracting the current gasoline price level from the gasoline price at a loan's origination, using regional gasoline price. This cost takes into account different miles per gallon of cars and is zero for EVs. "ln(Median household income)" is annual by state. "Unemployment" is monthly unemployment rate data by state and is seasonally adjusted. "CDD" and "HDD" refer to cooling and heating degree days, respectively, that measure how much and for how many days the outside air temperature was above or below a certain base temperature. Robust t-statistics are in parentheses. Significance levels are denoted by: *** p<0.01, ** p<0.05, * p<0.1. Source: SEC form ABS-EE, Edmunds, Bureau of Labor Statistics, Federal Housing Finance Agency, U.S. Census Bureau, FRED, U.S. Energy Information Administration, and NOAA.

Table 10: Robustness to Treatment Effects Using National Gas Price Shocks

Dependent variable:	60-Day Delinquency (Percent)				
	(1)	(2)	(3)	(4) May-Oct	(5) Nov-Apr
Gasoline Shock National	-0.0145***	-0.01427***	-0.0145***	-0.0048**	-0.0454***
	(-9.55)	(-9.4)	(-9.53)	(-2.53)	(-17.38)
EV*Gasoline Shock National	-0.0169***	-0.0224***	-0.0163***	-0.0221***	-0.0226***
	(-3.83)	(-4.97)	(-3.04)	(-3.96)	(-2.9)
ln(Median Household Income)	0.0588***	0.0744***	0.0588***	0.1367***	-0.0252
	(3.95)	(4.92)	(3.95)	(6.49)	(-1.2)
EV*ln(Median Household Income)		-0.4258***			
		(-5.61)			
Unemployment Rate	-0.0018***	-0.0018***	-0.0018***	-0.0021***	-0.0022***
	(-5.47)	(-5.45)	(-5.43)	(-4.92)	(-4.48)
CDD	0.00002***	0.00002***	0.00002***	0.00006***	
	(3.2)	(3.13)	(3.2)	(5.38)	
EV*CDD				-0.00003	
				(-1.22)	
HDD	-0.00001***	-0.00001***	-0.00001***		-0.00003***
	(-3.14)	(-3.1)	(-3.14)		(-4.52)
EV*HDD					-0.00007***
					(-3.34)
Loan FE	YES	YES	YES	YES	YES
Aging FE	YES	YES	YES	YES	YES
Month FE	YES	YES	YES	YES	YES
Observations	83,548,865	83,548,865	83,548,865	42,135,145	41,287,420
R-Squared	0.0955	0.0955	0.0955	0.1354	0.1384

Note: This table summarizes robustness results from evaluating equation (6), based on our sample of 6-year new car auto loans originated in between January 2017 and July 2023. "EV" is an indicator variable that equals one of the loan was originated on an electric vehicle (EV) or a hybrid vehicle, and zero if on an internal combustion engine vehicle (ICEV). The "Gasoline Shock" variables are calculated by subtracting the current gasoline price level from the gasoline price at a loan's origination, using regional gasoline price. This cost takes into account different miles per gallon of cars and is zero for EVs. "ln(Median household income)" is annual by state. "Unemployment" is monthly unemployment rate data by state and is seasonally adjusted. "CDD" and "HDD" refer to cooling and heating degree days, respectively, that measure how much and for how many days the outside air temperature was above or below a certain base temperature. Robust t-statistics are in parentheses. "Month FE" captures seasonal fixed effects. Significance levels are denoted by: *** p<0.01, ** p<0.05, * p<0.1. Source: SEC form ABS-EE, Edmunds, Bureau of Labor Statistics, Federal Housing Finance Agency, U.S. Census Bureau, FRED, U.S. Energy Information Administration, and NOAA.

Table 11: Comparison to Bena, Bian, and Tang (2024)

Dependent variable:	Interest Rate (%)					
Specification:	Our Specification			BBT Specification		
Subset:	Our Sample	Full Sample	BBT Sample	Our Sample	Our Sample	BBT Sample
	(1)	(2)	(3)	(4)	(5)	(6)
EV or Hybrid					0.000531***	0.000306***
					(9.877)	(7.271)
EV	-0.0226***	-0.0175***	-0.000499***	-0.00814***		
	(-129.5)	(-123.1)	(-2.948)	(-44.20)		
Hybrid	-0.00199***	-0.00235***	-0.00221***	0.00155***		
	(-39.32)	(-81.04)	(-65.69)	(28.35)		
Credit Score	[spline]	-0.000157***	-0.000122***	-0.000116***	-0.000116***	-0.000112***
		(-1008.0)	(-440.5)	(-628.2)	(-628.3)	(-480.9)
Payment-to-Income (PTI)	[spline]	0.0609***	0.0246***	0.0775***	0.0774***	0.0173***
		(179.7)	(42.60)	(224.5)	(224.2)	(44.16)
Loan-to-Value (LTV)	[spline]	-0.0177***	-0.0155***	-0.00605***	-0.00605***	0.000658***
		(-431.2)	(-219.8)	(-109.0)	(-109.0)	(12.13)
ln(Income)	[spline]	0.00152***	0.000461***			
		(71.09)	(12.48)			
ln(Vehicle Price)				-0.0142***	-0.0150***	-0.00501***
				(-150.3)	(-162.3)	(-45.92)
Income				0.186***	0.186***	-0.00807***
				(88.05)	(87.78)	(-4.274)
OrigMonth FE	YES	YES	YES			
Loan Term FE	YES	YES	YES			
State FE	YES	YES	YES			
Lender FE				YES	YES	YES
ABS Deal FE				YES	YES	YES
Year*State FE				YES	YES	YES
Make*Model FE				YES	YES	YES
Subvented FE				YES	YES	YES
Employment Verification FE				YES	YES	YES
Observations	4,067,636	8,148,396	1,938,722	4,013,605	4,013,605	1,938,394
R-Squared	0.480	0.440	0.308	0.703	0.702	0.489

Note: This table compares our results from Table 6 and Bena, Bian, and Tang (2024) ("BBT"). The dependent variable is interest rate in all columns. "PTI" and "LTV" refer to payment-to-income and loan-to-value ratios. Column (1) uses our sample and specification, including fixed effects and separate indicators for EVs ("EV") and hybrid vehicles ("Hybrid"). Columns (2) and (3) tests our specification on various samples: Column (2) uses the largest sample including loans of all terms and backed by cars from all automakers, and Column (3) uses BBT's sample. Column (4) tests our sample with BBT's fixed effects. Column (5) further switches to using the combined "EV or Hybrid" indicator as used by BBT. Finally, Column (6) replicates BBT's results by using both their sample and specification. Source: SEC form ABS-EE. Robust t-statistics in parentheses. Significance levels are denoted by: *** p<0.01, ** p<0.05, * p<0.1.

Table 12: Summary Statistics of Tranche-level ABS Data

	Obs	Mean	Std	Min	Max
	Panel A: By Engine and Issuer Type				
EV Share (%)	1,785	0.32	1.68	0.00	24.12
Hybrid Share (%)	1,785	3.80	8.72	0.00	100.00
Captive Indicator	1,785	0.597	0.491	0.000	1.000
	Panel B: Distribution Across Rating				
AAA	1,785	0.568	0.496	0.000	1.000
AA	1,785	0.093	0.291	0.000	1.000
A	1,785	0.214	0.410	0.000	1.000
BBB	1,785	0.065	0.247	0.000	1.000
Floating Rate	1,785	0.079	0.270	0.000	1.000
	Panel C: Rates and Spreads (Percent)				
Coupon Spread	1,782	0.60	1.14	-4.74	6.69
Z-Spread	1,693	0.154	1.164	-5.135	8.753
Excess Spread	1,782	5.60	5.91	-2.69	21.30
Credit Support	1,773	22	20	0	95

Note: This table provides summary statistics for the auto ABS comprised of the loans in our study. In Panel A, the shares are computed only out of 6-year loans in the ABS deal. EV share and hybrid share measure the share of loans in the securitization that are classified as EVs or hybrid vehicles. The captive indicator equals 1 if the ABS issuer is the financing arm of an automaker. In Panel B, each is measured as a share of tranches. In Panel C, coupon spread is the spread between the coupon rate on the auto ABS tranche and a comparable-maturity Treasury security at the month of issuance. Z-spread is calculated as the additional discount over the risk-free rate (proxied by the Treasury yield curve) necessary to align future expected cash flows with the price of the security at origination. Excess spread is the difference between the dollar-weighted average rate charged on loans in the ABS pool and the coupon rate on the ABS tranche. Credit support is the portion of the securitization intended to absorb losses. Source: Bloomberg Back Office Auto ABS, SEC form ABS-EE.

Table 13: ABS Results

Dependent variable:	Coupon Spread	Z-Spread	Excess Spread	Credit Support
	(1)	(2)	(3)	(4)
EV Share (%)	0.00240	0.00328	-0.185***	-0.232***
	(0.09380)	(0.2628)	(-5.854)	(-2.938)
Hybrid Share (%)	-0.0138***	-0.0109***	-0.0474***	-0.397***
	(-4.682)	(-4.928)	(-5.657)	(-12.11)
Captive Indicator	-0.257***	-0.0912**	-6.14***	-13.6***
	(-5.516)	(-2.240)	(-32.84)	(-19.30)
AAA	1.53***	0.886***	-2.47***	-5.25***
	(8.856)	(3.880)	(-5.992)	(-3.065)
AA	1.84***	1.16***	-2.50***	-4.01**
	(9.902)	(4.968)	(-5.073)	(-2.036)
A	1.08***	0.468**	-1.61***	-3.02
	(6.007)	(1.970)	(-3.534)	(-1.634)
BBB	2.53***	2.40***	0.195	7.15***
	(10.11)	(8.035)	(0.3469)	(2.970)
Observations	1,691	1,407	1,691	1,691
R-Squared	0.675	0.362	0.465	0.307
Year FE	YES	YES	YES	YES
Floating Rate FE			YES	YES

Note: This table reports parameter estimates from evaluating equation 8. The outcome variable in Column (1) is the coupon spread, calculated as the spread of the coupon rate on a tranche of the auto ABS at origination over a comparable-maturity Treasury yield, expressed in percent. The outcome in Column (2) is the ex-ante z-spread, calculated as the interest rate spread over the risk-free rate (in percent) needed to equate expected future cash flows with the price of the ABS tranche at origination, assuming an ABS single month mortality rate of 1.3. The outcome variable in Column (3) is the excess spread, calculated as the spread of the average weighted interest rate on auto loans comprising the ABS over the coupon rate on a tranche of the auto ABS, measured at origination and expressed in percent. The outcome variable in Column (4) is the percent of credit support for the ABS deal, defined as the percent of the deal that is subordinated relative to the total balance. In addition to the variables associated with the reported coefficients, explanatory variables include year of issuance, an indicator variable that equals 1 if the security has a floating rate, and an intercept. Sample is the set of publicly-placed auto ABS pools issued from 2017 to 2023. Robust t-statistics are presented in the parentheses below the coefficients. Source: Bloomberg Back Office Auto ABS, SEC form ABS-EE. Robust t-statistics in parentheses. Significance levels are denoted by: *** p<0.01, ** p<0.05, * p<0.1.

Internet Appendix

A Background on U.S. Environmental Regulations for Automakers and Subsidies

In the U.S, federal regulations for automakers are enforced by two standards: the Corporate Average Fuel Economy (CAFE) standards by the National Highway Traffic Safety Administration (NHTSA) and the greenhouse gas emission standards by the EPA.

In 1975, the first CAFE standards were established for new passenger cars, sport utility vehicles (SUVs), and light trucks. CAFE refers to average fuel economy, measured in miles per gallon (MPG) and weighted by sales of the automaker's vehicles. The initial law stipulated a roughly 50 percent increase in MPG to 27.5 MPG by model year 1985. In 2007, CAFE was updated to increase the standards to 35 MPG by model year 2020. In 2010, NHTSA and EPA jointly published harmonized CAFE and greenhouse gas emission rules to result in 34.1 MPG and CO2 emissions of 250 grams per mile (g/mile) by model year 2016; in 2012, these were extended to model year 2017-2025.

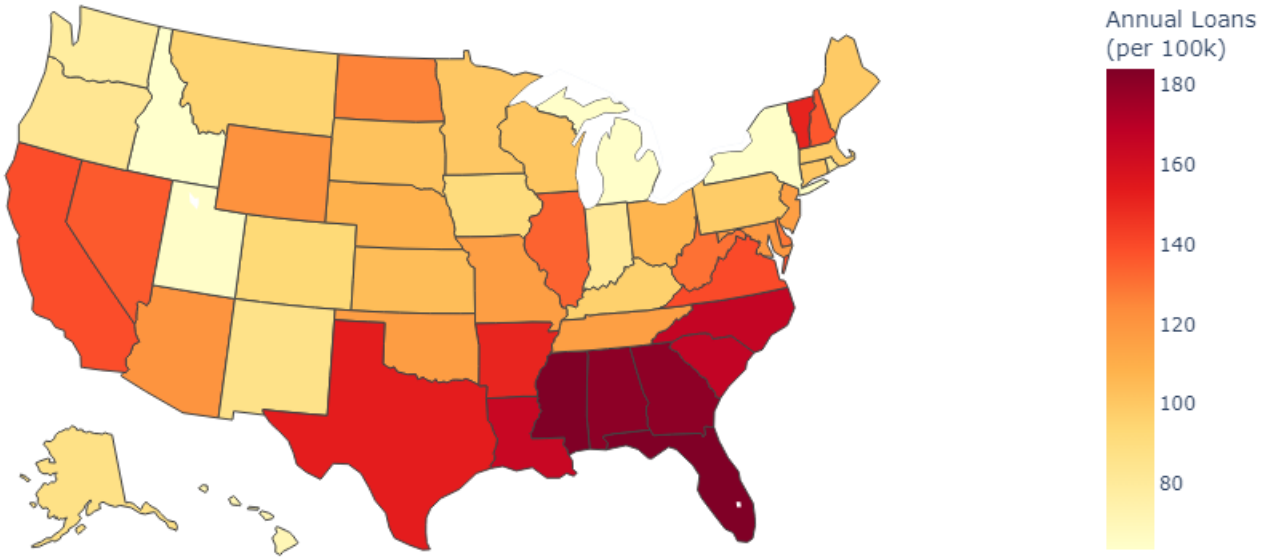
The CAFE and greenhouse gas emission standards were temporarily relaxed in 2020, with the Safer Affordable Fuel-Efficient (SAFE) Vehicles Rule for model year 2021-2026. Subsequently, the relaxed rule was reversed in 2021 as the Biden administration issued an executive order setting a target of at least 50 percent of new passenger cars and light-duty trucks to be zero-emission by 2030, accompanied by the "EV Acceleration Challenge."[1] In the same year, the EPA published new greenhouse gas emissions standards for passenger cars and light trucks for model year 2023-2026, targeting CO2 emissions of 161 g/mile in 2026. Since 2022, the NHTSA and EPA have each issued and finalized rules on stricter CAFE standards of 49 MPG for model year 2026 and greenhouse gas emission standards of 82 g/mile by model year 2032.

In the U.S., related subsidies for EVs and hybrid vehicles exist at various levels including federal, state, and city. At the federal level, the Energy Policy Act of 2005 introduced hybrid tax credits of up to $3,400. The Energy Improvement and Extension Act of 2008 and American Recovery Recovery and Reinvestment Act of 2009 extended the tax credits to up $7,500 for plug-in hybrid and electric vehicles, respectively, with households including the credit on their income tax filings. These tax credits phased out once a manufacturer sold 200,000 qualifying vehicles in the United States, which occurred for example for GM in 2018 and Toyota in 2022. However, the Inflation Reduction Act of 2022 re-introduced the tax credit of $7,500. In this case, the dealer filed the tax credit. The legislation also removed the phase-out cap applied to the auto manufacturers. At the state level, various tax credits and rebates (along with access to carpool lanes, reduced registration costs, rebates on housing charging station installation, and other incentives) have been implemented. For instance, both California and New York offer a $2,000 rebate for a new loan or a lease on EV. On top of state-level incentives, many city governments also offer another layer of incentives that often include rebates, parking incentives, and free or reduced-cost charging.

[1] https://www.whitehouse.gov/cleanenergy/ev-acceleration-challenge/.

B Additional Figures and Tables

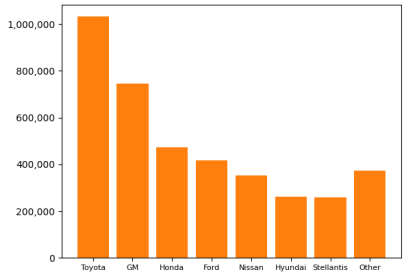
Figure B1: Geographic Distribution of Auto Loans in Data



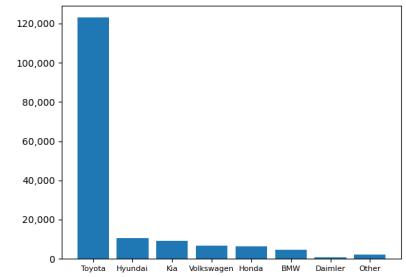
Note: This figure shows the geographic distribution of 6-year new car auto loans originated in between January 2017 to July 2023 and normalized by population. The distribution shows broad national coverage with concentrations in the Southeast and the Southwest from Texas and California. Source: SEC form ABS-EE.

Alt Text: This figure is a choropleth map showing the geographic distribution of 6-year new car auto loans originated between January 2017 and July 2023, normalized by population. The map displays a gradient of colors across the United States, with darker shades indicating higher concentration of loans. The distribution shows broad national coverage with particularly high concentrations in the Southeast and the Southwest, specifically Texas and California. The map demonstrates that the study's data represents loans from across the entire country, though with varying densities by region.

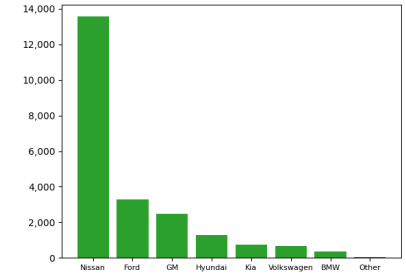
Figure B2: Number of Loans by Engine Type and Manufacturer



(a) Loans on ICEVs



(b) Loans on Hybrid Vehicles

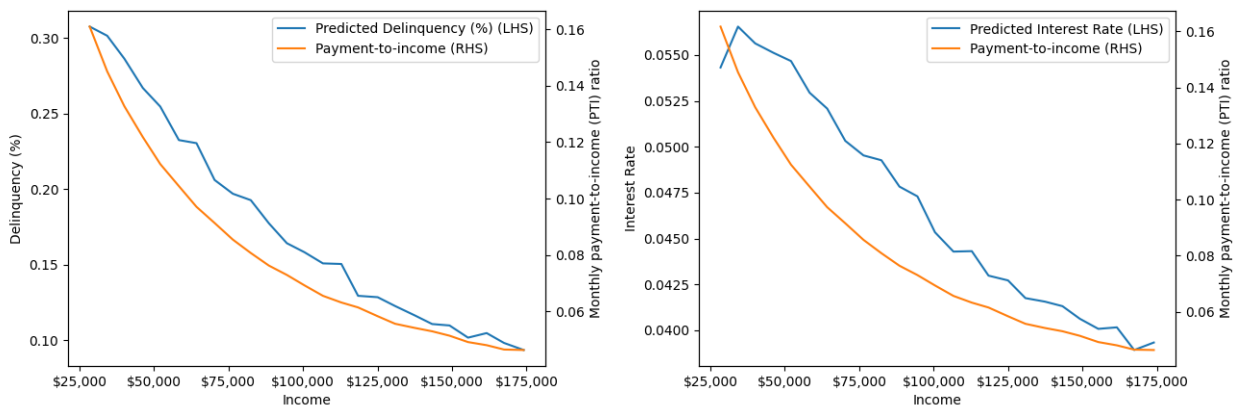


(c) Loans on EVs

Note: These figures show the number of loans that were made on internal combustion engine vehicles(ICEVs), hybrid vehicles, and electric vehicles(EVs) by each manufacturer, based on our data of 6-year new car auto loans from January 2017 to July 2023. Note that Tesla has not securitized auto loans during our sample period and some other car manufacturers used private label ABS; thus the sample does not contain some of the higher-end car manufactures. Instead, for EVs, the sample has a large number of Nissan (Leaf) and GM (Bolt) cars. Source: SEC form ABS-EE.

Alt Text: This figure consists of three bar charts showing the distribution of loans across manufacturers for each engine type. Panel (a) shows ICEVs, with Toyota, Honda, Nissan, and GM having the highest number of loans. Panel (b) displays hybrid vehicles, dominated by Toyota with over 100,000 loans, followed by Hyundai, Kia, and Honda with much lower counts. Panel (c) shows EVs, where Nissan leads with over 13,000 loans (primarily the Leaf model), followed by Ford and GM with approximately 3,000 and 2,000 loans respectively. The caption notes that Tesla is absent from the sample as they did not securitize auto loans during the sample period, and the EV sample is dominated by more mainstream models like the Nissan Leaf and GM Bolt.

Figure B3: Average Predicted Delinquency and Interest Rate by Income



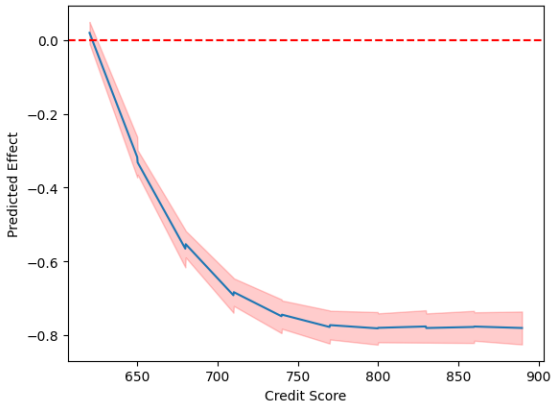
(a) Delinquency

(b) Interest Rate

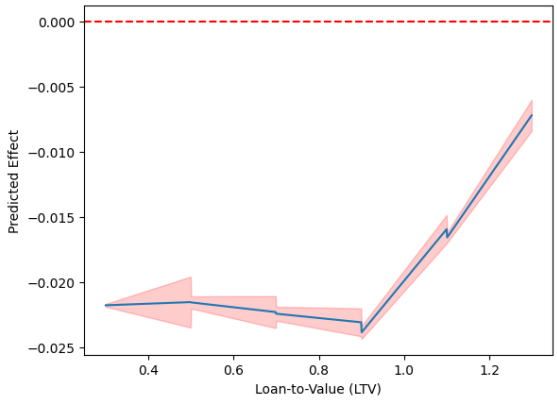
Note: Incomes between 1st and 90th percentile are shown. Source: SEC form ABS-EE.

Alt Text: This figure contains two line graphs showing relationships with income percentiles (1st to 90th) on the x-axis. Panel (a) displays average predicted delinquency rates on the y-axis, showing a clear negative relationship where higher incomes are associated with lower delinquency rates. Panel (b) shows average interest rates on the y-axis, which also decrease as income increases, though the relationship appears somewhat less steep than with delinquency. Together, these graphs illustrate how income is negatively associated with both credit risk and loan pricing.

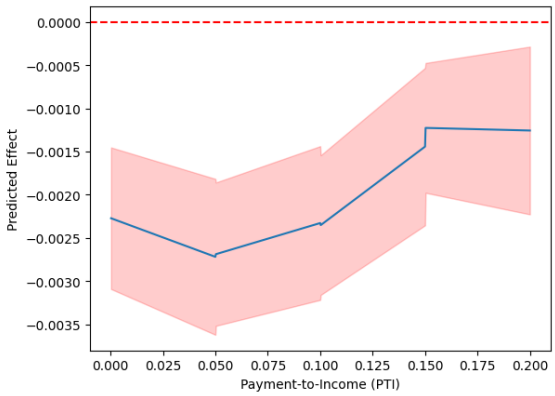
Figure B4: Splines from Underwriting Model of Credit Risk



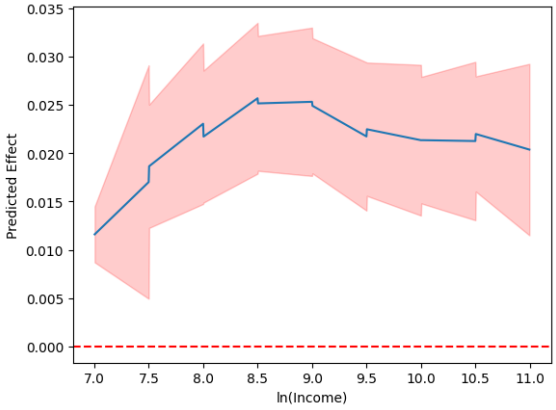
(a) Credit Score



(b) Loan-to-Value (LTV)



(c) Payment-to-Income (PTI)

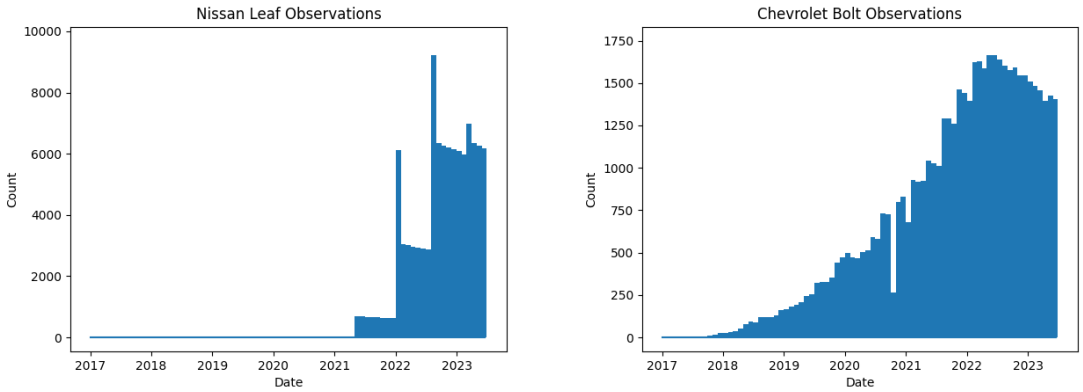


(d) ln(Income)

Note: These figures show the predicted effect of the underwriting variables: credit score, PTI, LTV, and income from the underwriting model of credit risk. The values come from the column (4) in Table 3 Source: SEC form ABS-EE.

Alt Text: This figure contains four line graphs showing the predicted effect of underwriting variables on credit risk. Panel (a) shows credit score (x-axis) versus predicted effect (y-axis), displaying a strong negative relationship where higher credit scores substantially reduce predicted delinquency. Panel (b) shows loan-to-value ratio with a positive relationship to delinquency risk that steepens at higher LTV values. Panel (c) displays payment-to-income ratio with a positive relationship to delinquency that becomes steeper at higher PTI levels. Panel (d) shows ln(Income) with a complex non-linear relationship, initially decreasing then increasing slightly at higher income levels. These graphs visualize the non-linear relationships captured by the spline functions in the credit risk model.

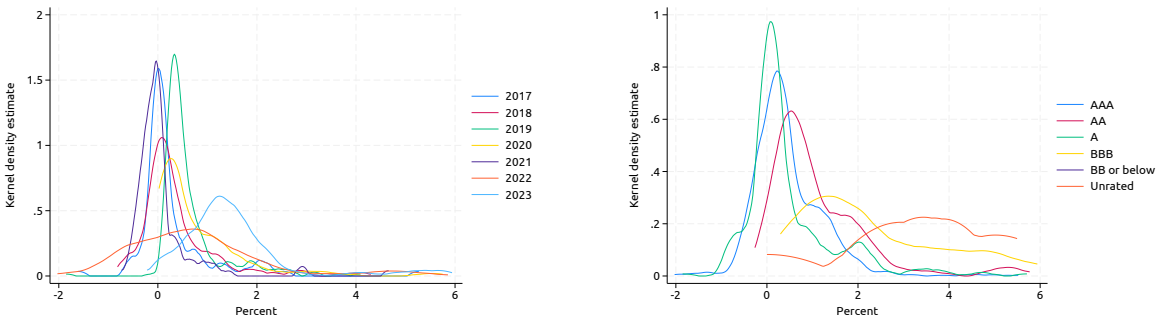
Figure B5: Leaf and Bolt Observations by Month



Source: SEC form ABS-EE.

Alt Text: This line chart displays the number of loan observations for Nissan Leaf and Chevrolet Bolt models over time. The x-axis shows months/years while the y-axis shows the number of observations. The chart reveals distinct patterns of loan originations for these two popular EV models in the sample, with varying peaks and valleys over the time period. This visualization helps demonstrate the temporal distribution of the most common EVs in the dataset

Figure B6: Auto ABS Coupon Spreads by Year and Rating



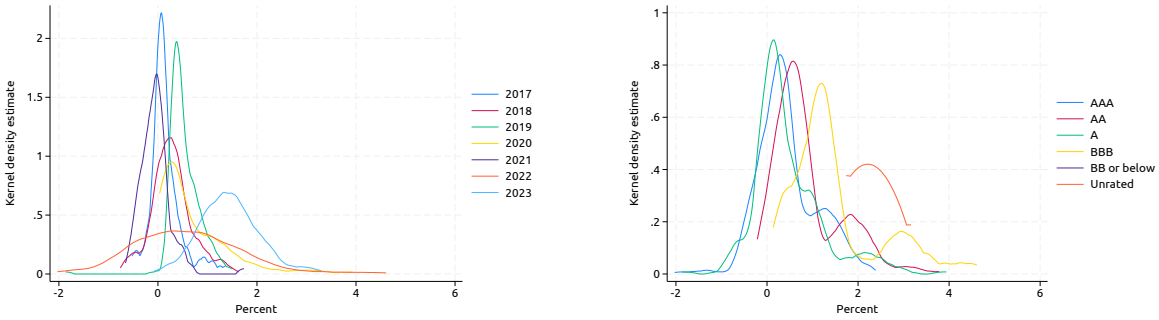
(a) By Year

(b) By Rating

Note: These figures show distributions of coupon spreads on tranches of publicly-placed auto ABS that we observe in our ABS-EE data, over time and across rating agency tranches AAA to BB or below. Source: Bloomberg Back Office Auto ABS, SEC form ABS-EE.

Alt Text: This figure contains two kernel density plots of coupon spreads on tranches of publicly-placed auto ABS. Panel (a) shows distributions by year from 2017-2023, with spreads on the x-axis (ranging from -2% to 6%) and density on the y-axis. The distributions shift rightward in later years, indicating widening spreads over time. Panel (b) shows distributions by credit rating from AAA to below-BB, with AAA tranches having the narrowest spreads centered near zero, and lower-rated tranches showing progressively wider spreads and greater dispersion. These plots illustrate how macroeconomic conditions and credit quality affect ABS pricing.

Figure B7: Auto ABS Z-spreads by Year and Rating



(a) By Year

(b) By Rating

Note: These figures show distributions of Z-spreads on tranches of publicly-placed auto ABS over time and across rating agency tranches AAA to BB or below that we observe in our ABS-EE data. Z-spread is the interest rate spread over the risk-free rate needed to equate expected future cash flows with the price of the ABS tranche at origination, assuming an ABS single month mortality rate of 1.3 % of loan aggregate amount prepay. Source: Bloomberg Back Office Auto ABS, SEC form ABS-EE.

Alt Text: This figure contains two kernel density plots of Z-spreads on tranches of publicly-placed auto ABS. Panel (a) shows distributions by year from 2017-2023, with Z-spreads on the x-axis (ranging from -2% to 6%) and density on the y-axis. Similar to coupon spreads, the distributions show shifting patterns across years. Panel (b) displays distributions by credit rating from AAA to below-BB, with AAA tranches having the narrowest Z-spreads concentrated near zero, and progressively wider and more dispersed spreads for lower-rated tranches. The caption notes that Z-spread is the interest rate spread over the risk-free rate needed to equate expected future cash flows with the ABS tranche price at origination, assuming a 1.3% monthly prepayment rate.

Table B1: Number of Loans by Engine Type and Origination Year

Origination year	Total	ICEV	Hybrid	EV
Total	4,096,082	3,910,601	163,037	22,444
Row percent	100	95.47	3.98	0.55
2017	806,086	781,438	23,989	659
Row percent	100	96.94	2.98	0.08
2018	787,264	764,137	18,646	4,481
Row percent	100	97.06	2.37	0.57
2019	615,795	598,532	15,948	1,315
Row percent	100	97.20	2.59	0.21
2020	679,695	659,970	18,805	920
Row percent	100	97.10	2.77	0.14
2021	660,628	611,123	44,620	4,885
Row percent	100	92.51	6.75	0.74
2022	460,682	414,923	36,583	9,176
Row Percent	100	90.07	7.94	1.99
2023	85,932	80,478	4,446	1,008
Row percent	100	93.65	5.17	1.17

Note: Authors' classification based on string-matching of make and model names/years using Car and Driver magazine, Kelley Bluebook, and Google. Engine type classifies a car into internal combustion engine vehicle (ICEV), hybrid vehicle, or electric vehicle (EV). Source: SEC ABS-EE.

Table B2: Robustness on Underwriting Model of Credit Risk

Dependent variable:	60-Day Delinquency (Percent)	
Subset:		Excl Tax Rebate Months
	(1)	(2)
EV	-0.102***	-0.0986***
	(-18.56)	(-17.66)
Hybrid	-0.0315***	-0.0312***
	(-12.86)	(-12.68)
Credit Score	-0.00236***	-0.00236***
	(-193.3)	(-193.2)
Payment-to-Income (PTI)	1.14***	1.14***
	(37.99)	(37.91)
Rebate-Adjusted LTV	0.232***	0.233***
	(67.46)	(67.49)
ln(Income)	0.0156***	0.0154***
	(8.730)	(8.636)
Aging*Calendar FE	YES	YES
Loan Term FE	YES	YES
State FE	YES	YES
Observations	83,689,616	83,593,664
R-Squared	0.003	0.003
AUROC	0.676	0.676
$Mean(ICEVDepVar)$	**0.202**	**0.202**
$\widehat{EV}/Mean(DepVar)$	**-50.6%**	**-48.9%**

Note: This table summarizes additional results on robustness tests, using subsamples, considering tax rebate environments. The dependent variable is defined as the empirical probability of a loan newly entering a 60-day delinquency in that period from a non-delinquency status in the previous period. "EV" and "Hybrid" are indicator variables flagging if the loan was extended to an electric vehicle (EV) or a hybrid vehicle, respectively, as opposed to an internal combustion engine vehicle (ICEV). In Column (1), we adjust LTV by the tax rebate and in Column (2), we exclude observations from April to June of the year following the purchase with a rebate. $Mean(ICEVDepVar)$ shows the mean of the dependent variable for ICEVs in the corresponding estimation and $\widehat{EV}/Mean(ICEVDepVar)$, hence, the economic magnitude of coefficient of interest off this sample mean of ICEVs. Robust t-statistics are in parentheses. Significance levels are denoted by: *** p<0.01, ** p<0.05, * p<0.1. Source: SEC form ABS-EE.

Table B3: Robustness Using Subsamples

Dependent variable:	60-Day Delinquency (Percent)			
Subset:	Bolt-Trax		Leaf-Versa	
	(1)	(2)	(3)	(4)
EV	-0.108***	**-0.0520****	-0.401***	-0.0675*
	(-4.150)	**(-2.093)**	(-7.846)	(-1.719)
Credit Score	-0.00214***	**[bucket-match]**	-0.00362***	[bucket-match]
	(-19.43)		(-14.97)	
Payment-to-Income (PTI)	3.75***	**[matched]**	6.32***	[matched]
	(7.678)		(8.835)	
Loan-to-Value (LTV)	0.195***	**[matched]**	0.241***	[matched]
	(3.815)		(3.534)	
ln(Income)	0.173***	**[matched]**	0.381***	[matched]
	(5.902)		(9.070)	
Aging*Calendar FE	YES		YES	
Loan Term FE	YES		YES	
State FE	YES		YES	
OrigYear FE		**[bucket-match]**		[bucket-match]
Observations	891,224	**235,018**	433,413	199,179
R-Squared	0.008	**0.001**	0.015	0.008
AUROC	0.852	**0.634**	0.877	0.925
$Mean(ICEVDepVar)$	**0.321**	**0.171**	**0.431**	**0.102**
$\widehat{EV}/Mean(DepVar)$	**-33.7%**	**-30.5%**	**-92.9%**	**-66.1%**

Note: This table summarizes results from an additional robustness using two subsamples, each based on a pair of EV and ICEV within a same manufacturer, the Bolt-Trax and the Leaf-Versa. The dependent variable is defined as the empirical probability of a loan newly entering a 60-day delinquency in that period from a non-delinquency status in the previous period, in percent. Columns (1) and (3) use OLS and (2) and (4) use propensity score matching. "EV" is an indicator variable flagging if the loan was extended to an electric vehicle (EV) or a hybrid vehicle, respectively, as opposed to an internal combustion engine vehicle (ICEV). $Mean(ICEVDepVar)$ shows the mean of the dependent variable for ICEVs in the corresponding estimation and $\widehat{EV}/Mean(ICEVDepVar)$, hence, the economic magnitude of coefficient of interest off this sample mean of ICEVs. Robust t-statistics are in parentheses. Significance levels are denoted by: *** p<0.01, ** p<0.05, * p<0.1. Source: SEC form ABS-EE.

Table B4: Credit Risk Results Using Payment Ratio Censored at 0

Subset:	Censored at 0					
Dependent variable:	Missed Principal Payment Ratio			Missed Principal+Interest Payment Ratio		
Estimation:	Tobit	Logit	Matched Sample	Tobit	Logit	Matched Sample
	(1)	(2)	(3)	(4)	(5)	(6)
EV	-0.191***	-0.199***	-0.0922***	-0.108***	-0.117***	-0.0480***
	(-68.49)	(-38.35)	(-30.25)	(-40.52)	(-32.70)	(-23.71)
Hybrid	0.00599***	-0.00826***		0.00619***	-0.00574***	
	(6.775)	(-5.180)		(7.515)	(-4.556)	
Credit Score	-0.000816***	-0.000959***	[bucket-match]	-0.000795***	-0.000788***	[bucket-match]
	(-277.2)	(-218.0)		(-323.3)	(-233.2)	
Payment-to-Income (PTI)	0.0346***	0.327***	[matched]	0.386***	0.427***	[matched]
	(5.084)	(36.91)		(71.67)	(65.12)	
Loan-to-Value (LTV)	-0.00232**	-0.00704***	[matched]	0.0316***	0.0105***	[matched]
	(-2.429)	(-5.104)		(39.48)	(9.943)	
ln(Income)	-0.0182***	0.0124***	[matched]	0.0178***	0.0252***	[matched]
	(-36.04)	(17.79)		(43.36)	(48.71)	
OrigMonth FE	YES	YES	[bucket-match]	YES	YES	[bucket-match]
Loan Term FE	YES	YES		YES	YES	
State FE	YES	YES		YES	YES	
Observations	1,354,779	1,354,779	983,191	1,846,323	1,846,323	1,488,088
AUROC	2.204	2.221	1.519	0.909	0.946	0.754
$Mean(ICEVDepVar)$	**0.210**	**0.210**	**0.142**	**0.144**	**0.144**	**0.087**
$\widehat{EV}/Mean(DepVar)$	**-90.9%**	**-94.5%**	**-64.9%**	**-74.7%**	**-81.2%**	**-55.4%**

Table B5: Interest Rate and Loan Pricing Results (As of Month 13)

	(1)	(2)	(3)
Dependent variable: Interest Rate			
EV		-0.0170***	-0.0176***
		(-52.34)	(-57.52)
Hybrid		-0.00240***	-0.00186***
		(-33.26)	(-28.50)
Credit Score	-0.000241***	-0.000241***	[spline]
	(-762.4)	(-760.3)	
Payment-to-Income (PTI)	0.0560***	0.0559***	[spline]
	(75.39)	(75.41)	
Loan-to-Value (LTV)	-0.0161***	-0.0161***	[spline]
	(-177.3)	(-177.6)	
ln(Income)	-0.00131***	-0.00126***	[spline]
	(-26.64)	(-25.60)	
OrigMonth FE	YES	YES	YES
Loan Term FE	YES	YES	YES
State FE	YES	YES	YES
Observations	2,114,083	2,114,083	2,114,083
R-Squared	0.377	0.377	0.448

Note: Robust t-statistics in parentheses. Significance levels are denoted by: *** p<0.01, ** p<0.05, * p<0.1.

Table B6: Explanations for Loan Pricing Differentials

Panel A: Using Creditworthiness Buckets Based on the First Principal Component of Underwriting Variables										
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Bucket:	(-5.0, -1.8]	(-1.8, -1.2]	(-1.2, -0.7]	(-0.7, -0.4]	(-0.4, 0.0]	(0.0, 0.4]	(0.4, 0.7]	(0.7, 1.2]	(1.2, 1.8]	(1.8, 5.0]
EV*Captive (α_1^n)	-0.0211***	-0.0149***	-0.0127***	-0.0170***	-0.0155***	-0.0165***	-0.0175***	-0.0171***	-0.0194***	-0.0207***
	(-15.61)	(-12.23)	(-12.02)	(-18.67)	(-18.79)	(-23.34)	(-28.78)	(-34.46)	(-48.30)	(-66.87)
EV*Non-Captive (α_2^n)	-0.0268***	-0.0135***	-0.00941***	-0.0159***	-0.00496*	-0.00295	-0.00666***	-0.00343*	-0.00288*	-0.000473
	(-8.140)	(-4.650)	(-3.410)	(-5.680)	(-1.880)	(-1.100)	(-2.830)	(-1.840)	(-1.740)	(-0.3500)
R-squared:	0.543									
Observations:	4,064,855									
OrigMonth FE	YES									
Loan Term FE	YES									
State FE	YES									

Panel B: Using Buckets Based on Credit Score									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Bucket:	(620, 650]	(650, 680]	(680, 710]	(710, 740]	(740, 770]	(770, 800]	(800, 830]	(830, 860]	(860, 890]
EV*Captive (α_1^n)	-0.0102***	-0.0140***	-0.0164***	-0.0177***	-0.0180***	-0.0190***	-0.0187***	-0.0191***	-0.0196***
	(-7.580)	(-13.21)	(-22.17)	(-31.14)	(-38.29)	(-43.58)	(-47.11)	(-48.24)	(-34.30)
EV*Non-Captive (α_2^n)	-0.0125***	-0.0186***	-0.00801***	-0.00869***	-0.00690***	-0.00495***	-0.00160	0.00180	0.0110**
	(-5.550)	(-8.640)	(-4.220)	(-4.900)	(-3.790)	(-3.050)	(-0.9000)	(0.7900)	(2.030)
R-squared:	0.524								
Observations:	4,045,759								
OrigMonth FE	YES								
Loan Term FE	YES								
State FE	YES								

Note: This table reports the results from []. In Panel A, the bucketing uses ten ($n = 1...10$) buckets of similar credit worthiness based on the first principal component of credit score, LTV, PTI, and $ln(Income)$. Source: SEC form ABS-EE. Robust t-statistics in parentheses. Significance levels are denoted by: *** p<0.01, ** p<0.05, * p<0.1.

C List of Electric and Hybrid Vehicles Identified in the ABS-EE Loan-level Data

List of Electric Vehicles

Make	Model	Count
nissan	leaf	13554
ford	mustang mach-e	3272
chevrolet	bolt ev	2274
hyundai	ioniq 5	948
kia	ev6	720
audi	e-tron	536
hyundai	kona electric	272
chevrolet	bolt euv	205
bmw	i4	188
mini	cooper se hardtop 2 door	166
volkswagen	id.4	140
genesis	gv60	54
toyota	bz4x	21
ford	f-150 lightning	19
nissan	ariya	13
tesla	model 3	7
kia	niro electric	6
cadillac	lyriq	6
kia	soul electric	4
volvo	c40 recharge twin	4
jaguar	i-pace	3
volvo	c40	3
hyundai	ioniq 6	2
volvo	xc40 bev	2
volvo	xc40 recharge	2
polestar	2	1
smart	fortwo	1
fiat	500e	1
volkswagen	e-golf	1

Source: SEC form ABS-EE. Authors' classification based on string-matching of make and model names/years using Car and Driver magazine, Kelley Bluebook, and Google searches.

List of Hybrid Vehicles

Make	Model	Count
toyota	rav4 hybrid	41429
toyota	prius	21745
toyota	camry hybrid	12028
toyota	sienna	10607
kia	niro	7288
toyota	highlander hybrid	7269
toyota	corolla hybrid	7231
toyota	venza	7064
toyota	prius plug-in hybrid	4871
hyundai	ioniq	4696
honda	insight	4533
audi	q5	3820
toyota	avalon hybrid	2055
toyota	prius prime	1899
hyundai	tucson hybrid	1835
hyundai	sonata hybrid	1796
honda	clarity plug-in hybrid	1553
lexus	rx 450h	1504
toyota	rav4 prime	1232
hyundai	elantra hybrid	1179
bmw	x5 xdrive40i	1089
lexus	es 300h	1067
hyundai	santa fe hybrid	928
lexus	nx 300h	855
chevrolet	volt	837
lexus	ux 250h	827
bmw	x5 sdrive40i	813
audi	a5	780
kia	sorento hybrid	763
ford	c-max	742
audi	a3	712
kia	sportage hybrid	675
audi	a4	599
toyota	prius c	474
bmw	540i sedan	456
mercedes-benz	gle450 4matic	442
audi	a6	389
bmw	m340i sedan	247
bmw	x5 xdrive45e	240
bmw	540i xdrive sedan	237
jeep	wagoneer	236
bmw	m340i xdrive sedan	231
toyota	prius v	227
bmw	530e sedan	227
audi	q8	214
mercedes-benz	glc350e 4matic	185
honda	accord hybrid	173
toyota	d highlander hybrid	172
bmw	330e sedan	151
mercedes-benz	e450	149
bmw	x3 m40i	133
kia	sorento plug-in hybrid	126
bmw	x3 xdrive30e	113
bmw	x5 xdrive40e	112
bmw	x6 xdrive40i	101
kia	optima hybrid	99
toyota	sequoia	96

Make	Model	Count
bmw	530e xdrive sedan	94
mini	cooper se countryman all4	92
bmw	m440i xdrive coupe	87
lexus	ct 200h	84
toyota	sienna awd	82
bmw	x4 m40i	69
bmw	330e xdrive sedan	67
lexus	nx 350h	64
kia	sportage plug-in hybrid	57
toyota	sequoia 4wd	54
honda	cr-v hybrid	49
mitsubishi	outlander phev	47
bmw	m440i xdrive gran coupe	46
volvo	xc60	36
hyundai	ioniq plug-in hybrid	36
bmw	m440i convertible	35
hyundai	sonata plug-in hybrid	35
honda	clarity	33
bmw	m440i coupe	33
mercedes-benz	gls450 4matic	31
toyota	sequoia 2wd	31
volvo	xc90	31
audi	a7	28
toyota	sienna 2wd	27
chrysler	pacifica hybrid	26
ford	fusion hybrid	25
bmw	m440i xdrive convertible	24
ford	c-max hybrid	23
volvo	xc40	21
bmw	x6 sdrive40i	21
honda	cr-z	18
ford	escape hybrid	16
bmw	m440i gran coupe	15
mercedes-benz	amg gle53 4matic plus	14
toyota	crown	9
mercedes-benz	c350e	8
lexus	ux	8
mercedes-benz	cls450	7
bmw	x7 xdrive40i	6
kia	niro plug-in hybrid	6
mazda	cx-90	5
bmw	330e xdrive	5
lexus	rx 350h	5
mercedes-benz	cls-class	4
bmw	x5	3
mercedes-benz	gls-class	3
toyota	sienna hybrid	2
bmw	i3	2
acura	mdx hybrid	2
lexus	gs 450h	2
lexus	ct	2
honda	cr-v hybrid awd	2
bmw	m340i	1
lexus	rx 500h	1
mercedes-benz	amg e53 4matic plus	1
acura	nsx	1

Source: SEC form ABS-EE. Authors' classification based on string-matching of make, model names and years using Car and Driver magazine, Kelley Bluebook, and Google searches.