Auto Finance in the Electric Vehicle Transition

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Abstract

Financing cost differentials tilt the calculus for households toward electric vehicles (EVs). Using 85 million observations on U.S. auto loans, we study households' credit risk by engine type, seek to uncover the sources and ask if credit risk differentials are being priced. We find that EV borrowers default 29% less relative to internal combustion engine vehicle (ICEV) borrowers with a back-of-the-envelope value of $1,457 in lender savings. To disentangle selection from ex post exposure to differential costs of running an EV, we implement a differential shock exposure by treatment model of Borusyak and Hull (2023). We find that a prolonged higher gasoline price regime could result in ICEV borrowers defaulting up to a 83% increase. Do lenders pass along these savings to borrowers? EV borrowers pay 2.2 percentage point lower interest rate, the equivalent of $2,711 in foregone payments. This lower rate is only for captive (manufacturer-based) lenders, not for bank and nonbank lenders, suggestive of policy and strategic motives by manufacturers, not a passing along of credit risk value. Another $1,457 is probably not being priced to households. Finally, we find that the ABS market knows, at least partially, allowing for less in loan loss reserves buffering the ABS, reflecting $233 in savings for the ABS issuer .

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1 Introduction

Household finance has a large role to play in facilitating the transition to electric vehicles (EVs), despite being largely absent from conversations. Roughly 80 percent of new automobile purchases are financed either with an auto loan or lease.[1] As of 2023:Q2, auto loans are the third largest category of consumer credit, behind mortgages and student loans, accounting for more than $1.6 trillion outstanding across 100 million loans.[2,3] This high rate of financing reflects both the natural role of finance in durable consumption. It also reflects the automaker business model of promoting car buying by selling attractive financing, a model which began in 1919 with the founding of the first "captive" auto finance company, The General Motors Acceptance Corporation (GMAC) (Olegario, 2016).

The EV transition, which started with the first hybrid car in 1901 (Appleyard, 2022), has taken over 100 years and a few milestones, such as a GM prototype in 1989 and the Toyota Prius a decade later, to accelerate and become an automotive engine transition. As of 2023, roughly 16 percent of new car sales are electric or hybrid vehicles.[4] A growing literature in transportation economics studies the relative cost of owning an EV versus an internal combustion engine vehicle (ICEV), including such costs as insurance, depreciation, maintenance, and fuel (Parker et al., 2021; Danielis et al., 2020; Sierzchula et al., 2014). Households respond to costs differentials, which additionally depend on micro-considerations of commuting and charging access. Yet, the literature finds that for millions of households, the netting of advantages and disadvantages leads to a close tally on which engine type is cheaper (Parker et al. (2021)). Thus, any cost difference that we uncover due to auto finance could have a meaningful impact at the margin in household decisions-making.

Our focus of why auto finance might be deferentially costly by engine type starts with credit risk. EV owners might represent a selection leading to information valuable for distinguishing credit risk (Stiglitz and Weiss (1981)). EVs might also insulate borrowers from gas price shocks and build a certainty into fuel expenses. On the other end, EVs may depreciate more rapidly due to resale risk (Schloter (2022), Bena, Bian, and Tang (2023)), thus incentivizing default more quickly.

The goals of our paper are to ask whether credit risk differs by engine type, to disentangle the drivers of differing credit risk, and then to ask whether the value of credit risk differentials

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

[2] Consumer credit is defined as credit card, student, and other consumer loans.

[3] Federal Reserve Bank of New York Household and Debt Report, May 2024. Retrieved May 20, 2024, https://www.newyorkfed.org/medialibrary/interactives/householdcredit/data/pdf/HHDC_2024Q1.

[4] https://www.reuters.com/business/autos-transportation/gas-electric-hybrid-vehicles-get-boost-us-ford-others-20

are priced to households, allowing for incentives in auto finance to affect the cost of ownership. The question of the pricing passthrough additionally allows our research to contribute to the study of economic transitions, which create opportunities and disruptions where some parties gain, and others lose. [5] Finance is one of the channels through which reinforcing distributions of gains and losses can occur.

Our data consist of more than 84 million monthly observations of loan performance, in a panel covering over 4 million auto loans in the United States from 2017 to mid 2023. These data comprise the population of auto loans which pool into publicly-placed auto ABS, with required reporting on the SEC's ABS-EE form.[6]

In our baseline underwriting model, we find that EV exhibit 29% lower defaults – measured in 60-day delinquencies and robust alternative measures. This baseline underwriting model controls for the set of underwriting variables used in loan decision-making (credit score, payment-to-income ratio, loan-to-value, and income) and absorbs calendar (monthly) interacted with aging time. Using the payment ratio measure of default (realized payments relative to scheduled payments), we estimate that the EV differential credit risk is worth $1,457 in foregone default losses for the lender.

These estimates in the baseline underwriting model do not answer the question of whether the credit risk differential effect is emerging from non-underwriting selection (e.g., home ownership) or from a treatment of realized lower variable costs of ownership. We follow Acemoglu, Autor, and Lyle (2004) and Sun and Shapiro (2022) in using a continuous variable version of a difference-in-difference, appealing to identification of a differential shock exposure by treatment of Borusyak and Hull (2023) and Bartik (1991). Following the vast literature on gas prices and demand for fuel-efficient cars, our differential shock is the regional gasoline price which exposes only the control group – ICEV owners – to a cost pressure on default.[7]

We find that the treatment effect of owning an EV insulates borrowers from energy price shocks, leading to lower delinquencies. If auto owners faced a standard deviation gasoline price shock that were to be sustained for a year (an aggressive assumption), EV owners would avoid 0.0188 in the

[5] 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 was the case after the Bubonic Plague in the 14th century, where disruptions caused labor capture of rents and reinforced labor-saving innovations. See Jedwab, Johnson, and Koyama (2022) for related literature.

[6] 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.

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

loan default rate, off a baseline annual default rate of 0.0228, compared to ICEV owners.

Are the lower risks being priced for consumers, or are intermediaries capturing the benefits? We next investigate interest rate pricing of the auto loans. The baseline predictive power of underwriting variables, calendar, term, and location is high, with R^2 statistics in excess of 0.48. In this frame, we add engine type. We find that, all else equal, lenders price EV loans with rates that are 2.2 percentage points lower than those on combustion engine loans, amounting to a \$2,711 lower cost of buying a car. It is a hugely important magnitude, relative to the baseline auto loan interest rates of 4.8% over our sample period.

This differential pricing might be due to automaker incentives and profit maximization.[8] In particular, manufacturers could subsidizes EV volume for reasons of mileage targets set by U.S. Environmental Protection Agency (EPA), incentives to show progress to affect Congress action, support for nascent EV parts supply chains, and/or the desire to clear production volumes for technology transition reasons. To distinguish these manufacturer incentives from credit risk, we re-estimate the interest rate specifications using only the set of loans extended by non-captive lenders. We find no differential interest rates for EVs in non-captive loans, and a small economic magnitude effect of hybrids having a lower rate of interest of 0.3% in interest rate points.

Thus, the evidence from non-captive lending suggests that the \$2,711 lower EV loan cost is not due to the passing back of the lower credit risk to households, but rather to manufacturer incentives. If so, our estimates together imply that EVs should be an additional \$1,457 cheaper (hence a total of \$4,168=\$2,711+\$1,457 cheaper) in cost of ownership due to the the finance channel, with the range difference of \$1,457 not being fully passed back to consumers.

We also look to the auto asset back security (ABS) market to uncover evidence of credit risk pricing. Especially if the credit risk differential we uncover is being priced to the household in the form of lower interest rates, we would expect the intermediary lender to also be demanding compensation for this lower risk from the ABS investors.

We map back our granular loan-level data to the auto ABS security that has been packaged and sold to ABS investors, allowing us to construct the share of the pool comprised of loans for EV or hybrid vehicles. We then look for pricing evidence in the pricing rate spreads (coupon spread over the risk free rate and the z-spread for specific tranches). We find no evidence that the EV share affects the ABS pricing spread. However, ABS securities have unique constructs of loan

[8]For example, Hankins, Momeni, and Sovich (2022) show how automakers pass through the cost shocks from tariffs to consumers via auto financing terms.

loss reserves, which are used to absorb waterfall defaults to enable on-time full payments to ABS investors of all tranches, until the credit support reserve is depleted. We find that these credit support loan loss reserve accounts hold less buffering reserves with a higher EV share. In economic magnitude, a standard deviation increase in the EV share (1.68% increase) implies lower reserves which the opportunity cost return value of $233 per EV, in a calculation comparable to the $1,457 in credit risk differential value per car.

Consistent with our goals, our overall punchline is also threefold. First, households with EVs default 30 percent less, with a large portion of this effect coming from lower ex post exposure to fuel price shocks. This better performance amounts to $1,457 additional payments on EV loans as calculated by back-of-the-envelope interference from payment ratio results. Second, in addition to federal and state incentives, EV loan borrowers enjoy a 2.2 percentage point interest rate financing subsidy in our sample. This subsidy means that EVs have been $2,711 cheaper than face value, after incorporating the amortization of interest costs. However and on top of this, finance markets do not seem to be yet fully pricing auto finance benefits back to the household, as if expected defaults were fairly priced in interest rates offered at origination, consumers would expect to see even lower costs. Third, ABS investors know about the differential credit risk and demand lower risk buffering in credit support loss reserves, which is worth $233 per EV to the ABS packager, who is generally also the auto loan lender.

Our results suggest a benefit from the separation of ABS markets to force further transparency and thus a pricing mechanism through financial markets. Our results also suggest that households themselves can unravel more value by factoring in the lower volatility of the costs of ownership into EV finance and purchase decisions. Finally, lenders, especially the manufacturer (captive) lenders have an ongoing role. They are already passing on pricing incentives in a large and somewhat unrecognized way. They seem, however, to not be pricing full pass-through (if any) of credit risk benefits to households.

We contribute to three strands of the literature. The first strand focuses on climate-related finance. Previous research shows that financing structures have a significant effect on investment in climate-related technologies. We provide evidence that the distribution of rents in auto lending between investors and households can support the introduction of further adoption of technology. Other research is more specifically focused on other household costs of EV adoption. Most of the focus of this literature is on tax credits, fuel cost, driving distances, as well as maintenance and the value of EVs for resale, incorporating depreciation factors and technological risk. For example, Parker et al. (2021) discuss the importance of the total costs of ownership in the adoption EVs. Schloter (2022) examines depreciation patterns for EVs and shows that, under some conditions, EV prices may depreciate faster than those for ICEVs. Danielis et al. (2020) finds access to charging is another potential cost of owning an EV. Bena, Bian, and Tang (2023) look at how technological risk affects financing costs via different rates of depreciation. While all of these costs are important, to date, little focus is placed on financing costs and the lower default risks of EV owners.

The second strand emphasizes household finance. Auto lending has been the subject of a range of research, with most focusing on imperfect information or bias in one form or another. 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. The literature has also been approached from the consumer 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. While mortgages or home equity loans can finance the purchase of solar panels, there is no direct connection between the loan and the object targeted for innovation.

The third strand is the general literature on financing of innovation, or the "funding gap," including financing from government subsidies.[9] Many studies have examined the role of financial markets in innovation (e.g., Brown, Fazzari, and Petersen (2009), Nanda and Nicholas (2014), and Nanda and Rhodes-Kropf (2017), among many more). On the other hand, innovation is also funded through government 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. 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. Yet, fewer papers have brought together subsidies in transformative innovation with finance's role in agent actions (see, for example, Howell (2017)).

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

2 Methodology

Our methodology proceeds in three steps. First, we study realized credit risk by engine type in defaults and payment ratios. Second, we ask whether any credit risk differential by engine type is reflected in the interest rate charged to borrowers, holding risk profiles constant. Finally, we look at how lower credit risk is allocated between ABS issuers and investors.

2.1 Credit Risk

Households secure auto financing either ahead of a car purchase through non-captive lending (a bank or non-bank) or, more often, at the time of sale through captive auto financing at the dealer. Captive financing is a mechanism for manufacturers to close auto sales, whereby salespeople secure deals by offering subsidies in the form of cash discounts on the sticker price or financing rate deals. Such subsidies are called subvents, or subventing the deal. Captive finance mandates a speedy process for loan approvals, as loan approvals are generally coincident with the decision to purchase a car. This implies that underwriting for auto loans tends to focus on a small set of applicant characteristics. The first step in our analysis is to level borrowers on these underwriting variables so that we can draw inferences related to credit risk specific to engine type that is over and above the factors influencing underwriting.

2.1.1 Baseline Underwriting Model of Default

Consider auto loan borrowers indexed by i, loan aging months indexed by $h : h = h(i)$, and calendar months indexed by t. We measure credit risk with two notions, both denoted with $default_{it}$, — the probability that a borrower defaults and the ratio of realized to scheduled payments. Our underwriting model specifies default at any time post-origination as a function of standard underwriting variables; namely, a borrower's cash flow ability to pay, as measured by the auto loan payment-to-income ratio, PTI_i and other characteristics that predict credit risk, $CreditRisk_i$ including credit score, income, loan-to-value ratio (LTV), and U.S. state of residence.[10] All of these variables are readily accessible: the dealer finance manager pulls credit history data from a registry, verifies a record of income, and incorporates the down payment information in the form of LTV and the

[10] According to the Bureau of Labor Statistics data, transportation expenses absorb around 16 percent of monthly income (https://data.bts.gov/stories/s/Transportation-Economic-Trends-Transportation-Spen/ida7-k95k/); furthermore, transportation expenses are also highly inelastic (Bertrand and Morse (2016)).

amortization information in the form of PTI.[11]

We augment the underwriting model variables with fixed effects for the interaction of calendar time with aging time, μ_{t*h}. We control for the exact number of aging months, reflecting "seasoning" patterns exhibited by auto loans (Kane, 2001). The absorbing of time effects uniquely for each origination date will remove selection of engine type correlated with buying a car at certain point of time in the business cycle as well as overall macroeconomic conditions affecting all auto borrowers in repayment ability. Finally, the baseline default model includes an indicator for the loan supporting the purchase of an electric vehicle, EV_i. The baseline equation model is as follows:

$$default_{it} = \beta_0 EV_i + \gamma_0 PTI_i + \Gamma CreditRisk_i + \mu_{t*h} + e_{it}. \tag{1}$$

Our parameter of interest, β_0, captures the differential default for a loan for an electric vehicle, holding all else equal on the underwriting profiles and time.

Manufacturers may have different underwriting models. Thus, for robustness, we compare default within samples of cars with the same auto body but different engines, such as the General Motors Trax and Bolt and the Nissan Leaf and Versa.

2.1.2 Sources of $\hat{\beta}_0$ Differential Credit Risk

Any difference in observed default by vehicle type, $\hat{\beta}_0$, could result from an incomplete underwriting model. The selection of EV buyers might pick up ex ante hidden wealth or cash flow stability not measured in the underwriting model or an ex post differential exposure of costs of car ownership. From the investor point of view, the distinction between these concepts is likely immaterial. Thus, in the empirical analysis, we draw out our main punchlines in aggregate. However, from the borrower, policy maker, or optimal contract designer point of view, the distinction is of interest.

A key selection unobservable, which could lead $\hat{\beta}_0$ to be different from zero, is home ownership. Because of the need for access to electricity sources to fuel an EV, EV owners are more likely to be homeowners. Conditional on observable credit scores and income, homeownership might proxy for wealth or buffer cash that matters for weathering times of duress. Other omitted selection profiling variables may exist, particularly ones that relate to unobservable family wealth or cash flow stability. For example, taste preference and employment sources may correlate with engine

[11] We assume that the household's choice of the value of the car as largely exogenous to the ultimate financing; in most cases, consumers choose the car first, then address the loan terms. See 17 CFR S 246.18, for underwriting standards for qualifying automobile loans.

selection and be proxies for unobserved credit risk.

Alternatively, a nonzero $\hat{\beta}_0$ might result from differential exposure to variable costs of operating an EV versus a ICEV. Our focus is primarily but not exclusively on fuel cost differentials across engine types. For example, operating costs for different engines necessarily are exposed to different price levels and volatility of the required fuel. Still, similar arguments can be made for other costs, such as maintenance, insurance, and depreciation (working through resale value effects), where EVs may have different costs compared to ICEVs.[12]

2.1.3 Ex Ante Cost of Ownership

To make progress on attributing $\hat{\beta}_0$ to mechanisms, we focus on variable costs of ownership differentials. First, we construct an enhanced PTI ratio, which measures a more complete expected cost of ownership including fuel, insurance, depreciation, car maintenance, and loan payment as follows:

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

The components of this variable are borrower- and car-specific and known at the time of origination, defined in terms of monthly payments. We cannot observe the within-state location of borrower i; thus we cannot estimate driving distance. Consequently, our fuel measure is the historical cost of fueling the vehicle chosen by i, defined at the time of purchase. Busse, Knittel, and Zettelmeyer (2013) find that gas price changes influence consumers' car buying decisions. Maintenance and depreciation naturally vary over the life of the car, using industry forecast models; thus, these measures vary over car aging.

We also create an expected fuel volatility measure, σ_i in a dollar metric to compare the swing of a standard deviation in electricity or gasoline prices locally in rolling average historical prices. This is particularly important in some states where both electricity and gasoline prices float. The estimated coefficient ζ_2 on this measure of fuel risk will serve as an informal certainty equivalent metric, in credit risk space.

Our estimating equation replaces PTI with the new costs variables as follows:

$$default_{it} = \beta_0^* EV_i + \zeta_1 E[Costs : Income]_{it} + \zeta_2 \sigma_i + \Gamma CreditRisk_i + \mu_{t*h} + e_{it}. \quad (3)$$

[12] The EPA reports average monthly maintenance costs over the life of a vehicle. Thus far, the evidence suggests low differences in maintenance for similar body cars with different engines. However, as EVs are simpler mechanically, the equal maintenance may be due to short term premium on mechanic's time, which could erode.

We are interested in how $\hat{\beta}_0$ evolves to $\hat{\beta}_0^*$.

2.1.4 Regional Gasoline Price Model of Default

In a second step, we focus on ex posts shocks to the cost of ownership. In particular, we use regional gasoline price fluctuations as a set of as-good-as-random shocks to the treatment, in a varying intensity of shock exposure by treatment model following Borusyak and Hull (2023). The technique is akin to a Bartik (1991) or shift-share formulation, but with our subjects being exposed to shocks of the intensity of treatment effect rather than to share exogeneities.

Our primary implementation using shock exposure identification takes a continuous variable difference-in-differences form, as that in Acemoglu, Autor, and Lyle (2004) and Sun and Shapiro (2022), using regional gasoline prices P_{it}^{RegOil} as the exogenous shock affecting only the ICEV control group:

$$default_{it} = \beta_0^{Oil} EV_i + \beta_1^{Oil} P_{it}^{RegOil} + \beta_2^{Oil} EV_i P_{it}^{RegOil} + \zeta_1 E[Costs : Income]_{it} + \mu_i + \mu_{t*h} + e_{it}. \quad (4)$$

Loan-level fixed effects μ_i control for selection differences of consumers into EV versus ICEV, including any differences in expectations about future fuel prices or volatilities. Our methodology relies on the plausible assumptions that (i) the ex-post realization of regional gasoline prices involve uncertainty resolution (gas prices are, at least to a degree, unpredictable) and (ii) the regional gas price realizations may affect the regional macroeconomic conditions for default for all vehicles through indirect channels but uncorrelated with engine selection except via the direct fuel costs channel. Indirect channel effects will be picked up by the un-interacted regional gas price variable. Indirect channels include potential correlates with oil prices such as market-based wealth, the costs of goods shipped including groceries, and income wages and opportunities.

We do two additional versions of the model from equation (4), replacing the price level of regional gasoline prices with the (a) rolling 12-month standard deviation of regional gasoline prices and the (b) rolling 12 month log average positive deviation (dropping negative deviations) from the expected oil price (the actual) at the month of purchase.

2.2 Credit Risk Pricing in Auto Loan Interest Rates

Our analysis of whether credit risk in auto loan finance differs by engine type leads to the next question of whether such credit risk is priced. We first examine household pricing differentials.

2.2.1 Interest Rate Model

Our model of the pricing of credit risk in auto finance interest rates, $rate_i$ is as follows:

$$rate_i = \alpha_0 EV_i + \Gamma_{rate} CreditRisk_i + \mu_{date} + \mu_{state} + \mu_{term} + \epsilon_i, \tag{5}$$

where we employ the underwriting credit risk variables (credit score, PTI, LTV, income) that are used in practice to control for lender pricing algorithms, as well as fixed effects for the origination month-year (*date*), U.S. *state*, and loan duration *term*. We implement $CreditRisk$ in linear form and also with a full set of splines as a piecewise linear formation.

2.2.2 Explanations for $\hat{\alpha_0}$ Pricing Differentials

A significant $\hat{\alpha_0}$ may emerge for several possible reasons. Our motivating story is that if we uncover a significant credit risk $\hat{\beta}_0$, we want to know if the intermediary prices such risk back to the household. In essence, who keeps the rents? However, explanations for the pricing differentials extend beyond our goal. We also have to consider the business strategy and political economy setting of why manufacturers might set different interest rates by engine type.

First, auto manufacturers face regulations that set the weighted average fuel economy at the manufacturer-level, with sales volume of each vehicle model as weights. In the United States, such regulation is enforced through Corporate Average Fuel Economy (CAFE) standards by the National Highway Traffic Safety Administration (NHTSA).[13] Most recently, 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. The implication is that many automakers selling in the United States, in particular, the ones that have traditionally had their production lines tilted towards ICEV, are increasingly coming under binding CAFE constraints. It would be reasonable to assume that such incentives lead to different business or pricing strategies (possibly via lower profit margins) to induce higher sales of EVs.

Second, the automakers may also take lower profits in the short term to induce EV production and sales volume in order to influence policy and supply chain decisions. Favorable policy actions might include passing federal and state appropriations for expanding charging infrastructure and related subsidies, and continuing of EV tax credits, which was under consideration in the Inflation Reduction Act of 2022 during our period. Higher EV sales can make a stronger case for the need for

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

such incentives and subsidies coming from the lawmakers. 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 leads automakers to adopt different business strategies for EVs, including the use of subsidies in interest rates. Unlike ICEVs, consumer's price sensitivity and the overall demand function is less known for EVs. Manufacturers may employ a pricing strategy that introduces a higher sticker price and then use or does not use subsidies (including lower interest rate) at the dealer to allow flexibility to price in EVs according to the market's 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 rapidly changing.

2.3 Credit Risk Pricing in Asset Backed Securities (ABS)

The final set of models analyze whether any credit risk differentials are passed through to the ABS investors. If credit risk varies by interest rate and if this 'rent' from the reduced risk is provided to households, we would expect that the intermediary captive or non-captive lender would collect the offsetting discount from the ABS investors. This would imply that the pricing of credit risk depends on the percentage of EVs in the ABS pool. We consider the credit risk pass-through in dimensions of the market pricing of the ABS security and in dimensions of the buffers of credit support intermediated between the loan pool and the ABS market.

The first gauge of a pricing spread is the coupon rate spread, which is the ABS's tranche coupon rate over a comparable-maturity Treasury security.[14] 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. In particular, 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:

$$P_{jk} = \sum_{t=1}^{n} \frac{cashflow_{jkt}}{1 + r_t + ZSpread_{jk}}. \tag{6}$$

Time variation in this measure enters through r_t, the expected risk-free discount rate at tenor t,

[14] Because auto ABS are often issued within a few cents of 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.

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.[15]

The third and fourth gauges of credit risk pass-through are embedded in intermediation spreads and loan loss reserves. 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, the excess spread (spread between weighted average (household) loan rate and (ABS) coupon rate) and the ABS loss reserve (a credit support account escrowed as a percentage of sum of face value of household auto loans in pool). 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. In our sample, ABS tend to be overcollateralized by a significant margin; that said, credit support can be lower for relatively higher quality ABS pools.

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:

$$y_{jk} = \eta_0 EV_j + \Gamma CreditRisk_{jk} + \mu_{year} + \varepsilon_{jk}. \tag{7}$$

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.

3 Data

Our primary data comes from SEC form ABS-EE, which contains loan-level data for loans securitized in public securities offerings of auto ABS, as ruled under SEC Regulation AB II, effective November 23, 2016.[16] The data disclosure required under the rule include both origination loan data and monthly loan performance. The final sample for our empirical analyses covers over 85 million observations on 4 million auto loans originated on new cars from January 2017 to July 2023.

[15] Our results remain robust to including realized z-spreads, calculated using actual cash flows (adjusted for prepayments) instead of expected cash flows.

[16] The requirement applies to all registered offerings backed by auto loans and leases, residential and commercial mortgages, and debt securities including re-securitizations. Information is available at https://www.govinfo.gov/content/pkg/FR-2014-09-24/pdf/2014-21375.pdf

3.1 Vehicle Characteristics

Our loan data include a description of the vehicle collateralizing each loan, including the manufacturer name, model name, and model year. We develop a vehicle name-model-year taxonomy to assign vehicles to EVs, hybrids, or ICEV categories. To do so, we hand-construct engine type classifiers using information from the EPA on EVs and hybrids in various model years[17] and then develop full attribution with manufacturer and model names found in Car and Driver magazine, Kelley Bluebook, and Google searches. We condition our classification on the car's model year to accommodate cases in which a manufacturer introduces EV or hybrid technology without an accompanying model name change. We also search for relevant strings that indicate for EVs or hybrids in vehicle model names, such as "HV," "PLUG-IN," "EV," and "E-." Taken together, we identify 113 hybrid models and 29 electric models among the total of 4,734 model names in our final data set. Appendix B provides details on the list of hybrid cars and EVs based on our classification.

Figure 2 displays the origination year distribution. The phase-in of reporting requirements as well as the general recovery of auto ABS securitization post-Global Financial Crisis resulted in a ramp up from 2017 to 2020, with volumes having a temporary decline during the COVID-19 pandemic, and a drop off in late 2022 through 2023 due to warehousing delays (Klee and Shin, 2020) and delays in purchase awaiting EV tax credits rules. Figure 3 illustrates geographic dispersion in origination, normalized to population. Our sample of auto loans has broad national coverage with concentrations in the Southeast and the Southwest from Texas and California.

Table 1 provides the distribution of engine type across the loan data. Overall, the proportion of vehicles flagged as hybrid or electric is around 5 percent of all loans, trending upwards in the sample. Figure 4 display the manufacturer distribution for ICEVs, hybrids, and EVs. Note that Tesla and some other car manufacturers use 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.

The vehicle value amount is measured as reported dealer invoice price. As shown in panel A of Table 2, for combustion engine vehicles, values average around $35,000, in line with the reported average of new car prices over our sample period.[18] Hybrid cars are a little more expensive than combustion engine cars, while EVs are $6,000 more expensive, on average.

Perhaps unsurprisingly, the higher car value mean is on the order of the tax credit available for

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

[18]https://www.bts.gov/content/new-and-used-passenger-car-sales-and-leases-thousands-vehicles.

some EVs. 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 credits to be taken on households income tax filings, not at the dealer. These tax credits phased out once a manufacturer sold 200,000 qualifying vehicles in the United States, which happened, for instance, for Tesla and GM in 2018 and Toyota in 2022. However, the Inflation Reduction Act of 2022 re-introduced the tax credit of \$7,500 (with dealer filing of the credits to the tax authority) and 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.

Because the tax credit may have been built into household or underwriting decision-making, we provide tax credit robustness in our results as follows. First, we adjust the loan-to-value (LTV) measure to subtract out the tax credit on the denominator in leveling on underwriting variables. We also consider credit risk in some models only after the spring of the year following purchase, to ensure robustness to the occurrence of the cash inflow of the tax credit realization from the IRS or tax rebate loans. However, an alternative way to think about the counterfactual with no tax credit is that perhaps EV car buyers find themselves with higher payments because they purchase a higher sticker price car and amortize the loan. However, this prediction on credit risk works in the opposite direction of our results.

3.2 Borrower and Loan Characteristics

We turn next to summary statistics for borrower characteristics, imposing a limits on our sample to being to new car borrowers, with a prime credit score above 620 (due to data scarcity of subprime EV borrowers), with monthly income above \$1,500 and below \$83,333 (to remove potential skew from irregularities in reporting) and with loan terms of 6+ years (the most common length in our sample (Katcher et al., 2024). Note that households choose vehicles based on their own targeting of payment feasibility (Hertzberg, Liberman, and Paravisini, 2018). Likewise, evidence on household decision-making suggests that when consumers shop for cars and take out loans, they have in mind a monthly payment that fits their budget constraint (Bertrand and Morse, 2011) as well as a potential down payment that they are willing to put forward for the loan (Einav, Jenkins, and Levin, 2012). Thus, we consider the term, loan amount, and payment-to-income to be predetermined borrower characteristics variables.

Panel A of Table 2 shows that whereas ICEV borrowers have credit scores around 740, EVs borrowers average at 788. Monthly income, derived from the reported payment-to-income ratio and monthly payment, is also higher from EV borrowers, with income averaging $\$13,309$ compared to $\$8,308$ for ICEV borrowers.

Loan amounts average $34,457 for ICEVs, $35,941 for hybrids, and $38,537 for EVs. Comparing this to the vehicle value amount, the loan amount does not rise as much as vehicle values do, leaving the loan-to-value (LTV) ratio—which we define as the original loan amount divided by the vehicle value amount—for EVs statistically significantly lower on average (0.945) than that for ICEV loans (1.011). 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. Monthly loan payments for ICEVs and EVs are fairly comparable, at $544 and $530, respectively, per month. With higher income for EV owners, the resulting PTI remains lowest for EV borrowers (0.062), compared to ICEV borrowers (0.087).

3.3 Fuel and Other Variable Costs Data

Information on fuel and other variable helps us to identify the treatment effect of owning an EV. To this end, we collect car-level data on depreciation, fuel, insurance, maintenance, repair costs, taxes, and fees. Panel C of Table 2 shows the summary statistics. Data on fuel price, including retail gasoline price and electricity price, is available by region from the U.S. Energy Information Administration (EIA). We obtain most other data on operating costs from Edmunds, matching to auto loans based on state and year-month.[19]

Overall, ownership costs are significantly larger for ICEVs than EVs. The most important contributor to this difference is the fuel cost, which is nearly as four times as high for ICEVs ($2,592) than EVs ($654). Not shown in this table, but the average coefficient of variation is substantially higher for regional gas price (0.23) than for regional electricity price (0.08) as well, adding to the importance of roles played by gas price and volatility in consumer's calculus that includes variable costs of operating a car and its certainty equivalent. Maintenance cost is also

[19]Data from the EIA is grouped by seven regions including West Coast, Rocky Mountain, Midwest, New England, Central Atlantic, Lower Atlantic, and Gulf Coast. Data from Edmunds covers the first five years over the car's life; we assume that all loans over five years have the same operating costs as those of fifth year loans in Edmunds.

significantly larger for ICEVs ($1,050) than EVs ($584) as well as repair cost, because ICEVs have to be regularly maintained of their engine and transmission, and also they have more number of moving parts that can be broken and need to be fixed. Interestingly, depreciation cost, which takes up the largest component of total cost, is slightly larger for ICEVs ($3,251) compared to EVs ($3,140). Insurance cost, taxes, and fees are marginally bigger for EVs than for ICEVs, due to generally higher vehicle prices of EVs.

3.4 Default Data

Our key variable of interest is loan default. We use two measurements. First, we use delinquencies, specifically being 60- or 30-days delinquent post the payment date. Empirically, we estimate only in the initiation into a delinquency, so as to not double count episodes of continuing delinquency.

Panel B of Table 2 presents delinquency rates. ICEV delinquency rates are observed to be 1.6 percentage point higher than that for hybrid vehicles, and 2.6 percentage points higher than for EVs for our main 60 day measure. Panel B provides monthly delinquency rates, which reflect the observed probability of a loan experiencing a 60-day delayed payment in any given month. This probability is 20 basis points for ICEVs, more than five times higher than that for EVs.

Second, we use realized-to-scheduled payments, specifically, the ratio of the monthly realized payment to the monthly scheduled payment. We provide two versions of this measure, one which excludes prepayments and other unexpected loan seasoning events ("Payment Ratio"), and another which includes some of these outcomes ("Raw Payment Ratio"). Panel B of Table 2 presents information on monthly realizations of the payment ratio and the raw payment ratio. For both measures, EV loans experience higher payment ratios, consistent with lower defaults and hence credit risk. Relative to ICEVs, these differences are statistically significant, and when cumulated over a year, could reflect substantially higher loan payments.

3.5 Credit Risk Pricing Data

3.5.1 Auto Loan Outcomes

As shown in Panel A of Table 2, EV loan interest rates (2.3%) are, on average, more than 2 percentage points lower than those for combustion engine loans (4.9%). And as with other credit dimensions, rates on hybrid loans fall between those for ICEVs and EVs (3.7%). Some of lower interest rates could reflect the propensity for lenders to offer "teaser" rates at loan origination.

Subvents in the form of interest rate promotions are active in captive auto lending. EVs are particularly likely to have a subvention on the loan: roughly 9,000 out of our sample of 22,000 EV loans have zero original interest rates, and 90 percent of EVs are listed as subvented (about half cash subvented, half rate subvented). Thus, we report rates 13 months after origination. Even so, 13 month interest rates are are not materially different from origination rates.

3.5.2 ABS Market Data

As of 2022Q4, the stock of outstanding auto ABS stood near $220 billion. [20,21] Table 3 summarizes characteristics for the $361 billion in publicly-placed auto ABS issued from 2017 to 2023 used in our sample. Our source is Bloomberg Finance LP, ABS Backoffice, which we merge with the SEC ABS-EE data to obtain aggregates of loan-level attributes. We cover 20 distinct issuers. A little over half of the issuers are captives, followed by banks and nonbank lenders. Captives account for roughly 60 percent of the securitizations.

Each auto ABS deal is comprised of tranches. Our data include tranche ratings from 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. Table 3 displays the distribution of credit ratings in our sample. A little less than 20 percent of the dollar value of ABS issued over our sample period was in subordinated tranches.

We construct the coupon spread using a daily zero-coupon yield estimated from a smoothed yield curve sourced from Gürkaynak, Sack, and Wright (2007).[22] Figure 6 displays the distribution of coupons and spreads on tranches of auto ABS over time and across rating agency tranches AAA to BB or below. Most spreads are between zero and 2 percentage points. However, the mean spread shifts over time, with higher spreads in the more recent part of the sample, likely reflecting in part macroeconomic factors. The 99th percentile of the spread distribution is around 6 percentage points, and can fall as low as -2 percentage points. Coupon spreads by rating are largely in line with expectations, with investment grade spreads relatively narrow and low, and the unrated tranche with notably higher mean and variance. Figure 7 presents the distribution of expected z-spreads over our sample, again by year and rating. The patterns are similar to those

[20] Refer to SIFMA, U.S. ABS issuance and outstanding, available at https://www.sifma.org/resources/research/us-abs-issuance-and-outstanding/.

[21] 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).

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

for coupon spreads, despite the difference in methodology.

Table 3 provides information on credit support measures. Because the loan rate charged to consumers is often higher than the coupon rate on securities, this "excess spread" offers a source of credit support for the deal. Across all tranches, the excess spread averages roughly 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 roughly 22 percent. This also varies substantially, to as much as 95 percent, likely reflecting deals with a higher share of subprime auto loans.

4 Results

4.1 Credit Risk Results

We begin with a univariate comparison of loan performance across engine types. Figure 1 plots the realized cumulative 60-day delinquency rates on the y-axis as measured across the aging month of the loan (months since origination) on the x-axis by engine type. Comparing results at 24 months, the cumulative delinquency of ICEV loans (the orange line), hybrid loans (the blue line), and EV loans (the green line) are respectively 4.29%, 1.74%, and 0.39%. At 48 months, these cumulative delinquencies increase, respectively, to 8.87%, 4.28%, and 1.68%. This figure depicts a major punchline of our paper. a large and persistent difference exists in default by engine. Of course, multivariate analysis of leveling on risk factors is necessary before drawing conclusions.

4.1.1 Results: Baseline Underwriting Model of Default

Table 4 presents the first set of results speaking to the baseline underwriting model of equation (1). We estimate our model in linear probability rather than logit because of computing power required to invert matrices with our very large sample of loans. The dependent variable in the odd (even) columns is default defined as a loan newly entering a 60-day (30-day) delinquency in that period from a non-delinquency status in the previous period. Columns (1) and (2) report the simplest depiction of default, akin to Figure (1), looking at differentials by engine with only aging absorbed. As reported in Column (1), we find that electric (hybrid) vehicles default 0.00156 (0.00109) less often per month or 0.0187 (0.0131) less often annually. Across all loans in our dataset, the annual default rate averages 2.36 percent (that is, 0.197 percent from Table 2 Panel B times 12). Thus, we find very large reductions for EVs and hybrids: 79 percent lower default rates for EVs and a 56 percent lower default rates for hybrids.

Column (2) shows that this result remains robust at the timing of 30 days delinquent and is approximately three times larger in economic magnitude but lower in percentage change terms. Going forward, we focus our discussion on 60-day delinquency rates, because of noise in inattention-driven delinquencies at the shorter horizon. In Columns (3) and (4), we absorb the effect of macroeconomic conditions by including year-month calendar interacted with aging months fixed effects, the precise number of months in the loan term, and state fixed effects to absorb state-level conditions. The coefficients on EV and hybrid only change marginally from Columns (1) and (2).

Columns (5) and (6) introduce the underwriting variables, allowing us to answer to what extent the default differences results from selection differential on observable credit risk. We focus our interpretation on Column (5). The key underwriting variables for vehicle loans are the borrower credit score, the borrower's monthly payment-to-income (PTI) ratio, the ratio of the loan amount to the vehicle value (LTV), and the natural log of borrower income. We find the expected signs on three of these variables; borrowers with low credit scores, high PTI, and high LTV default more. The log of income has the opposite of the predicted negative sign. One must condition that interprtation on the inclusion of PTI in the estimation. As such, the intuition is that those with higher incomes who are taking out a loan with the same PTI are at higher risk, which is intuitive. These variables have a very large presence in explaining variation of the model, with the t-statistic of credit score, for example, coming in at nearly 200.

With this absorbing of credit risk underwriting variables, the economic magnitude of our vehicle effects fall, as expected. We find that, all else equal in underwriting variables credit profiling and time, EV (hybrid) borrowers default by 29% (13%) less, in percentage change, than the mean engine, based on the coefficient -0.000557 (-0.000251).

Our sample is too short to expand on delinquency to estimate overall profitability of the loans, but we can take steps toward this goal in loan performance. We investigate how behavior on borrower payment relative to the scheduled payment—"payment ratio"—varies by engine type.

Table 5 re-estimates the original delinquency results in Table 4 but using the payment ratio as the dependent variable.[23] As Column (1) reports, we find results consistent with the delinquency

[23] Results using the raw payment ratio without any cleaning applied is reported in Column (4). For our main results in Columns (1)-(3), we use a cleaned payment ratio variable by removing loans with negative interest or principal payment amounts, loans with principal payments exceeding the outstanding loan balance, and lo ans with cumulative principal payments exceeding the loan amount. Also 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

measure of default. The payment ratio is statistically significant and larger by 0.0424 for EV loans, once we condition on the underwriting controls and include the year-month for electric vehicles. In Column (2), we absorb macroeconomic conditions by adding year-month interacted with aging months fixed effects, and in Column (3), we additionally introduce controls for underwriting variables. As reported in Column (3), We find that EV loan borrowers pay 3.78 percentage points more of their due monthly payments when compared to ICEVs. For hybrids, we find the opposite result; that is, hybrid loan borrowers pay 3.49 percentage points less monthly. The out-performance by EV loans remain robust even after controlling for the broader payment behaviors over the lifetime for the loan, including prepayments and paydowns (see Appendix D Table 3).

Taken together, these monthly payment results show that EV loans pay a higher percentage of their monthly obligation, even when controlling for underwriting variables. In a back-of-the-envelope calculation, we multiply the estimate from Column (3) of Table 5 with the average EV loan amount of $38,537. This calculation illustrates that EV loans outperform comparable ICEV loans by $1,457 in additional payments over the life of the loan.

4.1.2 Ex Ante Cost of Ownership Model Results

In Table 4, we levelled borrowers on credit risk underwriting observables and a saturation of time effects, still uncovering a significant difference in credit risk by engine type. We now seek to uncover why. We begin by considering whether what we are finding relates to the cost of ownership of an EV versus a ICEV.

In our first specifications, columns (1) to (4) of Table 6, we build off of Parker et al. (2021) to compare the costs of operating EVs of the same car body (e.g., Golf versus E-Golf, etc). In our data, we have two pairs of such vehicles with sufficient sample size – Bolt-Trax and Leaf-Versa. By re-running our estimation only within these pairs, we add an extra level of comparison on all else equal. Focusing on Columns (3) and (4) (we have more data on the GM Both-Trax comparison), we find that not only are the results from Table 4 robust, they are conservative by half in economic magnitude. Out previous estimate found that EV loans default by 0.000577 less that ICEVs; in Column (3), Bolt loans default by 0.00133 less that Trax, all esle equal on underwriting variables and time.

In Columns (5) and (6) of Table 6, we take a different view of leveling cars on cost of ownership, instead directly adding in the dynamic estimate of the cost of ownership for the particular vehicle-

amount is listed as zero.

vintage, including the payment of the loan. As described previously, this variable is dynamic in that depreciation and maintenance change over time, but in a way that is known ex ante. We also include the expected energy volatility measure for the vehicle loan state, calculated as the existing volatility of electricity or gasoline price in the recent history of the state at the time of car purchase.

We find that the cost of ownership variable carries high explanatory power of predicting default, with a t-statistic of 55.12 in column 5. Furthermore, the magnitude is meaningful. The mean total cost of ownership: income ratio is 0.0884. With 8.8% of monthly income being spent on average on car direct costs and depreciation, transportation is a large expense. If this expense were to increase by 10% , the estimate 0.00975 would predict a 4.7% increase in default probability. Our ex ante measure of fuel volatility, however, predicts default with economic immaterial and incorrect signed results.

Our objective in including these ex ante cost of ownership was to understand to what extent our estimate of the EV effect on default (with the main magnitude being a coefficient of 0.000577 on EV for 60 day delinquency) erodes in the presence of other explanations for differential default by engine type. In columns (5) and (6), we find the opposite; the EV coefficient surprisingly increases to - 0.000930, consistent with the fact that the EV coefficient in the Trax-Bolt and Leaf-Versa results are also larger. We conclude that we are being very conservative in interpreting 0.000577.

4.1.3 Results: Regional Gas Price Model of Default

To what extent is the residual unexplained default differential between ICEV and EV due to the ex post impact of being exposed to differential fuel costs? Equation 6 in our methodology section laid out the estimating equation for Table 7. The important feature of the estimation is in the inclusion of the loan fixed effect. The focus of the estimation abstracts from selection by credit risk, and we can focus on the interaction of combustion engine (ICEV) with the regional gasoline price. We also include the time-varying cost of ownership in the specification, for the aspects of cost other than fuel, and include macroeconomic controls for the median monthly household income, unemployment, and house price index (HPI) at the state level.

Under the assumptions of Borusyak and Hull (2023), any coefficient on ICEV interacted with the regional gas price can be interpreted as a 'treatment' effect of owning an ICEV, insulating EV borrowers from expense shocks, leading to lower delinquencies. In Column (1), we find that a \$1.00 increase in gas prices results in a 0.00157 higher monthly default rate, or 0.0188 higher annual default rate for ICEV loans. Of note, one standard deviation of gas prices is slightly lower than

$1.00, at $0.76. Using this increment, a one standard deviation swing in gas prices, if sustained for a year, would result in a 0.0188 lower default over a year, off a baseline annual default of 0.0228, a 83% decline. Column (3) report similar results in our payment ratio specification, limited to non-prepay borrowers, where the ICEV loans exhibit lower payment to scheduled payments with higher gasoline prices.

These results are robust to instead isolating the effect in the Trax-Bolt sample. We caveat these robustness results that our sample of Leaf EVs and non-prepay Bolt borrowers is narrow, thus columns (4) and (5) are only the GM sample and only the delinquency measures of performance.

4.2 Results: Pricing of Auto Loan Interest Rates

We turn to the second question: Are the estimated credit risk differentials priced? In a competitive market, one would expect this pricing would be passed on to households, compensating EV owners for lower risk. We take that up in this section.

We start with Figure 5, where we plot histograms of interest rates by engine type after matching the number of observations in the subsample of each engine type by the year and month of origination. The distribution of EV interest rates are markedly to the left of those on other vehicle types, with a significant mass at zero. Even for the loans with nonzero rates, the EV bars are shifted to the left. Graphically, EVs have lower interest rates, both because of large numbers of rate subvents (especially the zero interest loans) and becuase of other loans not seemingly subvented.

4.2.1 Interest Rate Pricing in Underwriting Credit Risk Model

Table 8 reports the estimation of the effect of engine type on the interest rate, controlling for underwriting observables as well as for term, origination month-year, state, and income group fixed effects. In Column (1), we estimate the predictive power of interest rate by the four important underwriting variables and the aforementioned fixed effects and in Columns (2)-(3), we add in the vehicle engine type. Note that the sample size reflects our collapsing to the 4 million loan decisions at origination, one observation per loan.

The key insight from Column (1) is summarized in the large R-square of 0.42 and the very large t-statistics on the underwriting variables. These results are not surprising, as the data collection by the SEC and our formulation follows industry practice.

Turning to Column (2), we find that an EV loan carries a 2.22 percentage points lower interest rate. The hybrid loan carries a 0.25 percentage points lower rate. We pause to emphasize the economic magnitude of the EV result, which is hugely different interest rate compared to the overall sample mean from the summary statistics of 4.8%. Column (3) reproduces Column (2), but fleshes out the non-parametrics of the credit score, payment-to-income, and loan-to-value relationship to interest rate in a node and slope spline specification. The R-square increases to 0.48 with the splines and the economic magnitude of the EV loan's association with interest rate also slightly increases to 2.23 percentage points.

Overall, the interest rate results are robust with an economic magnitude of around 2.2 percentage points on interest rate savings on EV loans. With an average EV loan of $38,537 and duration of 73 months, this implies a savings of $2,711 over the duration of the loan, even without factoring in the cash back. This amount is equivalent to 6.6 percent of the EV car value. To compare to the default savings for the lender, a reduction in default of 0.000577 per month translates to cumulative lower likelihood of default of 0.0413 for a full 73-month term. This back-of-the-envelope comparison suggests that the interest rate discount is more than fully compensating the EV household borrower for the selection effect of lower credit risk.

4.2.2 Results: Explanations for $\hat{\alpha_0}$ Pricing Differentials

How can we make sense of such a large rate reduction for EVs? As we introduced in the methodology, several possible stories may be at play, including pricing for credit risk differentals, manufacturing incentives to reducing their margins to move EVs off the shelf and clear inventory to make way for second generation models, and manufacturer volume incentives for reasons of average miles-per-gallon fleet regulations or incetives to nudge Congressional tax credits.

When we look to Columns (4)-(5) in Table 8, we find that that, controlling for all else, EV loans are positively associated with being subvented both through cash-back or by promotional rates. The results are statistically significant and also economically significant, implying an increase by around 20% points for getting a cash-back subvention, in particular.

Note that teaser rates are not the norm in auto lending, as they are in credit cards. Yet, to rule out the possibility that rate subventions might be affecting the loan pricing results, Appendix D Table 4 tests robustness by running the same specifications based on a subsample of loans that are at their 13th month-mark since origination (because promotional rates are usually for a year). The coefficients on the EV flag decrease a little bit to around -0.018 but stay statistically significant.[24]

[24]In the raw data, the reporting period interest rate variable is almost always reported to be the same as the original interest rate, which we consider to be a reporting/data error. For this test on loans at 13th month-mark, we create our own monthly interest rate variable by annualizing the ratio of monthly owed interest payments to outstanding

How can we make progress on the attribution of the 2.2% interest rate differential to stories of manufacturer incentive versus credit risk? The answer is simple, but requires a caveat. We look to evidence from auto financing that is not from captive auto lenders—i.e., banks and fintech lenders. Our caveat is that borrowers are not apples-for-apples in these two samples. We control for the same underwriting variables, but must rely on the assumption of the credit risk model making all else equal.

In Table 9, we repeat the specifications of Table 8, but only for non-captive finance loans. We find that EV and ICEV loans, all else equal, are priced statistically equivalent. Note that this finding brings us closer to the evidence in Bena, Bian, and Tang (2023), based on European data, that EV loans do not get better rates. [25]

Overall, the evidence suggest that credit risk differentials are not driving the entire differing engine type interest rates, and may not be driving any of it at all. We summarize our results so far as follows. We find that EVs financing costs are 2.2 percentage point less, which translates to an average savings of $2,711, if taking the cash flow impact in the amortization on the mean priced car at the mean interest rate. If lenders are not including credit risk in their rebated rates and were to do so, the households would face another $1,457 worth in lower auto finance costs.

4.3 Results: Pricing of Auto ABS

A second way to understand whether differential credit risk is being priced is to look to the auto ABS market. If the intermediaries provide lower pricing to households because of credit risk, they surely would extract that compensation from the ABS market as well. This compensation could be extracted in one of two ways. First, when the ABS issuer sells off the tranches to ABS buyers, they deferentially price the security by the rates of fixed income security return offered. Second, when the ABS issuer prepares the pool, this intermediary sets aside credit support (loan loss reserves) to be the first source of buffering of delinquencies and default in the waterfall. The pricing of engine type in the pool, if any, may show up in extent to credit support, as a percentage of the overall dollar magnitude of the sum of the aggregated loan amounts.

loan balance.

[25] In Bena, Bian, and Tang (2023) find that EV financing is more expensive in interest rates, with mechanism evidence of technology risk in resale value. Their classification of EV includes hybrids, unlike our separate treatments of EVs and hybrids.

4.3.1 Spreads over the Risk Free Rate at ABS Issuance

Table 10 presents the results from estimating equation 7. The first three columns of the table evaluate the pricing of the coupon spread above the risk free rate, and how this spread might vary by the percentage of EVs and hybrids in the ABS pool. Looking at Column (1), the share of EVs in an ABS pool does not appears to 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 9 basis points, an economically meaningful amount.

Column (2) includes controls for whether the ABS is issued by a captive finance company. Spreads are 45 basis points narrower for captive issuers than for other issuers. Column (3) adds controls for tranche rating into the specification. The difference in spreads between AAA and BBB is around 1.5 percentage points, with unrated being the omitted category. Columns (2) and (3) reinforce the baseline results in Column (1) that there is no evidence for pricing difference based on EV share.

The results for the z-spread are consistent with those for the coupon spread. The 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.[26] Looking across columns (4) to (6), we find no statistical difference in pricing for EVs in z-spreads. We continue to find a negative pricing for hybrids.

4.3.2 ABS Pricing via Credit Support for Waterfall Loss Reserve Accounts

ABS issuers might incorporate differing credit risk pricing for engine types by adjusting the amount of loan loss reserves escrowed for absorbing the delinquencies so that the waterfall of cash flow payments to the lowest tranches does not get impacted until such credit support gets depleted.

Table 11 looks at two measures of loss reserve accounts established to buffer risk and ensure that ABS investors receive full payments under most scenarios. First is the excess spread, 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. It is measured at origination and expressed in percent. The excess spread captures the amount of spread that the intermediary has to support operations, including the setting up of the credit support loan loss reserves, and margins. The second dependent variable,

[26]This is the standard prepayment assumption reported in the Bloomberg data.

the credit support, is defined as the percent of the total balance of loans that is held in escrow as loan loss reserves.

Columns (1) to (3) of Table 11 provides results asking whether EVs are priced deferentially in the setting up of loan loss reserves via the excess spread. We find that the cushion against default arising from the excess spread is smaller for EVs than for ICEVs. Focusing on column (1), the coefficient on the EV share variable is -0.222 and statistically significant. A one standard deviation increase in the EV share (an increase in the percent of EVs by 0.0168) results in a narrowing of the excess spread narrows by about 72 basis points. This effect attenuates to some degree once the controls are included, especially the control for the captive designation. With all controls, the results suggest that a one standard deviation increase in the EV share results in a 38 basis point narrower excess spread.

While statistically significant, the savings in the excess spread may not be economically meaningful. A back-of the envelope calculation can help to put this result into context. Suppose $1 billion in auto loans were pooled into the auto ABS. And suppose the share of EVs increased by 1 percent, or $10 million. The credit support savings to the issuer with this reduction in the excess spread suggests that, for every 265 EV loans included in a pool, the savings to the captive issuer is roughly $22,200, or about $84 dollars per EV. This pales in comparison to the $1,457 credit risk differential value. Taken together, our results suggest that the ABS issuers are not fully pricing in the lower default or higher cash flows observed on EV loans, but are also not unaware.

In columns (4) to (6), the dependent variable is the credit support, defined as the loan loss reserve account, expressed in percent of the overall ABS dollar value . We find results very consistent with columns (1) to (3). Focusing on Column (6), the coefficient on EV share is -0.321 and significant. A a one standard deviation increase in the EV share (0.0168 in percentage points) implies 0.00054 less of the ABS face value to be held in reserve. We want to turn this magnitude into a benefit to the overall pool that every EV provides. To do this, we assume that the funds held in escrow garner a return of the risk free rate and are lost at the mean default rate on the underlying loans. If instead they were deployed into the securitization, they would garner for the intermediary the coupon rate. Thus, this differential, in total dollars, can be attributed to EVs. The 0.00054 less of the ABS face value held in reserve translates to a benefit of $233 per EV in the pool.

Taken together, we find that the ABS markets know of lower default risk of EV loans, and prices this fact in via credit support. However, the pass-through of better-performing EV loans to auto ABS pricing is incomplete relative to the $1,457 in credit risk value.

5 Conclusion

We show that auto finance—auto loans and the auto ABS that pool those loans—can support the transition to electric vehicles (EVs). Auto loans backing EVs default 29 percent less in percentage change terms relative to traditional ICEVs, robust to considerations for differing costs of ownership. An estimate of the value of the differential credit risk comes from the overall payments received, which are $1,457 higher for EVs. A meaningful portion of this lower risk stems from the borrower's insulation from gasoline price shocks.

With these punchlines in differential credit risk in hand, we turn to asking whether the markets involved in auto loans are pricing this differential to households and ABS investors. In other words, who is benefiting in terms of capturing some of the rents from the transition.

We find a staggeringly large (-2.2%) difference in interest rates that households pay on auto loans, all else equal, for EVs. This result, however, could be due to a number of factors. Manufacturers had a large incentive to see EV sales volumes because of mile-per-gallon regulations, influence on Congress to pass tax credit legislation, supplier scaling motives, or just wanting the first generation cars to clear inventory. Some of such stories would be consistent with Bena, Bian, and Tang (2023), who study technology obsolescence stories of EV/hybrid loan pricing in Europe. Our results on non-captive lenders indeed confirms that our auto interest rate pricing results like do not reflect a pricing of credit risk differentials, which would allow the household to benefit perhaps up to another $1,457 equivalent in interest rates.

Finally, we turn the ABS pricing of risk, studying the fixed income rates and the loan loss reserve credit support accounts. We find support that the ABS market participants know that the EV share in the ABS pool implies lower risk. This mechanism happens in the credit support side of the ABS market, not direct rate pricing. In particular, our results suggest that a standard deviation higher EV share results in a benefit to the pool of $233 per EV.

References

Acemoglu, Daron, David H. Autor, and David Lyle (2004). "Women, War, and Wages: The Effect of Female Labor Supply on the Wage Structure at Midcentury". In: *Journal of Political Economy* 112(3), pp. 497–551. DOI: 10.1086/383100. eprint: https://doi.org/10.1086/383100. URL: https://doi.org/10.1086/383100.

Adams, William, Liran Einav, and Jonathan Levin (2009). "Liquidity constraints and imperfect information in subprime lending". In: *American Economic Review* 99(1), pp. 49–84.

Appleyard, Bryan (2022). *The Car: The Rise and Fall of the Machine that Made the Modern World.* Pegasus Books.

Bakshi, Tanya and Jonathan Rose (2021). "What Happened to Subprime Auto Loans During the Covid-19 Pandemic?" In: *Chicago Fed Insights*. URL: https://www.chicagofed.org/publications/blogs/chicago-fed-insights/2021/what-happened-subprime-auto-loans.

Bartik, Timothy J. (1991). *Who Benefits from State and Local Economic Development Policies?* Books from Upjohn Press wbsle. W.E. Upjohn Institute for Employment Research. ISBN: ARRAY(0x4f9796b8). URL: https://ideas.repec.org/b/upj/ubooks/wbsle.html.

Bena, Jan, Bo Bian, and Huan Tang (2023). "Financing the Global Shift to Electric Mobility". In: *Available at SSRN 4526150*.

Beresteanu, Arie and Shanjun Li (2011). "Gasoline prices, government support, and the demand for hybrid vehicles in the United States". In: *International Economic Review* 52(1), pp. 161–182.

Bertrand, Marianne and Adair Morse (2011). "Information Disclosure, Cognitive Biases, and Payday Borrowing". In: *The Journal of Finance* 66(6), pp. 1865–1893. DOI: https://doi.org/10.1111/j.1540-6261.2011.01698.x. eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1111/j.1540-6261.2011.01698.x. URL: https://onlinelibrary.wiley.com/doi/abs/10.1111/j.1540-6261.2011.01698.x.

Bertrand, Marianne and Adair Morse (2016). "Trickle-Down Consumption". In: *Review of Economics and Statistics* 98 (5), pp. 863–879.

Borusyak, Kirill and Peter Hull (2023). "Non-Random Exposure to Exogenous Shocks". In: *Econometrica* 91(6), pp. 2155–2185.

Brown, James R, Steven M Fazzari, and Bruce C Petersen (2009). "Financing innovation and growth: Cash flow, external equity, and the 1990s R&D boom". In: *The Journal of Finance* 64(1), pp. 151–185.

Busse, Meghan R, Christopher R Knittel, and Florian Zettelmeyer (2013). "Are consumers myopic? Evidence from new and used car purchases". In: *American Economic Review* 103(1), pp. 220–256.

Butler, Alexander W, Erik J Mayer, and James P Weston (May 2022). "Racial Disparities in the Auto Loan Market". In: *The Review of Financial Studies* 36(1), pp. 1–41. ISSN: 0893-9454. DOI: 10.1093/rfs/hhac029. eprint: https://academic.oup.com/rfs/article-pdf/36/1/1/48135025/hhac029.pdf. URL: https://doi.org/10.1093/rfs/hhac029.

Campbell, Sean et al. (2011). "Securitization markets and central banking: An evaluation of the term asset-backed securities loan facility". In: *Journal of Monetary Economics* 58(5). Carnegie-

Rochester Conference on public policy: Normalizing Central Bank Practice in Light of the credit Turmoil, 12–13 November 2010, pp. 518 –531. ISSN: 0304-3932. DOI: https://doi.org/10.1016/j.jmoneco.2011.05.003. URL: http://www.sciencedirect.com/science/article/pii/S0304393211000468.

Danielis, Romeo et al. (2020). "Drivers' preferences for electric cars in Italy. Evidence from a country with limited but growing electric car uptake". In: *Transportation Research Part A: Policy and Practice* 137, pp. 79–94. ISSN: 0965-8564. DOI: https://doi.org/10.1016/j.tra.2020.04.004. URL: https://www.sciencedirect.com/science/article/pii/S0965856420305590.

Einav, Liran, Mark Jenkins, and Jonathan Levin (2012). "Contract Pricing in Consumer Credit Markets". In: *Econometrica* 80(4), pp. 1387–1432. DOI: https://doi.org/10.3982/ECTA7677. eprint: https://onlinelibrary.wiley.com/doi/pdf/10.3982/ECTA7677. URL: https://onlinelibrary.wiley.com/doi/abs/10.3982/ECTA7677.

Faltin-Traeger, Oliver, Kathleen W. Johnson, and Christopher Mayer (2010). "Issuer Credit Quality and the Price of Asset Backed Securities". In: *The American Economic Review* 100(2), pp. 501–505. ISSN: 00028282. URL: http://www.jstor.org/stable/27805047 (visited on 07/24/2023).

Gürkaynak, Refet S., Brian Sack, and Jonathan H. Wright (2007). "The U.S. Treasury yield curve: 1961 to the present". In: *Journal of Monetary Economics* 54(8), pp. 2291–2304. ISSN: 0304-3932. DOI: https://doi.org/10.1016/j.jmoneco.2007.06.029. URL: https://www.sciencedirect.com/science/article/pii/S0304393207000840.

Hall, Bronwyn H and Josh Lerner (2010). "The financing of R&D and innovation". In: *Handbook of the Economics of Innovation*. Vol. 1. Elsevier, pp. 609–639.

Hankins, Kristine W, Morteza Momeni, and David Sovich (2022). "Does trade policy affect consumer credit? The role of captive finance."". In.

Hausman, Jerry A (1979). "Individual discount rates and the purchase and utilization of energy-using durables". In: *The Bell Journal of Economics*, pp. 33–54.

Hertzberg, Andrew, Andres Liberman, and Daniel Paravisini (Mar. 2018). "Screening on Loan Terms: Evidence from Maturity Choice in Consumer Credit". In: *The Review of Financial Studies* 31(9), pp. 3532–3567. ISSN: 0893-9454. DOI: 10.1093/rfs/hhy024. eprint: https://academic.oup.com/rfs/article-pdf/31/9/3532/25521785/hhy024.pdf. URL: https://doi.org/10.1093/rfs/hhy024.

Howell, Sabrina T (2017). "Financing innovation: Evidence from R&D grants". In: *American economic review* 107(4), pp. 1136–1164.

Jedwab, Remi, Noel D Johnson, and Mark Koyama (2022). "The economic impact of the Black Death". In: *Journal of Economic Literature* 60(1), pp. 132–178.

Kane, Mary (2001). "Salomon Smith Barney Guide to Mortgage-Backed and Asset-Backed Securities". In: John Wiley and Sons: New York. Chap. 2, pp. 69–104.

Katcher, Bradley et al. (2024). "One Month Longer, One Month Later? Prepayments in the Auto Loan Market". In.

Klee, Elizabeth C. and Chaehee Shin (May 2020). *Post-crisis Signals in Securitization: Evidence from Auto ABS*. Finance and Economics Discussion Series 2020-042. Board of Governors of the

Federal Reserve System (U.S.) DOI: 10.17016/FEDS.2020.042. URL: https://ideas.repec.org/p/fip/fedgfe/2020-42.html.

Klier, Thomas and Joshua Linn (2010). "The price of gasoline and new vehicle fuel economy: evidence from monthly sales data". In: *American Economic Journal: Economic Policy* 2(3), pp. 134–153.

Knittel, Christopher R (2011). "Automobiles on steroids: Product attribute trade-offs and technological progress in the automobile sector". In: *American Economic Review* 101(7), pp. 3368–3399.

Kontz, Christian (2023). "Do ESG investors care about carbon emissions? Evidence from securitized auto loans". In.

Li, Shanjun, Christopher Timmins, and Roger H Von Haefen (2009). "How do gasoline prices affect fleet fuel economy?" In: *American Economic Journal: Economic Policy* 1(2), pp. 113–137.

Muehlegger, Erich and David S Rapson (2022). "Subsidizing low-and middle-income adoption of electric vehicles: Quasi-experimental evidence from California". In: *Journal of Public Economics* 216, p. 104752.

Nanda, Ramana and Tom Nicholas (2014). "Did bank distress stifle innovation during the Great Depression?" In: *Journal of Financial Economics* 114(2), pp. 273–292.

Nanda, Ramana and Matthew Rhodes-Kropf (2017). "Financing risk and innovation". In: *Management science* 63(4), pp. 901–918.

Olegario, Rowena (2016). *The Engine of Enterprise: Credit in America*. Harvard University Press. ISBN: 9780674051140. URL: http://www.jstor.org/stable/j.ctvjf9wwm (visited on 01/02/2023).

Parker, Nathan et al. (July 2021). "Who saves money buying electric vehicles? Heterogeneity in total cost of ownership". English (US). In: *Transportation Research Part D: Transport and Environment* 96. Publisher Copyright: © 2021 Elsevier Ltd. ISSN: 1361-9209. DOI: 10.1016/j.trd.2021.102893.

Schloter, Lukas (2022). "Empirical analysis of the depreciation of electric vehicles compared to gasoline vehicles". In: *Transport Policy* 126, pp. 268–279. ISSN: 0967-070X. DOI: https://doi.org/10.1016/j.tranpol.2022.07.021. URL: https://www.sciencedirect.com/science/article/pii/S0967070X22002074.

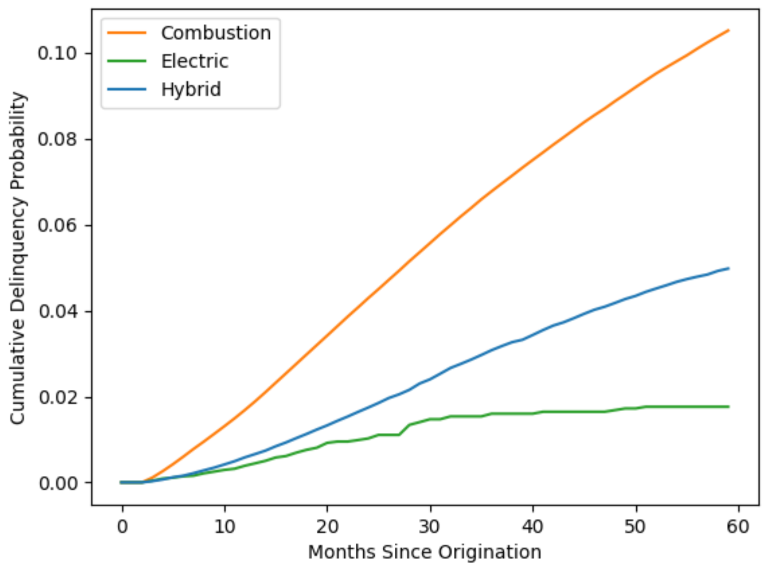
Sierzchula, William et al. (2014). "The influence of financial incentives and other socio-economic factors on electric vehicle adoption". In: *Energy policy* 68, pp. 183–194.

Stiglitz, Joseph E. and Andrew Weiss (1981). "Credit Rationing in Markets with Imperfect Information". In: *The American Economic Review* 71(3), pp. 393–410. ISSN: 00028282. URL: http://www.jstor.org/stable/1802787 (visited on 12/09/2023).

Sun, Liyang and Jesse M. Shapiro (2022). "A Linear Panel Model with Heterogeneous Coefficients and Variation in Exposure". In: *Journal of Economic Perspectives* 36(4), pp. 193–204. DOI: 10.1257/jep.36.4.193. URL: https://www.aeaweb.org/articles?id=10.1257/jep.36.4.193.

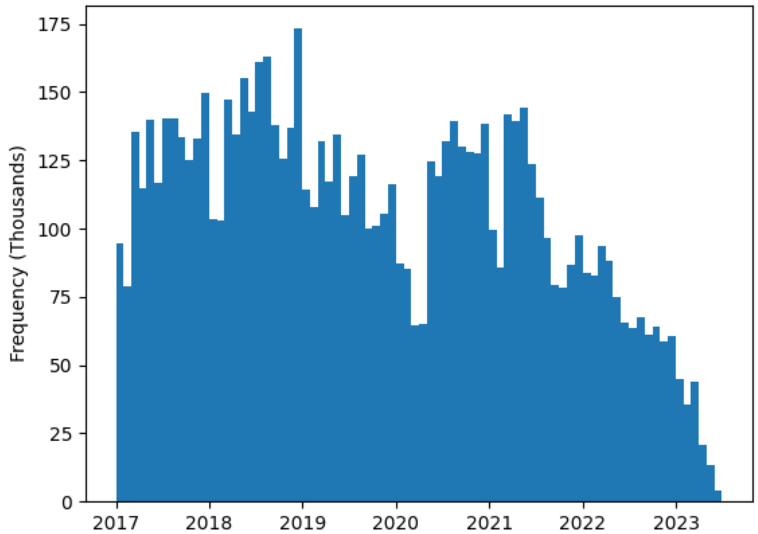
Figures and tables

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



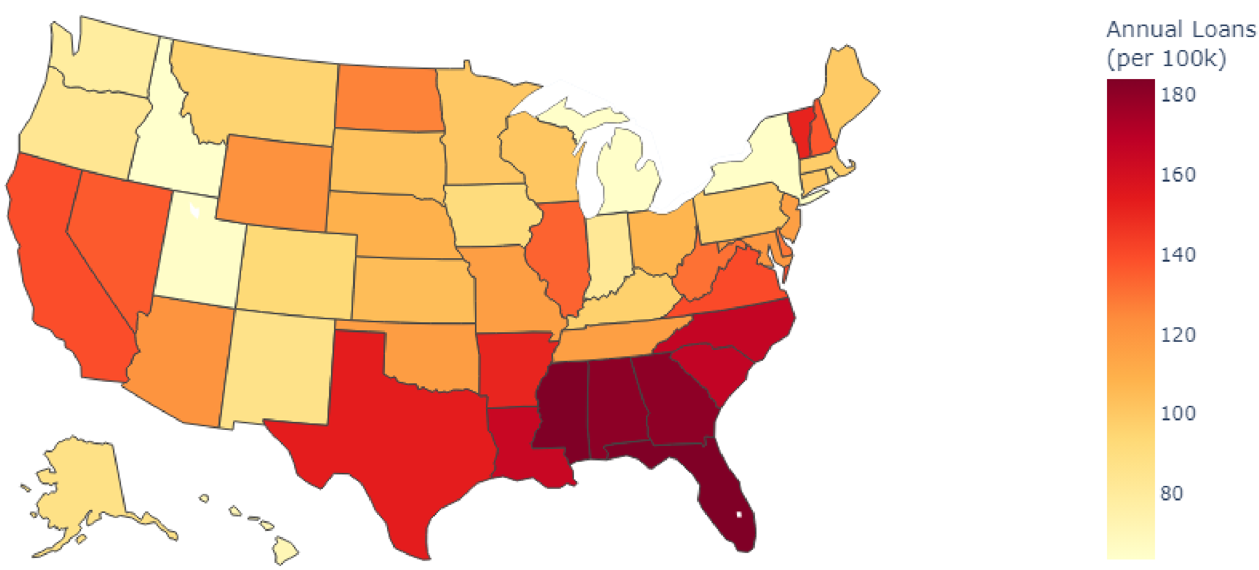
Source: SEC form ABS-EE. This figure shows cumulative 60-day delinquency rates by months since origination and by engine type, based on our data sample consisting of 6-year new car auto loans originated in between January 2017 to July 2023. Specifically, we define a loan to be 60-day delinquent when it newly enters the 60-day delinquency in that period. Denominators capture the entire set of loans that exist at each month mark after origination.

Figure 2: Origination Dates of Auto Loans in Data



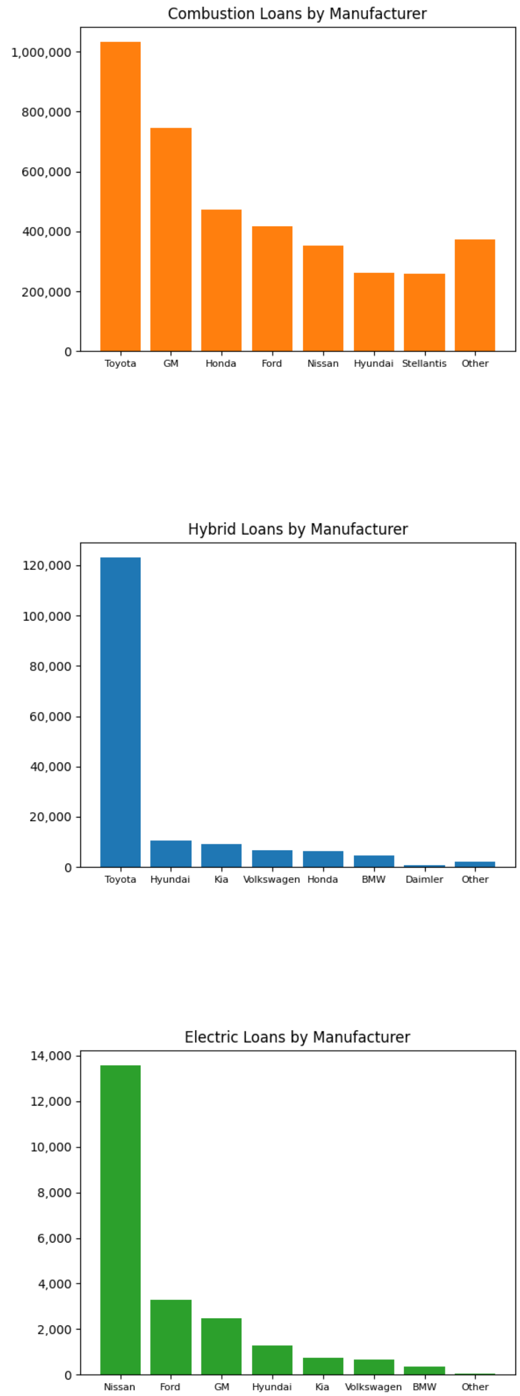
Source: SEC form ABS-EE. This figure shows a histogram of origination dates for 6-year new car auto loans captured in our data sample from January 2017 to July 2023.

Figure 3: Geographic Distribution of Auto Loans in Data



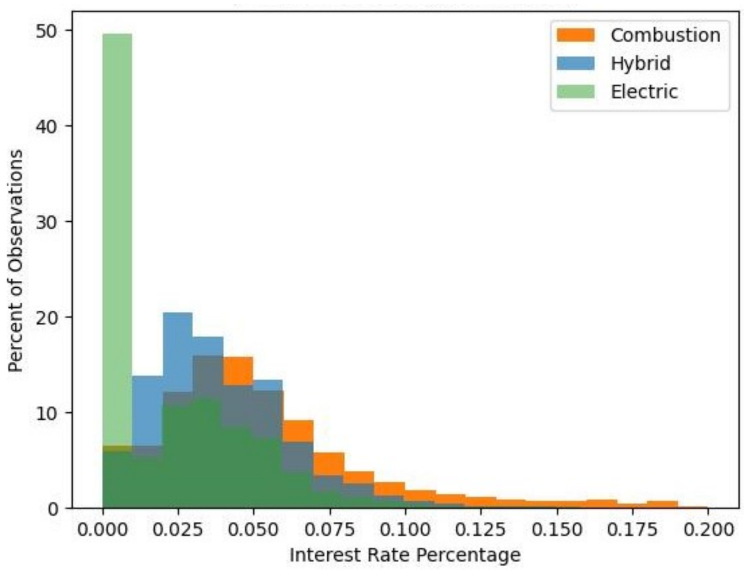
Source: SEC form ABS-EE. This figure shows the geographic distribution of 6-year new car auto loans originated in between January 2017 to July 2023.

Figure 4: Engine Type by Manufacturer



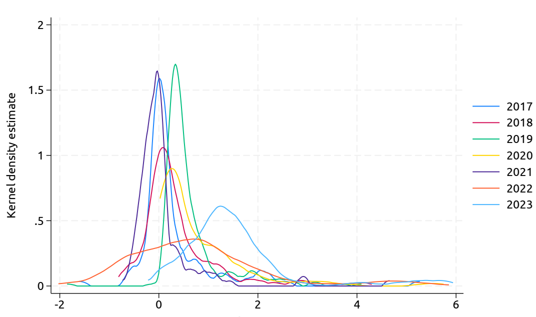
Source: SEC form ABS-EE. These figures show the number of loans on ICEV, hybrid and EV cars by manufacturer.

Figure 5: Auto Loan Interest Rates by Engine Type

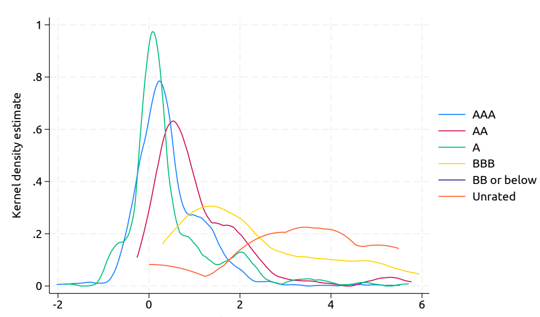


Source: SEC form ABS-EE. This figure shows the density plot of original interest rates of auto loans in our data, broken down by engine type. Number of observations in the subsample of each engine type is matched by the year and month of origination to account for various macroeconomic factors that might affect origination patterns on ICEVs and EVs.

Figure 6: Auto ABS Coupon Spreads by Year and Rating

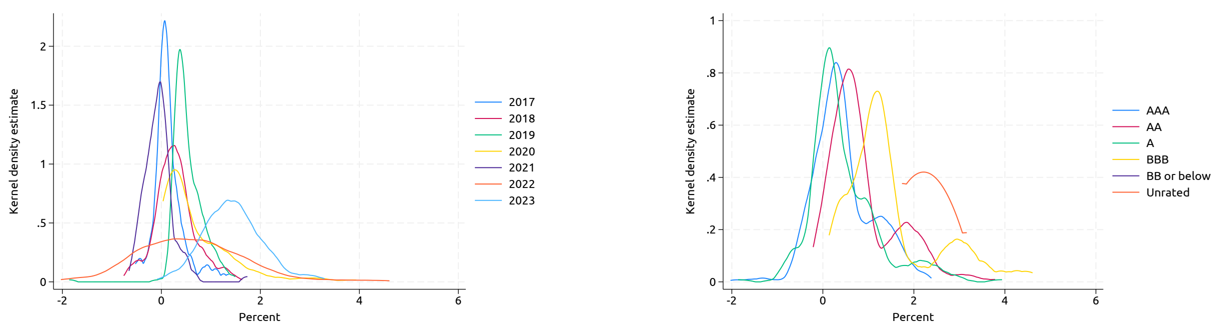


(a) By Year



(b) By Rating

Figure 7: Auto ABS Z-spreads by Year and Rating



(a) By Year

(b) By Rating

Table 1: Engine Type by Origination Year

Origination year	Total	Combustion	Hybrid	Electric
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	90.06	79.41	1.99
2023	85,932	80,478	4,446	1,008
Row percent	100	93.65	5.17	1.17

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

Table 2: Summary Statistics of Auto Loans in Data

	All		Combustion		Hybrid		Electric	
	Mean	Std	Mean	Std	Mean	Std	Mean	Std
Panel A: Cross-section of Auto Loans								
Vehicle value amount ($)	34,929	12,559	34,867	12,640	35,586***	10,498	40,881***	10,438
Credit score	742	69	741	69	763***	62	788***	59
Monthly income ($)	8,380	6,800	8,308	6,745	9,429***	7,517	13,309***	8,324
Loan amount ($)	34,538	13,014	34,457	13,042	35,941***	12,112	38,537***	13,324
Loan-to-value	1.011	0.231	1.011	0.231	1.022***	0.228	0.945***	0.213
Scheduled payment ($)	546	251	544	249	609***	277	530***	277
Payment-to-income	0.087	0.045	0.087	0.045	0.079***	0.045	0.062***	0.043
Loan term (months)	74	2	74	2	74***	1	73***	2
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
Rate subvention	0.323	0.467	0.318	0.466	0.418***	0.493	0.405***	0.491
Cash back	0.377	0.485	0.378	0.485	0.314***	0.464	0.496***	0.500
Paid down	0.416	0.493	0.418	0.493	0.402***	0.490	0.282***	0.450
Prepay	0.250	0.433	0.254	0.435	0.195***	0.396	0.0880***	0.283
Payment ratio	2.393	4.589	2.406	4.619	2.123***	3.824	2.167***	4.605
N	4,096,083		3,910,601		163,038		22,444	
Panel B: Panel of Auto Loans								
30-Day Delinquency	0.00538	0.07313	0.00548	0.07384	0.00282***	0.05300	0.00124***	0.03523
60-Day Delinquency	0.00183	0.04278	0.00188	0.04326	0.00082***	0.02861	0.00034***	0.01857
Payment ratio	1.571	5.111	1.574	5.130	1.506***	4.589	1.611***	5.140
Raw payment ratio	1.572	5.112	1.575	5.131	1.506***	4.590	1.610***	5.141
N	84,675,532		81,420,320		3,058,310		196,902	
Panel C: Annual Ownership Costs								
Depreciation ($)	3,251	2,482	3,251	2,504	3,256***	1,763	3,140***	2,701
Fuel ($)	2,545	817	2,592	794	1,428***	391	654***	54
Insurance ($)	769	99	769	99	764***	90	845***	56
Maintenance ($)	1,050	562	1,050	561	1,076***	584	616***	423
Repairs ($)	417	284	420	285	336***	248	355***	203
Taxes & fees ($)	760	1,063	758	1,065	822***	1,028	795***	862
Total Cost ($)	8,801	3,526	8,848	3,538	7,691***	2,922	6,412***	3,259
Panel D: Macroeconomic Variables								
Regional gas price ($)	3.008	0.758	2.996	0.754	3.277***	0.791	3.811***	0.698
Expected fuel volatility	267	118	271	117	154***	62	22***	23
Median household income ($)	74,237	11,390	74,080	11,352	78,277***	11,639	82,387***	9,895
HPI	540	175	536	174	630***	186	743***	185
Unemployment rate	4.794	2.483	4.795	2.484	4.790***	2.501	4.149***	1.581
N	78,815,894		75,787,426		2,846,481		181,987	

Note: This table summarizes the main 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. The asterisks on the hybrid and EV columns represent results from t-tests on differences in means compared to the combustion engine. Panel A captures the cross-section of loans;"Scheduled payment" refers to monthly loan payment for the first observation of a loan. "Interest rate," " Month 13 interest rate," "Rate Subvention," "Cash back," "Delinquency," "Paid down," "Prepay," and "Payment ratio" are in fraction. "Delinquency" measures the fraction of loans that ever experience a 60-day delinquency during the data period. Panel B represents the complete panel over the period; all variables are in fraction. "30/60-Day delinquency" measures the average fraction of loans that newly enter the 30- or 60-day delinquency in each year-month of the panel data. Panel C presents car-specific summary statistics on annual ownership costs. Panel D summarizes macroeconomic controls, covering the same period 2017-2023. "Unemployment" is monthly unemployment rate data by state. "HPI" refers to quarterly housing price index by state. Both the unemployment rate and price index are seasonally adjusted. 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 3: Summary Statistics of ABS Data— Tranche-level

	Obs	Mean	Std	Min	Max
Panel A: By Engine and Issuer Type					
EV Share	1,785	0.00324	0.0168	0.0000	0.241
Hybrid Share	1,785	0.0380	0.0872	0.0000	1.00
Captive	1,785	0.597	0.491	0.0000	1.00
Panel B: By Rating					
AAA	1,785	0.568	0.496	0.0000	1.00
AA	1,785	0.0930	0.291	0.0000	1.00
A	1,785	0.214	0.410	0.0000	1.00
BBB	1,785	0.0650	0.247	0.0000	1.00
Floating rate	1,785	0.0790	0.270	0.0000	1.00
Panel C: Rates and Spreads (Percent)					
Coupon Spread	1,782	0.00596	0.0114	-0.0474	0.0669
Ex-ante Z-spread	1,485	0.000412	0.00931	-0.0345	0.0565
Realized Z-spread	1,485	0.00182	0.00735	-0.0199	0.0557
Excess Spread	1,782	0.0560	0.0591	-0.0269	0.213
Credit Support	1,773	0.219	0.196	0.0000	0.949

Note: In Panel A, the shares are computed only out of 6-year loans in the ABS deal. In Panel B, each is measured as a share of tranches. Source: SEC form ABS-EE, Bloomberg Finance LP, ABS Backoffice.

Table 4: Delinquency Results

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable: Delinquency rate (days):	60	30	60	30	60	30
EV	-0.00156***	-0.00455***	-0.00202***	-0.00537***	-0.000577***	-0.00157***
	(-32.85)	(-40.25)	(-38.10)	(-43.84)	(-10.68)	(-12.67)
Hybrid	-0.00109***	-0.00273***	-0.000690***	-0.00190***	-0.000251***	-0.000656***
	(-45.59)	(-48.14)	(-28.32)	(-32.91)	(-10.28)	(-11.35)
Credit score					-0.0000236***	-0.0000720***
					(-193.1)	(-262.1)
Payment-to-income ratio (percent)					0.0114***	0.0284***
					(37.72)	(46.04)
LTV ratio					0.00234***	0.00565***
					(67.56)	(74.56)
ln (income)					0.000152***	0.00107***
					(8.501)	(27.32)
Observations	84,659,100	83,924,681	84,659,100	83,924,681	83,756,295	83,025,206
R-squared	0.000	0.000	0.001	0.002	0.003	0.007
Aging FE	YES	YES				
Aging*Calendar FE			YES	YES	YES	YES
Term Duration Month FE			YES	YES	YES	YES
State FE			YES	YES	YES	YES

Robust t-statistics in parentheses
*** p<0.01,** p<0.05,* p<0.1

Note: This table summarizes the results on default based on our sample of 6-year new car auto loans originated in between January 2017 and July 2023. The dependent variable is the main default variable, defined as a loan newly entering a 60- or 30- day delinquency in that period from a non-delinquency status in the previous period. Source: SEC form ABS-EE.

Table 5: Monthly Payment Results

	(1)	(2)	(3)	(4)
Dependent variable:	Payment Ratio	Payment Ratio	Payment Ratio	Raw Payment Ratio
EV	0.0424***	0.0830***	0.0378***	0.0333***
	(3.404)	(6.612)	(2.981)	(2.624)
Hybrid	-0.0659***	-0.0387***	-0.0349***	-0.0320***
	(-25.52)	(-14.73)	(-13.14)	(-11.98)
Credit Score			-0.000274***	-0.000307***
			(-30.32)	(-34.13)
Payment-to-income ratio (percent)			0.747***	0.771***
			(33.80)	(35.04)
LTV ratio			-0.288***	-0.289***
			(-94.95)	(-95.68)
ln(income)			0.112***	0.112***
			(68.10)	(68.72)
Observations	77,557,511	77,557,507	76,750,019	78,320,435
R-Squared	0.001	0.002	0.002	0.002
Aging FE	YES			
Aging*Calendar FE		YES	YES	YES
Term Duration Month FE		YES	YES	YES
State FE		YES	YES	YES

Robust t-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Note: This table summarizes the results on payment ratio (borrower payment relative to scheduled payment) based on our data of 6-year new car auto loans originated in between January 2017 and July 2023. In columns (1)-(3), we use cleaned payment ratio variable by removing loans with negative interest or principal payment amounts, loans with principal payments exceeding the outstanding loan balance, and loans with cumulative principal payments exceeding the loan amount. Also 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. Results using the raw payment ratio are reported in column (4). Source: SEC form ABS-EE.

Table 6: Robustness on Delinquency Results

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable: Delinquency rate (days)	60	30	60	30	60	30
Subset:	Leaf-Versa	Leaf-Versa	Trax-Bolt	Trax-Bolt		
EV	-0.00500***	-0.0104***	-0.00133***	-0.00322***	-0.000930***	-0.00153***
	(-9.204)	(-10.05)	(-4.706)	(-4.776)	(-15.19)	(-10.59)
Hybrid					-0.000373***	-0.000593***
					(-13.00)	(-8.755)
Credit Score	-0.0000346***	-0.0000784***	-0.0000214***	-0.0000850***	-0.0000241***	-0.0000747***
	(-14.50)	(-16.61)	(-19.35)	(-30.19)	(-181.4)	(-247.1)
Payment-to-income ratio (percent)	0.0851***	0.145***	0.0426***	0.0939***		
	(10.03)	(9.407)	(7.822)	(7.166)		
LTV ratio	0.00104	0.00357**	0.00148***	0.00704***	0.00246***	0.00673***
	(1.413)	(2.333)	(2.661)	(5.208)	(73.99)	(89.94)
ln(income)	0.00505***	0.00932***	0.00219***	0.00515***	0.000932***	0.00233***
	(10.56)	(10.06)	(6.252)	(5.997)	(35.95)	(44.77)
Cost-to-income ratio					0.00975***	0.0211***
					(55.12)	(61.04)
Energy Volatility					-0.00000150***	-0.000000229
					(-13.78)	(-0.9273)
Observations	432,337	427,451	887,139	873,746	71,692,855	71,048,511
R-Squared	0.015	0.020	0.008	0.014	0.003	0.007
Aging*Calendar FE	YES	YES	YES	YES	YES	YES
Term Duration Month FE	YES	YES	YES	YES	YES	YES
State FE	YES	YES	YES	YES	YES	YES

Robust t-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Note: This table summarizes the results on delinquency based on a subsample of two pairs of EV and ICEV within a same manufacturer, the Bolt-Trax and the Leaf-Versa. This subsample was taken from the full sample of 6-year new car auto loans originated in between January 2017 and July 2023. The dependent variable in this table is the main default variable, defined as a loan newly entering a 60- or 30- day delinquency in that period from a non-delinquency status in the previous period. Source: SEC form ABS-EE.

Table 7: Treatment Results of Differential Exposure to Gasoline Pricing

	(1)	(2)	(3)	(4)	(5)
Dependent variable:	60	30	Payment Ratio	60	30
Subset:			No Prepay	Trax-Bolt	Trax-Bolt
Regional gas price	-0.00117***	-0.00188***	0.0287***	-0.00502***	-0.00838***
	(-7.223)	(-7.319)	(11.61)	(-3.127)	(-3.270)
ICEV*Regional gas price	0.00157***	0.00252***	-0.00381**	0.00201**	0.00604***
	(21.37)	(17.45)	(-2.344)	(2.364)	(5.539)
Cost-to-income ratio (percent)	0.0230***	0.0860***	-0.605***	0.0180	0.0907***
	(14.86)	(42.06)	(-31.77)	(1.037)	(3.933)
ln(Median household income)	0.000443	0.00123	-0.0178*	0.000689	0.00712
	(0.4831)	(1.068)	(-1.853)	(0.06674)	(0.5340)
ln(HPI)	-0.00914***	-0.0153***	-0.196***	0.0156	0.00213
	(-11.53)	(-15.33)	(-26.23)	(1.359)	(0.1482)
Unemployment Rate	0.000196***	0.000344***	-0.0000981	0.000106	-0.0000785
	(8.383)	(10.91)	(-0.2922)	(0.4621)	(-0.2438)
Observations	62,643,524	62,643,524	43,114,439	712,771	712,771
R-Squared	0.473	0.416	0.130	0.499	0.415
Loan FE	YES	YES	YES	YES	YES
Aging*Calendar FE	YES	YES	YES	YES	YES
Term Duration Month FE	YES	YES	YES	YES	YES

Robust t-statistics in parentheses

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 8: Interest Rate and Loan Pricing Results

	(1)	(2)	(3)	(4)	(5)
Dependent variable:	Interest Rate	Interest Rate	Interest Rate	Subvent: Cash back	Subvent: Rate
EV		-0.0218***	-0.0226***	0.198***	0.0248***
		(-117.2)	(-129.5)	(62.44)	(8.384)
Hybrid		-0.00250***	-0.00194***	-0.0170***	0.0262***
		(-44.91)	(-38.35)	(-14.20)	(23.40)
Credit Score	-0.000229***	-0.000228***	[spline]	0.000104***	0.000622***
	(-980.2)	(-975.5)		(28.53)	(182.3)
Payment-to-income ratio (percent)	0.0928***	0.0930***	[spline]	-0.168***	-0.416***
	(165.9)	(166.4)		(-19.23)	(-50.99)
LTV ratio	-0.0181***	-0.0182***	[spline]	-0.218***	0.355***
	(-268.2)	(-269.7)		(-186.9)	(326.5)
Observations	4,050,220	4,050,220	4,050,220	4,050,222	4,050,222
R-Squared	0.420	0.422	0.480	0.094	0.145
OrigMonth FE	YES	YES	YES	YES	YES
Term FE	YES	YES	YES	YES	YES
State FE	YES	YES	YES	YES	YES
Income FE	YES	YES	YES	YES	YES

Robust t-statistics in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 9: Interest Rate and Loan Pricing Results (Non-captive)

	(1)	(2)	(3)	(4)	(5)
Dependent variable:	Interest Rate	Interest Rate	Interest Rate	Subvent: Cash back	Subvent: Rate
EV		0.00338***	0.00322***	-0.0316***	-0.0288***
		(5.182)	(5.301)	(-4.038)	(-5.781)
Hybrid		-0.00254***	-0.00309***	-0.106***	-0.0148***
		(-6.331)	(-7.866)	(-25.13)	(-5.519)
Credit Score	-0.000270***	-0.000270***	[spline]	-0.000471***	-0.0000267***
	(-386.5)	(-386.5)		(-72.96)	(-6.481)
Payment-to-income ratio (percent)	0.130***	0.130***	[spline]	-0.0835***	0.0389***
	(80.11)	(79.97)		(-6.004)	(4.386)
LTV ratio	0.0318***	0.0318***	[spline]	-0.0532***	0.116***
	(133.6)	(133.7)		(-26.13)	(89.75)
Observations	689,764	689,764	689,764	689,766	689,766
R-Squared	0.528	0.528	0.550	0.418	0.092
OrigMonth FE	YES	YES	YES	YES	YES
Term FE	YES	YES	YES	YES	YES
State FE	YES	YES	YES	YES	YES
Income FE	YES	YES	YES	YES	YES

Robust t-statistics in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 10: ABS Pricing

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable:	Coupon Spread	Coupon Spread	Coupon Spread	Z-spread	Z-spread	Z-spread
EV Share	0.011	0.022	0.024	0.001	0.007	0.007
	(0.476)	(0.935)	(1.02)	(0.0642)	(0.498)	(0.609)
Hybrid Share	-0.011 **	-0.010 **	-0.010 **	-0.009 **	-0.009 **	-0.010 **
	(-4.12)	(-4.22)	(-5.4)	(-4.47)	(-4.42)	(-4.85)
Captive		-0.441 **	-0.259 **		-0.24 **	-0.161 **
		(-8.1)	(-5.26)		(-4.95)	(-3.77)
Rating						
AAA			0.836**			1.051 **
			(5.33)			(7.52)
AA			1.441 **			1.269 **
			(8.06)			(8.58)
A			0.8**			0.596**
			(4.82)			(3.91)
BBB			2.463**			2.086**
			(11.4)			(11.8)
Observations	1687	1687	1687	1422	1422	1422
R-squared	0.152	0.186	0.349	0.179	0.194	0.346

Robust t-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

This table reports parameter estimates from evaluating equation 7. The outcome variable in columns (1) through (3) 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 columns (4) through (6) 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. 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.

Table 11: ABS Pricing of Risk via Loan Loss Reserves

Dependent variable:	(1) Excess Spread	(2) Excess Spread	(3) Excess Spread	(4) Credit Support	(5) Credit Support	(6) Credit Support
EV Share	-0.419**	-0.228**	-0.222**	-0.829**	-0.334**	-0.321**
	(-8.92)	(-7.14)	(-7.06)	(-7.18)	(-4.21)	(-4.04)
Hybrid Share	-0.122**	-0.113**	-0.111**	-0.586**	-0.559**	-0.553**
	(-4.68)	(-7.21)	(-7.2)	(-7.99)	(-11.5)	(-11.6)
Floating rate	-0.121	0.607	1.03 **			
	(-0.254)	(1.68)	(2.77)			
Captive		-7.74 **	-7.52 **		-20.1 **	-19.0 **
		(-32.9)	(-31.2)		(-21.9)	(-20.2)
Rating						
AAA			-1.62 **			-2.18
			(-3.96)			(-1.29)
AA			-1.74 **			-1.97
			(-3.57)			(-1.01)
A			-0.624			0.434
			(-1.38)			(0.235)
BBB			0.754			8.38 **
			(1.19)			(3.37)
Year						
2018	-0.946	-0.0615	-0.0912	2.01	4.14	4.11
	(-1.59)	(-.119)	(-.179)	-0.901	-1.93	-1.95
2019	-0.558	0.152	0.131	-1.98	-0.379	-0.427
	(-0.976)	(0.29)	(0.254)	(-0.912)	(-0.174)	(-0.20)
2020	0.698	2.06 **	1.99 **	-0.581	2.72	2.41
	(1.19)	(3.97)	(3.89)	(-0.264)	(1.29)	(1.16)
2021	2.52 **	3.3 **	3.29 **	1.81	3.46	3.28
	(4.01)	(6.24)	(6.27)	(0.805)	(1.64)	(1.58)
2022	-0.0724	0.631	0.698	5.87 **	7.47 **	7.66 **
	(-0.114)	(1.16)	(1.3)	(2.64)	(3.56)	(3.7)
2023	-1.51 *	-0.273	-0.231	5.19 *	8.13 **	8.32 **
	(-2.31)	(-0.494)	(-0.424)	(2.21)	(3.67)	(3.81)
Intercept	6.06 **	9.76 **	10.8 **	22.5 **	32.5 **	32.6 **
	(12.1)	(19.8)	(17.6)	(11.7)	(15.7)	(12.7)
Number of observations	1687	1687	1687	1678	1678	1678
R-squared	0.0929	0.499	0.513	0.0804	0.335	0.352

This table reports parameter estimates from evaluating equation 7. The outcome variable in columns (1) through (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 in columns (4) through (6) 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.

Appendix

A Background on U.S. Environmental Regulations on Automakers

In the United States, federal regulations for automakers are enforced by two standards: one is Corporate Average Fuel Economy (CAFE) standards by the National Highway Traffic Safety Administration (NHTSA) and another is greenhouse gas emission standards by the Environmental Protection Agency (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 about 50% 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, later to be extended to model year 2017-2025 in 2012.

The standards had been temporarily relaxed in 2020—the Safer Affordable Fuel-Efficient (SAFE) Vehicles Rule relaxed the CAFE and greenhouse gas emission standards for model year 2021-2026—and were subsequently 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 "EV Acceleration Challenge."[27] 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.

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

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

Table 1: 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.

Table 2: List of Hybrid Vehicles

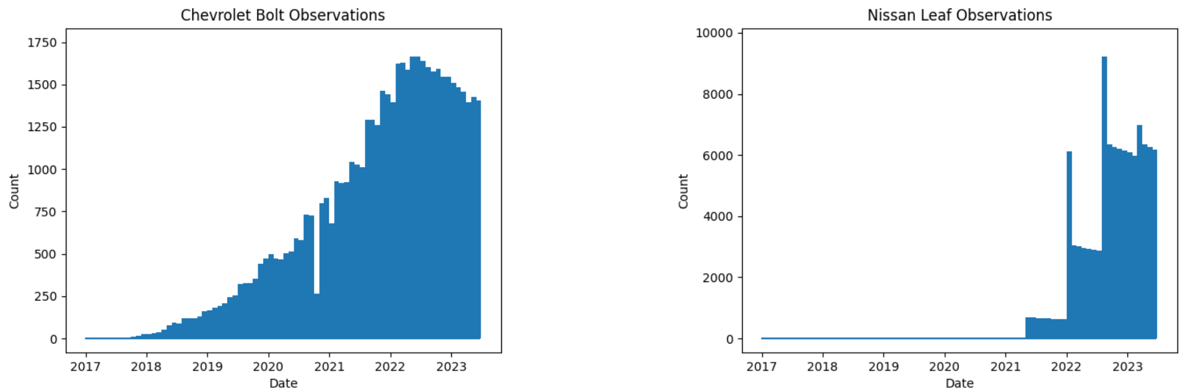
Make	Model	Count
toyota	rav4 hybrid	41429
toyota	prius	21745
toyota	camry hybrid	12028
toyota	sienna	10607
kia	niro	7288
toyota	highlander hybrid	7269
toyota	corolla hybrid	7231
toyota	venza	7064
toyota	prius plug-in hybrid	4871
hyundai	ioniq	4696
honda	insight	4533
audi	q5	3820
toyota	avalon hybrid	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 and model names/years using Car and Driver magazine, Kelley Bluebook, and Google searches.

C Nissan Leaf and Chevrolet Bolt Observations

Figure 1: Leaf and Bolt Observations by Month



D Robustness Tests

Table 3: Cumulative Payment Results

	(1)	(2)	(3)	(4)
Dependent variable:	Paid Down	Prepay	Payment Ratio	Payment Ratio
Subset:			Not Paid Down	No Prepay
EV	-0.0292***	-0.0384***	0.0784***	0.0915***
	(-9.341)	(-18.90)	(53.88)	(7.539)
Hybrid	0.0449***	0.0109***	0.0115***	-0.000552
	(36.87)	(11.10)	(21.89)	(-0.1960)
Credit Score	-0.0000873***	-0.000376***	0.000754***	0.00123***
	(-23.13)	(-113.9)	(314.4)	(89.60)
Payment-to-income ratio (percent)	0.344***	0.570***	-0.651***	-0.977***
	(37.97)	(71.43)	(-110.3)	(-28.60)
LTV ratio	-0.142***	-0.0771***	0.0149***	-0.242***
	(-118.6)	(-71.98)	(19.47)	(-47.35)
ln(income)	0.0418***	0.0606***	-0.0407***	-0.0589***
	(63.27)	(104.1)	(-103.5)	(-22.48)
Observations	4,002,597	4,002,597	2,274,269	2,912,892
R-Squared	0.075	0.084	0.244	0.015
OrigMonth FE	YES	YES	YES	YES
State FE	YES	YES	YES	YES
Term Duration Month FE	YES	YES	YES	YES

Robust t-statistics in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Note: This table summarizes the results on payment ratio (borrower payment relative to scheduled payment) based on our data of 6-year new car auto loans originated in between January 2017 and July 2023. Since prepayment and paydown are borrower-specific behaviors, we collapse the analysis to one observation per loan in columns (1)-(2). "Paid Down" is equal to 1 if a borrower has, at some point, paid more than 1.2 times what they cumulatively owe and 0 otherwise. "Prepay" is equal to 1 if the borrower pays down the full amount of the loan and 0 otherwise. Turning to the main point of the table, Columns (3) and (4) re-estimate loan performance as measured by the payment ratio over the life of the loan for loans that are not paid down and loans that do not prepay, respectively, using the the full panel data and subsetting on the loans that are not identified as either paid down or prepaid. We use nominal yield curve from https://www.federalreserve.gov/data/yield-curve-tables/feds200628_1.html.
Source: SEC form ABS-EE.

Table 4: Interest Rate and Loan Pricing Results (As of Month 13)

	(1)	(2)	(3)
Dependent variable: Interest Rate			
EV		-0.0174***	-0.0183***
		(-51.63)	(-57.12)
Hybrid		-0.00108***	-0.000446***
		(-12.96)	(-5.763)
Credit Score	-0.000235***	-0.000234***	[spline]
	(-703.5)	(-702.0)	
Payment-to-income ratio (percent)	0.0665***	0.0665***	[spline]
	(83.20)	(83.13)	
LTV ratio	-0.0193***	-0.0193***	[spline]
	(-192.5)	(-192.9)	
Observations	2,014,939	2,014,939	2,014,939
R-Squared	0.348	0.349	0.413
OrigMonth FE	YES	YES	YES
Term FE	YES	YES	YES
State FE	YES	YES	YES
Income FE	YES	YES	YES

Robust t-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1