Auto Finance in the Electric Vehicle Transition

Elizabeth Klee, Adair Morse, Chaehee Shin*

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Abstract

Financing cost differentials tilt the calculus for households toward electric vehicles (EVs), a previously unrecognized transition role. Using 85 million observations on U.S. auto loans, we study household's auto loan interest rates and defaults. We present four findings. First, EV owners default 30 percent less relative to internal combustion engine vehicles (ICEVs). This is partly attributable to insulation from gasoline price shocks: a one standard deviation increase in gas prices results in 1 percentage point lower default rate for EVs relative to ICEVs. Back-of-the-envelope calculations suggest such default is worth \$980 in savings, if they were priced to households. Second, loans for EVs carry a 2.2 percentage point lower interest rate, the equivalent of \$1,974 in savings on a \$34,000 vehicle. Third, this lower rate is only for captive (manufacturer-based) lenders, not for bank and nonbank lenders. Manufacturers hence may be passing on \$1,974 of operating profits to consumers for policy and innovation reasons, while the lower credit risk of EV borrower (another \$980) is probably not being priced to households. Finally, the lower credit risk is also not passed in economic magnitude to investors in the ABS market. Our findings argue for emphasizing finance in the EV calculus and separating ABS markets.

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*Klee: Federal Reserve Board, elizabeth.c.klee@frb.gov; Morse: Haas School of Business, UC Berkeley, adair@berkeley.edu; Shin: Federal Reserve Board, chaehee.shin@frb.gov

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 auto lease.[1] Auto loans are the third largest category of consumer credit, behind mortgages and student loans, accounting for more than $1.5 trillion in outstanding balances across 100 million loans as of 2023:Q3 (see Figure 1).[2,3] This high rate of financing reflects both the natural role of finance in durables expenditure and the automaker-specific model that promotes car buying with attractive financing, a model which began in 1919 with the founding of 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] Previous research shows that incentives and costs of owning and operating EVs—for example, financial incentives and maintenance costs—and location-specific microcosts—such as commuting distance, access to non-premium charging infrastructure, and fuel differential costs—influence consumer decisions to transition from internal combustion engine vehicles (ICEVs) to EVs (Parker et al., 2021; Danielis et al., 2020; Sierzchula et al., 2014). Thus, any cost difference that we uncover due to auto finance will matter at the margin in the overall calculation for households.

Our research sheds light on the rent capture during the current period of economic transition in transportation and energy. Economic transitions usually create opportunities and disruptions, where some parties gain, and others lose. Consider for example, the term 'robber baron' and its applications to the new railroad and electrification monopolies disrupting shipping transit routes and kerosene. The rents from these transitions were captured by a few disrupters. Yet, at other times, the distribution of rents can be self-reinforcing, supporting the transition. This was also the case after the bubonic plague in parts of north-western Europe in the fourteenth century, where disruptions caused labor capture of rents and reinforced labor-saving innovations (see Jedwab, Johnson, and Koyama (2022) for related literature). Finance is one of the channels through which

[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 2023. Retrieved July 13, 2023, https://www.newyorkfed.org/medialibrary/interactives/householdcredit/data/pdf/HHDC_2023Q1.

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

reinforcing distributions of gains and losses can occur.

Our paper studies the potential for auto finance to accelerate the EV transition through the allocation of rents to households. The mechanism we explore is the savings in the costs of finance emerging from the market pricing of reduced default. EVs use electricity as fuel; households thus face reduced exposure to oil price levels and volatility. A key question is whether there are lower implied default risks in auto loans and better loan performance because of this reduced exposure, and furthermore, whether these lower risks are evident in the household loan pricing and the subsequent securitization of these loans into auto asset-backed securities (ABS). If such gains were to be passed to households in the price of lending, then the costs of EV purchasing and owning would decline, accelerating EV adoption.

Our goals are threefold. First, we assess to what extent the default profile for EV loan borrowers differs from that for ICEV borrowers. Second, we ask whether those differences emerge from selection of the credit risk profile of EV borrowers sorting in a Stiglitz and Weiss (1981) and Stiglitz and Weiss (1983) information provision or from a treatment effect of owning the EV. Finally, we test who may be realizing gains from the lower default realization of EV lending and how welfare is affected by this distribution. We do this by exploring the pass through of pricing from lenders to households (interest rate) and from ABS investors to lenders (securities prices).

Our research sheds light on the possibility that, by separating EV loan finance from ICEV finance, a competitive market for EV-ABS could ensure the transfer rents to households in the form of lower rates on auto loans. Thus, we calculate the implications of our research to a household level, both in terms of dividing the rents as well as facilitating the EV transition.

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 early 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. These data have been used by Bakshi and Rose (2021) to explore the effect of forbearance on auto loan defaults during the pandemic and by Klee and Shin (2020) to identify asymmetric information in auto ABS.

Our primary loan-level performance outcome is 60-day past due delinquency on monthly auto loan payments ("default") with a term (the most common) of 6 years. We show that in raw data, loans backing EVs have only one-fifth of the monthly default rate as combustion engine loans. This comparison is not apples-for-apples in selection on observables used in the underwriting such as credit score, payment-to-income ratio, loan-to-value, and income. Once we adjust for these variables and adjust for aging crossed with calendar time, EVs default 30 percent less in percentage change terms; hybrids default 13 percent less. We also study a payment-to-scheduled payment ratio, dropping prepays and paydown boorrowers, to translate credit risk into a dollar (profit) magnitude. In payments, EV borrowers, all else equal, have a higher payment ratio of 0.0284, equivalent to \$980 over the life of the loan in inference.

These estimations do not answer the question of whether the pricing effect is emerging from unobservables (e.g., home ownership), or from selection on credit risk or from expected treatment of lower (and less volatile) variable costs in the form of gasoline prices. To address the possibility that there could be both selection and treatment effects, 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.[5]

We find that the treatment effect of owning an EV insulates borrowers from expense shocks, leading to lower delinquencies. A standard deviation of gasoline prices, if sustained for a year, would result in a 0.0103 lower default over a year, off a baseline annual default of 0.0228. Are these lower risks known and being priced for consumers, or are intermediaries capturing these lower risk benefits?

For the question of the capture of the rents from the economic progress of lower expense volatility resulting from EVs, we turn to investigate the interest rate associated with auto loans. The baseline predictive power of underwriting variables, calendar, term, and location is high, with R-squared statistics in excess of 0.42. 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 \$1,970 lower cost of buying a car. It is an enormous 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. In particular, manufacturers could subsidizes EV volume for reasons of EPA mileage targets, 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 manufacture incentives

[5]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.

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 $1,974 lower EV loan interest rate is not due to the passing back of the lower credit risk to households, but rather to manufacturer incentives to reach EPA targets or otherwise clear EV inventory. If so, our estimates together imply that EVs should be an additional $1,974- $2,954 cheaper in cost of ownership due to the the finance channel, with the range difference of $980 not being fully passed back to consumers.

In our final evidence to ascertain whether credit risk differentials are being included in finance market calculations, we turn to ABS pricing. If lower default risk is the mechanism, the ABS market should also be providing rents that get passed through to the consumer.

We map back our granular loan-level data to the auto ABS deals that package and sell the loans to investors. Our outcome of interest is the coupon spread over comparable-maturity Treasury securities at issuance for various tranches of auto ABS, and we supplement this with a look at the implied spread over the life of the security. We ask whether the composition of the pool in terms of loans for EV or hybrid vehicles affects the pricing. Across tranches, we find little consistent evidence that spreads narrow with higher shares of EV loans in the pool. We find some significant effects that ABS poolers place EV loans in packages with higher credit profiles (lower credit support), but the economic magnitude of these significant effects are very small.

Our overall punchline is thus 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 $980 in additional total payments from EV loans as calculated by back-of-the-envelope interference from payment ratio results. EV loan borrowers get a 2.2 percentage points of interest rate subsidy in our period, on top of federal and state subsidies. This subsidy in the finance mechanism means that EVs have been $1,974 cheaper than face value, once incorporating amortization of interest costs. However and on top of this, the finance markets do not seem to be yet fully pricing the auto finance benefits, $980, back to the household. In fair pricing of defaults in terms of the origination interest rates, consumers would expect to see even lower costs. One solution would be the separation of ABS markets to force this pricing mechanism through the finance systems.

We contribute to three strands of the literature. The first strand focuses on climate-related finance. Previous research has found 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 that particularly associated with 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 (2012a) 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 climate change. 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 or for climate change.

Therefore, lastly, we contribute to the general literature on financing of innovation, or the "funding gap," including that from government subsidy.[6] Many studies have examined the role of financial markets in innovation. For instance, Brown, Fazzari, and Petersen (2009) find that financing greatly matters especially for young firms. Nanda and Nicholas (2014) look at associations of bank distress in the Great Depression era and the following dearth of innovation. More recently,

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

Nanda and Rhodes-Kropf (2017) show that a "hot" market of investors may be needed to fund highly novel innovations. 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 spend as much resources to improve other vehicle attributes such as engine power from 1980 to 2006 amid lack of government incentivizations. 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. Howell (2017) finds that government subsidy spurs innovation by easing financing constraints.

2 Background on Auto Finance and Climate Policy

2.1 Auto Lending and Securitization

Households seeking to secure financing for a vehicle purchase can do so ahead of time with a financial institution, or they can use the captive financing offerings, offerings by the manufacturer (or a subsidiary contracted) provided at the point of sale of the auto. Captive auto financing is somewhat unique of a vehicle in that auto manufacturers may use financing as a funnel to apply subsidies to secure deals. These seeming subsidies may be priced back into the sticker price of the vehicle and then returned to the household either in cash discounts or financing rate deals. Such actions are called subvents, or subventing the deal.

From the perspective of the potential borrower, the underwriting experience of auto loan borrowing is not very different from other consumer credit markets. While there is some variation in stringency and standards across lenders and vehicles, underwriting for auto loans tends to focus on a small set of applicant and vehicle characteristics. Included are the applicant's credit score, payment-to-income ratio, debt-to-income ratio, history of delayed payments, the number of auto loans outstanding, and documentation that the borrower has at least 24 months of credit history.[7] Lenders obtain the applicant's credit report to extract such underwriting data and use income information to calculate the borrower's monthly effective payment to income ratio. Income or employment are verified if there are gaps or other irregularities in typical underwriting variables.

Supporting credit availability for auto loan demand is the securitization of auto loan supply. As of 2022Q4, the auto asset backed security (ABS) outstanding balance stood near \$220 billion.[8]

[7] 17 CFR §246.18, Underwriting standards for qualifying automobile loans.

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

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). The U.S. auto ABS market is comprised of two sectors: publicly-placed auto ABS and privately-placed auto ABS, in addition to a lending market that produces loan assets not ultimately securitized.

Auto lending markets exhibit a few differences from the housing asset backed security market, i.e. mortgage backed securities (MBS) markets. First, unlike the majority of mortgage loans, auto loans are ultimately pooled into MBS under government or agency guarantee programs. Thus, auto ABS is more akin to credit card ABS markets, with credit risk being the first order consideration for mobilization of liquidity. Second, in a significant portion of auto ABS (what is called the captive market), the lender, depositor, sponsor, administrator and servicer are all be the same company (i.e., the automaker's financing arm). In mortgages, these entities are often different and unrelated. In these scenarios, investment banks act as book runners and as managers of the securities offering. These differences from the MBS market may explain the different experience of auto ABS during the MBS 2008-2009 crisis.

A third difference of auto ABS from the MBS market relates to repossession. Delinquency on an auto loan puts a borrower at risk of repossession of the vehicle. While exact implementation varies by state, in some jurisdictions, even after only one missed payment, a lender can enter a borrower's property to take possession of a vehicle without notice.[9] Borrowers may have the right to pay any outstanding obligations plus applicable fees to purchase the car that the lender repossessed, although lenders are not always obligated to notify borrowers if the repossessed car is available for sale or at auction. These conditions stand in sharp contrast to mortgages, where in many jurisdictions, homeowners receive a notice of foreclosure well before any potential eviction, and there exist a range of mitigation processes or services to help borrowers avoid foreclosure.[10]

This aspect of auto ABS—the very real threat of repossession—even if it is not generally evoked so rapidly, implies that households are likely to make auto repayments higher than other consumer credit in a pecking order of bills to pay. Empirical evidence supports this ordering during some

[9] https://consumer.ftc.gov/articles/vehicle-repossession#When.

[10] See, for example, https://www.hud.gov/topics/avoiding_foreclosure.

periods.[11,12] This, in turn, likely makes lower hurdle rates on the supply of credit, leading to a complete credit market across potential borrowers.

2.2 Regulatory Background

In the United States, related 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."[13] 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.

Evolution of stricter CAFE and greenhouse gas emission standards gives two important implications in our setting of auto market. First, it increasingly makes the U.S. automakers, in particular the ones that have traditionally produced ICEVs, become subjected to more binding constraints

[11] Jacob Conway and Matthew Plosser, "When Debts Compete, Which Wins?" Federal Reserve Bank of New York Liberty Street Economics (blog), March 1, 2017, http://libertystreeteconomics.newyorkfed.org/2017/03/when-debts-compete-which-wins.html.

[12] William J. Arnesen, Jacob Conway, and Matthew Plosser, "Who Pays What First? Debt Prioritization during the COVID Pandemic," Federal Reserve Bank of New York Liberty Street Economics, March 29, 2021, https://libertystreeteconomics.newyorkfed.org/2021/03/who-pays-what-first-debt-prioritization-during-the-covid-pandemic.html.

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

in terms of production of ICEVs. This may lead to different sales or pricing strategies to induce higher sale of EVs, as we will more closely examine later in Section 6.3. Second, stricter standards reduce the depreciation rate of EVs, thereby encouraging the overall demand for EVs. Difference in adoption of stricter standards across jurisdictions will create differentials in depreciation speeds of EVs in each jurisdiction (for instance, Europe versus the United States).

3 Data

Our primary data comes from SEC form ABS-EE, which contains loan-level data that all filings of prospectuses for public securities offerings of auto ABS must submit under SEC Regulation AB, effective November 23, 2016.[14,15] Details on constructing the final data sample are described below in the following subsections. In the end, 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 under 6-year (the most common) term.

Figure 2 displays information on the origination year captured in our final data sample. In part reflecting the phase-in of reporting requirements as well as the general recovery of auto ABS securitization post-Global Financial Crisis, loan issuance ramped up from 2017 to 2020, dropped considerably at the onset of the COVID-19 pandemic, and subsequently recovered. The drop-off in late 2022 through 2023 likely reflects the warehousing delay (Klee and Shin, 2020), as well as some uncertainty and considerations related to tax credits for EVs.

Figure 3 illustrates geographic dispersion in origination for our sample based on public ABS filings. Although there are some pockets of concentration, our sample of auto loans has broad national coverage. Per 100,000 inhabitants, we capture the most car loans from the Southeastern part of the country, along from Texas and California. Our data also captures a relatively high number of auto loans per 100,000 inhabitants from New Hampshire and Vermont. The data captures relatively few from New York and some mid- and western states than other areas.

We also augment the loan-level data with various macroeconomic datasets. Below, we describe our main variables related to vehicle engine taxonomy, borrower and loan characteristics, and loan performance outcomes coming from the loan-level data, as well as the macroeconomic controls.

[14] The requirement applies to all registered offerings backed by auto loans and leases, residential and commercial mortgages, and debt securities including re-securitizations.

[15] Information is available at https://www.govinfo.gov/content/pkg/FR-2014-09-24/pdf/2014-21375.pdf.

3.1 Vehicle Engine Taxonomy

Our loan data include a description of the vehicle collateralizing each loan, such as the manufacturer name, model name, and model year. The data do not classify loans by engine type. Thus, our first data task is to 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 available from the EPA on EVs and hybrids in various model years.[16] We then complement this information with known 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-." We classify all remaining vehicles as combustion engines. 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 A provides details on the list of hybrid cars and EVs based on our classification.

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. Reflecting the growing popularity of hybrid and EVs, the distribution is right-skewed by origination year. Specifically, the share of hybrid and EVs grows steadily through 2020, and then jumps up considerably to closer to 10 percent of all loans in 2022.

3.2 Borrower and Loan Underwriting Characteristics

Our final dataset contains key attributes of borrowers and loan underwriting.

Borrower Characteristics Table 2 provides summary statistics on borrower characteristics in our data by engine type. Asterisks on the hybrid and EV statistics indicate that the estimated statistic for these engine types are statistically significantly different from those for combustion engines. In general, means are statistically and significantly different across almost all variables.

An important applicant characteristic is the value of the vehicle. 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. Also, in limiting our analysis to new car loans, we

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

avoid potential asymmetric information on car value inherent in the used car market. 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.[17] Hybrid cars are a little more expensive than combustion engine cars, while EVs are $6,000 more expensive, on average.

In addition to the car value, observable characteristics of successful loan applicants include underwriting variables obtained from the credit report or on the loan application. A key underwriting variable is the borrower's credit score. We limit our analysis to prime borrowers only (credit score above 620), because of the scarcity of subprime borrowers buying EV models. As shown in panel B, credit scores for combustion engine loans average around 740, and, for EVs, average at 788.

We derive the borrower's monthly income from the payment-to-income ratio, using separately reported information on the monthly payment. We limit to loans with monthly income above $1,500 and below $83,333. Consistent with greater ability-to-pay supporting higher credit scores, monthly income is significantly higher for hybrid or EV loan applicants than for ICEV applicants.

Loan Underwriting Characteristics

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, 2012b). Thus, we consider the loan amount, payment, and thus payment-to-income to be predetermined underwriting variables. We focus on 6+ year loan terms for a couple of reasons. First, this is the most common offering by lenders in our sample. Second, terms have been found to be a mechanism for households to choose payments to meet ability-to-pay feasibility (Hertzberg, Liberman, and Paravisini, 2018).

As shown in Panel A of Table 2, loan amounts average $34,867 for ICEVs, slightly higher at $35,586 for hybrids, and $40,881 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 ratio for EVs statistically significantly lower on average (0.945) than that for ICEV loans (1.011). Hybrid vehicle loans also experience lower LTVs than combustion engine loans, although to a lesser extent. High LTVs are characteristic of auto loans more generally; our data fall into generally reported norms.

Consumers generally focus on monthly loan payments to satisfy household budget constraints.

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

Monthly loan payments for combustion engine borrowers and EVs are lower ($544 and $530, respectively, per month) than those for hybrid ($609 per month). Lenders also look at monthly loan payments, and focus on payment-to-income ratios in typical underwriting standards and thus in our specifications. In our data, the payment-to-income ratio remains lowest for EV borrowers, as higher incomes apparently dominate monthly payments on ability to pay.

3.3 Loan Terms: Interest Rates and Subvention

The original interest rate on a loan and whether the loan was subvented are outcomes from the credit underwriting process. As can be seen from Panel A of Table 2, EV loan interest rates (2.3%) are, on average, more than two percentage points lower than those for combustion engine loans (4.9%). And as with other credit dimensions, rates on hybrid loans are in-between those for ICEVs and EVs (3.7%). A question arises as to whether these differences in the distribution of interest rates reflect origination patterns. In particular, because EV loans are concentrated in the latter half of our sample, and may be influenced by near-zero interest rates in the wake of the COVID-19 pandemic, there may be a mechanical relationship between our observed EV rates relative to others.

Notably, even after controlling for timing-related macroeconomic factors, EVs have lower interest rates. In Figure 4, 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, and very few loans with annual percentage rates lower than 10.

Some of lower interest rates could reflect the propensity for lenders to offer "teaser" rates at loan origination. These incentives, along with cash back at origination, constitute two major types of subvention of auto loans. Figure 5 show how these subventions shift the distribution of interest rates to the left, based on our ABS-EE data. Subvented loans have around 3.8 percentage points less interest rate than non-subvented loans. In particular (not shown in the figures), 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).

3.4 Loan Performance

The SEC's regulation ABS-EE requires auto ABS issuers to file granular, loan-level data at a monthly frequency until the ABS maturity date. This reporting structure allows us to track the performance of each outstanding loan comprising the ABS. Using this panel data provides a window into studying the effect of the engine type and the borrower characteristics on performance outcomes, as well as the impact of the broader macroeconomy.

Our key variable of interest is loan delinquency. For our baseline, we define a loan to be delinquent if a loan newly enters a 60- or 30- days delinquency in that period from a non-delinquency status in the previous period. 60- (30-) day delinquency means a payment being 90 (60) days past the billing date because a borrower has 30 days to pay from the billing date. We focus on only the initiation into a delinquency to only pick up current distress, with results not being driven by continuing delinquency.[18]

Panel A of Table 2 presents overall 60-day delinquency rates for the sample as a whole as well as across engine types. The differences are striking: combustion engine 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. Panel B gives a breakdown by monthly delinquency rates, which reflect the observed probability of a loan experiencing a 60-day delayed payment in any given month. For ICEVs, this probability is 20 basis points, more than five times higher than that for EVs. Taken together, these observations, along with the differences in applicant profiles across vehicle engine types, form the heart of the analysis that follows.

3.5 Macroeconomic Controls

To implement our research design, we need to pair the performance data with macroeconomic variables that affect households ability to make repayments. We use macroeconomic variables that determine the ability of borrowers to repay their loans, and those that are specific to differential costs for operating ICEVs versus hybrid or EVs. For borrowers' ability to repay, we focus on state-level economic conditions, allowing us to use state-level differentials to identify impacts of geography varying pressures on the ability to pay. We use state-month unemployment rate data by state from the Bureau of Labor Statistics and quarterly housing price index by state from the Federal Housing Finance Agency. Both the variables are seasonally adjusted. Finally, data on annual median household income by state is from U.S. Census Bureau.

Information on energy prices helps us to identify the treatment effect of owning an EV. To this end, we obtain monthly data on crude oil price data (West Texas Intermediate) from FRED

[18]A loan can enter and exit delinquency each period and thereby show up as delinquent multiple times over its life. In a future draft, we also will consider other performance metrics, including charge-offs, and overall profitability of loans.

(Figure 6). In addition, we add conventional retail gasoline price and tax data by region from the U.S. Energy Information Administration, matching to auto loans based on state and year-month.

Table 3 presents summary statistics for our macroeconomic conditioning variables. On an incidence-weighted basis, the unemployment rate averages around 4.5 percent over the sample period. Of note, there are extreme observations on unemployment during our sample period—upwards of 30 percent at an annual rate—reflecting the extraordinarily sharp contraction following the onset of the COVID-19 pandemic. The house price index, or HPI, also has decent variability, with the coefficient of variation around 20 percent. Annual median household income (Income) by state centers around $70,000, and varies considerably across location.

3.6 Auto ABS

Our sample of auto ABS largely reflects securities issued by finance arms of automakers, often called "captive" issuers. While captives accounted for roughly one-third of overall auto ABS issuance in 2022, the predominance of captives in our sample reflect choices made in the above analysis.[19] For example, to control for heterogeneity in our analysis of EVs, we eliminated loans backing used cars and loans from subprime borrowers. This elimination implies that our sample leans towards captive auto loans, as banks and nonbanks tend to be relatively more active in subprime and used car lending than captive auto lenders.

Table 4 summarizes characteristics for the $361 billion in publicly-placed auto ABS issued from 2017 to 2023 used in our sample. We cover 20 distinct issuers. A little over half of the issuers are captives, followed by banks and nonbank lenders. These patterns are also reflected in the number of distinct securitizations over our sample period. Captives account for roughly 60 percent of the securitizations in our sample, followed by banks with 25 percent and nonbanks with 15 percent. The breakdown of dollar value by type of issuer largely reflects the counts: Out of a total of $361 billion in securitizations, $225 billion are from captives, $87 billion from banks, and $50 billion for nonbanks.

Captive auto issuers also extend the majority of EV loans in our sample. Of the $1.38 billion in EV loans, captive auto lenders account for $1.30 billion. The captive proportion is also high for hybrids. Taken together, these proportions indicate that our ABS results related to EVs predominately reflect the actions of the captive auto lenders. That said, we highlight where differences

[19] See S&P Global, https://www.spglobal.com/ratings/en/research/articles/230215-u-s-auto-loan-abs-tracker-full-year-and-december-2022-performance-12637333.

could arise across lender types.

Each auto ABS deal is comprised of tranches. These tranches carry varying levels of credit risk that depend on the probability of absorbing losses and the amount of losses absorbed given default. In broad terms, there are two types of tranches: senior and subordinated. Holders of the senior tranches receive priority in payment over the holders of subordinated tranches. Within the senior and subordinated tranches, there are further divisions into securities that carry credit ratings from S&P or Moodys. While our data includes reporting from both agencies, 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.

Figure 7 displays the distribution of senior versus subordinated tranches and credit ratings in our sample. As shown in Figure 7a, most of the dollar value of issuance is senior, with a little less than 20 percent of the dollar value in subordinated tranches. As shown in Figure 7b, most tranches are investment-grade, and carry the agencies' highest ratings. However, there is also an unrated equity tranche, which sits in the first loss position in case borrowers default on the underlying loans.

4 Preliminary Evidence on Defaults by Engine Type

To compare loan performance across engine types, Figure 8a plots 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. The results are striking. The blue line in the figure illustrates that combustion engines have the highest cumulative delinquency rate, peaking at more than 10 percent at 60 months after origination. Hybrid vehicles (the green line) experience a lower cumulative delinquency rate, at 4 percent. The pattern is noticeably different for electric vehicles. The cumulative default rate levels off at 30 months after origination, nearly 8 percentage points below the peak for combustion engines.

This figure depicts a major punchline of our paper. An economically and statistically meaningful difference exists in default by engine, summarized by the simple difference between the aging profiles, both with and without controls for macroeconomic factors.[20] Of course, this differential most likely reflects both selection of credit profile, as well as the treatment effect of owning an EV. Yet, the overall effect is presumably that which is most important to investors in the auto ABS market. The rest of our paper seeks to disentangle these two, but a reader's natural first question

[20]We present the statistical table version of these figures as a column in the results section.

might ask to understand whether these figures simply reflect the time period of origination and the macroeconomic conditions over which the aging period spans. Thus, in Figure 8b, we show that the figure remains relatively similar after having orthogonalizing monthly default to year-month time effect interacted with aging. In a way, this orthogonalization exercise removes some of the selection (who is apply for an auto loan at each month in time) and some of the treatment effect (are the macroeconomic conditions differentially picking up sensitivity to default). However, we tackle these issues in great detail later. For now, our modest objective is to show that the documented effect in Figure 8a is robust to incorporating time effects.

5 Methodology: Disentangling Treatment from Selection

5.1 Framework

Our empirical framework for a borrower's decision to default on an auto loan adapts the treatment model of Imbens (2004). We closely 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).

Consider auto loan borrowers indexed by i , and calendar months indexed by t up to end time T. A random utility model of latent utility U^*_{it} of the decision to default that is conditional on borrower origination characteristics and macroeconomic factors is given by

$$U^*_{it} = \Gamma^{\text{origin}\,\prime} Z^{\text{origin}}_i + \mu^{calendar*aging}_{it} + e_{it}. \tag{1}$$

Borrowers possess a vector of predetermined factors that serve as the underwriting of credit risk at the time of application and origination of the loan, including credit score, income, payment-to-income (PTI) and loan-to-value (LTV). We label them by the vector Z^{origin}_i. We consider the loan interest rate as determined in the lending process; however, it may be that interest rates also capture some credit risk information that is observable to the lender but unobservable to the econometrician. Thus, sometimes we include interest rates in the vector Z^{orig}_i. Also included is the borrower's state of residence, to control for other potentially unobserved local factors associated with default.

We include fixed effects of the interaction of calendar time with aging time, denoted by $\mu^{calendar*aging}_{it}$.

Absorbing at this detail 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. Thus, the interaction of these two variables will absorb any default utility mapping to the exposure to macroeconomic conditions that varies by origination year or the aging of the loan payoff timing. For example, borrowers who bought a new car in a recessionary period may have greater resilience (lower default utility) to worsening macroeconomic conditions due to unobservable wealth. Likewise, borrowers near the end of the aging of a loan may have default utilities of getting to the end payment that affect their choice to weather macroeconomic conditions with a higher preference for paying off the auto loan in their pecking order of bill payments.

Random utility is not observable to the econometrician, who instead observes the borrower's decision to default. The discretized default decision U_{it} corresponds to the latent utility U_{it}^* as follows:

$$U_{it} = 1 \text{ iff } U_{it}^* > 0, \text{ and} \tag{2}$$

$$U_{it} = 0 \text{ iff } U_{it}^* \leq 0. \tag{3}$$

Under the assumption of error term e_{it} being distributed *iid* extreme value, the random utility formulation maps to a logistic distribution with mean 0 and variance $\pi^{2/3}$. Hence, a logit estimation could be employed to uncover the estimates for parameters Γ^{origin} and $\mu_{it}^{calendar*aging}$:

$$logit(U_{it}) = \Gamma^{\text{origin}\,\prime} Z_i^{\text{origin}} + \mu_{it}^{calendar*aging} + \epsilon_{it}. \tag{4}$$

5.2 Introducing Treatment in Framework

In our setting, the treatment is the engine type; individuals with different engines are exposed to the different prices and fluctuations of required fuel in running their vehicles. We abstract from maintenance cost differentials, as we expect the path of these costs to be invariant to changes in gas prices.[21]

Adding a linear engine indicator to the logit specification renders a candidate β (treatment effect estimator) from:

$$logit(U_{it}) = \beta_{base} W_i + \Gamma^{\text{origin}\,\prime} Z_i^{\text{origin}} + \mu_{it}^{calendar*aging} + \epsilon_{it}. \tag{5}$$

[21]The EPA generally reports average monthly maintenance costs over the life of a vehicle; our assumption is consistent with this view.

Using the W notation of Imbens (2004), each borrower is exposed to a single treatment W_i, either the control (ICEV as represented by $W_i = 0$) or the treatment (EV as represented by $W_i = 1$). [22] Each borrower has two possible utility of default pathways over time, $(U^*_{i,t=1..T}(W_i = 0), U^*_{i,t=1..T}(W_i = 1))$ – or in shorthand $(U^*_i(0), U^*_i(1))$. However, only one set is realized and thus observable.

β_{base} captures, in a rough sense, the combined selection and treatment effect on default performance. For holders of the loan-related asset (ABS holders), whether the default probability comes from engines-specific costs exposure affecting repayment or a Stiglitz-Weiss sorting effect of the profile of borrowers may be of academic interest only. Even so, the econometrician, policy makers, and architects of the financial intermediation structures are interested in disentangling selection from treatment.

There are three general classes of reasons why estimated treatment effects may be inaccurate: reverse causality, simultaneity, and confoundedness (omitted variable bias and selection on unobservables). Reverse causality might imply that future defaults are already in progress and cause a choice of a vehicle today, which is possible but unlikely in timing and in the decision to buy a new auto. Likewise, simultaneity would imply that some other factor is both causing the choice of engine and the default utility pathway. It is possible to imagine distress stories of some desire to have a particular car because of a impending bankruptcy or job loss event looming, but why that might suggest a selection into EV or ICEV is not clear.

5.3 Confoundedness

The particular remaining concern with the candidate treatment effect estimator β_0 is that it may suffer from confoundedness in selection on unobservables. The unconfoundedness assumption of Rosenbaum and Rubin (1983) is given by:

$$(U^*_i(0), U^*_i(1)) \perp W_i \mid (Z^{\text{origin}}_i, \mu^{calendar*aging}_{it})$$

which says that if the set of borrowers selecting into the treatment of EV had instead been treated with the control engine, these borrowers would have reacted similarly to the control engine treatment (e.g., to the gasoline fuel fluctuations) as the control group who actually selected into the control group, all things ceteris paribus in $(Z^{\text{origin}}_i, \mu^{calendar*aging}_{it})$.

[22] For simplicity of exposition, we consider only ICEVs and EVs, but generalize to include hybrids in the empirical analysis.

To call out the immediate candidate violation to that assumption, one might argue that selection on homeownership represents a problem for the unconfoundedness assumption. Homeownership, which we do not see, might predict selection into the EV treatment, all else equal, because of the need for electricity plugs to charge an EV. If homeownership also is correlated with the reaction in the borrower's default utility to ex post conditions on electricity or gasoline prices, the β_{base} from the logit equation has the confounding effect of both selection and treatment.

5.4 Shock Exposure Identification

Our solution to confounding effects of homeownership and any other unobservables causing selection bias in ascribing the treatment effect is to employ a set of as-good-as-random shocks to the treatment, using identification off varying intensity of shock exposure described in 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 implementation using shock exposure identification takes a continuous variable difference-in-differences form, as that in Acemoglu, Autor, and Lyle (2004), using regional gasoline prices as the exogeneity shock affecting only the control group of ICEVs. Loan-level fixed effects control for selection differences of consumers into EV versus ICEV, including a potential difference in expectations about future gasoline prices. Busse, Knittel, and Zettelmeyer (2013) find that a change in gas price factors in consumers' car buying decisions. Our methodology relies on the plausible assumptions that the ex-post realization of regional gasoline prices involve some uncertainty resolution (gar prices are, at least to a degree, unpredictable) and that the differing effect of time-varying regional gasoline prices on default is unconfounded.

However, our assumption allows for the possibility that the realization of regional gas prices affects the overall macroeconomic condition for default for all vehicles through channels, other than the direct fuel costs channel. These effects will be picked up by the un-interacted regional gas price variable. Indeed, oil prices are likely correlated with market-based wealth, the costs of goods shipped including groceries, and many other good and services. Oil prices are also likely correlated with employment and income growth. We make an unconfoundedness assumption only on the interaction of regional gas prices with the engine type.

We specify our oil price model, with the regional gasoline price for individual i's region as $P_{it}^{RegionOil}$ and employ the estimator proposed by Acemoglu, Autor, and Lyle (2004) and Sun and Shapiro (2022) to address confounded treatment a difference-in-differences setting with heterogeneous treatment effects.

$$logit(U_{it}) = \beta_1 P_{it}^{RegionOil} + \beta_2(1 - W_i)P_{it}^{RegionOil} + \mu_{it}^{calendar} + \mu_i^{loan} + \epsilon_{it}. \tag{6}$$

We include loan fixed effects, μ_i, to isolate the times of a shock particularly affecting ICEVs. $\hat{\beta_1}$ is the baseline correlation of oil prices with repayment ability, working for all types of vehicles, thus not through the mechanism of a vehicle variable cost. $\hat{\beta_2}$ is our parameter of interest, capturing the shock exposure unique to combustion engines, as a continuous time difference-in-differences specification. [23,24]

6 Household Finance Results

We turn to our main empirical specifications. We first estimate a series of default estimations to understand the extent to which the univariate differences in default by engine type documented previously reflect credit risk differentials. Then we turn to our regional gasoline price formulation to seek for evidence on a treatment effect; i.e., to what extent does the ex post exposure to fuel cost differentials cause the default pattern uncovered. We then step back and ask if any credit-adjusted default differences are being priced into loan interest rates provided to households.

After concluding the analysis at the household-facing level, we turn to the ABS market, asking to what extent the spread of differences in default is passed to the ABS investors in their pricing spread.

6.1 Default Results and Underwriting Selection

Table 5 presents the first main set of default results. We control for the exact number of aging months, reflecting "seasoning" patterns exhibited by auto loans (Kane, 2001). 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.[25] The dependent variable is the main default variable, defined

[23] In a future version, we will also consider a model of heterogeneous effects of the gasoline price shock across combustion vehicle borrowers by the EPA's gas mileage estimate.

[24] We can also, in future versions, implement a full quasi-Bartik specification as a shift share. We need three more pieces of information to avail ourselves of this estimation strategy. First, we need to evaluate how much of each borrower's budget constraint is attributable to operating costs for the vehicle. Our data include information on payment-to-income ratios. We take these ratios and back out the borrower's implied income. Second, we then calculate the borrower's monthly cost of operating the automobile as a share of income. And third, we then weight this share by the change in gasoline prices associated with the shock.

[25] In future drafts we will present subsample estimations with logit specifications to ensure economic magnitude interpretations are valid as we are estimating in the sigmoidal range of logistic distribution.

as a loan newly entering a 60- or 30- day delinquency in that period from a non-delinquency status in the previous period, as defined in Section 3.4.

Columns 1 and 2 report the simplest depicting of default, looking at differentials by engine with only aging absorbed. Under this specification, any significant difference by engine type will capture both selection into engine types and treatment effects of owning the engine type. 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 0.197 percent. Thus, we find very large reductions for EVs and hybrids: 79 percent drop in default rates for EVs and a 55 percent drop in 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. However, this larger effect must be gauged relative to the overall 30-day delinquency rate, which is significantly higher than the 60-day delinquency rate. When we undertake this exercise, we see that the reduction in delinquency owing to the engine type is actually lower in percentage change terms at the 30-day delinquency point than at the 60-day point. Going forward, we focus our discussion on 60-day delinquency rates to infer economic magnitudes and relevance.

In columns 3 and 4, we absorb the effect of macroeconomic conditions by including year-month calendar interacted with aging months fixed effects. We also include the precise number of months in the loan term and state fixed effects to absorb state-level policy (e.g. gas price, standard of living, and tax effects). 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 an unpredicted, positive, sign, suggesting that those with a higher income who are taking our 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 dispersion, the economic magnitude of our vehicle effects falls. In percentage change, EV (hybrid) borrowers default 29% (13%) change less than all borrowers based on the coefficient -0.00058 (-0.00025), controlling for calendar and aging timing, state effects, term, and the important underwriting of credit risk variables used in vehicle loans.

Robustness

In Table 5, we try to level borrowers on credit risk underwriting observables, loan term, location, aging, and calendar time. Included in the underwriting observables is the LTV of the vehicle loan to loan value. Yet, we can do one step better for leveling people on vehicle characteristics by following the literature that compares the EV to the same vehicle body in the combustion engine version. For instance, Parker et al. (2021) compare the costs of operating EVs vehicles of the same car body (Trax versus Bolt, Versa versus Leaf, Golf versus E-Golf, etc).

In our data, we have two pairs of such vehicles with sufficient sample size– the Bolt-Trax and the Leaf-Versa. In both cases the car is the same body, just ith different engines. By re-running our estimation only within these pairs, we add an extra level of comparison on all else equal. Table 6 reports these results. 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 5 robust, they are conservative by half in economic magnitude.

Payment Results

We have established that EV loans perform better as shown by their lower delinquency rates. Our sample is too short to turn delinquency into overall profitability of the loans, but we can take steps toward this alternative calculation in performance. We investigate how borrower payment relative to scheduled payment ('payment ratio') behavior varies by engine type. The ratio of payments made to payments owed may fluctuate and may be affected by paydown and prepayment behavior; thus we implement this analysis in steps.

Table 7 re-estimates the original delinquency results in table **??** but using the payment ratio as the dependent variable. As reported in column 1, we find that electric (hybrid) vehicles pay 0.0370 more (0.0719 less) per month than combustion vehicles. In column 2, we absorb macroeconomic conditions by adding year-month interacted with aging months fixed effects. Finally, in column 3, we introduce controls for underwriting variables. Based on the coefficients for EVs (hybrids) in column 3 of 0.0284 (-0.313), electric (hybrid) vehicles pay 2.84% more (3.13% less) of their due monthly payments when compared to combustion vehicles.

Since this analysis focuses on monthly payments, it remains agnostic to broader payment behaviour over the lifetime of the loan, for example prepayment and paydown behavior. Since prepayment and paydown are a borrower-specific behavior, we collapse the analysis to one observation per loan. This enables us to institute an ad hoc, but reasonable rule that a paydown loan is one in which a borrower has, at some point, paid more than 1.2 times what they cumulatively owe and that a prepay loan is one in which the borrower pays down the full amount of the loan. This collapsing also enables us to avoid the noise of temporary delinquents who cure in our overall inference. We then re-estimate table 7 in this collapsed form.

Columns 1 and 2 look at the paydown and prepayment rate of loans by vehicle type. We find that electric (hybrid) loans pay down 0.0292 less (0.0457 more) while they prepay 0.0386 less (0.0144 more) over the lifetime of the loan. Note that in unreported estimations, we find that if we subset to loans that have non-zero original interest rates, then we find electrics pay down 0.0309 more and prepay 0.0137 more.

Turning to the main point of the table, Columns 3 and 4 reestimate loan performance in the payment ratio over the life of the loan for loans that are not paiddown and loans that do not prepay, respectively. Focusing on EVs, Column 3 (excluding paydowns) and column 4 (excluding prepayments) shows that EV loans have payment ratios that are 0.0784 and 0.0886 higher, respectively, than ICEV loans. In the final two columns, we discount payments by the yield curve at origination in order to capture that even if a lender recoups all payments a delinquent borrower owes. The results are little changed by this discounting.

Taken together, these payment results show that EV loans pay a higher percent of their due payments, even when controlling for underwriting variables. A conservative approach to measuring this out-performance of electric loans, is to take our result that electrics pay 2.84% more of payment owed monthly as shown in column 3 of table 7. A back-of-the-envelope calculation combined with the average loan amount of $34,538 yields a conclusion that an EV loan would pays $980 more than a comparable ICEV loan over the lift of the loan term.

6.2 Regional Gas Price Default Model Results

To what extent is the residual unexplained default differential between ICEV and EV due to the treatment impact of being exposed to differential fuel costs? Equation 6 in our methodology section laid out the estimating equation for Table 9. 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 treatment effects estimated off the interaction of combustion engine with the regional gasoline price.

We find that the treatment effect of owning an EV insulates borrowers from expense shocks, leading to lower delinquencies. In column 1, we find that a \$1.00 increase in gas prices results in a 0.00144 higher monthly default rate, or 0.0174 higher annual default rate for combustion engines that is foregone by owning an EV. 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 0.0103 lower default over a year., off a baseline annual default of 0.0228. As shown in columns (3) and (4), these results are robust to adding macroeconomic controls for the median household income in an area as well as a generalized house price index (HPI).

This result suggests that the residual result from Table 5 – that which is not explained by credit risk observables and macroeconomic time –is likely due to what we are calling a treatment effect, the ex post lower exposure to gasoline costs.

6.3 Interest Rate and Pricing of Loan Results

The interest rate is an outcome variable of particular interest. Our paper started with the question asking to what extent EVs loans might have systematically different default rates. Our hypothesis was that if this was true, the pricing of EV loans could be different (i.e., lower) such that the households buying EVs might receive fair pricing (again presumable lower) in their purchase of the car durable. But, this statement presumes that the market has not already understood all of the estimations we have reported thus far and transferred the benefits of lower credit risk back to the household.

Table 10 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, and state fixed effects. In columns 1 and 2, we estimate the interest rate predictive power by the four important underwriting variables, location, and time. In Column 2, 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 main punchline 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 implies 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 and loan-to-value relationship to interest rate in a node and slope spline specification, provided graphically as Figure 9b. With an average vehicle price of $34,711 and duration of 60 months, this implies a savings of $1,974 over the duration of the loan, even without factoring in the cash back. This amount is equivalent to 5.7 percent of the 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 0.0346 for a full 60-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.

How can we make sense of such a large rate reduction for EVs? Several possible stories (or a mixture of these stories) may be at play. We explore two possibilities in particular. First, it may be that auto financiers are already pricing in lower default by the EVs to the household. Second, it could be that the manufacturer may be reducing their margins to move EVs off the shelf and clear inventory to make way for second generation models. To tease out these two, we look to evidence from auto financing that is not captive—i.e., banks and fintech lenders. In Table 11, we repeat the specifications of Table 10, 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. [26] Yet, our evidence from non-captive financiers is compelling but may not be decisive as to disentangling the two mechanisms for the interest rate price differential of 2.22 percentage point.

Other stories are also possible. As described in Section 2.2, U.S. auto manufacturers—especially the ones that have traditionally strong sales on ICEVs—may be binding to CAFE and greenhouse gas emissions standards and this may lead to strategies inducing EV sales. Alternatively, auto lenders profit more in servicing, or they want to make their tax credit quotas to encourage Congress to pass new legislation. It may also be that manufacturers are offering ICEV offsetting subsidies by way of cash subvents. (The word "subvent" in the context of auto loans translates to monetary incentives aimed at closing a transaction.) However, Column 3 shows this not to be the case; EVs

[26] 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.

(but not hybrids) are 20 percent more likely to have a cash back subvent.

Overall, we summarize our results so far as follows. We find that EVs financing costs 2.22 percentage point less, with an average savings of $1,974. At least some of this savings, if not all, is being passed directly from the manufacturers' margins to households. It is likely that lower credit risk costs incurred by the lenders are not being included in this calculation. If lenders were to also include the lower credit risk costs, the households would also face another $980 in lower auto finance costs. Thus, in sum, we find that auto finance has been costing $1,974 less, and could cost a total of $2,960 less if both credit risk and manufacturer incentives were priced to consumers. In the next section, we turn to the ABS market to see if the differential default is being priced in that other segment of the auto finance.

7 EV Loans and Auto ABS

As discussed above, the data we use for our analysis of delinquency and sensitivity of loan payments to shocks are derived from the loans backing publicly-placed auto ABS. In this section, we take a closer look at the auto ABS and explore the interaction between EV loans and the characteristics of the securities created from them.

7.1 EV Loans and ABS Characteristics

We now take a closer look at the link between EV loans and ABS characteristics. We begin with pricing.

An issue we confront, and as observed by Faltin-Traeger, Johnson, and Mayer (2010), prices for auto ABS at issuance tend to be close to par. In our sample, all observed ABS tranche prices are greater than 99 cents on the dollar and more than a quarter are priced at par. Consequently, we turn to other measures to gauge whether the share of EVs affects auto ABS characteristics.

One of the measures we consider is the spread of the coupon rate on the tranche of the auto ABS over comparable-maturity Treasury securities at issuance reported in the Bloomberg data. To form the spread, we use a daily zero-coupon yield estimated from a smoothed yield curve using the methodology discussed in Gürkaynak, Sack, and Wright (2007).[27] We use the yield curve estimated for the ABS issuance date and linearly interpolate spreads as needed.

Figure 10 displays the distribution of coupons and spreads on tranches of auto ABS over time

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

and across tranches. As shown in Figure 10a, 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.

Another measure we consider is the Z-spread associated with an ABS tranche. The z-spread is calculated as the interest rate (in percent) needed to equate expected future cash flows with the price of the ABS tranche at origination. Specifically, the Z-spread is the implied spread over the risk-free discount rate that is necessary for the discounted expected cash flows to match the market price for the security. The formula for the Z-spread is:

$$P_{ij} = \sum_{t=1}^{n} \frac{\text{cashflow}_{ijt}}{1 + r_t + \text{Z-spread}_{ij}} \tag{7}$$

where P is the dirty price (does not account for accrued interest), and r_t is the expected risk-free discount rate at tenor t in the current period, which we proxy by the zero coupon constant maturity Treasury yield at tenor t. The Z-spread is the solution to a nonlinear programming problem, and by construction, the Z-spread is constant over the life of the security.

Of note, our calculation is a simplification of an option-adjusted spread, which accounts for the refinancing option implicit in auto loans—if rates were to fall, it could be economically advantageous for borrowers to refinance. Option-adjusted spreads, for example, are often used when evaluating MBS. However, the refinancing incentive is much more meaningful for mortgages than for auto finance, and empirically, auto loan refinancings are infrequent relative to mortgages. As such, our simplification likely does not bias our results substantially. We assume semi-annual coupon payment cash flows, as well as a lump sum par payment in the final period.

Figure 11 presents the distribution of z-spreads over our sample, again by year and rating. The patterns are similar to those for coupon spreads, despite the difference in methodology. Again, mean z-spreads generally center between zero and 2 percentage points, with notably wider distributions in the recent period. Higher-rated tranches have lower z-spreads, as these securities presumably have lower risk. Of note, not all unrated tranches have prices in our data, leading to a truncated z-spread distribution for the riskiest tranche.

We estimate the following linear regression model to explore how the share of EVs in an auto

ABS influences the spread measure of the tranche:

$$s_{ij} = \alpha + \beta_1 \text{EV}_j + \beta_2 \text{Hybrid}_j + \beta_3 X_{ij} + \epsilon_{ij}. \tag{8}$$

The dependent variable s_{ij} is the outcome under consideration, either the coupon spread at issuance or the calculated z-spread for security i of ABS pool j at the time of ABS issuance. EV_i is the share of EVs in pool j expressed in percent; similarly, Hybrid_j is the share of hybrids. X_{ij} is a matrix of characteristics of security i in pool j that could potentially be significantly correlated with spreads. We focus on the issuer type (bank, captive or nonbank) and rating (AAA to nonrated). We also include year fixed effects to control for broad macroeconomic factors as well as the auto ABS issuer.

Table 12 presents the results from estimating equation 8. The first three columns of the table evaluate the correlation between the coupon spread, the EV share and the hybrid share. 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 7 basis points, an economically meaningful amount.

Columns (2) and (3) add controls for tranche rating into the specification. As shown in column (2), the coefficients on the share of EVs or hybrids in the auto ABS change little from the baseline results in column (1). In addition, the controls for ratings are not statistically significant, suggesting that the year fixed effects absorb much of the spread variation, consistent with Figure 10. Column (3) asks whether there could be some important interactions between the EV share and the tranche rating. Once the baseline effects plus the interactions are taken into account, there appears to be little difference from the results presented in column (1), although the coefficient on the hybrid share attenuates in significance.

Columns (4) and (5) include controls for whether the ABS is issued by a captive finance company. All else equal, as shown in column (4), spreads are narrower for captive issuers than for other issuers, with the coefficient suggesting that this difference is around 30 basis points and is statistically signfiicant. Column (5) investigates whether there are important interactions between the EV share and issuer type that have effects on spreads. The coefficient on the EV*captive interaction term is not statistically different from zero, suggesting little differential pricing at issuance.

Column (6) combines all controls into one specification. With all controls included, the message remains the same: there is little evidence, or at best, mixed evidence, that there is a significant correlation between the EV share or the hybrid share in an ABS deal and the coupon spread at issuance.

The results for the z-spread are consistent with those for the coupon spread. The results reported in column (7) suggest that the share of EVs in the ABS pool does not statistically significantly influence the z-spread implied by initial pricing of the security. However, the share of hybrid vehicles does influence this spread. A one standard deviation increase in the share is associated with a 6 basis point decline in the z-spread, an economically meaningful amount. Column (8) introduces the ratings controls; z-spreads are generally narrower for higher-rated securities. Column (9) is consistent with little interaction between z-spreads, ratings and EV or hybrid share. Including the issuer type in column (10) leads to similar conclusions as it did for the coupon spread, where captive finance companies generally capture a lower z-spread than other types of issuers. However, there is some marginal evidence that z-spreads for captive issuers could be somewhat wider with a higher EV share. Even so, the net effect is small: a one standard deviation increase in the EV share for captive issuers boosts z-spreads by less than a basis point. With all controls included in column (12), we again see that there is little statistically significant association between the share of EVs or hybrids in an ABS tranche and the expected spread over the life of the security.

With our pricing results in hand, we turn to evaluate quantity-related matters. The first exercise explores the share of the dollar value of each ABS denoted as "senior" for loss absorbing purposes in each ABS pool. As observed above, on average, EV loans experience lower default rates. Including EV loans in an ABS pool could imply lower risk of loss absorption, and consequently, issuers could offer relatively more senior tranches than subordinated to investors.

To investigate the possibility that the share of EV loans in an ABS is correlated with the senior tranche share, we estimate parameters for the following specification:

$$\text{Senior}_j = \alpha + \beta_1 \text{EV}_j + \beta_2 \text{Hybrid}_j + \beta_3 X_j + \epsilon_j. \tag{9}$$

Senior_j is the share of the dollar value of auto ABS j denoted as senior. EV_j is the share of the dollar value of loans associated with EVs; similarly, Hybrid_j is the share of the dollar value associated with hybrids. X_j is a vector of ABS issuer characteristics that potentially could be associated with the share in the senior tranche. We focus our attention on whether the securitization is associated with a captive issuer to control for potential systematic differences in securitization practices across issuer types. ϵ_j is an error term robust to heteroskedasticity or autocorrelation of unknown form. We measure all shares at issuance, using data on ABS issuance from Bloomberg.

Our results are presented in Table 13. The results reported in column (1) suggest that a one standard deviation increase in the EV share (1.6 percentage points) leads the share in the senior tranche to rise by 1.8 percentage points. The impact of the hybrid share is somewhat larger; a one standard deviation increase in the hybrid share leads to a 2.9 percentage point rise in the senior tranche. Column (2) illustrates that including controls for captive issuers attenuates these marginal effects to some degree. Reflecting this, in the third column, we interact captive with the share of EVs or hybrids in the securitization. Summing across the interaction terms, with a one standard deviation increase in the share of EVs in the pool, we see that captives tend to shift the ABS portfolio more towards the senior tranche than other issuers do, with a one standard deviation increase in the EV share leading to roughly an 80 basis point increase in the senior tranche. That captives are more responsive to the share of EVs suggests either greater information related to the performance of EV loans relative to other loans, or a greater willingness to promote these loans to risk-averse investors, or both. Overall, the R^2 statistics reported towards the bottom of column (3) indicate that our specification explains roughly half of the variation in the dependent variable. Moreover, the AIC and BIC statistics confirm that the inclusion of the interaction terms adds more to our understanding of the determinants of the senior tranche than it subtracts through bias from overfitting the model.

With our results for the overall share of ABS in the senior tranche in hand, we now turn to the ratings distribution within the senior tranche. We evaluate the following specification:

$$\text{Tranche}_{ij} = \alpha + \beta_1 \text{EV}_j + \beta_2 \text{Hybrid}_j + \beta_3 \text{Rating}_{ij} + \beta_2 X_j + \epsilon_{ij}. \tag{10}$$

Our parameters of interest are the vector β_1. These are the estimated coefficients on Rating_{ij}, the share of ratings tranche i in ABS pool j, where the ratings span those shown in Figure 7. X_j is the set of controls for the ABS as a whole investigated in the previous exercise, and ϵ_{ij} is an error term robust to heteroskedasticity or autocorrelation of unspecified form.

The next set of columns looks within the composition of the senior tranche and investigates whether there are differences in the shares in higher-quality tranches that depend on EVs. By contrast with our observations regarding the senior-subordinated split, we find little evidence of reallocation of tranches with respect to EVs. Column (4) reports parameter estimates of our baseline specification detailed in equation 10. As shown in the top two lines of the table, our estimated parameters β_1 and β_2 are not statistically different from zero, suggesting that the share of EVs or hybrids in a securitization have little impact on the share allocated to different ratings tranches. This result potentially has implications regarding the demand for the tranches by investors. In particular, pension funds, mutual funds, and other intermediaries have holding limits on securities according to ratings. If the allocation across tranches is invariant to EVs and hybrids, it could suggest that investors are not appropriately capturing benefits related to lower expected defaults of EV loans. We return to this issue a little later in the section.

Column (5) incorporates controls for the tranche rating. The estimated coefficients confirm our conclusions from Figure 7: the AAA tranche is on average the largest, while the AA tranche is larger.[28] Column (6) interacts the EV share and the hybrid share with the rating. These estimated coefficients are not statistically different from zero, suggesting little interaction between rating and engine type. Our results appear robust to issuer type: controls related to whether the issuer is a captive issuer have statistically insignificant coefficients. In addition, the BIC appears to worsen with the inclusion of those controls. More generally, the amount of variation explained by these shares is notably lower than for the senior/subordinated breakdown.

Taken together, our results suggest that the pass-through of better-performing EV loans to auto ABS pricing is incomplete. For every marginal dollar placed in an EV loan, prices on ABS should rise and spreads should narrow; we see little evidence of this phenomenon. This suggests some opportunity to use EV loans to support the desirability of lower-rated ABS tranches, as well as perhaps to boost those ratings, thereby tapping into demand from institutional investors that must restrict holdings to better-rated debt. More generally, the results suggest some pass-back to issuers of including EVs in ABS pools, providing another avenue for finance to support the EV transition.

8 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 30 percent less in percentage change terms relative to traditional ICEVs. This lower risk flows through to the borrower in loan terms, and part of the lower default rate is attributable to insulation from gasoline price shocks.

[28]Some tranches have missing ratings, resulting in the loss of roughly 5 percent of the sample from column (4).

These lower default rates are reflected in higher initial prices for auto ABS, although the pass-through is incomplete for lower-rated tranches.

In future work, we intend to extend our results to incorporate a full Bartik estimator for the gasoline sensitivity results, as well as to include a back-of-the-envelope estimate of potential gains from more EVs in auto ABS. We hope that our work informs the conversation on the role of finance in the transition to sustainable energy.

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.

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 (2012a). "Contract pricing in consumer credit markets". In: *Econometrica* 80(4), pp. 1387–1432.

Einav, Liran, Mark Jenkins, and Jonathan Levin (2012b). "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.

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.

Imbens, Guido W. (2004). "Nonparametric Estimation of Average Treatment Effects Under Exogeneity: A Review". In: *The Review of Economics and Statistics* 86(1), pp. 4–29. URL: https://ideas.repec.org/a/tpr/restat/v86y2004i1p4-29.html.

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.

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.

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.

Rosenbaum, Paul R. and Donald B. Rubin (1983). "The Central Role of the Propensity Score in Observational Studies for Causal Effects". In: *Biometrika* 70(1), pp. 41–55. ISSN: 00063444. URL: http://www.jstor.org/stable/2335942 (visited on 11/18/2023).

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.

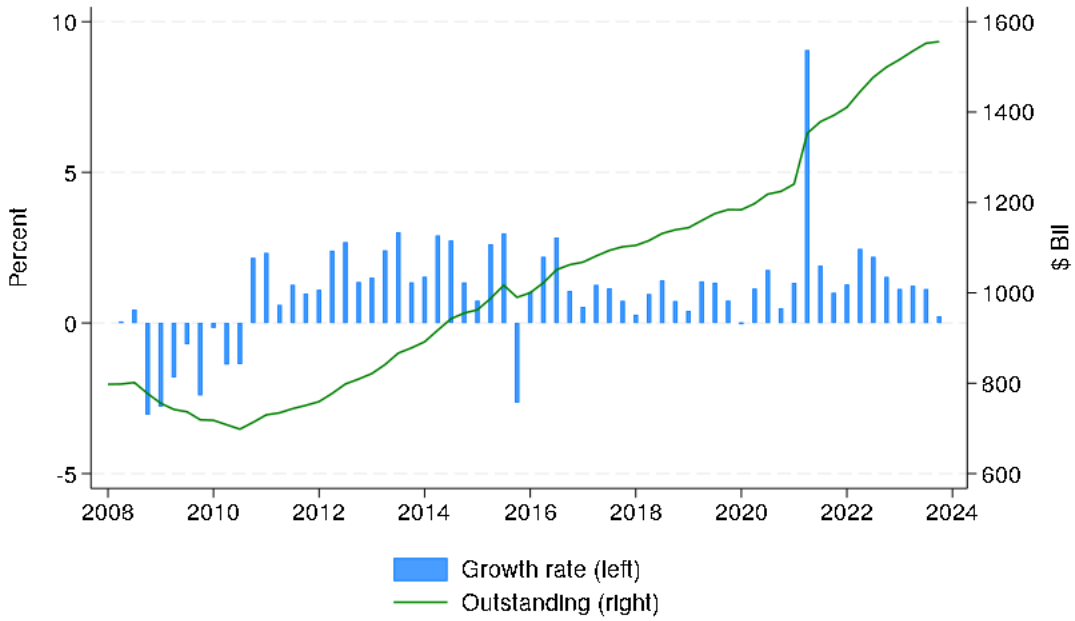
Stiglitz, Joseph E. and Andrew Weiss (1981). "Credit Rationing in Markets with Imperfect Information". In: *The American Economic Review* 71(3), pp. 393–410. ISSN: 00028282. URL: http://www.jstor.org/stable/1802787 (visited on 12/09/2023).

Stiglitz, Joseph E. and Andrew Weiss (1983). "Incentive Effects of Terminations: Applications to the Credit and Labor Markets". In: *The American Economic Review* 73(5), pp. 912–927. ISSN: 00028282. URL: http://www.jstor.org/stable/1814662 (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.

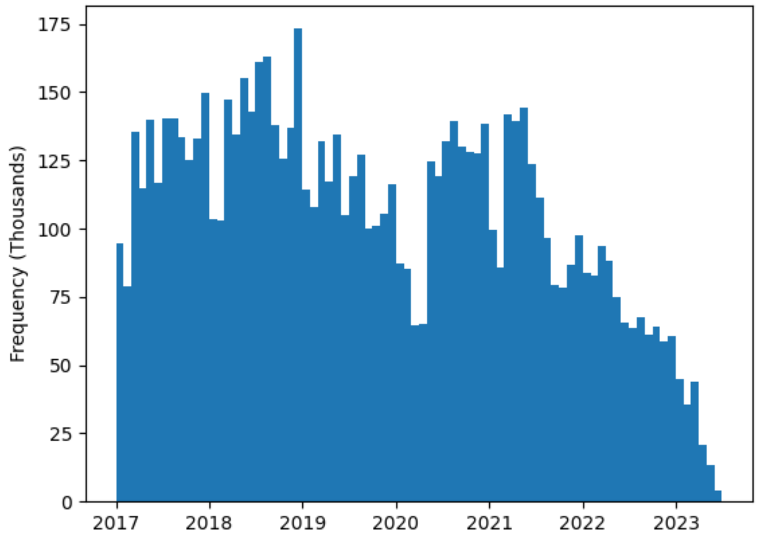
Figures and tables

Figure 1: Auto Loans: Outstanding and Growth Rate, 2008-2023



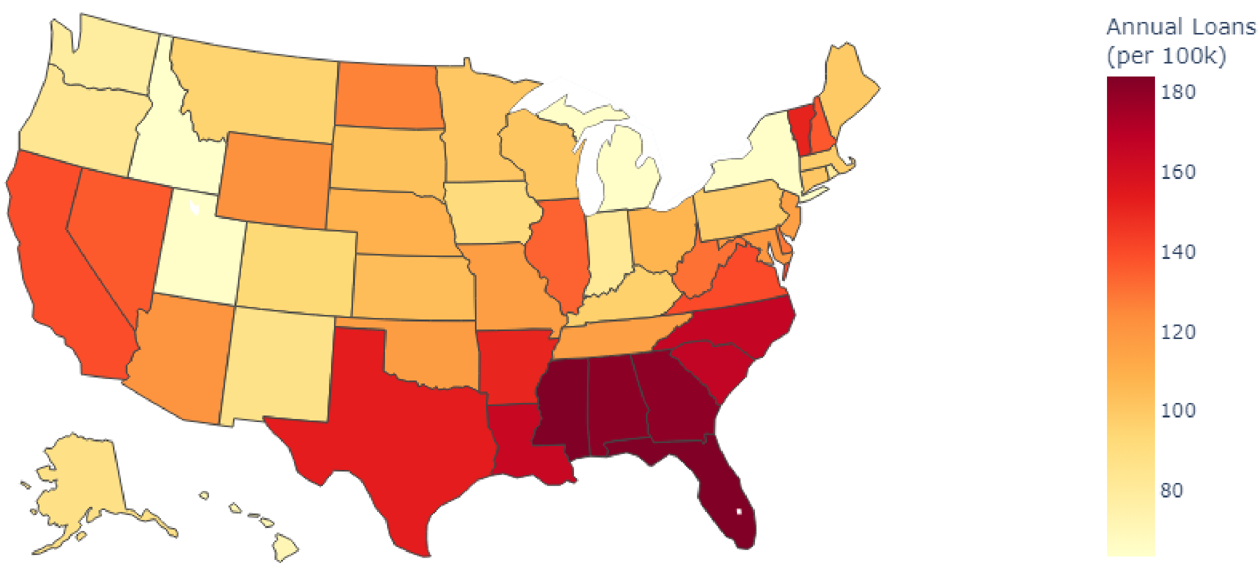
Source: Board of Governors of the Federal Reserve System (US), Motor Vehicle Loans Owned and Securitized [MVLOAS], retrieved from FRED, Federal Reserve Bank of St. Louis; https://fred.stlouisfed.org/series/MVLOAS, March 19, 2024.

Figure 2: Origination Dates of Auto Loans in Data



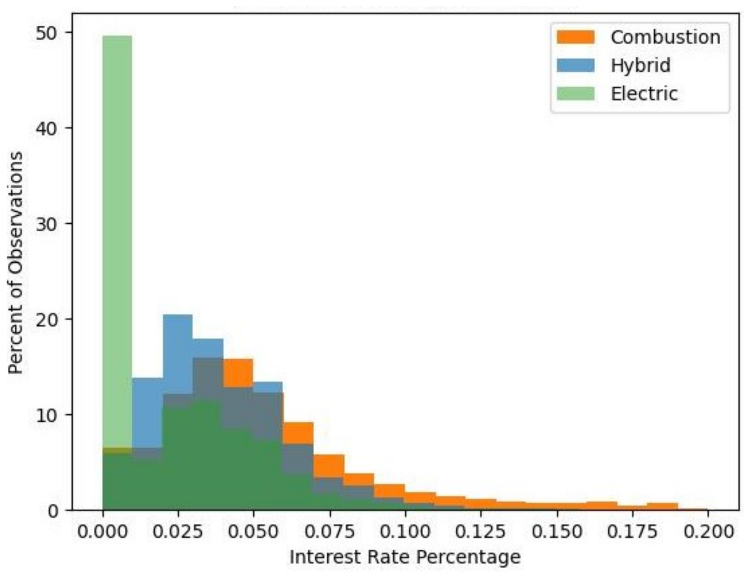
Source: SEC form ABS-EE. This figure shows a histogram of origination dates for 6-year new car auto loans captured in our data sample from January 2017 to July 2023.

Figure 3: Geographic Distribution of Auto Loans in Data



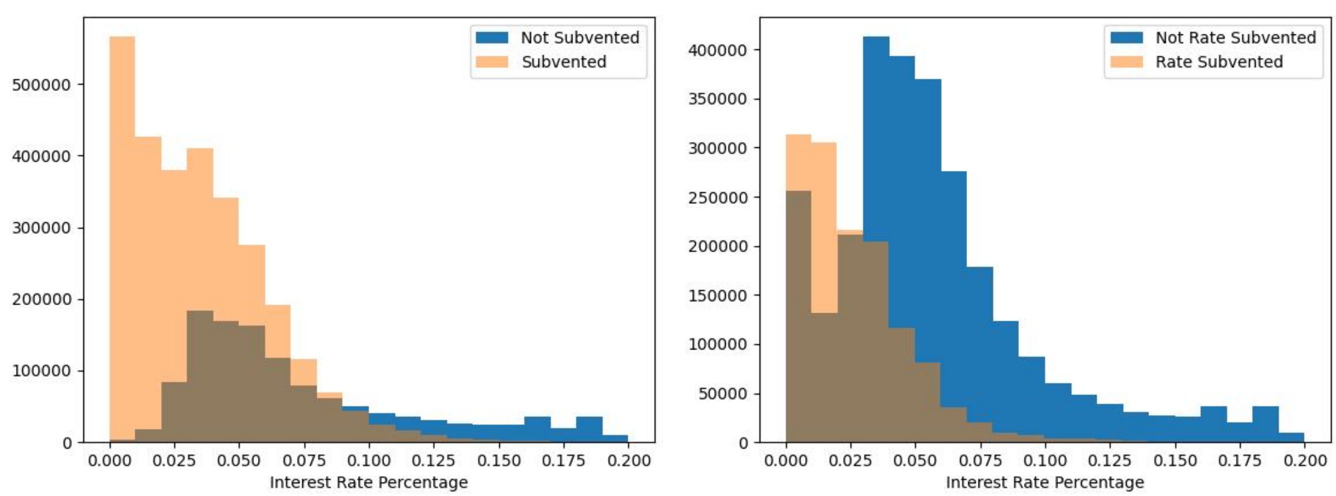
Source: SEC form ABS-EE. This figure shows the geographic distribution of 6-year new car auto loans originated in between January 2017 to July 2023.

Figure 4: 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 5: Subvention and Interest Rate



(a) All Subvented Auto Loans

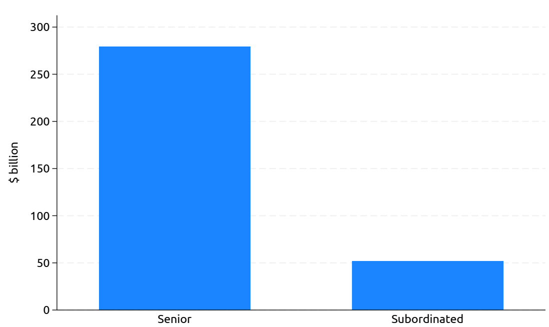
(b) Auto Loans with Rate Subvention

Source: SEC form ABS-EE. These figure shows the frequency histograms of original interest rates of auto loans in our data, broken down by whether the loan is subvented or not. An auto loan can be subvented in various ways, including through rate subvention and cash back.

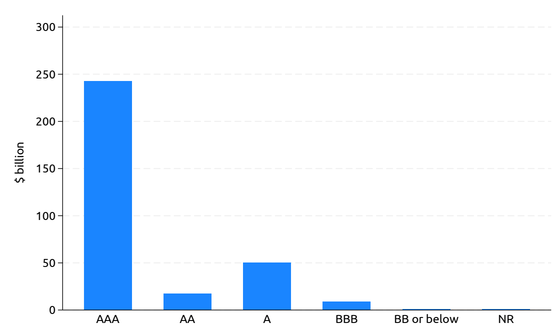
Figure 6: West Texas Intermediate Price, Dollars Per Barrel, Monthly

Source: Federal Reserve Bank of St. Louis, Spot Crude Oil Price: West Texas Intermediate (WTI) [WTISPLC], retrieved from FRED, Federal Reserve Bank of St. Louis; https://fred.stlouisfed.org/series/WTISPLC, March 19, 2024.

Figure 7: Auto ABS Tranches and Ratings

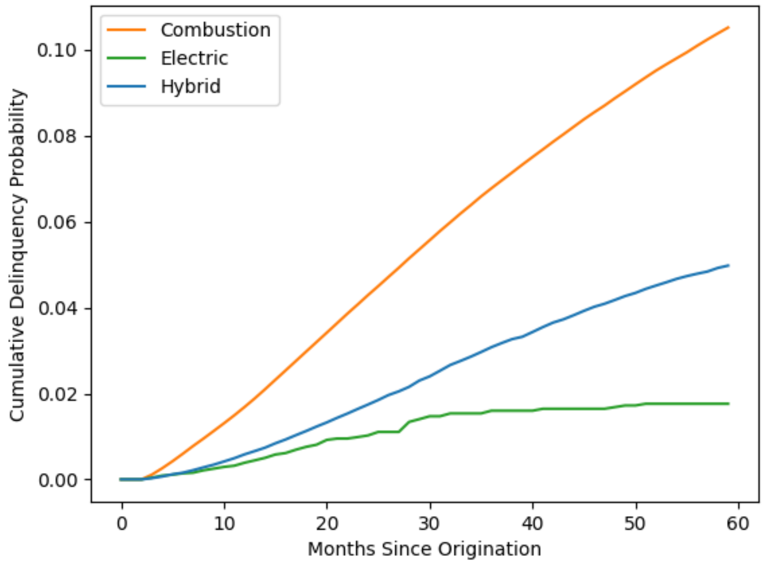


(a) Senior and Subordinated Tranches

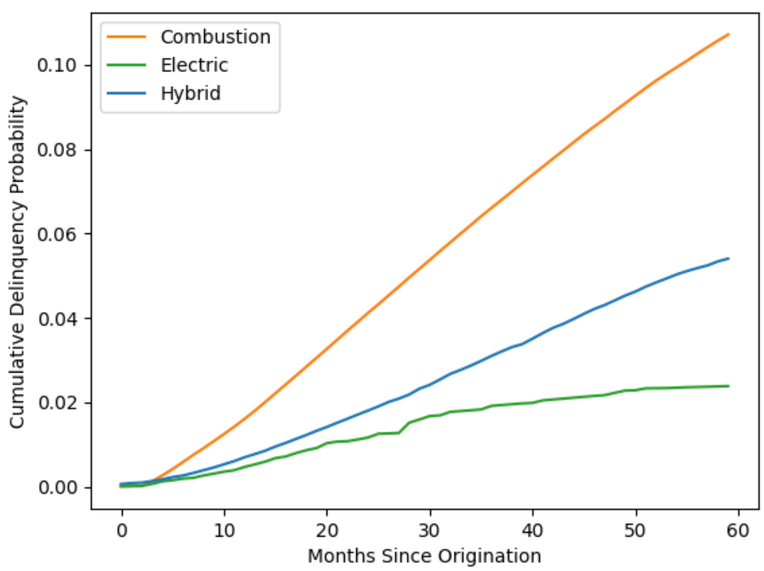


(b) Ratings Distribution

Figure 8: Cumulative 60-day Delinquency Rates by Engine Type



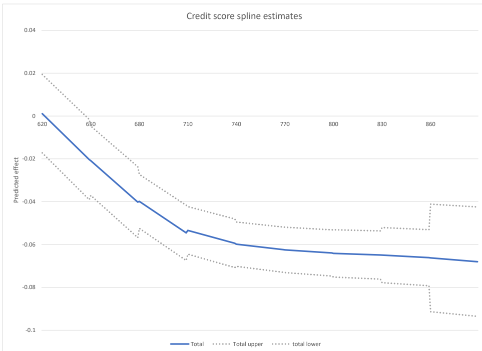
(a) Without Time Fixed Effects



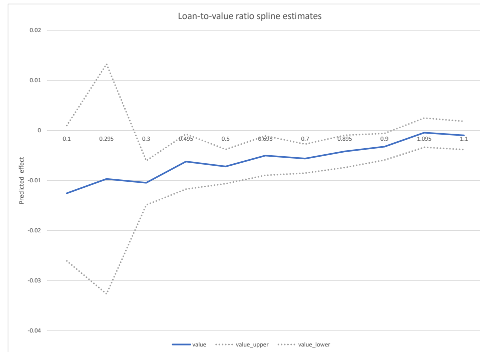
(b) With Time Fixed Effects

Source: SEC form ABS-EE. These figures show 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 9: Credit Score and LTV Spline Estimates



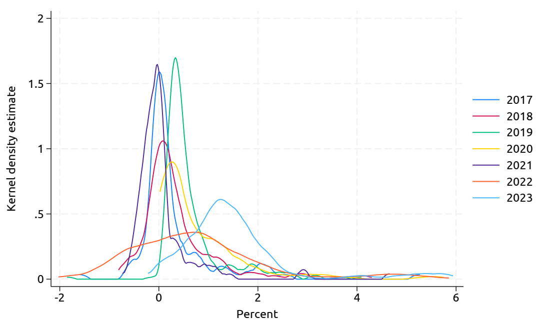
(a) Credit score spline



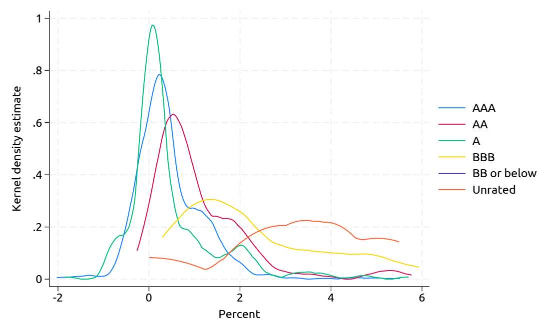
(b) Loan-to-value ratio

Note: These are estimates used in columns (6) and (7) of Table 10. Source: SEC form ABS-EE.

Figure 10: Auto ABS Coupon Spreads by Year and Rating

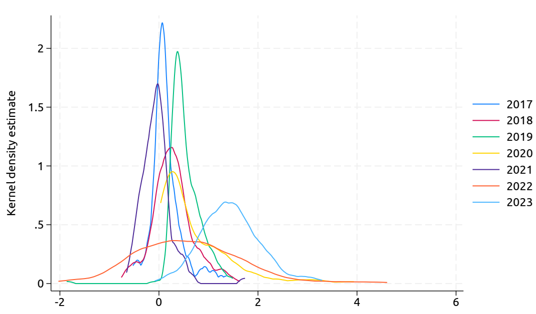


(a) By Year

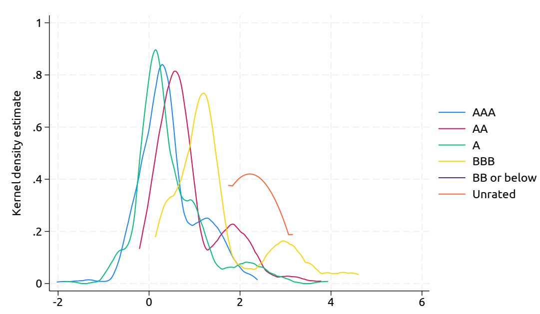


(b) By Rating

Figure 11: Auto ABS Z-spreads by Year and Rating



(a) By Rear



(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	90.07	7.94	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								
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
Original 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
Original loan term (months)	74	2	74	2	74***	1	73***	2
Original interest rate (%)	4.8	3.8	4.9	3.8	3.7***	2.3	2.3***	2.7
Rate Subvention (%)	32.3	46.7	31.8	46.6	41.8***	49.3	40.5***	49.1
Cash Back (%)	37.7	48.5	37.8	48.5	31.4***	46.4	49.6***	50.0
Delinquency (%)	2.805	16.513	2.883	16.732	1.300***	11.326	0.272***	5.206
N	4,096,083		3,910,601		163,038		22,444	
Panel B: Panel Data								
Monthly delinquency (%)	0.197	4.429	0.201	4.477	0.092***	3.036	0.035***	1.872
N	84,675,532		81,420,320		3,058,310		196,902	

Note: This table summarizes the main variables used in our empirical analyses. Panel A captures the cross-section of loans and Panel B represents the complete panel over the period. The asterisks on the hybrid and EV columns represent results from t-tests on differences in means compared to the combustion engine. "Scheduled payment" refers to monthly loan payment for the first observation of a loan. "Delinquency" in Panel A measures the percentage of loans that ever experience a 60-day delinquency during the data period. "Monthly delinquency" in Panel B measures the average percentage of loans that newly enter the 60-day delinquency in each year-month of the panel data. Source: SEC form ABS-EE.

Table 3: Summary Statistics of Macroeconomic Variables

	N	Mean	Std	Min	Max
Unemployment	85,262,306	4.79	2.48	1.70	30.60
HPI	85,262,306	540	175	220	1,153
Income Per Capita ($)	85,262,306	60,900	9,359	36,340	100,971
Crude Oil Price ($)	85,262,306	68.68	20.60	16.55	115
National Gas Price ($)	85,262,306	2.98	0.68	1.66	4.71
Retail Gas Price ($)	85,262,306	3.03	0.76	1.43	5.37
Retail Gas Tax ($)	85,262,306	0.53	0.14	0.18	0.87

Note: This table summarizes macroeconomic controls used in conjunction with our auto loan dataset. These variables cover the same period from January 2017 to July 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. "Income" is annual median household income by state. "Crude Oil Price" is monthly price data of West Texas Intermediate. "National Gas Price," "Retail Gas Price," and "Gas Tax" each refer to conventional retail gasoline price at national and regional levels and regional tax data. Source: Bureau of Labor Statistics, Federal Housing Finance Agency, U.S. Census Bureau, FRED, and U.S. Energy Information Administration.

Table 4: Auto ABS Characteristics

Issuer	Issuer type	Number of securitizations	Total face amount ($ billions)	EV loans ($ millions)	Hybrid loans ($ millions)
Ally	Bank	15	14.8	25.94	57.42
AmeriCredit	Captive	19	21.0	4.06	2.45
BMW	Captive	5	5.1	40.46	698.24
California Republic	Bank	2	0.8	0.19	0.84
Capital One	Bank	7	10.2	19.99	81.01
CarMax	Nonbank	18	25.0	0.00	5.81
Exeter	Nonbank	13	10.1	0.23	0.34
Fifth Third	Bank	3	3.7	12.79	19.65
Ford Credit	Captive	16	21.7	215.14	23.09
GM Financial	Captive	22	28.4	62.27	62.15
Honda	Captive	22	30.7	0.00	733.71
Hyundai	Captive	18	21.4	214.77	1,476.18
Mercedez-Benz	Captive	6	8.1	0.09	90.88
Nissan	Captive	13	14.9	420.77	0.08
Santander	Bank	43	54.6	13.19	47.94
Toyota	Captive	25	35.8	0.00	5,665.22
USAA	Nonbank	2	1.0	1.50	2.45
Volkswagen	Captive	5	6.7	60.23	588.93
World Omni	Captive	25	24.0	1.14	1,842.25

Source: SEC form ABS-EE.

Table 5: 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)
Constant	0.00201***	0.00600***	0.00199***	0.00598***	0.0149***	0.0421***
	(282.6)	(387.4)	(283.3)	(388.8)	(83.69)	(108.6)
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. Source: SEC form ABS-EE.

Table 6: Robustness on Delinquency Results

	(1)	(2)	(3)	(4)
Dependent variable: Delinquency rate (days):	60	30	60	30
Subset:	Leaf-Versa	Leaf-Versa	Trax-Bolt	Trax-Bolt
EV	-0.00500***	-0.0104***	-0.00133***	-0.00322***
	(-9.204)	(-10.05)	(-4.706)	(-4.776)
Credit score	-0.0000346***	-0.0000784***	-0.0000214***	-0.0000850***
	(-14.50)	(-16.61)	(-19.35)	(-30.19)
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***
	(1.413)	(2.333)	(2.661)	(5.208)
ln (income)	0.00505***	0.00932***	0.00219***	0.00515***
	(10.56)	(10.06)	(6.252)	(5.997)
Constant	-0.0202***	-0.0252***	-0.00530*	0.0126
	(-4.905)	(-3.112)	(-1.661)	(1.597)
Observations	432,337	427,451	887,139	873,746
R-squared	0.015	0.020	0.008	0.014
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

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

Table 7: Monthly Payment Results

Dependent variable: Payment Ratio	(1)	(2)	(3)
EV	0.0370***	0.0699***	0.0284**
	(2.963)	(5.569)	(2.235)
Hybrid	-0.0719***	-0.0380***	-0.0313***
	(-27.92)	(-14.50)	(-11.80)
Credit Score			-0.000404***
			(-44.92)
Payment-to-income ratio (percent)			0.894***
			(40.73)
LTV ratio			-0.321***
			(-106.7)
ln(income)			0.118***
			(72.33)
Constant	1.585***	1.584***	1.089***
	(2,771)	(2,773)	(67.56)
Observations	78,554,933	78,554,929	77,733,060
R-Squared	0.001	0.002	0.002
Aging FE	YES		
Aging*Calendar FE		YES	YES
Term Duration Month FE		YES	YES
State FE		YES	YES

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

Table 8: Cumulative Payment Results

	(1)	(2)	(3)	(4)	(5)	(6)
Depedent variable:	Paid Down	Prepay	Payment Ratio	Payment Ratio	Payment Ratio NPV	Payment Ratio NPV
Subset:			Not Paid Down	No Prepay	Not Paid Down	No Prepay
EV	-0.0292***	-0.0386***	0.0784***	0.0886***	0.0785***	0.0894***
	(-9.333)	(-18.91)	(53.87)	(7.284)	(53.65)	(7.268)
Hybrid	0.0457***	0.0114***	0.0114***	-0.000794	0.0115***	-0.000419
	(37.72)	(11.54)	(21.83)	(-0.2799)	(21.75)	(-0.1467)
Credit Score	-0.0000948***	-0.000383***	0.000755***	0.00121***	0.000763***	0.00120***
	(-25.23)	(-116.3)	(314.9)	(86.80)	(316.0)	(87.77)
Payment-to-income ratio (percent)	0.348***	0.577***	-0.652***	-0.935***	-0.659***	-0.953***
	(38.58)	(72.37)	(-110.4)	(-26.98)	(-110.9)	(-27.66)
LTV ratio	-0.141***	-0.0753***	0.0150***	-0.253***	0.0144***	-0.253***
	(-118.6)	(-70.46)	(19.60)	(-48.78)	(18.73)	(-49.23)
ln(income)	0.0415***	0.0607***	-0.0408***	-0.0563***	-0.0410***	-0.0564***
	(63.21)	(104.5)	(-103.7)	(-21.23)	(-103.6)	(-21.33)
Constant	0.237***	0.0294***	0.762***	1.09***	0.759***	1.10***
	(35.16)	(4.949)	(194.2)	(41.63)	(192.1)	(42.40)
Observations	4,050,983	4,050,983	2,278,494	2,930,075	2,278,488	2,929,999
R-Squared	0.078	0.086	0.244	0.014	0.244	0.015
OrigMonth 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

Table 9: Treatment Results of Differential Exposure to Gasoline Pricing

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent variable: Delinquency rate (days):	60	30	60	30	60	30	60	30
Subset:					Trax-Bolt	Trax-Bolt	Trax-Bolt	Trax-Bolt
Regional gas price	-0.00140***	-0.00195***	-0.00238***	-0.00177***	-0.00520***	-0.00742***	-0.00535***	-0.00597**
	(-9.873)	(-8.291)	(-15.02)	(-7.000)	(-3.538)	(-3.014)	(-3.196)	(-2.277)
Combustion*Regional gas price	0.00131***	0.00191***	0.00135***	0.00194***	0.00151*	0.00479***	0.00177**	0.00519***
	(18.36)	(13.84)	(18.82)	(13.96)	(1.946)	(4.772)	(2.292)	(5.135)
ln (Median household income)			0.00108	0.00173			-0.00662	0.00279
			(1.156)	(1.599)			(-0.744)	(0.229)
ln (HPI)			-0.0203***	-0.0119***			0.0282*	0.00343
			(-19.68)	(-12.83)			(1.931)	(0.258)
Unemployment rate			0.0000908***	0.000214***			0.00000620	-0.000300
			(3.822)	(6.887)			(0.0282)	(-0.988)
Constant	0.00797***	0.0171***	0.125***	0.0703***	0.0222***	0.0353***	-0.0778	-0.0213
	(20.30)	(28.11)	(11.13)	(5.931)	(5.011)	(4.639)	(-0.642)	(-0.153)
Observations	84,503,050	84,503,050	73,989,469	73,989,469	899,939	899,939	805,464	805,464
R-squared	0.454	0.403	0.457	0.405	0.466	0.395	0.468	0.396
Loan FE	YES	YES	YES	YES	YES	YES	YES	YES
Aging*Calendar FE	YES	YES	YES	YES	YES	YES	YES	YES
Term Duration Month FE	YES	YES	YES	YES	YES	YES	YES	YES
State FE	YES	YES	YES	YES	YES	YES	YES	YES

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

Table 10: 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		-0.0221***	-0.0228***	0.192***	0.0322***
		(-119.0)	(-130.7)	(60.78)	(10.89)
Hybrid		-0.00245***	-0.00186***	-0.00501***	0.0212***
		(-44.00)	(-36.85)	(-4.176)	(18.90)
Credit Score	-0.000230***	-0.000229***	[spline]	0.000119***	0.000605***
	(-980.7)	(-976.2)		(32.54)	(177.5)
Payment-to-income ratio (percent)	0.0909***	0.0915***	0.0635***	-0.197***	-0.363***
	(161.9)	(163.3)	(118.0)	(-22.27)	(-44.13)
LTV ratio	-0.00250***	-0.00291***	[spline]	-0.0942***	0.373***
	(-9.339)	(-10.90)		(-19.50)	(82.69)
ln (LTV)	-0.0137***	-0.0135***	-0.0207***	-0.106***	-0.0254***
	(-59.85)	(-58.73)	(-45.11)	(-24.56)	(-6.326)
ln (income)	0.000716***	0.000893***	-0.000960***	-0.00937***	-0.0143***
	(18.83)	(23.50)	(-26.31)	(-14.62)	(-23.98)
Constant	0.302***	0.298***	0.247***	1.17***	-0.316***
	(229.2)	(226.6)	(74.52)	(45.20)	(-13.07)
Observations	4,051,804	4,051,804	4,051,804	4,051,806	4,051,806
R-Squared	0.420	0.422	0.479	0.099	0.145
OrigMonth FE	YES	YES	YES	YES	YES
Term FE	YES	YES	YES	YES	YES
State FE	YES	YES	YES	YES	YES

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

Table 11: 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		0.00355***	0.00338***	-0.0323***	-0.0303***
		(5.466)	(5.511)	(-4.135)	(-6.103)
Hybrid		-0.00248***	-0.00294***	-0.106***	-0.0141***
		(-6.192)	(-7.417)	(-25.08)	(-5.276)
Credit Score	-0.000271***	-0.000271***	[spline]	-0.000472***	-0.0000347***
	(-389.4)	(-389.4)		(-73.01)	(-8.450)
Payment-to-income ratio (percent)	0.134***	0.134***	0.124***	-0.0534***	0.102***
	(80.49)	(80.31)	(75.16)	(-3.709)	(11.13)
LTV ratio	0.0442***	0.0443***	[spline]	0.0396***	0.511***
	(41.63)	(41.63)		(4.477)	(90.96)
ln (LTV)	-0.0107***	-0.0106***	-0.118***	-0.0817***	-0.341***
	(-12.90)	(-12.86)	(-36.62)	(-10.92)	(-71.82)
ln (income)	-0.00527***	-0.00528***	-0.00528***	0.00498***	0.0231***
	(-45.89)	(-46.02)	(-46.97)	(4.562)	(33.33)
Constant	0.346***	0.346***	1.01***	0.997***	1.77***
	(74.02)	(74.02)	(43.61)	(22.55)	(62.99)
Observations	689,843	689,843	689,843	689,845	689,845
R-Squared	0.527	0.527	0.546	0.418	0.098
OrigMonth FE	YES	YES	YES	YES	YES
Term FE	YES	YES	YES	YES	YES
State FE	YES	YES	YES	YES	YES

Robust t-statistics in parentheses

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

Table 12: EVs and ABS: Spreads

	Dependent variable: Coupon spread						Dependent variable: Z-spread					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
EV share	0.00736	0.0213	-13.9 **	0.0187	-0.211	-13.5 **	-0.0112	-0.00829	-0.277	-0.00257	-.289 **	-0.275
	-0.251	-0.707	(-78)	-0.644	(-1.17)	(-49.8)	(-.86)	(-.66)	(-1.4)	(-.197)	(-3.15)	(-1.54)
Hybrid share	-.00755 **	-.00681 **	-0.00385	-.00773 **	-.00695 *	-0.00516	-.00513 **	-.00476 **	-0.00228	-.00522 **	-0.004	-0.00338
	(-3.04)	(-3.19)	(-.57)	(-3.15)	(-2.23)	(-.792)	(-3.17)	(-3.27)	(-.345)	(-3.29)	(-1.83)	(-.529)
					(-.733)	-0.232					(-1.6)	(-.738)
Rating												
AAA		-2.6	-5.06 **			-4.94 **		-0.979 **	-0.991 **			-0.895 **
		(-1.51)	(-88.7)			(-73.4)		(-9.49)	(-9.11)			(-8.36)
AA		-1.95	-4.49 **			-4.38 **		-.576 **	-.589 **			-.509 **
		(-1.13)	(-49.8)			(-44.5)		(-5.22)	(-4.97)			(-4.36)
A		-2.6	-5 **			-4.88 **		-1.02 **	-1.01 **			-.926 **
		(-1.5)	(-54.5)			(-50.3)		(-9.1)	(-8.56)			(-8)
BBB		-0.847	-3.29 **			-3.26 **						
		(-.489)	(-19.3)			(-19.4)						
EV*Rating												
AAA			13.9 **			13.4 **			0.29			0.098
			(79.20)			(58.40)			(1.46)			(0.51)
AA			14.3 **			13.8 **			0.318			0.145
			(54.30)			(46.90)			(1.53)			(0.72)
A			13.8 **			13.3 **			0.198			0.00968
			(75.70)			(55.60)			(0.99)			(0.05)
BBB			13.7 **			13.3 **						
			(20.40)			(19.10)						
Hybrid*Rating												
AAA			-0.00243			-0.00155			-0.00328			-0.00115
			(-.344)			(-.223)			(-.486)			(-.172)
AA			-0.00137			-0.00153			-0.00444			-0.00456
			(-.162)			(-.184)			(-.627)			(-.666)
A			-0.00472			-0.00462			-0.000637			0.0000335
			(-.584)			(-.599)			(-.086)			-0.00464
Captive				-.323 **	-.342 **	-.194 **				-.234 **	-.25 **	-.186 **
				(-5.6)	(-5.05)	(-3.38)				(-6.55)	(-5.71)	(-4.8)
EV*Captive					0.231	0.0862					0.29 **	0.197 *
					(1.27)	(0.49)					(3.17)	(2.58)
Hybrid*Captive					-0.00339	0.001					-0.00505	-0.00227
Number of observations	1343	1301	1301	1343	1343	1301	1240	1205	1205	1240	1240	1205
R-squared	0.199	0.379	0.399	0.221	0.223	0.405	0.359	0.483	0.49	0.384	0.391	0.504
AIC	3586	3166	3136	3550	3551	3126	2116	1816	1813	2069	2060	1785
BIC	3638	3238	3239	3607	3618	3240	2168	1883	1910	2125	2126	1898

This table reports parameter estimates from evaluating equation 8. The outcome variable in columns (1) through (6) 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 (7) through (12) is the z-spread, calculated as the interest rate (in percent) needed to equate expected future cash flows with the price of the ABS tranche at origination. 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 13: EVs and ABS Structure

	Senior tranche: Overall			Within senior tranche: Ratings			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
EV share	0.01047 **	0.005578 *	0.1529	-0.0008	-0.00063	-0.00069	0.02564
	(3.80)	(2.05)	(1.31)	(-.338)	(-.271)	(-.614)	(1.18)
Hybrid share	0.003303 **	0.002673 **	0.005704 **	0.000256	0.000167	0.000361	0.000509
	(3.78)	(4.19)	(2.76)	(0.71)	(0.46)	(1.32)	(1.10)
Captive		0.1535 **	0.2064 **				0.02236 *
		(6.78)	(6.57)				(2.27)
EV*Captive			-0.149				-0.02718
			(-1.28)				(-1.26)
Hybrid*Captive			-0.004927 *				-0.00017
			(-2.24)				(-.239)
Rating							
AAA					0.04617 **	0.04765 **	0.04723 **
					(7.26)	(6.48)	(6.46)
AA					-0.1789 **	-0.18 **	-0.1856 **
					(-38.2)	(-33.4)	(-29.2)
EV*Rating							
AAA						7.57E-05	0.000179
						(0.02)	(0.05)
AA						0.000658	0.001335
						(0.30)	(0.43)
Hybrid*Rating							
AAA						-0.00025	-0.00028
						(-.467)	(-.542)
Intercept	0.8283 **	0.7308 **	0.6904 **	0.2354 **	0.2013 **	0.2001 **	0.1837 **
	(63.30)	(32.50)	(23.40)	(54.50)	(39.30)	(40.10)	(19.10)
Number of observations	249	249	249	896	856	856	856
R-squared	0.051	0.252	0.293	0.001	0.037	0.037	0.043
AIC	-214.217	-271.332	-281.686	-1385.73	-1345.89	-1343.97	-1343.31
BIC	-203.665	-257.262	-260.582	-1371.34	-1322.13	-1315.46	-1300.54

The left panel of the table provides parameter estimates from evaluating equation 9. The dependent variable is the senior tranche share of the ABS pool. The right part of the table provides parameter estimates from evaluating equation 10. The sample is limited to senior tranches only. The dependent variable is the share of the ABS with various investment-grade ratings. Robust t-statistics are in parentheses. ** $p < .01$,* $p < .05$. Sources: Bloomberg Back Office Auto ABS, ABS-EE, and authors' calculations.

Appendix

A List of Electric and Hybrid Vehicles in Our 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
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.

B Nissan Leaf and Chevrolet Bolt Observations

Figure 1: Leaf and Bolt Observations by Month