Financing the Global Shift to Electric Mobility *

Abstract

Using comprehensive auto loan data from Europe, we document a gap in financing terms between Electric Vehicles (EVs) and non-EVs. EVs, compared to non-electric models in the same car family or pair, are financed with higher interest rates, lower loan-to-value ratios, and shorter loan durations. We show that the primary driver of this EV financing gap is the technological risk associated with EVs. The rapid and uncertain evolution of EV technologies accelerates technology obsolescence, diminishing the resale value of EVs. In response, lenders charge higher interest rates on EV loans. Consumer demographics, lenders' market power, and macroeconomic factors contribute minimally to the EV financing gap. Overall our findings highlight that technological carbon-transition risk is priced in financing terms of green durable assets consumption.

Keywords: Green financing, Car loans, Electric vehicle, Electric vehicle battery, Battery technology, Technological risk, Technological obsolescence

JEL Codes: G21, G23, G50, O33

*The usual disclaimer on errors applies.

1 Introduction

Electric vehicles are anticipated to be a key component of future global mobility systems, helping to reduce the impacts of transportation on climate change and air quality. The European Union adopted a law in 2023 that requires carmakers to achieve a 100 percent reduction in CO2 emissions from new cars sold by 2035. This regulation would effectively prohibit the sale of new fossil fuel-powered vehicles in the 27-country bloc. The law also establishes a 55 percent reduction in CO2 emissions for new cars sold from 2030 compared to 2021 levels. Concurrently, the U.S. White House announced public and private commitments to have 50 percent of all new vehicle sales be electric by 2030 as part of a historic transition to electric vehicles (EVs) under the EV Acceleration Challenge.[1]

In discussions surrounding the global transition to electric mobility, there is a lack of emphasis on the significance of consumer financing in the adoption of electric vehicles. This void occurs despite the crucial role that financing terms play in households' decisions to purchase durable assets. When considering car purchases, prior research shows that consumers are highly sensitive to both the prices of vehicles and the financing terms offered by auto loans.[2] Importantly, consumers mention a lack of affordability as the primary concern when considering the adoption of EVs.[3] To this end, the consumer financing channel may play a key role in the speed of the transition to electric mobility.

In this paper, we provide a comprehensive analysis of the rapidly growing EV loan market and document a significant, systematic gap in the financing terms—interest rate, loan-to-value ratio, maturity—between EVs and conventional cars. EVs, compared to non-electric models in the same car family or pair, are financed with a higher interest rates, lower loan-to-value ratios, and shorter loan durations. We then investigate the factors that drive the

[1] See "Fit for 55: Council adopts regulation on CO2 emissions for new cars and vans" and "FACT SHEET: Biden-Harris Administration Announces New Private and Public Sector Investments for Affordable Electric Vehicles".

[2] There has been extensive work on demand elasticity to loan terms in the auto loan markets (see Charles et al., 2008; Adams et al., 2009; Einav et al., 2012; Argyle et al., 2020, 2021, for example).

[3] See, for example, "New data reveals that many Europeans struggle to afford electric cars" and "Deloitte: Affordability Concerns Slow the Road to an Electrified Future".

gap in the EV financing terms. Can this gap be explained by specific technological risks associated with EVs, the strengthening demand for green products among consumers, or the market power of car manufacturers and lenders? Answering these questions will help us better understand magnitudes and sources of economic costs of green financing.

We utilize comprehensive data covering 15 million car loans in Europe, sourced from public disclosures made by issuers of auto loan asset-backed securities. This dataset provides information on loan terms, borrower and lender characteristics, and vehicle models associated with each loan. Most EVs in our sample are plug-in hybrid (PHEV) and non-plug-in hybrid (HEV) vehicles, which have an internal combustion engine (ICE) vehicle as a direct counterpart. Our analysis thus focuses on comparing the financing terms between EV and non-EV loans within the same car family or pair. This unique setting ensures that the underlying vehicle models are similar in all characteristics except for the type of engine. To illustrate the comparisons we perform, for example, in family "x3" offered by Bayerische Motoren Werke AG (BMW) we compare the non-EV version model "x3 xDrive30d" to its PHEV counterpart "x3 xDrive30e". Similarly, for Toyota Motor Corporation (TOYOTA), we compare the non-EV version model "Camry Business Edition 2,5-l-VVT-i" to its HEV counterpart "Camry Business Edition Hybrid: 2,5-l-VVT-i". We create these car pairs manually from millions of car loans, which is a novel and distinct contribution of our analysis.

We document a systematic gap in the financing terms between EV and non-EV models. EV loans exhibit a 0.29-percentage-point higher interest rate, a 4.7-percentage-point lower loan-to-value ratio, and a 2.5-month shorter loan maturity. These differences represent 6.5%, 6.7%, and 5.4% of the respective sample averages. We demonstrate the robustness of the 'EV financing gap' by employing a wide range of alternative methodologies. This includes estimating different regression specifications, using different sets of control variables at both borrower and loan levels, and examining different subsamples and sample periods. Even when conducting the most stringent fixed-effect comparison—incorporating fully interacted fixed effects for car model family, finely defined geographic regions, lender, and year—the observed gap in financing terms remains quantitatively similar to our baseline results.

The rest of our analysis examines explanations for the EV financing gap. We demonstrate that the relatively higher cost of financing for EVs is primarily driven by the risks associated with the technologies integrated in these vehicles. Several reasons can explain why technological risks result in higher financing costs for EVs. First, rapid advancements in battery technology may reduce the lifespan and value of current HEVs/PHEVs. Lenders might be concerned that the battery technology powering current HEVs/PHEVs could soon become outdated. Indeed, existing batteries have insufficient capacity and charge slowly, leading to unprecedented amounts of public and private funding being allocated to advancing battery technology research and development. As a result, lenders may increase financing costs to account for this additional collateral risk. Second, lenders may perceive current HEVs/PHEVs as risky due to the limited availability of reliable long-term performance and maintenance data. Third, lenders may worry about reduced resale prices for EVs, as the circular economy necessary for the success of EVs is still in its early stages, resulting in a lack of a well-functioning secondary market. Due to these factors, lenders face heightened risk when financing EVs and likely assign lower residual values to EVs compared to non-EVs.

To test this hypothesis, we construct measures of the intensity and dispersion of innovations in EV-related technologies. The intensity measure captures the speed of technological change, while the dispersion captures the uncertainty surrounding the direction of advancements in EV-related technologies. Both intensity and dispersion affect the pace at which existing EV technologies become obsolete. To construct the intensity measure, we use the list of clean auto industry patent groups from Aghion et al. (2016) to calculate the number of patents granted in these technology groups every month and normalize it by the total number of patents in the parent category, i.e., subclasses.

We focus on battery technology to measure dispersion of innovations. While the first modern lithium-ion battery was commercialized in the early 1990s, recent innovations have increasingly opened new avenues for more efficient and renewable energy storage solutions such as the flow battery, solid-state battery, and metal battery, which were first patented in 2012, 2015, and 2018, respectively. To construct the measure, we identify the universe of USPTO patents that mention the term "battery" in their titles and aggregate the titles to extract all battery-related bigrams. The count of unique battery-related bigrams in each month serves as a proxy for the number of technological directions in battery technology being pursued at that month. We also construct the Herfindahl-Hirschman Index (HHI) using the quantity of unique bigrams and their corresponding frequencies extracted from patents in each month. A lower HHI corresponds to a greater number of distinct directions for technological advancement that are comparable in size. A greater number of unique bigrams or a lower HHI thus both proxy higher uncertainty/disagreement about the future direction of battery technologies.

Using these two sets of innovation measures, we show that the presence of technological risks specific to EV cars is the primary explanation for why EV-loans are pricier. We focus on interest rate while controlling for the LTV and maturity of the loan and refer to the gap in interest rate between EVs and non-EVs as the "EV spread". We show that the EV spread disappears when our measures of the intensity and dispersion of innovations in EV-related technologies have values in the lowest quartile. In both cases, the point estimates are both statistically and economically insignificant. More importantly, a higher level of our measures of the intensity and dispersion of innovations in EV-related technologies is associated with a larger EV spread. A one quartile increase in the intensity of clean patenting widens the EV spread by 0.148 p.p. Similarly, a one quartile increase in the dispersion of battery-related technological directions widens the EV spread by 0.136 p.p.

To establish a tighter connection between technological risks and the EV spread, we leverage the monthly residual value assessments provided by lenders for all vehicle leases, a practice mandated by public disclosure requirements. Consistent with the amplified technological risks inherent to EVs compared to non-EVs, we show that lenders attribute lower residual value estimates to EVs at the commencement of the lease. Importantly, these initial estimates are more susceptible to downward revisions for EVs compared to non-EVs throughout the lease duration, particularly during periods of heightened intensity and dispersion of innovations in EV-related technologies captures by our measures. Last, we explore the heterogeneity in lenders' exposure to residual value risks at the loan level. Consistent with lenders pricing in the higher residual value risks associated with EVs, we find that the EV spread widens substantially when the ex-ante default risk is higher or when lenders, instead of the borrowers, own the vehicles before maturity via a leasing agreement.

One may argue that other factors might contribute to the high financing costs of EVs. For instance, loans with EVs as the underlying asset may have a higher default risk. Buyers of EV cars may exhibit a lower demand sensitivity with respect to price and are thus willing to pay a higher price for their loans. Also, possible differences in lender market power in the EV vs. non-EV loan market segment may lead to the documented EV spread. Finally, EV and non-EV loans may have differential exposures to macro factors that drive interest rates. We present evidence that these alternatives explanations account for either little or only a small fraction of the EV spread.

First, we compare the future performance of EV and non-EV loans within the same car model family while controlling for loan and borrower characteristics and including an extensive set of fixed effects. Our estimation yields close to zero and insignificant difference in the default probability between EV and non-EV loans. Therefore, the EV spread cannot be driven by higher default risk of EV loans.

Second, EV purchasers might have different characteristics from traditional vehicle buyers. For example, if EV purchasers have a lower demand elasticity with respect to the interest rate or a higher willingness to pay for the loan, lenders would charge a higher price for EV loans in an imperfect competition setting. To test this hypothesis, we exploit variations in regional (Nomenclature of Territorial Units for Statistics three digit level or NUTS3-level) demographic composition, assuming that the demand for EVs are functions of these demographic factors. We detect a significant and positive EV spread across a wide range of NUTS3 regions that differ in demographic composition, suggesting that the EV spread is prevalent regardless of the buyer characteristics. While we find that the EV spread is positively associated with GDP per capita as well as median population age, and negatively associated with the share of the female population, the economic significance of these relationships is relatively minor. For example, dividing the localities into four quartiles by the share of the female population, we estimate a 0.435-p.p. EV spread in the first quartile and a 0.329-p.p. spread in the last quartile. Hence, the difference in the demographic composition of EV versus non-EV purchasers cannot account for the majority of the EV spread.

Third, we rule out market power as an explanation for the documented EV spread. If EV lenders have more market power in the local auto loan market than non-EV lenders, they might be able to charge a higher markup for loans. To measure market power, we use the respective number of lenders that originate loans in the EV and the non-EV segments in each region (NUTS3-level). We also calculate the HHI specific to each loan segment based on both the number and amount of loans extended by each lender. In addition, we count the overall number of active lenders and compute HHI in any given region (i.e., regardless of whether they operate in the EV or non-EV loan market), to account for the entry of existing lenders into the EV/non-EV loan segment. We find, if anything, that the EV spread tends to be lower when competition in the loan market is less fierce.

In summary, we document a systematic gap in financing terms between EVs and non-EVs — EVs are financed with a higher interest rate, a lower loan-to-value ratio, and a shorter maturity. Risks associated with fast and uncertain clean car and battery technologies explain most of the financing gap. These results suggest that current PHEVs/HEVs are "transition assets" heavily exposed to technological carbon-transition risk. Our findings further suggest that carbon-transition risk is reflected in the financing terms of green durable assets consumption and reveal how much households pay for this risk. While constrained by a unique empirical design that utilizes car loans from a specific time period, our findings suggest that technological risks, such as obsolescence risk, are reflected in household finance products and are therefore economically significant for households.

Literature review

To the best of our knowledge, we are the first to document the systematic gap between EV and non-EV loans. There has been extensive work on demand elasticity to loan terms in the auto loan markets (see Charles et al., 2008; Adams et al., 2009; Einav et al., 2012; Argyle et al., 2020, 2021, for example). Yet, empirical work on the EV loan segment is scarce due to the nascency of this market segment. Consistent with our finding, Kontz (2023) shows that auto asset backed securities with low-emissions have a 6.5% higher issuance spread.

Our paper contributes to the literature on climate change that is concerned with the pricing of climate change risk. Bolton and Kacperczyk (2023) highlight the importance of climate transition risk—the uncertain rate of adjustment toward carbon neutrality—and estimate the size of a carbon-transition risk premium present in international firms' stock returns. We add to this work by studying the pricing of carbon-transition risk in the context of household finance and identifying a specific channel by which shocks to technological innovation contribute to this transition risk. We show that rapid technological changes create uncertainty about the collateral value of EVs, which makes lenders demand premium on financing of these "green" durable assets.[4] The evidence we provide is consistent with arguments in Lanteri and Rampini (2023) that, if both "clean" and "dirty" technologies are used in equilibrium, clean capital is more difficult to finance due to its limited collateralizability. We show that EV loans have lower loan-to-value ratios, which is a direct prediction of their model. We also provide evidence on an additional collateral financing channel that is not present in Lanteri and Rampini (2023). Specifically, we show that EVs depreciate relatively faster and their collateral value is often revised downward due to technological progress, which further contributes to higher financing cost associated with EVs.[5] Moreover, while

[4] Related work on climate change and debt contracts studies how climate risks affect the financing cost of firms. For example, Huynh and Xia (2021) study climate change news risk and Seltzer et al. (2022) examine regulatory risks. Ivanov et al. (2022) show that carbon pricing policies lead to worsening debt financing conditions for high-emission firms as banks mitigate their exposure to climate transition risks.

[5] In a related paper, Atanasova and Schwartz (2019) examine the uncertainty about the depreciation of stranded assets and their impact on firm value due to climate policy risk in the oil and gas industry.

previous studies focus on the cost of financing for green *production*, our research complements this literature by studying the cost of financing for green *consumption* in the form of EV purchases.

Our study also relates to the empirical literature investigating returns on green versus brown assets. Using bond yields as proxies for expected future returns, prior work estimates a negative "greenium" where yields on green bonds are lower than those of their non-green counterparts (Pástor et al., 2022).[6] Observing lower expected returns on green assets is consistent with equilibrium models where investors have green tastes and/or green assets are a better hedge against climate risk (Pástor et al., 2021). We differ from this work by studying ex ante returns on car loans contracts that are popular among households. Using loans on pairs of EVs and non-EVs, we detect a positive greenium. This finding might seem inconsistent with the arguments in Pástor et al. (2021), but it is not. We show that EVs, relative to non-EVs, are expected to have a lower residual value in the future and that their residual value is further revised downward due to technological risks. We argue that, via this technological obsolescence risk channel, there is a difference in loan profitability between EVs and non-EVs that is reflected in the loan terms at loan origination.[7] Our results are consistent with this channel dominating auto lenders' willingness to accept a lower return in exchange for financing "green" cars, if they have green tastes.

Last, our work complements prior research on the factors influencing EV demand, which so far has focused on the direct cost of EVs, government subsidies, and intrinsic consumer preferences (Archsmith et al., 2022). Muehlegger and Rapson (2022) and Muehlegger and

[6] Baker et al. (2022) and Zerbib (2019) also estimate negative greenium using different samples and methodologies. In contrast, Larcker and Watts (2020) document economically identical pricing for green and non-green issues of municipal bonds and concludes that investors appear unwilling to forgo wealth to invest in environmentally sustainable projects.

[7] Our study is related to the literature investigating asset-pricing effects of innovation, particularly the adoption of new technologies and displacement risk. Gârleanu et al. (2012) study asset prices throughout the technology-adoption cycle in the presence of large infrequent technological innovations which are embodied into new capital vintages. Gârleanu et al. (2012) argue that innovation introduces an unhedgeable displacement risk due to lack of intergenerational risk sharing. Kogan et al. (2020) explore behavior of asset prices when technological progress leads to losses through creative destruction as new technologies make old capital and processes obsolete.

Rapson (2023) study the causal impact of EV subsidies on the demand for EVs in California. Gallagher and Muehlegger (2011) evaluate how hybrid vehicle sales respond to various tax and non-tax incentives in the US. Li et al. (2017) show that a dollar spent on charging infrastructure will induce more EV demand than a dollar spent on consumer purchase subsidies. Other work examines how demand for EVs varies across demographic groups and finds income and education to be strongly correlated with EV adoption (Borenstein and Davis, 2016; Archsmith et al., 2022). More broadly, Aron-Dine et al. (2023) present survey evidence that German households' preference for green assets are correlated with political preference, education, and gender. Our research contributes to this strand of literature by documenting low-cost auto financing as a potential enabling factor for EV adoption.

2 Data and Variable Construction

2.1 Data sources

European Data Warehouse (EDW) EDW GmbH is part of the ABS Loan Level Data initiative established by the European Central Bank (ECB) to provide data warehousing services and full disclosure for investors in asset-backed securities. EDW provides standardized loan-level data for car loans securitized by European banks and captive lenders since 2013. EDW has collected over 20 million records and relevant documentation for car loans from over 300 distinct asset-backed securities issued by 19 lenders. For each loan, the dataset covers more than 70 variables. These variables include loan terms (loan amount, interest rate, maturity, and LTV), the manufacturer and model of each car, and borrower characteristics as of the loan origination date (credit score, income, location, etc.), as well as loan performance histories over the entire life of each loan.

We also construct measures of local loan market competition using the EDW loan datasets. For each NUTS3-level region, we compute the number of lenders, market concentration (HHI) based on the number of loans originated by each lender and the volume of loans originated by each lender. Moreover, we construct this set of measures for the EV-specific loan market and non-EV-specific loan market, respectively. We refer to them as the segment-specific competition measures.

EV-volumes EV-volumes is a database for global electric vehicle sales. It offers monthly registrations on all types of electric vehicles by country and model. We use this dataset to examine the coverage of our sample of cars in asset-backed securities.

PatentsView PatentsView provides detailed bibliographical information on all the patents applied through U.S. Patent & Trademark Office (USPTO). Using this data, we identify EV-related technological advancements based on the International Patent Classification (IPC) and title of each patent.

VentureXpert The commercialization of technological improvements or breakthroughs often starts from venture capital (VC) investment in new technologies. VentureXpert provides company insights from early-stage start-ups and their financing rounds. We narrow down to start-ups in the auto industry and compute the amount of VC investment and the relative importance of these investment out of all VC investment.

data.europa.eu We construct various control variables at the NUTS3-level regions. These regions generally have a population of 150,000 to 800,000 inhabitants. We collect the following demographics information that are available at NUT3-level and that may affect consumer preferences for EVs: population, population density, income, age, gender, and birth rate.

In addition to common demographic variables, we obtain NUTS-level election results from Schraff et al. (2023). We then use the regional share of votes for green parties in European parliamentary elections as the proxy for the local green preferences. We identify green parties as parties with green ideology. Examples include The Greens - The Green Alternative from Austria (abbreviated as BRUNE), Europe Ecology – The Greens from France (EELV), Greens / Alliance 90 – Citizens' Movement from Germany (GRUNE). The electoral cycle is five years and most of the variations in this variable, therefore, comes from the cross-section.

FRED We obtain various macroeconomic indicators from the Federal Reserve Bank of Saint Louis. These indicators include the 10-Year Treasury Yield Minus 3-Month Treasury Yield ("T10Y3M"), Moody's Seasoned Aaa Corporate Bond Minus Federal Funds Rate ("AAAFF"), Moody's Seasoned Aaa Corporate Bond Minus Baa Corporate Bond ("AAABAA"), CBOE Volatility Index ("VIXCLS"), log return on the S&P 500 index ("SPXret"), Crude Oil Returns (calculated based on Crude Oil Prices: Brent - Europe, or "DCOILBRENTEU"). These macroeconomic factors may differentially affect the pricing of EV versus non-EV loans.

2.2 Key variable construction

EV indicator An important step is to disentangle EVs from non-EVs using reported information on car manufacturers and models. The "manufacturer" and "model" fields in the EDW data are noisy. For each manufacturer, there can be thousands of unique values in the model field, since lenders report this field following their own format with different precision levels. For example, for the same model BMW 330e, one lender reports "330e" but another one reports "BMW 330e i Performance 190kw". Different languages might also be used since many banks in the sample, such as Santander and Deutsche Bank, are not from English-speaking countries.

We follow a couple of steps to clean up car model names and flag EVs. First, we compile a complete list of official model names for EVs using information from EV-volumes. Second, for each manufacturer, we use regular language expressions to match all the unique model values to the list of official model names. We set different thresholds for each manufacturer and for each lender to determine a match vs. a non-match, depending on the level of accuracy and the language of the model field. We set rather conservative thresholds given the noise in the data. Third, for any non-matches, we manually check each case and decide whether the reported model is an EV or not.

Car model family and pair To ensure that EVs and non-EVs are comparable in all other aspects except for their engine type, we manually bundle car models that belong to the same family and determine if they are close pairs. More importantly, some manufacturers have introduced hybrid versions of their gasoline cars. This allows us to form pairs and compare EVs and non-EVs that are otherwise identical. We go through all the car models of the ten manufacturers to identify their naming conventions. For example, for BMW, we categorize all models into the following families: 1 series, 2 series, 8 series, X series, Z series, and i series. For example, "BMW X3 xDrive30e" is the plug-in hybrid version of "BMW X3 xDrive30". We provide a detailed description of all the car families and pairs that contain EVs in Appendix A.

EV-related technological risks We measure the risks associated with technologies embedded in EVs using a wide array of variables. We employ both patent data and VC investment data to capture both the *intensity* and *dispersion* of innovation in EV-related technologies.

We start by constructing three sets of variables to capture the *intensity* of relevant innovations. First, we consider the number of patents granted in the five- to eight-digit IPC, referred to IPC "main groups", that have been identified as clean technology groups in Aghion et al. (2016) (henceforth "ADHMV2016") in each calendar month. Second, we expand the aforementioned clean technology classes using the co-classification of patents, following the approach in Yan and Luo (2017).[8] We then similarly compute the number of patents in the expanded clean technology groups in each month.

Second, in addition to absolute level of clean patenting, we are also interested in the importance of these patents relative to innovation in comparable technology space. To achieve this, for both the ADHMV2016 list and the expanded list, we scale the number of

[8]The co-classification between any technology group pair (at IPC "main groups" level) is defined as the count of shared patents normalized by the total count of unique patents in each pair of groups. We calculate this relevance ratio and update the list of relevant IPCs on a yearly basis. The technology groups that have a higher-than-90-percentile relevance ratio with any ADHMV2016 technology group are included in the expansion of the original list.

patents in clean technology groups over the total number of patents in the corresponding technology subclasses (four-digit IPC). The subclasses that encompass the clean technology groups are mostly auto-related technology. Both variables are calculated for each calendar month.

Third, to capture the commercialization of these technologies, we compute the dollar value of VC investments in the EV-related startups and the share of that relative to total VC investment in each calendar month. To identify EV-related startups, we perform keyword search in their company descriptions. We use the following keyword list: "EV(s)", "battery", "batteries", "electric vehicle(s)", "electric car(s)", "automobile(s)", "fuel cell(s)", "lithium".

We continue by considering the *dispersion* in battery-related innovations. The dispersion captures the uncertainties about the directions of future advancements in EV and battery technologies. To measure dispersion, we first identify the universe of USPTO patents that mention "battery" in the title. We pool all these titles together and consider each battery-related bigram (e.g., lithium battery, solid battery, flow battery, metal battery) as a direction of future battery technology. We then count the number of unique battery-related bigrams as a proxy for the number of technological directions regarding battery. Next, using the unique number of bigrams and their respective frequency in each calendar month, we construct the monthly HHI of technological directions in battery. A greater number of unique bigrams or a lower HHI corresponds to higher uncertainties and more disagreement about the future direction of battery technologies.

2.3 Sample and EV growth

Our sample contains car loans originated between January 2010 and August 2021 and securitized by European lenders.[9] We focus on 10 brands of manufacturers that produce both EVs and non-EVs: BMW, Ford, Honda, Hyundai, Lexus, Mercedes, Peugeot, Toyota, Volkswagen, and Volvo.[10]

[9] Although the EDW started to provide data in 2013, some loans in the securitized portfolios were originated years before 2013. We downloaded the data in August 2021.

[10] Other manufacturers are either insignificant in EDW data or produce in one market only, such as Tesla.

Table 1 Panel A shows the EV loan volume and share for the 10 manufacturers that have a presence in the EV market. The largest three car manufacturers in the EDW dataset are Volkswagen, Peugeot, and BMW, while the top three EV manufacturers are Toyota, Volkswagen, and BMW. In terms of the percentage of EVs, Lexus, Toyota, and BMW top the ranking.

We evaluate the coverage of EVs in our sample using external EV sales data from EVvolumes. Between 2015-2019, EV loans in our sample represent 6.8%, 7.2%, 6.5%, 8.3%, and 7.9% of all EV sales in the 11 countries covered by EDW. The stable coverage suggests that lenders do not significantly change their securitization practices regarding EVs loans.[11]

Figure 1 depicts the total number of EV loans and the share of EV loans over all auto loans by year. Both series reveal the exponential growth of the EV loan originations. This is not surprising given the same trend in EV sales in Europe and globally, which we show in Appendix Figure B.1, using market-level data from EVvolumes.

2.4 Summary statistics

In Table 1 Panel B, we report summary statistics of the loans terms. The average loan has a 4.55% annual interest rate, 70% LTV ratio, and a 46-month maturity. In Appendix Table B.1, we report the characteristics of EV loans separately. The average non-EV loans have a higher rate of 4.95%, a higher LTV ratio of 83%, and a longer maturity of 47-month maturity. Although the average loan terms appear more favorable for EV loans, we show in the next section that once we account for borrower-, lender-, market-, and car model-specific characteristics, the gap flips signs.

Comparing the performance of EV and non-EV loans, EV loans appear to be less likely to default than non-EV loans as of August 2021, the end of our sample period. For example, the share of non-performing (defaulted) loans is 4.7% (0.8%) for non-EVs, it is 4.2% (0.4%) for EVs.

[11] We focus on the data after 2015 because the data points from EVvolumes before 2015 is sparce. We do not report the coverage in 2020 as some loans originated in 2020 are yet to be securitized at the time of data collection.

Panel A of Table 2 shows the summary statistics of the technological risk measures. The average monthly log number of clean patents granted based on the ADHM2016 definition is 5.65, which accounts for 2% of the auto-related patents. Expanding the ADHM2016 definition to include other relevant technology groups, we find that the average log number of clean patents granted increases to 8.91. The dispersion in battery innovation is substantial, with the average monthly number of battery bigrams reaching 25, and the respective HHI of battery bigrams being 0.11.

At the three-digit NUTS level, the markets for EV and non-EV loans exhibit different degrees of competition. The average number of EV lenders is 3, and it is 8.9 for non-EV loans. A similar pattern can be found in the HHI based on either the number of loans or loan volume. The average market has an HHI of 0.81 for EV loans and 0.43 for non-EV loans. Market power, therefore, plays a potential role in loan pricing.

3 The Gap in Financing Terms Between EV and Non-EVs

This section formally compares the contractual terms of EV and non-EV loans. We identify the gap in the financing terms between EV and non-EV within the same model family or model pair, defined in the previous section. Specifically, we estimate the following regression:

$$Y_i = \gamma_g + \theta_{region,t} + \alpha_{lender} + \alpha_{deal} + \beta EV_i + \theta' X_i + \varepsilon_i. \tag{1}$$

where i denotes car loan, t denotes the loan origination year, g denotes model family or pair. $region$ is defined at NUTS3-level. We consider various outcome variables, denoted by Y_i, including the interest rate of the loan, LTV, and maturity. EV_i is a dummy variable that equals one when the car is an EV and zero otherwise. Variables capturing borrower and other loan characteristics are summarized in vector X_i. We include car value, borrower income, income verification status, customer type, employment status, rate basis, loan origination channel, product type, amortization type, payment frequency, and payment method in the most extensive specification. We further include high-dimensional fixed effects in the regression.

γ_g control for model-family-specific demand or supply shocks, and $\theta_{region,t}$ absorb regional time-varying shocks. In our tightest specification, we also include family×region×year fixed effects, $\gamma_{g,region,t}$, to absorb any supply or demand shocks at the NUTS-3 regional level that are specific to each car family of a particular brand. In addition, we include lender fixed effects, α_{lender}, to control for any time-invariant lender characteristics. Similarly, we include deal fixed effects, α_{deal}, to control for deal-specific factors that influence loan terms. The coefficient of interest is β, which captures the difference in loan terms of an EV relative to a non-EV within the same brand, model family or model pair, originated in the same market at the same time by the same lender to borrowers that are similar based on observable characteristics. Standard errors are double clustered by at the deal and region (NUTS3) level.

Table 3 reports the regression results. The identification of the coefficient of interest β relies on the comparison of EVs and non-EVs within the same car model family. In the last three columns of each panel, we include the income of the borrower and a variable indicating whether this income is verified (or self-reported without verification) as control variables. The financing terms offered to EVs are consistently less favorable compared to non-EVs within the same brand, model family, and model pair. For example, in columns 4-6 of Panel A, where we add borrower controls, EVs loans have a 0.29 p.p higher interest rate, a 4.7 p.p. lower LTV ratio, and a 2.5-month shorter maturity. These differences are economically sizeable, representing 6.5%, 6.7%, and 5.4% of the sample average for interest rate, LTV, and maturity. In Panels B and C, we use tighter fixed effect structures – model family×NUTS3×month fixed effects and model family×NUTS3×year×lender fixed effects, respectively. This ensures that our results are not driven by shocks specific to a car model family in a given region in certain year or month and financed by a certain lender. In other words, we control for the changes in the market structure of lenders or car dealers as well as shifts in the demographics of car buyers of certain models and liquidity shocks to the lender (Benetton et al., 2022). The point estimates under the tighter fixed effect structures (Panels

B-C, columns 4-6) are similar to those in our main specification.

In Table 4, we repeat the analysis with model-pair fixed effects. This reduces the sample size by 3/4 because we require the EV models to have a non-EV close counterpart that shares common features in all observable dimensions except for the engine type. The results remain similar in the restricted sample: EV loans have a higher rate, a lower LTV, and a shorter maturity. To maintain a larger sample size and a broader coverage of car manufacturers, we use the within-family comparison as our main specification and refer to the fixed effects in Panel A of Table 3 as our "baseline FE".

Robustness checks In Figure 2, we show that our results are robust to various alternative samples and specifications. We first consider five alternative samples, starting with a regression sample of loans originated from 2015 and 2018 onwards. This was motivated by the surge of consumer interests in EVs in more recent years, which may affect the loan pricing. Second, we drop leases from the regression sample, which account for 30% of the sample, and focus on car loans. Next, we apply the sampling criteria in Benetton et al. (2022).[12] Last, we restrict the sample to EV and non-EV loans that fall on the common support of control variables and fixed effect units. Put it differently, this ensures that we are strictly comparing the EVs and non-EVs from the same model family, originated by the same lender in the same year, to similar consumers from the same region, and the that the loans are included in the same deal.

In addition, we apply alternative regression specifications, including replacing the family fixed effect with make (i.e., manufacturer) fixed effects, adding product type fixed effects, and controlling for additional borrower characteristics such as customer type, employment status, rate basis, loan origination channel. We also replace NUTS3 $\times$ year fixed effects with NUTS3 $\times$ year-month fixed effects and lender $\times$ NUTS3 $\times$ year fixed effects to control for local shocks that vary within a given year and differential exposure to local shocks across

[12] Specifically, we only keep loans associated with cars purchased by individuals and priced in Euros, and that have monthly payment schedule and fixed rates.

lenders, respectively. Finally, we double cluster the standard errors by lender and NUTS3 instead of deal and NUTS3.

The point estimates and their 95% confidence intervals from these alternative regressions are displayed in Figure 2. At the top of each panel, we show the baseline point estimate for ease of comparison. For all three outcome variables — interest rates, LTV, and maturity — the magnitudes of the estimated coefficient of the EV indicators are largely similar across these robustness tests and are always significant at 5% level. Based on this, we conclude that our results are not driven our choice of a particular sample and specification.

Last, we exclude the 10 manufacturers and the top 10 lenders one by one from the sample and repeat the analysis. Appendix Figure C.1 report the estimation results for the three outcome variables, interest rate, LTV, and maturity, separately. The stability of the estimated coefficients ensures that our results are not driven by any specific manufacturers or lenders. The point estimates are statistically indistinguishable from our baseline estimates.

4 Default Probability and Residual Value

We posit that the unfavorable financing terms of EVs are driven by a higher cost of lending faced by EV lenders. In this section, we present evidence that it is a larger loss given default (LGD), rather than a greater default probability that explains the higher financing cost for EVs.

4.1 Default probability

One may argue that the EV financing gaps originate from a higher default probability associated with EV loans. To investigate this possibility, we use the monthly loan performance reports in the EDW data. This information is mandatory and is available once a loan enters the securitized loan portfolio and till the loan matures or exit from the portfolio. Specifically, to capture default risks, we use the account status field, which can take ten different values, from performing to defaulted and arrears.[13]. Based on the monthly account status

[13]The ten possible account statuses are: Performing (1); Restructured-no arrears (2); Restructured - arrears (3); Defaulted (4); Arrears (5); Repurchased by Seller - breach of reps and warranties (6); Repurchased by Seller - restructure (7); Repurchased by Seller - special servicing (8); Redeemed (9); Other (10).

as of August 2021, we construct four ex-post performance measures indicating if a loan is ever (1) non-performing or repurchased by seller, (2) non-performing, (3) in arrears, or (4) in default. A loan is considered non-performing either when it is in arrears or in default. A loan is repurchased by sellers when it is in default or the loan has been restructured due to forbearance. The summary statistics in Table 1 show that EV loans seem to experience a lower, instead of higher, unconditional default probability. We formally examine the difference in default risks between EV and non-EV loans by regressing the four performance measures on the EV indicator using the regression specification in Equation 1 and the baseline fixed effect in Table 3 Panel B. We include origination year fixed effects to compare loans from the same vintage. The results are reported in Table 5. Columns 1-4 show that there is no significant difference in the default risks of EV and non-EV loans. The point estimates of the coefficient for *EV* are always insignificant both statistically and economically. In columns 5-8, we additionally include interest rate, LTV, and maturity as explanatory variables and find similar results. Therefore, the EV financing gap cannot be explained by a higher default probability.

4.2 Residual value

Next, we show that the loss given default is higher for EVs, and the gap in financing terms widens when the ex ante default probability is higher. To gauge loss given default, we exploit the residual value reported by lenders. More specifically, for all securitized leases, lenders are required to report the vehicle's residual value, which reflects lenders' estimates of the vehicle value at the end of the lease term. The residual value at loan origination depends on the concurrent market conditions, new technological advances, general economic conditions, and the vehicle's perceived reliability, safety and resale value. Lenders closely monitor these factors and keep these estimates up to date.[14]

We show that EVs have lower residual value than non-EVs at loan origination and that

[14]Based on our interviews with Autovista, the largest company that sells residual value estimates to lenders in Europe, lenders hire technology experts and typically have quarterly or even monthly meetings to review their residual value estimates.

the likelihood of a *downward* adjustment in residual value estimates is higher for EVs over the course of the lease. Table 6 reports the results from estimating Equation 1, where the outcome variables are all related to the residual value of the vehicle or the adjustment of this value. Specifically, we construct the five measures: (i) the percentage of residual value over vehicle price, (ii) the monthly depreciation rate (in p.p.), calculated as total depreciation (in p.p.) divided by the length of the financing contract, (iii) an indicator for whether the lender has revised the residual value estimate during the course of the loan, (iv) an indicator for whether the lender revised the residual value estimate downwards during the course of the loan, and (v) whether the lender has never adjusted the residual value estimate downwards (i.e., only upward adjustments in the residual value estimate).

We find consistent results that lenders estimate the residual value of EVs to be lower than that of non-EVs within the same model family (columns 1-2), controlling for other financing terms such as interest rate and LTV. Importantly, lenders are more likely to adjust the residual value of EVs during the course of the financing contract (column 3). These adjustments tend to be downward adjustments and not upward ones (columns 4-5).

Having established that EV loans are more exposed to residual value risks, we provide additional evidence that the gaps in interest rates, LTV, and maturity are consistently larger when lenders are more exposed to residual value risks, that is, when the ex ante default probability is higher. To show this, we construct a direct measure of ex ante default – whether the loan is fully guaranteed. In addition, we also compare leases to loans because the former product exposes EV lenders to more residual value risks as lenders effectively own the vehicle until the lease expires.

Table 7 reports the results. Interacting the indicator for full guarantee with the EV indicator, we find that the gaps between EV and non-EV loans narrow by 0.16-p.p in interest rates, 2-p.p in the LTV ratio, and 1.1-month in maturity (Panel A). Compared to loans, The EV financing gaps in leases widen substantially with a 0.35-p.p increase in interest rates and a 5.8-p.p decrease in the LTV ratio. These results suggest that lenders charge a higher interest rate because of the greater LGD associated with EV loans. When the default probability is high or when lenders own the vehicles, the residual value or the LGD matters more and has a greater impact on the EV financing gap.

5 Can WTP and Competition explain the EV spread?

In the rest of the paper, we delve into the mechanism for the less favorable loan terms for EVs. We focus on the interest rate dimension while controlling for LTV and maturity and refer to the gap in interest rate as the "EV spread".

Before turning to technological risks, we discuss alternative factors that could contribute to this EV spread: the first relates to consumers' higher WTP for EV loans and the second is weaker market competition in the EV loan segments. We show that consumers' WTP and competition can explain either little or only a small fraction of the EV spread. For those factors that have a mild impact on EV premium.

5.1 Demand elasticity

EV purchasers and traditional vehicle buyers might have different characteristics. When EV purchasers have a lower demand elasticity with respect to the interest rate or a higher willingness to pay for the loan, lenders could charge a higher price for EV loans as long as they have some market power. To test this hypothesis, we construct various proxies for consumer's WTP, including the local demographics, car price premium relative to certain benchmarks, and the Media Climate Change Concerns Index.

We start by exploiting variations in regional demographic composition, assuming that the demand for EVs are functions of these demographic factors. We study the following variables that are widely available at NUT3-level: population size, population density, GDP per capita, share of females, median age, birth rates, and share of votes for green parties. These factors are shown to affect green preferences in Europe(Aron-Dine et al., 2023).

We estimate our baseline regression equation for each of the NUTS3-level region, which yields a region-specific EV spread.[15] Then we plot in scatter the region-specific EV spread

[15]This requires replacing the NUTS3 $\times$ year fixed effects with year fixed effects.

against an array of demographics to visually inspect the relationship between the two. Figure 3 presents the results, where each subfigure concerns one demographic variable and each dot in the figure represents a NUTS3-level region. Significant and insignificant EV spread estimates are denoted in blue circles and red diamonds, respectively.

Two patterns are worth noting. First, the point estimates are mostly above zero, suggesting that EV spread persistently exists across regions that vary widely in their demographics. This also confirms that the baseline estimate of EV spread is not driven by a small set of regions. Second, across all figures, we fail to find strong, visually evident relationships between the magnitude of the EV spread and the six local demographic attributes. This suggests that the differences in the demographic composition of EV versus non-EV purchasers cannot account for the majority of the EV spread.

Next, we examine the relationship between EV spread and demographics using the following regression equation, where we add the interaction term $EV_i \times D_{region,t}$ to the baseline specification in Equation 1:

$$Y_i = \gamma_g + \theta_{region,t} + \alpha_l + \beta EV_i + \delta EV_i \times D_{region,t} + \theta' X_i + \varepsilon_i. \tag{2}$$

This specification includes the baseline fixed effects and borrower characteristics, as well as the LTV and maturity of the loan. Our coefficients of interest are δ and β. To facilitate the interpretation of the coefficients, we use the quartiles of the continuous demographic variables $D_{region,t}$ and code it as a categorical variable that takes values from 0 to 3 instead of 1 to 4. With this transformation, we can conveniently interpret β as the average EV spread for the regions in the first quartile of a specific demographic distribution. δ then captures the change in the EV spread moving from a lower quartile to the next quartile.

Table 8 Panel A presents the results. We first find that the magnitude the EV spread does not depend on local population size (column 1), population density (column 2), birth rates (column 6), and share of votes for green parties in European parliamentary elections (column 7). Based on the estimated coefficient of the *EV* in the respective columns, the average EV spread in regions with non-missing demographic information ranges between 0.3 and 0.4 percentage points. Next, GDP per capita and median age have a positive but economically small association with the spread. For example, column 3 suggests that the average EV spread in regions in the lowest quartile of GDP is 0.272 p.p., and moving to the last quartile, we observe an average spread of 0.373 p.p. ($= 0.272 + 0.035 \times 3$). Last, EV spread is negatively associated with the share of the female population, with the spread in the first quartile being 0.435 p.p., and that in the last quartile being 0.329 p.p..

The small coefficients of the interaction terms suggest that while the differential demand elasticity or willingness to pay for EV versus non-EV has an impact on the EV spread, it cannot explain the majority of it.[16]

One may argue that the regional demographic profiles are too coarse a proxy for local consumers' willingness to pay (WTP) for EVs and EV loans. To address this concern, we construct additional sets of measures of WTP. Our second set of measures leverages the car purchase price available at the loan level. First, to gauge whether consumers pay an EV price premium, we compute the average price difference between EVs and non-EVs within the same model family in any given year. This EV price premium therefore varies at the family-year level. Second, we compute the degree to which consumers overpay for a certain car model. We take the difference between the purchase price and a benchmark price, the latter of which is the average price paid by consumers in the same year, or in the same year and NUTS3-level region, for the same car model (same family and engine type). Note that these variables vary at the loan level and can be alternatively interpreted as consumer sophistication. The idea is that consumers who shop around for the best car sale deal are presumably more sophisticated than those who overpay relative to the benchmark price.[17]

[16] In untabulated regressions, we find that controlling for all demographic variables simultaneously does not change the finding.

[17] We also discuss the role of EV purchase incentives in Appendix Appendix F. While we find a higher EV spread in the presence of EV purchase incentives, these incentives do not weaken the explanatory power of technological risk.

Our last set of measures for WTP is the monthly Media Climate Change Concerns Index, constructed by Ardia et al. (2022). The MCCC index is a proxy for unexpected changes in climate change concerns computed from news articles published on the same day. It takes into account the quantity of climate-related news stories as well as the extent of negativity in these news stories and the emphasis placed on risk. Besides the MCCC aggregate index, we also consider the four subindexes based on new article themes: business impact, environmental impact, societal debate, and research. To the extent that climate concerns exert an influence on consumers' WTP for EVs and EV loans, the temporal fluctuations in the indexes should result in time-series variations in the WTP for EVs and EV loans.

Following the same regression specification, we find that these additional proxies for WTP for EVs or consumer sophistication do not explain the EV spread: the interaction terms are consistently insignificant. The results are reported in Appendix Table D.1 and Appendix Table D.2 .

5.2 Lenders' market power

Lenders' market power could also contribute to the EV spread. If EV auto lenders have more market power than non-EV auto lenders in the local auto loan market, they might charge a higher price for loans. To measure market power, we use the respective number of lenders that originate EV and non-EV loans in each region (NUTS3-level). We also calculate the HHI specific to each loan market based on both the number and amount of loans extended by every lender. In addition, to capture potential market competition, we calculate the number of active lenders and HHI in a given region (regardless of whether they operate in the EV or non-EV loan market). This measure is useful because existing lenders that did not originate EV loans in the past may enter the EV loan markets or vice versa.

We find that market power does not explain the EV spread. If anything, the relationship is the opposite of our prediction. Table 8 Panel B reports the regression results of Equation 2, where we replace the demographic variables with measures of competition. We apply the same quartile transformation to facilitate the interpretation of the estimates. Moreover, we replace HHI with 1−HHI so that a larger value corresponds a higher level of competition. The coefficients on the interaction terms are all positive and sometimes significant, suggesting that the EV spread tends to be lower when competition in the EV loan market is less fierce or when lenders have more market power.

We also visualize the relationship between region-specific EV-spread and the degree of competition in the respective region. In Figure 4, we observe only a weak relationship between market power and NUTS3-level EV spread, corroborating our claim that the higher financing cost of EVs is unlikely to be driven by market power.

5.3 Macroeconomic factors

EV sales are affected by supply chain disruptions, macroeconomic uncertainty, as well as commodity and energy prices. When the price of EVs is high or the supply is low, consumers that choose to pay for an expensive EV may have a high willingness to pay for the loan as well. To rule out the possibility that differential exposure to macro factors can lead to the EV spread, we examine the role of various macro indicators described in Section 2 and report the results in Appendix Table D.3. None of the coefficients on the interaction term between the EV indicator and the macro factors are significant, suggesting that macroeconomic factors, including energy prices, do not impact the EV spread.

6 Can technological risks explain the EV spread?

In this section, we present present robust evidence that the EV spread is primarily driven by the risks associated with technologies embedded in EVs.

As a new and fast-evolving product, EVs are presumably perceived by lenders to be a riskier type of collateral than non-EVs. First, lenders lack reliable data on EV performance regarding its range, asset life, and maintenance requirements. Second and more importantly, EV-related technology, particularly battery technology, has advanced significantly in the past decade, with ongoing progress being made at a remarkable pace. In 2022 alone, over 100,000 patents related to battery technology are filed globally. The assets underlying auto loans today could become obsolete in a few years. The generous warranties provided on EVs compared to non-EVs suggest that EVs are indeed subject to more technological risks. Table B.2 summarizes the warranty by car make and engine type. While the median warranty for EV is 96 months/160,000 miles, it is 48 months/100,000 for non-EVs. We, therefore, conjecture that the EV spread reflects the higher technological risks associated with EVs.

6.1 EV spread and technological risks

To establish the link between technological risks and the cost of EV financing, we construct measures of advancements in battery technologies or other technologies that are instrumental to EVs. We show that both the intensity and dispersion of EV-related innovations explain a substantial part of the EV spread. Similar to the tests above, we use the quartile transformation of the technological risk measures. In addition, we gradually include in the regression the interaction terms between the EV indicator and the demographic factors or competition measures that have a significant association with the EV spread. All control variables are standardized to have a zero mean and a standard deviation of one to make the key coefficients comparable across specifications.

Table 9 focuses on the intensity of EV-related innovation using the ADHMV2016 list. The results on the log number of clean patents are reported in Panel B, and the results on the share of patents in the clean technology groups relative to all patents in the subclasses are reported in Panel B. In column 1, we only include the baseline fixed effects, and borrower and loan characteristics. In column 2, we add the interaction terms between EV and standardized log(GDP), the share of female population, and median age. In column 3, we control for the interaction between the EV and the NUTS3-level HHI based on loan volume. In column 3, we include all these control variables that exhibit a significant association with the EV spread in previous analysis.

The patterns are consistent across all specifications. The coefficient on the standalone EV dummy is not significantly different from zero, suggesting negligible EV spread in the months where technological risks are in the lowest quartile. For example, once we control for the impact of demographics and competition, as shown in column 4, the point estimate of the EV coefficient approaches zero. However, moving up in the distribution by one quartile increases the EV spread substantially, by 0.148 percentage points. This suggests a close to 0.5 p.p. higher EV spread between the highest and the lowest quartile of technological risks. Results are quantitatively similar when we use the share of clean patents to measure the intensity of EV-related innovations, as in Panel B.

In Table 10, we present evidence that the dispersion in battery innovation plays an equally important role in determining the EV spread. In Panel A, we measure the dispersion using the HHI of battery-related bigrams in the titles of all patents. In Panel B, we use the number of unique battery-related bigrams. A lower HHI or a greater number of unique bigrams corresponds to higher uncertainties and more disagreement about the future direction of battery technologies.

According to Panel A of Table 10, there is a moderate EV spread (0.17 p.p) in the months where the dispersion in battery innovation is in the lowest quartile. Moving up in the distribution of dispersion by one quartile increases the EV spread by 0.136 p.p. Including the interaction between lenders' market power and the EV indicator eliminate the EV spread in columns 3 and 4 for lowest quartile of dispersion. In Panel B, the baseline EV spread is statistically insignificant throughout specifications and the inter-quartile difference in the EV spread ranges between 0.160 and 0.180 p.p..

In Appendix Section E, we show that our results are robust to other measures of technology advancements. The first set of alternative measures are based on the expanded list of clean technology groups, described in Section 2. Table E.1 presents the results. Similar to our main results, we find that the EV spread is zero in the month with the lowest quartile of the log number of clean patents. The spread even turns negative when we normalize the number of clean patents by the number of patents in the corresponding technology subclasses.

Moreover, we gauge the technology advancements using the amount of VC investments in EV-related startups that we identify based on the company descriptions. As such, we expect to find a higher EV spread in months with more VC investments. Table E.2 presents results consistent with our prediction.

6.2 Residual values and technological risks

To further tighten the link between technological risks and EV spread, we take advantage of the monthly residual value estimates on each vehicle lease in EDW. In section 3, we show that EVs have lower residual value than non-EVs at loan origination and that the likelihood of a downward adjustment in residual value estimates is higher for EVs over the course of the lease. Now, we take advantage of the panel structure of the residual value estimates and examine the evolution of these estimates in relation to the technological risks. We estimate the following regression equation:

$$Y_{i,t} = \gamma_i + \theta_t + \delta EV_i \times Tech_t + \varepsilon_{i,t}, \tag{3}$$

where $Y_{i,t}$ captures the residual value estimate of loan i in calendar month t. We consider two measures for each car, the estimated residual value in log dollar terms and an indicator for whether the residual value estimate in a given month is lower than that at loan origination. We include loan fixed effects to absorb any time-invariant car- or loan-level characteristics. We also add year-month fixed effect to control for the impact of macroeconomic factors and market conditions on residual values. The key variable of interest is the interaction term between technological risks and the EV indicator. Its coefficient, δ, captures how the residual value estimates of EVs respond to technological shocks relative to that of non-EVs. As before, we use quartiles of the continuous technological risk variables $Tech_t$ and code it as a categorical variable that takes values from 0 to 3.

Table 11 reports the results, where measures of technological risks are constructed using the clean patent definition in ADHMV2016 in Panel A and battery-related bigrams in patent titles in Panel B. Across all technological risk measures and outcome variables, we find that when the intensity and dispersion of innovation in EV technologies go up, lenders are more likely to revise the residual value estimates of EVs downward relative to non-EVs. For example, according to column 3 of Panel A, the residual value of EVs decreases by 0.9% more relative to non-EVs, if the number of clean patents moves up by one quartile in the distribution. Similar results are found in Panel B. when we examine the dispersion in battery technology. In the presence of higher uncertainties or more disagreement about the future direction of battery technologies, lenders become more pessimistic in their residual value estimates.

Taking stock, the analysis of the residual value, especially its dynamics, lends strong support to the relationship between EV-specific technological risks and the EV spread.

7 Conclusion

We provide the first comprehensive analysis of the rapidly growing EV loan market and document a significant, systematic gap in the financing terms—interest rate, maturity, loan-to-value ratio—between EVs and non-EVs. EVs are costlier to finance and this financing gap can be explained by the risks associated with technologies embedded in EVs. While most policy discussions of the global shift to electric mobility focus on the affordability of EVs in terms of their purchase price, less attention is paid to the role of consumer financing of EVs. Our research fills this gap and can inform public policies that aim at making EV financing more accessible. Nascent initiatives include Bank Australia's decision to stop offering loans for new fossil fuel cars from 2025.

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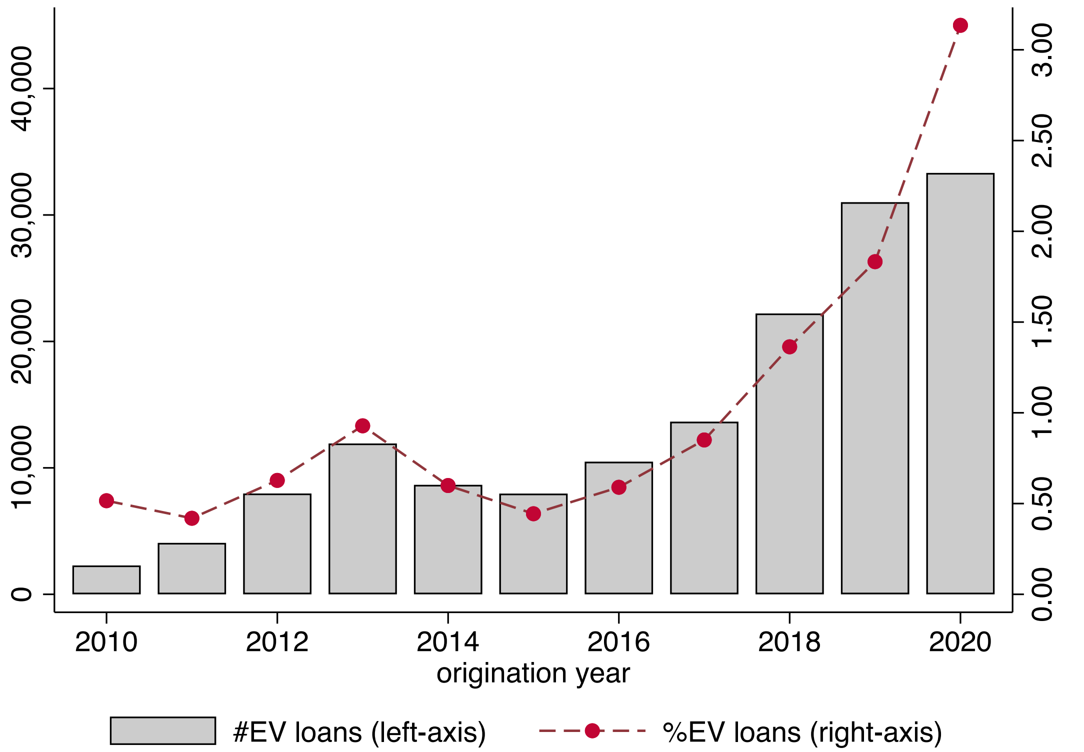
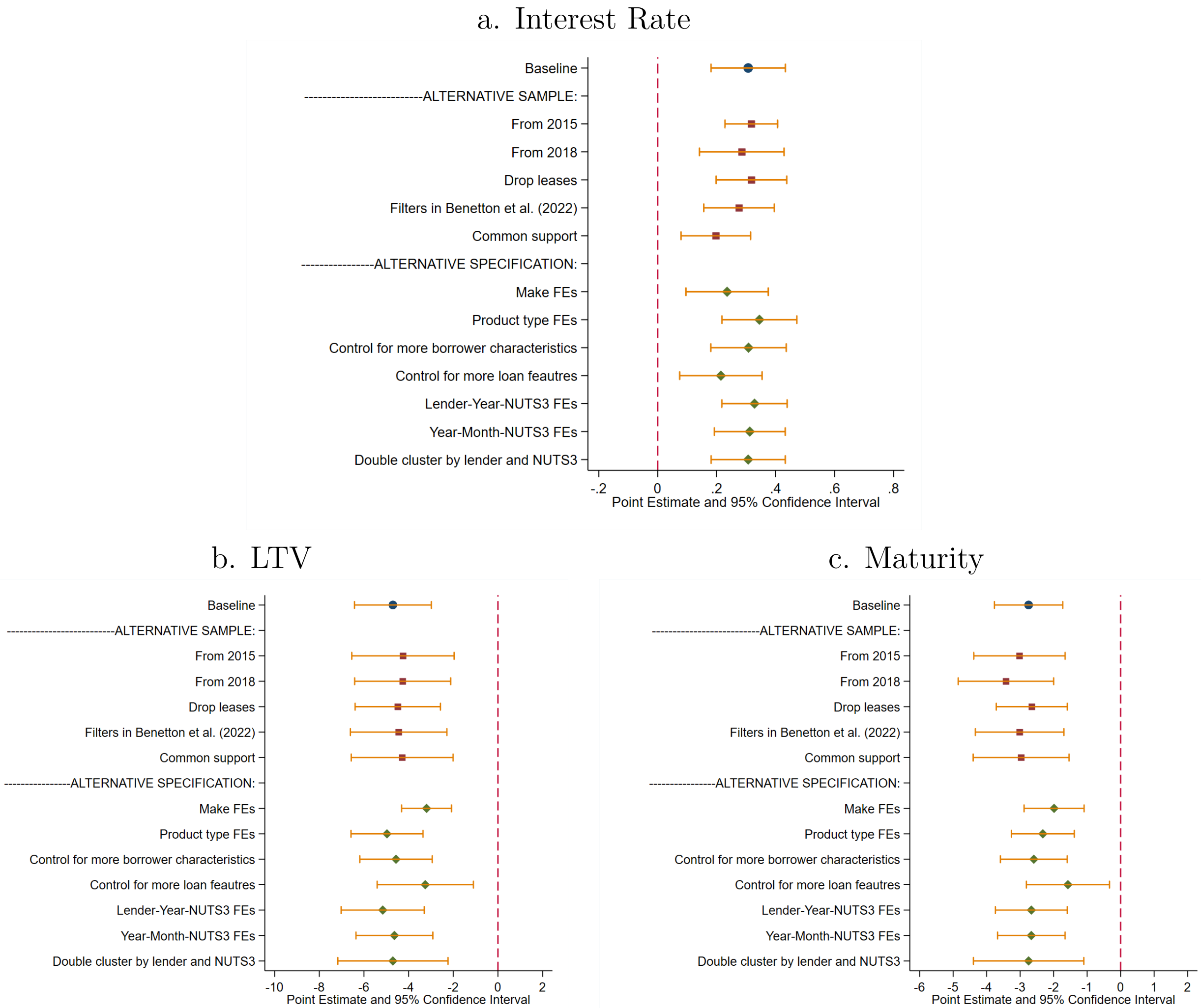
Figure 1: Growth of EV Loans



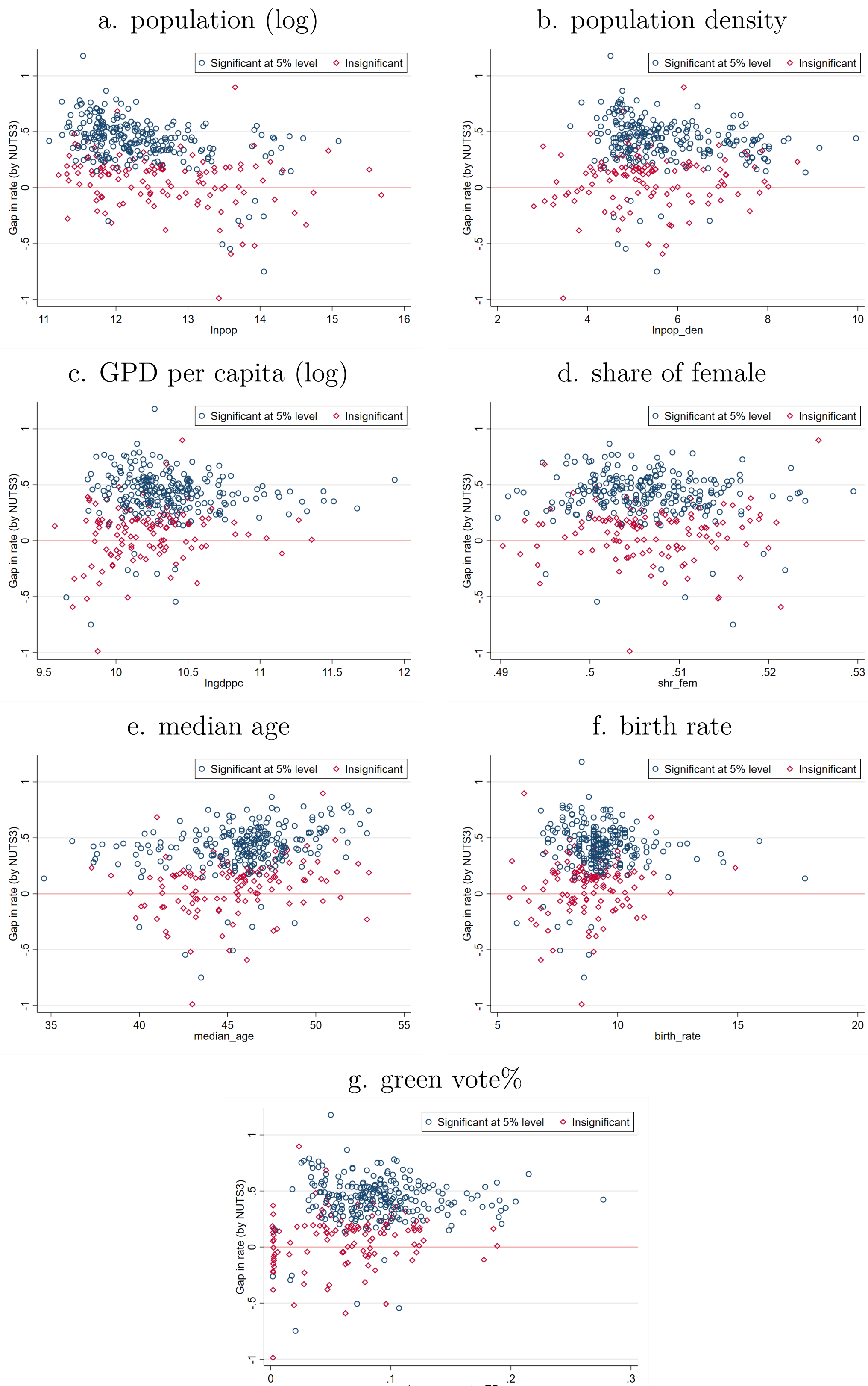
NOTE.—Figure 1 illustrates the total number of EV loans originations (left axis) and the percentage of EV loan (right axis) over all auto loans in our sample period 2010-20.

Figure 2: Alternative Samples and Specifications



NOTE.—Figure 2 presents the point estimates of the EV indicator using alternative regression samples and regression specifications for each of the three outcome variables: interest rate, LTV, and maturities in the three panels.

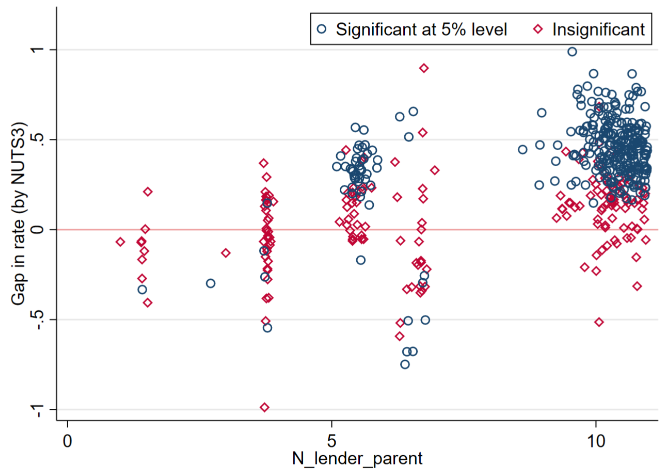
Figure 3: Demographics and EV Spread by NUTS3



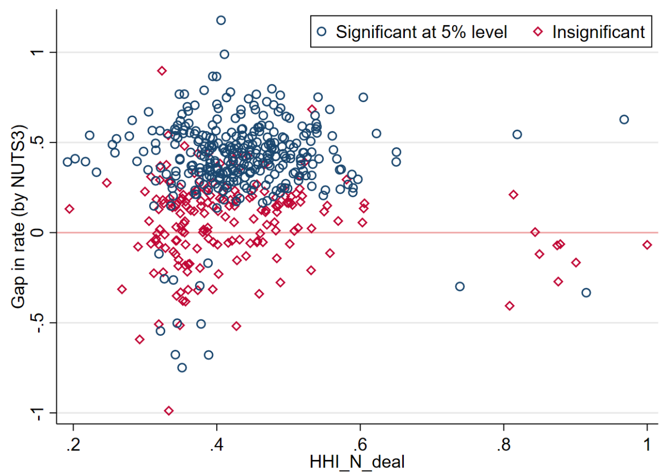
NOTE.— This figure plots the NUT3-level cross-sectional relationship between the estimated EV spread and local demographics. The NUTS3 level EV spread is estimated using all loans originated in a given NUTS3 over our sample period.

Figure 4: Market Power and EV Spread by NUTS3

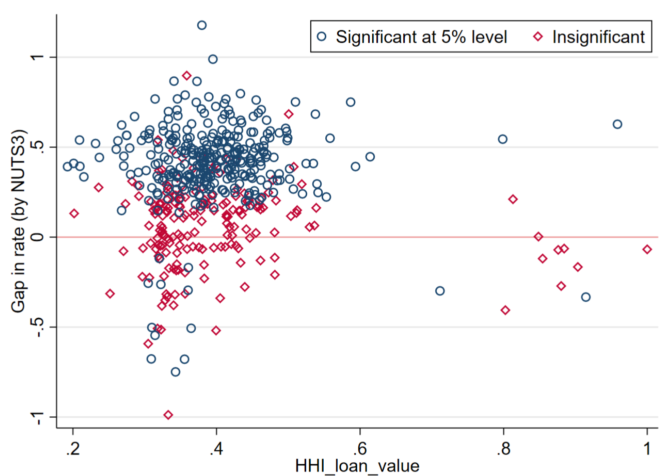
a. number of lenders



b. HHI (#loans)



c. HHI ($loans)



Note.— This figure plots the NUT3-level cross-sectional relationship between the estimated EV spread and measures of local market power. The NUTS3 level EV spread is estimated using all loans originated in a given NUTS3 over our sample period.

Table 1: Summary Statistics on Loan Characteristics

Panel A. Loan origination by make

	#EV loans	#non-EV loans	%EV loans
bmw	26,916	1,204,727	2.23
ford	1,049	1,218,112	0.09
honda	2,325	109,564	2.12
hyundai	5,679	589,120	0.96
lexus	3,271	6,114	53.50
mercedes	850	577,041	0.15
peugeot	15,215	2,083,269	0.73
toyota	94,498	545,624	17.32
volkswagen	30,170	8,752,623	0.34
volvo	2,594	165,066	1.57

Panel B. Loan characteristics

	mean	sd	p10	p25	p50	p75	p90	count
rate	4.552	1.90	3.00	3.50	4.00	5.50	6.90	182,567
LTV	70.231	24.19	37.46	52.04	75.00	90.00	100.00	159,432
maturity	46.131	14.52	35.00	36.00	48.00	60.00	60.00	180,934
car value (log)	9.902	0.55	9.19	9.57	9.92	10.30	10.54	182,567
income (log)	10.262	0.81	9.39	10.04	10.24	10.69	11.18	128,028
income verified	0.327	0.47	0.00	0.00	0.00	1.00	1.00	182,567
non-performing or repurchased by seller	0.085	0.28	0.00	0.00	0.00	0.00	0.00	182,567
non-performing	0.042	0.20	0.00	0.00	0.00	0.00	0.00	182,567
arrears	0.041	0.20	0.00	0.00	0.00	0.00	0.00	182,567
default	0.004	0.06	0.00	0.00	0.00	0.00	0.00	182,567
redeemed	0.190	0.39	0.00	0.00	0.00	0.00	1.00	182,567

NOTE.—Panel A presents the number of EV loans, number of auto loans, and the percentage of EV loans. Panel B presents summary statistics on loan characteristics. The sample period is January 2010 to August 2021.

Table 2: Summary Statistics of Explanatory and Control variables

Panel A. Technological risk

	mean	sd	p10	p25	p50	p75	p90	count
Intensity of battery innovation								
number of clean patents ADHM2016 (log)	5.65	0.31	5.24	5.59	5.73	5.82	5.94	2,924,417
share of clean patents ADHM2016	0.02	0.00	0.01	0.02	0.02	0.02	0.02	2,924,417
number of clean patents (log)	8.91	0.20	8.73	8.81	8.92	9.06	9.16	2,924,417
share of clean patents	0.53	0.03	0.47	0.52	0.54	0.55	0.56	2,924,417
Dispersion in battery innovation								
HHI of battery bigrams (monthly)	0.11	0.02	0.09	0.09	0.11	0.13	0.14	2,924,417
number of battery bigrams (monthly)	35.00	6.58	27.00	31.00	35.00	40.00	43.00	2,924,417
HHI of battery trigrams (monthly)	0.04	0.01	0.03	0.04	0.04	0.05	0.06	2,924,417
number of battery trigrams (monthly)	60.20	11.20	45.00	53.00	60.00	68.00	73.00	2,924,417
VC investments								
VC investment in EV (log)	4.84	5.50	0.00	0.00	0.00	10.45	13.18	2,924,417
share of VC investment in EV	0.01	0.02	0.00	0.00	0.00	0.00	0.05	2,924,417

Panel B. Other control variables

	mean	sd	p10	p25	p50	p75	p90	count
Demographics								
population (log)	12.87	1.13	11.64	12.03	12.63	13.52	14.48	2,924,417
population density	727.53	1297.48	86.20	135.30	258.60	788.70	2095.90	2,924,417
GDP per capita (log)	10.31	0.34	9.90	10.09	10.29	10.47	10.73	2,924,417
share of female	0.51	0.01	0.50	0.50	0.51	0.51	0.52	2,924,417
median age	44.94	3.07	40.90	42.60	45.50	46.90	48.60	2,924,417
birth rate	9.10	1.43	7.50	8.20	9.00	9.80	10.80	2,924,417
green votes%	0.08	0.05	0.00	0.04	0.08	0.11	0.14	2,866,532
Competition								
number of lenders	8.87	2.93	4.00	7.00	10.00	11.00	11.00	2,924,417
HHI (#loans)	0.42	0.11	0.29	0.35	0.41	0.49	0.55	2,924,417
HHI ($loans)	0.38	0.11	0.27	0.32	0.37	0.44	0.49	2,924,417
number of EV lenders	3.01	1.41	1.00	2.00	3.00	4.00	5.00	38,068
EV HHI (#loans)	0.81	0.14	0.60	0.73	0.83	0.91	1.00	38,068
EV HHI ($loans)	0.77	0.16	0.53	0.65	0.79	0.88	1.00	38,068
number of non-EV lenders	8.85	2.94	4.00	7.00	10.00	11.00	11.00	2,886,349
non-EV HHI (#loans)	0.43	0.11	0.29	0.35	0.41	0.49	0.55	2,886,349
non-EV HHI ($loans)	0.39	0.11	0.27	0.32	0.37	0.44	0.50	2,886,349
Macro indicators								
T10Y3M	1.65	0.59	0.89	1.16	1.58	2.14	2.52	2,924,417
AAAFF	3.14	0.76	2.03	2.42	3.27	3.83	4.07	2,924,417
AAABAA	0.89	0.23	0.67	0.69	0.87	0.99	1.27	2,924,417
VIXCLS	14.93	3.64	10.54	12.40	14.20	16.79	19.39	2,924,417
SPXret	0.01	0.02	-0.03	-0.01	0.01	0.02	0.03	2,924,417
Crude Oil return	-0.02	0.10	-0.13	-0.06	0.01	0.06	0.08	2,924,417

NOTE.—This table presents the summary statistics of the measures of EV-related technological risks and NUT3-level control variables. The sample period is January 2010 to August 2021.

Table 3: Financing Terms of EVs and non-EVs: Baseline

Panel A. within-family comparison

	(1) rate	(2) LTV	(3) maturity	(4) rate	(5) LTV	(6) maturity
EV	0.175**	−6.776***	−2.228***	0.294***	−4.704***	−2.480***
	(0.08)	(1.18)	(0.53)	(0.06)	(0.87)	(0.50)
lender FE	Y	Y	Y	Y	Y	Y
deal FE	Y	Y	Y	Y	Y	Y
family FE	Y	Y	Y	Y	Y	Y
nuts3 × year FE	Y	Y	Y	Y	Y	Y
borrower controls	N	N	N	Y	Y	Y
Observations	14,765,390	14,087,065	14,713,677	7,906,809	7,458,371	7,906,823
R-sq	0.693	0.391	0.373	0.720	0.327	0.327

Panel B. within-family comparison, family×geography×month FE

	(1) rate	(2) LTV	(3) maturity	(4) rate	(5) LTV	(6) maturity
EV	0.116**	−6.053***	−1.784***	0.236***	−4.462***	−2.327***
	(0.06)	(1.18)	(0.39)	(0.05)	(0.96)	(0.44)
lender FE	Y	Y	Y	Y	Y	Y
deal FE	Y	Y	Y	Y	Y	Y
family × nuts3 × month FE	Y	Y	Y	Y	Y	Y
borrower controls	N	N	N	Y	Y	Y
Observations	13,409,107	12,723,168	13,359,861	6,726,222	6,264,739	7,746,956
R-sq	0.784	0.537	0.538	0.821	0.510	0.398

Panel C. within-family comparison, family×geography×year×lender FE

	(1) rate	(2) LTV	(3) maturity	(4) rate	(5) LTV	(6) maturity
EV	0.146**	−5.914***	−2.102***	0.239***	−4.616***	−2.223***
	(0.06)	(1.11)	(0.44)	(0.06)	(1.02)	(0.46)
deal FE	Y	Y	Y	Y	Y	Y
family × nuts3 × year × lender FE	Y	Y	Y	Y	Y	Y
borrower controls	N	N	N	Y	Y	Y
Observations	14,260,895	13,586,590	14,209,386	7,471,046	7,028,766	7,471,057
R-sq	0.755	0.478	0.479	0.783	0.430	0.443

NOTE.—This table shows the difference in financing terms between EVs and non-EVs within the same model family. In all columns, we include deal FE and car value in log form. In columns 4-6, we control for borrower income and the verification status of income. *EV* is an indicator variable for whether the car model is classified as electric. Panel A includes lender and NUT3×year fixed effects; Panel B includes lender and family×month×NUTS3 FE; Panel C include family×month×NUTS3×lender FE. The sample period is January 2010 to August 2021. Standard errors double clustered by security and NUTS3-level region are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 4: Financing Terms of EVs and Non-EVs: A Within-Car-Pair Comparison

	(1) rate	(2) LTV	(3) maturity	(4) rate	(5) LTV	(6) maturity
EV	0.051	−2.636	−1.666***	0.128**	−3.792**	−1.708**
	(0.06)	(1.74)	(0.57)	(0.05)	(1.80)	(0.79)
lender FE	Y	Y	Y	Y	Y	Y
deal FE	Y	Y	Y	Y	Y	Y
pair FE	Y	Y	Y	Y	Y	Y
nuts3 × year FE	Y	Y	Y	Y	Y	Y
borrower controls	N	N	N	Y	Y	Y
Observations	3,857,198	3,540,581	3,856,455	3,147,949	2,983,847	3,147,961
R-sq	0.708	0.374	0.365	0.701	0.394	0.354

NOTE.—This table shows that our results hold when we compare EV and non-EVs within the same car model pair. We apply the same controls and fixed effect structure as the baseline specification. In columns 4-6, we control for borrower income and the verification status of income. *EV* is an indicator variable for whether the car model is classified as electric. The sample period is January 2010 to August 2021. Standard errors double clustered by security and NUTS3-level region are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 5: Default Risk Does Not Explain the EV Spread

	non-performing repurchased by seller (1)	non-performing (2)	arrears (3)	default (4)	non-performing repurchased by seller (5)	non-performing (6)	arrears (7)	default (8)
EV	−0.004	−0.006	−0.006	0.000	0.000	−0.003	−0.003	0.001
	(0.01)	(0.00)	(0.00)	(0.00)	(0.01)	(0.00)	(0.00)	(0.00)
rate					0.003***	0.003***	0.002***	0.001***
					(0.00)	(0.00)	(0.00)	(0.00)
LTV					0.001***	0.001***	0.001***	0.000***
					(0.00)	(0.00)	(0.00)	(0.00)
maturity					0.000**	0.000***	0.000***	0.000***
					(0.00)	(0.00)	(0.00)	(0.00)
lender FE	Y	Y	Y	Y	Y	Y	Y	Y
deal FE	Y	Y	Y	Y	Y	Y	Y	Y
family FE	Y	Y	Y	Y	Y	Y	Y	Y
nuts3 × year FE	Y	Y	Y	Y	Y	Y	Y	Y
borrower controls	Y	Y	Y	Y	Y	Y	Y	Y
mean outcome var.	0.076	0.041	0.039	0.006	0.076	0.041	0.039	0.006
Observations	7,458,362	7,458,362	7,458,362	7,458,362	7,458,362	7,458,362	7,458,362	7,458,362
R-sq	0.203	0.033	0.032	0.009	0.208	0.042	0.040	0.011

NOTE.—This table presents the difference in performance between EV and non-EV loans. In columns 1-4, we use as outcome variable whether the loan is non-performing or repurchased by sellers, non-performing, in arrears, or in default. A loan is non-performing either because it is in arrears or it is in default status. In columns 5-8, we additionally include loan rate, LTV, and maturity as control variables. In all columns, we include lender-, deal-, car family-, NUT3×year- fixed effects, and control for car value (in log form), borrower income, and the verification status of income. We additionally control for LTV and term of the loan. The sample period is January 2010 to August 2021. Standard errors double clustered by security and NUTS3-level region are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 6: Residual Values of EVs Are Lower Than Non-EVs

	(1) RV/price %	(2) depreciation rate (monthly p.p.)	(3) RV adjustment ever (0/1)	(4) RV adj. down ever (0/1)	(5) RV adj. down never (0/1)
EV	−0.048***	0.179***	0.025***	0.023***	0.002
	(0.01)	(0.02)	(0.01)	(0.01)	(0.00)
rate	0.000	0.000	0.001	0.001	−0.000
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
LTV	0.000	0.003***	0.001**	0.001**	0.000***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
maturity	0.001		0.003***	0.003***	0.000**
	(0.00)		(0.00)	(0.00)	(0.00)
lender FE	Y	Y	Y	Y	Y
deal FE	Y	Y	Y	Y	Y
family FE	Y	Y	Y	Y	Y
nuts3 × year FE	Y	Y	Y	Y	Y
mean outcome var.	0.403	1.743	0.125	0.114	0.011
Observations	1,261,987	1,261,987	1,370,360	1,370,360	1,370,360
R-sq	0.357	0.220	0.293	0.284	0.070

NOTE.—This table compares the residual value estimates of EVs and non-EVs. The outcome variables from left to right are the percentage of residual value over vehicle price, the monthly depreciation rate (in p.p.), an indicator for whether the lender has revised the residual value estimate during the course of the financing contract, an indicator for whether the lender has ever revised the residual value estimate downward, and whether the lender has never adjusted the residual value estimate downward (i.e., only upward adjustments), respectively. In all columns, we include lender-, deal-, car family-, NUT3×year- fixed effects. We additionally include the interest rate, LTV, and maturity of the loan as explanatory variables (except for column 2 since maturity serves as the denominator in calculating monthly depreciation rate). The sample period is January 2010 to August 2021. Standard errors double clustered by the month of loan origination and NUTS3-level region are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 7: Financing Terms of EVs and Non-EVs: Effect of Lenders' Exposure to Residual Value Risks

Panel A. ex ante default probability

	(1)	(2)	(3)
EV	0.343***	−5.142***	−3.008***
	(0.08)	(0.78)	(0.46)
EV × full guarantee	−0.166*	1.903*	1.120***
	(0.09)	(1.01)	(0.41)
full guarantee	−0.021	3.071***	1.892***
	(0.02)	(0.36)	(0.22)
lender FE	Y	Y	Y
deal FE	Y	Y	Y
family FE	Y	Y	Y
nuts3 × year FE	Y	Y	Y
borrower controls	Y	Y	Y
loan controls	Y	Y	Y
Observations	7,454,508	7,454,508	7,454,508
R-sq	0.723	0.329	0.320

Panel B. lease vs. loan

	(1)	(2)	(3)
EV	0.303***	−4.206***	−2.711***
	(0.07)	(0.98)	(0.52)
EV × lease	0.345*	−5.784***	0.229
	(0.20)	(1.68)	(1.13)
lease	−1.605***	−24.090***	−5.618
	(0.34)	(6.01)	(3.89)
lender FE	Y	Y	Y
deal FE	Y	Y	Y
family FE	Y	Y	Y
nuts3 × year FE	Y	Y	Y
borrower controls	Y	Y	Y
loan controls	Y	Y	Y
Observations	7,458,362	7,458,362	7,458,362
R-sq	0.724	0.329	0.318

NOTE.— This table examines if the gap in financing terms between EVs and non-EVs varies depending on the lenders' exposure to the residual value risks. In Panel A, we study ex ante default probability and measure it with loan guarantee status. In Panel B, we differentiate between leases and loans. The controls and fixed effect structure are the same as in Columns 4-6 of Table 3. The sample period is January 2010 to August 2021. Standard errors double clustered by security and NUTS3-level region are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 8: WTP and Market Power Do not Explain the EV spread

Panel A. demographics

	interest rate						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
EV	0.399***	0.330***	0.272***	0.425***	0.322***	0.316***	0.361***
	(0.10)	(0.07)	(0.05)	(0.07)	(0.05)	(0.09)	(0.06)
EV × population (log)	−0.014						
	(0.02)						
EV × population density		0.021					
		(0.02)					
EV × GDP per capita (log)			0.035***				
			(0.01)				
EV × share of female				−0.032**			
				(0.01)			
EV × median age					0.061***		
					(0.01)		
EV × birth rate						0.029	
						(0.02)	
EV × green votes%							0.007
							(0.02)
lender FE	Y	Y	Y	Y	Y	Y	Y
deal FE	Y	Y	Y	Y	Y	Y	Y
family FE	Y	Y	Y	Y	Y	Y	Y
nuts3 × year FE	Y	Y	Y	Y	Y	Y	Y
borrower controls	Y	Y	Y	Y	Y	Y	Y
loan controls	Y	Y	Y	Y	Y	Y	Y
Observations	5,272,999	4,801,024	4,012,753	5,272,999	4,018,758	4,798,651	5,184,418
R-sq	0.763	0.770	0.768	0.763	0.787	0.770	0.758

Panel B. lender market power

	interest rate					
	(1)	(2)	(3)	(4)	(5)	(6)
EV	0.228***	0.253***	0.154**	0.228***	0.257***	0.153**
	(0.06)	(0.07)	(0.07)	(0.06)	(0.06)	(0.06)
EV × number of segment lenders	0.080					
	(0.06)					
EV × 1-segment HHI (#loans)		0.078				
		(0.06)				
EV × 1-segment HHI ($loans)			0.133**			
			(0.06)			
EV × number of lenders				0.085*		
				(0.05)		
EV × 1-HHI (#loans)					0.045	
					(0.04)	
EV × 1-HHI ($loans)						0.102***
						(0.03)
lender FE	Y	Y	Y	Y	Y	Y
deal FE	Y	Y	Y	Y	Y	Y
family FE	Y	Y	Y	Y	Y	Y
nuts3 × year FE	Y	Y	Y	Y	Y	Y
borrower controls	Y	Y	Y	Y	Y	Y
loan controls	Y	Y	Y	Y	Y	Y
Observations	7,458,362	7,458,362	7,458,362	7,458,362	7,458,362	7,458,362
R-sq	0.728	0.728	0.728	0.728	0.728	0.728

NOTE.— This table shows that consumer demographics and market power of lenders do not explain the EV spread. We interact various demographic variables and measures of local competition with the EV indicator. In all columns, we include lender-, deal-, car family-, NUT3×year- fixed effects, and control for car value (in log form), borrower income, and the verification status of income. We additionally control for LTV and term of the loan. The sample period is January 2010 to August 2021. Standard errors double clustered by security and NUTS3-level region are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 9: Technological Risks and the EV Spread: Intensity of Clean Patenting

Panel A. the number of clean patents (in log form) - ADHMV2016

	interest rate			
	(1)	(2)	(3)	(4)
EV	0.101	0.099	−0.000	0.009
	(0.10)	(0.11)	(0.10)	(0.12)
EV × number of clean patents ADHMV2016 (log)	0.162***	0.154***	0.156***	0.148***
	(0.03)	(0.03)	(0.03)	(0.03)
baseline FE, borrower & loan controls	Y	Y	Y	Y
EV × demographic controls	N	Y	N	Y
EV × competition controls	N	N	Y	Y
Observations	2,816,501	2,816,501	2,816,501	2,816,501
R-sq	0.805	0.805	0.805	0.805

Panel B. the share of clean patents relative to all auto patents - ADHMV2016

	interest rate			
	(1)	(2)	(3)	(4)
EV	0.039	0.044	−0.048	−0.033
	(0.08)	(0.10)	(0.09)	(0.11)
EV × share of clean patents ADHMV2016	0.169***	0.159***	0.161***	0.152***
	(0.02)	(0.03)	(0.02)	(0.03)
baseline FE, borrower & loan controls	Y	Y	Y	Y
EV × demographic controls	N	Y	N	Y
EV × competition controls	N	N	Y	Y
Observations	2,816,501	2,816,501	2,816,501	2,816,501
R-sq	0.805	0.805	0.805	0.805

Note.— This table shows the role of technological risks in explaining the EV spread. We interact various measures of EV-related technological risks with the EV indicator. In Panel A, we measure the intensity of innovation in EV-related technologies using the number of clean patents (in log form), and in Panel B we use the share of clean patents relative to all patents in the corresponding parent groups (subclasses). Both measures are derived using the classification of clean patents in Aghion et al. (2016). To facilitate the interpretation of the coefficients, we divide these measures based on the quartiles and use the categorical values (0, 1, 2, 3). We include the interaction terms of EV indicator and demographic variables (population density, GDP per capita, median age) in column 2, the interaction term of that with competition (segment HHI - $loans) in column 3, and both in column 4. In all columns, we include lender-, deal-, car family-, NUT3×year- fixed effects, and control for car value (in log form), borrower income, and the verification status of income. We additionally control for LTV and term of the loan. The sample period is January 2010 to August 2021 in both panels. Standard errors double clustered by security and NUTS3-level region are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 10: Technological Risks and the EV Spread: Dispersion in Battery Technology

Panel A. HHI of the unique bigrams in battery patent titles

	interest rate			
	(1)	(2)	(3)	(4)
EV	0.170**	0.166*	0.079	0.085
	(0.08)	(0.09)	(0.08)	(0.10)
EV × 1-HHI of battery bigrams	0.136***	0.129***	0.129***	0.123***
	(0.02)	(0.02)	(0.02)	(0.02)
baseline FE, borrower & loan controls	Y	Y	Y	Y
EV × demographic controls	N	Y	N	Y
EV × competition controls	N	N	Y	Y
Observations	2,816,501	2,816,501	2,816,501	2,816,501
R-sq	0.805	0.805	0.805	0.805

Panel B. number of unqiue bigrams in battery patent titles

	interest rate			
	(1)	(2)	(3)	(4)
EV	0.074	0.077	−0.010	0.002
	(0.09)	(0.10)	(0.10)	(0.11)
EV × number of battery bigrams	0.180***	0.169***	0.170***	0.160***
	(0.03)	(0.03)	(0.03)	(0.03)
baseline FE, borrower & loan controls	Y	Y	Y	Y
EV × demographic controls	N	Y	N	Y
EV × competition controls	N	N	Y	Y
Observations	2,816,501	2,816,501	2,816,501	2,816,501
R-sq	0.805	0.805	0.805	0.805

NOTE.— This table shows the role of technological risks in explaining the EV spread. We interact various measures of EV-related technological risks with the EV indicator. In Panel A, we measure the intensity of innovation in EV-related technologies using the number of clean patents (in log form) and the share of clean patents relative to all patents in the corresponding parent groups (subclasses). In Panel B, we use the HHI of battery-related bigrams in the title of patents and the unique number of battery-related bigrams in the title of all patents (in log form). All measures are constructed at the monthly frequency. To facilitate the interpretation of the coefficients, we divide these measures based on the quartiles and use the categorical values (0, 1, 2, 3). In all columns, we include lender-, deal-, car family-, NUT3×year- fixed effects, and control for car value (in log form), borrower income, and the verification status of income. We additionally control for LTV and term of the loan. The sample period is January 2010 to August 2021 in both panels. Standard errors double clustered by security and NUTS3-level region are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 11: Technological Risks affect Residual Values

Panel A. intensity of clean patenting - ADHMV2016

	below origination RV (0/1)		RV (log)	
	(1)	(2)	(3)	(4)
EV × number of clean patents ADHMV2016 (log)	0.032***		−0.009***	
	(0.01)		(0.00)	
EV × share of clean patents ADHMV2016		0.028**		−0.004*
		(0.01)		(0.00)
loan FE	Y	Y	Y	Y
Year-month FE	Y	Y	Y	Y
mean outcome var.	0.296	0.296	9.384	9.384
Observations	20,891,354	20,891,354	20,734,647	20,734,647
R-sq	0.938	0.938	0.990	0.990

Panel B. dispersion in battery technology

	below origination RV (0/1)		RV (log)	
	(1)	(2)	(3)	(4)
EV × 1-HHI of battery bigrams (monthly)	0.022**		−0.006***	
	(0.01)		(0.00)	
EV × number of battery bigrams (monthly)		0.020**		−0.006**
		(0.01)		(0.00)
loan FE	Y	Y	Y	Y
Year-month FE	Y	Y	Y	Y
mean outcome var.	0.296	0.296	9.384	9.384
Observations	20,891,354	20,891,354	20,734,647	20,734,647
R-sq	0.938	0.938	0.990	0.990

Note.— This table shows the relationship between technological risks and the residual value estimates of EVs and non-EVs. Two measures related to residual values are constructed for each car over the course of the financing contract: an indicator for whether the residual value estimate in a given month is lower than that at loan origination (column 1 and 2) and the estimated residual value in log dollar terms (column 3 and 4). We interact various measures of EV-related technological risks with the EV indicator. In Panel A, we measure the intensity of innovation in EV-related technologies using the number (in log form) and the share of clean patents relative to all patents in the corresponding parent groups. In Panel B, we measure the dispersion in battery technology using the number (in log) and HHI of battery-related bigrams in the title of patents. All measures are constructed at the monthly frequency. To facilitate the interpretation of the coefficients, we divide these measures based on the quartiles and use the categorical values (0, 1, 2, 3). In all columns, we include loan and year-month fixed effects. The sample period is January 2010 to August 2021 in both panels. Standard errors double clustered by loan and calendar year-month are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Financing the Global Shift to Electric Mobility

Online Appendix

Jan Bena   Bo Bian   Huan Tang

A Classification of EVs, model family, and model pair

In this Appendix section, we describe the classification of EVs, car model family, and car model pairs. Different car manufactures follow different naming conventions. We refer to as "family" the series or the most general car model categories within a brand. For BMW, family will be the 1 to 8 series, X, Z, and i series. For Toyota, family will be the different car model names, like Corolla, Camry, and RAV4.

We refer to as "pair" the combination of family and engine displacement provided in the data field AA45. Models within the same pair are identical in all observable specifications except for motor type. When the displacement information is not provided in the original data, we code pair as missing. Therefore, the pair variable is only coded for loans with detailed car model specifications.

We manually code the EV indicator for all unique model names available in the EDW data, based on the combination of make, family, and model specifications in data field AA45. A car model is assigned a EV flag if it is plug-in hybrid (PHEV), non-plug-in hybrid (HEV), battery powered (BEV), and general hybrid (GHEV).

Below we illustrate how we classify family and pair using BMW as an example. Table A.1 shows the exhaustive list of model families and pairs that offer both EV and non-EV models. There are eight model families (series) that offer EV options. For example, in family "x3", BMW offers the non-EV version "x3 xDrive30d" and the EV counterpart "x3 xDrive30e". These two models only differ in the engine type, where *d* stands for diesel and *e* for electric.

Table A.1: BMW - EV Family and Pair

Family	Pair	Non-EV example	EV example
2er	2er 225	BMW 2-sarja 225 F45 Active Tourer 225i A xDrive Business Sport	BMW 2-SARJA F45 Active Tourer 225xeA Business Luxury Navi Plus Panorama Glass Roof Driving Asst. P
	2er active-tourer	2er-Reihe Active Tourer Diesel (F45	2er-Reihe Active T. Allrad Hybrid (
3er	3er 320	BMW 320 d A Luxury TwinPower Turbo F30 Sedan *Huipputarjous korko 2.9% ilman kuluja + kasko 0e vuode	BMW 320 F31 Touring 320e A Business M Sport
	3er 330	BMW 330 Gran Turismo F34 330i A xDrive Gran Turismo Business Exclusive M Sport	BMW 3-SARJA F30 Sedan 330eA Business Exclusive Edition Sport Navi HiFi
	3er 335	BMW 335 I A E93 CABRIO **OIKEALLA V?RILL? JA VOIMAKONEELLA**	BMW 335i ACTIVEHYBRID SEDAN A
	3er f30	BMW 3-sarja F30 Sedan A xDrive Business Exclusive	3er-Reihe Hybrid (F30)
5er	5er 520	BMW 5-SARJA 520d Turbo A F11 Touring Busin Auto Luxury Line / Navi / HIFI / Vetokoukku / Mukautuvat	520 ACTIVE HYBRID GA
	5er 530	BMW 530 F07 Gran Turismo TwinPower Turbo M-Sport xDrive 190Kw Autom. Webasto Prof.Navi Comfort Ac	BMW 5-SARJA G30 Sedan 530e A iPerformance Launch Edition Sport # 20 -tuumaset / HIFI / Sport-Line
	5er 545	BMW 545 IA E60/N62	545e xDrive Limousin
	5er f10	BMW 5-sarja i TwinPower Turbo F10 Sedan Busi18	SERIE 5 F10 ACTIVEHYBRID 5
	5er g30	5er-Reihe Diesel Allrad (G30)	5er-Reihe Hybrid Allrad (G30)
	5er g31	5er-Reihe Kombi Allrad Diesel (G31)	5er-Reihe Kombi Hybrid Alrrad (G31)
7er	7er 730	BMW 730 D TwinPower Turbo AUT FACELIFT K. WEBASTO ADAPT.	730I Active Hybrid
	7er 740	BMW 740 D AUT XDRIVE M-SPORT LASERVALOT BMW HUOLTOSOPIMU	BMW 7-sarja 740 Le iPerformance A xDrive G12 Sedan Business Exclusive M-Sport Automaatti Neliveto
	7er 745	Baureihe 7 (E65/E66) (2001->) 745i	BMW 745Le xDrive Sedan (AA) 4ov 2998cm3 A
	7er f01	7er-Reihe Allrad Diesel (F01)	7er-Reihe Hybrid (F01)
	7er f02	7er-Reihe Allrad Diesel (F02)	7er-Reihe Hybrid (F02)
	7er g11	7er-Reihe Allrad Diesel (G11)	7er-Reihe Hybrid (G11)
x1	x1 25	BMW X1 xDrive25d TwinPower Turbo A E84 Business Sport 160kW	BMW X1 F48 xDrive25e A Charged Edition M Sport
x2	x2 25	X2 25D XDRIVE MSPORT AUTO	BMW X2 F39 xDrive 25e A Charged Edition M sport
x3	x3 30	BMW X3 xDrive30d TwinPower Turbo A F25 M-Sport - Lhes kaikin saatavissa olevin varustein-	BMW X3 xDrive30e Farmari (AC) 4ov 1998cm3 A
x5	x5 40	BMW X5 xDrive40d A TwinPower Turbo E70 SAV - HUD - IMUOVET - Adaptiivinen vakkari	BMW X5 F15 xDrive40e PURE EXCELLENCE ADAPT. LED-AJOVALOT 360-KAMERAT PANORAMA COMFORT-PENKIT NA
	x5 f15	X5-Reihe Diesel Allrad (F15)	X5-Hybrid (F15)

Table A.2: Toyota - EV Family and Pair

Family	Pair	Non-EV example	EV example
auris	auris 18	Toyota TOYOTA AURIS Monikyttajoneuvo (AF) 4ov 1364cm3	Toyota Auris 1 8 HSD Linea Sol Plus 5ov. Nyt korko 2 9% ilman kuluja ja kasko 0EUR vuodeksi 5.-10.9
camry	camry 25	Camry Business Edition 2,5-l-VVT-i, 131 kW (178 PS) Limousine Stufenloses Automatikgetriebe	Camry Business Edition Hybrid: 2,5-l-VVT-i, 131 kW (1 Limousine Stufenloses Automatikgetriebe
chr	chr 18	CHR ADVANCE 122 CC	TOYOTA C-HR 1 8 Hybrid Premium Edition Musta-ruskea osanahkaverhoilu - Bi-LED-ajovalot - Navi - L
	chr 20	C-HR Style Selection 2,0	Toyota C-HR 2 0 Hybrid Limited Launch Edition
corolla	corolla 18	Toyota COROLLA VERSO 1.8 VVT-i Sol LOHKO+SP KAHDET HYVT RENKAAT AUT. ILMASTOINTI HYV HK SUOMIA	Corolla Business Edition 1,8-l-Hybrid Touring Sports Stufenloses Automatikgetriebe
	corolla 20	Toyota Corolla Verso 2 0 D-4D 116 Linea Sol 7p Business	Corolla Business Edition 2,0-l-Hybrid Touring Sports Stufenloses Automatikgetriebe
rav4	rav4 25	RAV 4 2.5 HDF SQUARE COLLECTION+FP	Toyota RAV4 2 5 Hybrid AWD Premium - Vetokoukku Adaptiivinen vakionopeudensdin Peruutuskamera N
yaris	yaris 15	Yaris Style Selection White 1,5-l -VVT-iE 5-TÃŒrer stufenloses Automatikgetriebe	TOYOTA Yaris 1 5 Hybrid Launch Edition 5ov Toyota Touch with Go -mediakeskus suomenkielisell na

Table A.3: Volkswagen - EV Family and Pair

Family	Pair	Non-EV example	EV example
golf	golf 10	Volkswagen GOLF Variant Comfortline 1 0 TSI 85 BLUEM DSG - Suomiauto 1-omistaja Lohkolmmitin	VOLKSWAGEN Golf Variant Variant 1 0 eTSI (MHEV) 81 kW DSG-automaatti
	golf 14	VOLKSWAGEN Golf Variant Comfort 1.4 Tsi 103 kw Dsg-aut Nyt korko 2 9% ilman kuluja + kasko 0 e vuode	Volkswagen GOLF GTE 1.4 TSI 150kW/204hv DSG-AUTOMAATTI
	golf 15	VOLKSWAGEN Golf Sportsvan Comfortline 1 5 TSI EVO 96 kW (130 hv) DSG-automaatti Football Edition	VOLKSWAGEN GOLF First Edition 1 5 eTSI 110 kW (MHEV) DSG-automaatti
jetta	jetta 14	VOLKSWAGEN Jetta Comfort 1 4 TSI 92 kW (125 hv) Blue-Motion Technology DSG-automaatti	VOLKSWAGEN Jetta Hybrid 1 4 TSI 110 kW (150 hv) DSG-automaatti
passat	passat 14	Volkswagen Passat Variant Comfortline 1 4 TSI 90 kW (122 hv) DSG-automaatti BlueMotion Technology Hy	Volkswagen Passat 1.4 GTE Variant Plug-In Hybrid 160kW Autom.Navi LED-Valot Adapt.Cruise CarPlay
touareg	touareg 30	VOLKSWAGEN Touareg 3 0 V6 TDI 180 kW (245 hv) 4MOTION BlueMotion Technology Tiptronic-automaatti R-L	TOUAREG 3.0 HYB

Table A.4: Peugeot - EV Family and Pair

Family	Pair	Non-EV example	EV example
3008	3008 16	PEUGEOT 3008 Active Pack 120 VTi (Korko 1 69% ja 1. er? kes?kuussa!)	3008 1.6 HYBRID ALLURE PACK E-EAT8
	3008 20	3008 BUSINESS PACK 2.0L HDI 150CH FAP BVM6 +OPT	3008 HYBRID4 104G 2.0L HDI 163 CH FAP BMP6 +ACC
308	308 16	PEUGEOT 308 SW Premium Plus 1.6 HDi 110 FAP Korko 1 69% ja 1. er? kes?kuussa!	308 1.6 PureTech 225 SW GT Kb
508	508 16	Peugeot 508 1.6 8V E-HDI ALLURE S&S ""CIEL"" SW ROBO	508 SW 1.6 HYBRID GT LINE E-EAT8
	508 20	Peugeot 508 2.0 16V HDI ACTIVE ""CIEL"" 163CV SW AUT	508 RXH 2.0 HDI HYBRID4 LIMITED EDITION

Table A.5: Hyundai - EV Family and Pair

Family	Pair	Non-EV example	EV example
i30	i30 16	Hyundai I30 1 6 GDI ISG iNNOVATION **Korko 1% ja 3 kk lyhennysvapaata**	i30 Kombi 1.6 CRDI 48V-Hybrid DCT N-Line
kona	kona 10	Hyundai Kona Monikyttajoneuvo (AF) 5ov 998cm3 1.0 TGDI FRESH MY 20	Hyundai Kona N-Line 1.0 T-GDI Hybrid 48V
	kona 16	HYUNDAI Kona 1.6 T-GDI 177 hv 4WD 7-DCT-aut. Comfort MY19 WLTP	Hyundai KONA 1 6 hybrid 141 hv 6-DCT Comfort MY20
tucson	tucson 20	Hyundai 5D TUCSON MPV 2.0 J-81BP-4X4/263 2.0i GLS 4WD A/C	HYUNDAI Tucson 2.0 CRDi 48V hybrid 4WD 8AUT Premium Exclusive MY19

Table A.6: Lexus - EV Family and Pair

Family	Pair	Non-EV example	EV example
es	es 300	Lexus ES300 Executive	LEXUS ES300 2 5 Hybrid Comfort Navi
gs	gs 300	Lexus 4D GS300 SEDAN 3.0 AUTOMATIC-GRS190L-BETQHW/285	GS 300H NG LUXE 17
	gs 450	LEXUS GS450 0	Lexus GS 450h V6 Executive A KORKO NYT ALK.1 99%
is	is 200	LEXUS IS SALOON 200t F-Sport 4dr Aut	Lexus Is200h
	is 300	Lexus IS 300	LEXUS IS 300h F-SPORT PREMIUM SPORT+ ALUSTANS??T? AVAIMETON NAVI L?MM + ILMAST. S?HK. PENKIT MUIS
nx	nx 25	LEXUS NX 2.5H ECVT 4WD MY15	LEXUS NX ESTATE 300H 2.5 LUXURY 5DR
	nx 300	NX 300 EXECUTIVE	Lexus NX 300h Hybrid A AWD Executive NAHKAT NAVI LASIKATTO ACC CRUISE YMS.
rc	rc 300	RC 300	Lexus LEXUS RC300H Coup (AD) 2ov 2494cm3
rx	rx 400	LEXUSRX40033V6PRESIDENT	LEXUS RX 400hybrid 4WD Nyt korko 2.9% ilman kuluja +kasko 0e vuodeksi 1.7 saakka !
	rx 450	RX TOUS CHEMIN 450	LEXUS RX 450h Hybrid 4WD A F Sport Lhes kaikilla varusteilla / Led / ML Premium Surround / 360

Table A.7: Honda - EV Family and Pair

Family	Pair	Non-EV example	EV example
civic	civic 13	CIVIC 1.3 DSI I-VTEC HY.EL.EC	CIVIC 1.3 DSI I-VTEC HYBRID EXECUTIVE
	civic 14	HONDA Civic 1 4i Sport Business 5d *Korko 2 9 % ilman kuluja ja kasko vuodeksi 0 ? 10.9.asti *	HONDA Civic 4D 1.4i CVT AT Hybrid (ESITTELY)
crv	crv 20	HONDA CR-V 2 0i Elegance Plus Automaatti neliveto Xenon-valot lasikatto ym..	HONDA CR-V ESTATE 2000 2.0 I-MMD HYB
jazz	jazz 13	Jazz 1.3 CVT-Automatikgetriebe Comfort	Jazz 1,3 IMA Hybrid Exclusive CVT
	jazz 14	Honda JAZZ 1.4i LS 5d AT 1-OMISTAJALTA HUOLLETTU AUTOMAATTIVAIHTEINEN	JAZZ 1.4 HYBRID ELEGANCE

Table A.8: Ford - EV Family and Pair

Family	Pair	Non-EV example	EV example
cmax	cmax 20	Ford Grand C-Max 2 0 TDCi 163 hv PowerShift autom. Titanium Business A6 5-ovinen(webasto 7henk)	FORD Grand C-Max 2 0 TDCi 140 hv PowerShift autom. Titanium Business A6 5-ovinen
	cmax cb3	Grand C-Max (CB7)(2010->) Champions Edit	CMAX 2010 GD C-MAX 2TDCI140FAP
fiesta	fiesta 11	Ford Fiesta 1 1 85hv M5 Titanium 5-ov. Driving Asst. Pack 7 Comfort Pack 1 AAC	Fiesta Cool & Connect 1.1 l 63 kW / 85 P
	fiesta 12	Ford FIESTA Viistoper (AB) 4ov 1242cm3 1.2 Trend	FIESTA 3-TÃŒRER 1,2 44KW 5
	fiesta 125	Ford FIESTA VAN 1 25 82 Trend (MY13)Korko 1 9% ja 3 kk lyhennysvapaata	Fiesta Viva, 1.25 60 kW 5
	fiesta 13	Ford FIESTA 1.3i Ambiente 5-OVINEN! JUURI KATSASTETTU!	Fiesta 1.3 l 8V, 51 kW, 3
	fiesta 14	Ford FIESTA 1 4 96hv Titanium Autom 5ov **Korko 2 9% ja 1. er? hein?kuussa!**	FIESTA 1,4 59KW
focus	focus cb8	Focus Turnier (CB8)(2011->) Champions Ed	Focus Lim. (CB8)(2011->) ELECTRIC
galaxy	galaxy 22	Ford Galaxy 2 2TDCi 200 hv autom. Ghia Business A6 5-ovinen	FORD GALAXY 2,2 147KW
kuga	kuga 20	FORD Kuga 2 0 EcoBlue 190hv A8 AWD Titanium X Launch Edition 5-ovinen	FORD Kuga 2 0 TDCi 150 hv Diesel PowerShift AWD Titanium Business Automaatti NELIVETO
	kuga 25	Kuga 2,5 Turbo Titanium 4x4 Aut.	FORD Kuga 2 5 Ladattava hybridi (PHEV) 225hv CVT FWD Titanium X Launch Edition 5-ovinen
mustang	mustang 46	2D Mustang 4.6 GT Hatcbag -T82H/272	FORD MUSTANG 4.6 GT 235KW
puma	puma 10	Puma ST Line X 1.0 E	FORD Puma 1 0 EcoBoost Hybrid (mHEV) 155hv M6 ST-Line X Launch Edition 5-ovinen
transit	transit 125	AMBULANCE G-MAX TYPE A1 TRANSIT 125CV FINITION TRE	FORD Transit Custom 340 (1 0 EcoBoost 125 hv) PHEV 1-AUTO Etuveto Trend Van N1 L1H1
	transit 20	FORD Transit Van etuveto 300M 2 0TDI 100 av.3300. Nyt korko 2 9% ilman kuluja ja kasko 0EUR vuodeksi	FORD Transit Custom 320 2 0TDCi 130 hv mHEV M6 Etuveto Trend Van N1 L2H1

Table A.9: Volvo - EV Family and Pair

Family	Pair	Non-EV example	EV example
v60	v60 d2	Volvo V60 D2 Momentum Business A (MY13.4)	Volvo V60 PLUG IN HYBRID 2.4D Autom.
	v60 d3	Volvo V60 D3 Automat. City Safety Webasto Vetokoukku 2alut. Hihna vaihdettu	V60 T6 AWD 304ch Summum Gear
	v60 d5	VOLVO V60 D5 Momentum A *Korko 2 9% ilman kuluja ja ilmainen kasko vuodeksi 31.7.asti*	VOLVO V60 D5 AWD Plug in hybrid
	v60 d6	Volvo V60 D6 AWD Pure Edition nro.53 VOC + Driver Support	Volvo V60 D6 AWD Twin Engine R-Design plug in hybrid 162kW Autom. Webasto Navi P.kamera Volvo on
v70	v70 d5	Volvo V70 D5 AWD Summum aut. AC seats Dynaudio Premium Audio BLIS Adaptive Cruise Bluetooth.	Volvo 5D 5D V70 Plug In Hybrid
xc90	xc90 20	VOLVO XC90 DIESEL ESTATE 2.0 D5 Powe	VOLVO XC90 2.0 T8 Plug-in Hybrid Inscription ACC 7-paik

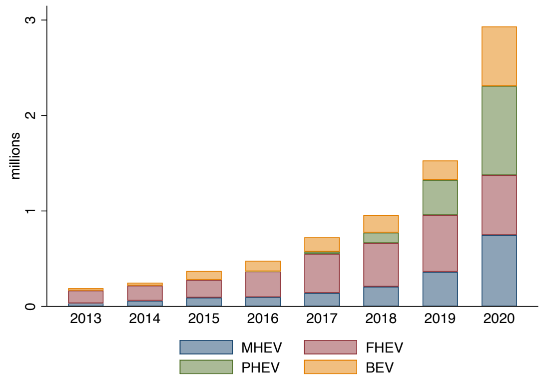
Table A.10: Mercedes - EV Family and Pair

Family	Pair	Non-EV example	EV example
aclass	a250	MERCEDES-BENZ A 250 BE A AMG-LINE 211HV *KUNNON KARKKI! NIGHT PANORAMA HARMAN KARDON ILS COMAND	MERCEDES-BENZ A 250 e A sedan Business Style Edition EQ Power
bclass	b180	Mercedes-Benz B 180 CDI 5d Autom. Siisti kuntoinen Suomi-Auto Rahoituskorko alk.1 9 % voimassa 31.1	B-Klasse (BM 246)(11.2011->) B 180 Score
	b250	Classe B / B 250 AUTOMATIC 4MATIC PREMIUM	MERCEDES-BENZ B 250 Electric Drive Aut
cclass	c200	MERCEDES-BENZ C 200 CDI BE A Premium Business Facelift Korko 1 95 / kotiintoimitus 0 EUR / ILS /	Mercedes-Benz C 200 T A Hybrid Business Avantgarde
	c205	MERCEDES-BENZ C-farmari (S205) Mercedes-AMG C 43 4Matic T A WLTP	C-Klasse Kombi Diesel/Hybrid (S205)
	c300	MERCEDES-BENZ C 300 CDI BE T 4MATIC A AVANTGARDE KORKO 1.9%	MERCEDES-BENZ C 300 e 4Matic A Business Avantgarde Edition EQ Power
	c350	Mercedes-Benz C 350 CDI 4MATIC Farmari (AC) 4ov 2987cm3 A	MERCEDES-BENZ C 350 E AUTOMAT TOURING AVANTGARDE NAVIGAATTORI BURMESTER AUDIO 360 KAMERA ILS-VAL
eclass	e212	E-Klasse Kombi Diesel Allrad (W212)	E-Klasse Kombi Diesel/Hybrid (W212)
	e213	E-Klasse Kombi Diesel Allrad (W213)	E-Klasse Diesel Hybrid (W213)
	e250	Mercedes-Benz E 250 CDI BE Avantgarde 204 hv Autom. AMG-Sport Pack SUOMI-AUTO ! LUUTA LAKAISI HINNA	E 250 Elegance BlueEfficiency CDI Aut.
	e300	MERCEDES-BENZ E 300 Bluetec 7G-Tronic Plus Avantgarde	Mercedes-Benz E 300 de A AMG-Line EQ Power Plug In Hybrid Distronic Plus Widescreen HUD 360 Pan
	e350	Mercedes-Benz E 350 CDI BE A Tydellinen merkkiliikeen huoltohistoria Kilometreihin nhden hienoss	MERCEDES-BENZ E 350 AVANTGARDE Limousine Plug-in Hybrid Benzin/Elektro AMG AMG Styling paketti -
gla	gla 250	MERCEDES-BENZ GLA 250 4Matic A Premium Business	MERCEDES-BENZ GLA 250 e A Business EQ Power
glc	glc 253	GLC CoupÃ© Diesel Allrad (C253)	GLC CoupÃ© Hybrid Allrad (C253)
	glc 300	MERCEDES-BENZ GLC 300 d 4Matic A Business Facelift	Mercedes-Benz C GLC 300 e 4MATIC Viistoper (AB) 5ov 1991cm3 A
	glc 350	MERCEDES-BENZ GLC GLC 350 D 4MATIC Viistoper (AB) 5ov 2987cm3 A	Mercedes-Benz GLC 350 e 4Matic Luxury Package Burmester Sporttinahat IHC+ Comand 360
gle	gle 350	Classe GLE / GLE 350 D 4M EXCLUSIVE PLUS (DA1/DA2) COUP+	MERCEDES-BENZ GLE 350 350e COUPE 4MATIC EQ POWER
	gle 500	Mercedes Benz GLE 500 0	MERCEDES-BENZ GLE 500 e 4matic A 442hv Ladattava Hybridi Airmatic Tutkat Park Assist Kulutus 3
sclass	s221	MERCEDES-BENZ S 4D S 500 SEDAN 4MATIC-221186-4X4/317	S-Klasse Lang Hybrid (V221)
	s222	S-Klasse Lang Allrad Diesel (W222)	S-Klasse Lang Hybrid (V222)
	s300	S 300	Mercedes-Benz S 300 BLUETEC HYBRID Sedan (AA) 4ov 2143cm3 A
	s400	Classe S / S 400D 4MATIC PREMIUM PLUS	Mercedes-Benz S 400 HYBRID Sedan 0
	s500	Mercedes-Benz S 500 4MATIC Sedan (AA) 4ov 4663cm3 A	Mercedes-Benz S 500 PLUG IN HYBRID Sedan (AA) 4ov 2996cm3 A
	s560	Classe S / S 560 PREMIUM PLUS	MERCEDES-BENZ S S 560 e Sedan (AA) 4ov 2996cm3 A

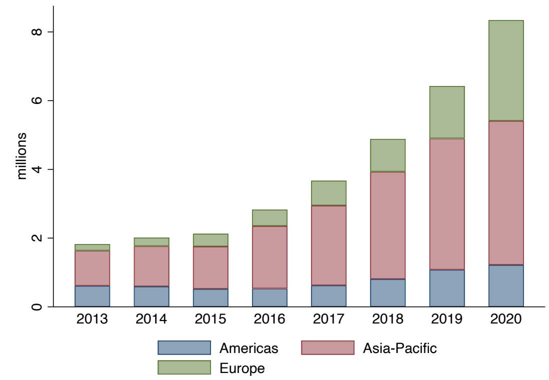
B EV Growth

B.1 Sales by vehicle type and region

a. Europe only

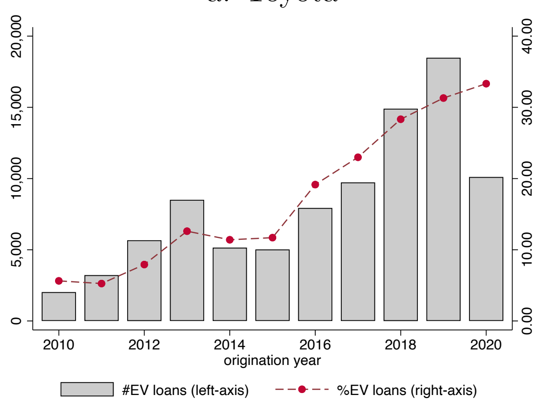


b. Worldwide

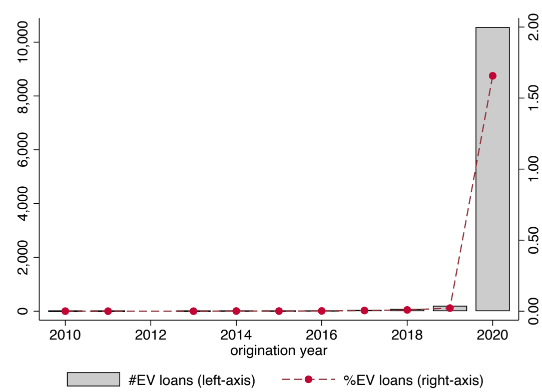


B.2 Loans by make

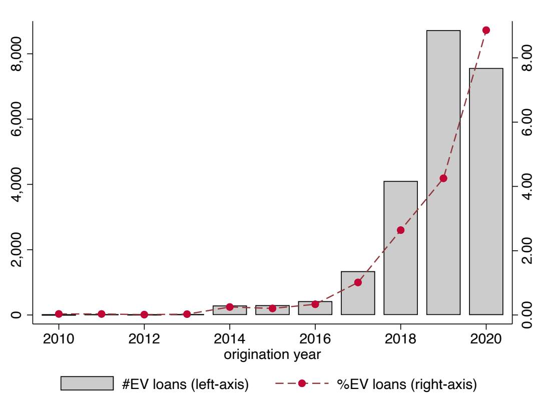
a. Toyota



b. Volkswagen



c. BMW



d. Peugeot

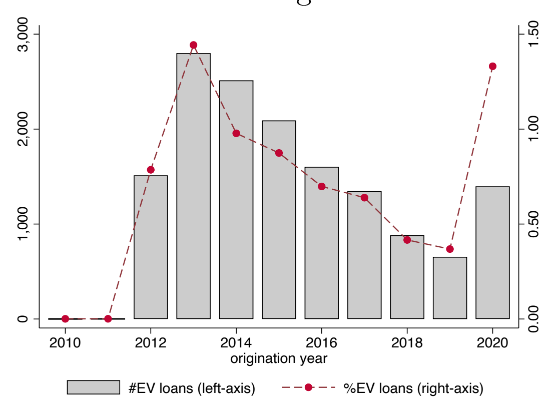


Table B.1: Loan Characteristics by Vehicle Type

Panel a. EV loans

	mean	sd	p10	p25	p50	p75	p90	count
rate	4.552	1.90	3.00	3.50	4.00	5.50	6.90	182,567
LTV	70.231	24.19	37.46	52.04	75.00	90.00	100.00	159,432
maturity	46.131	14.52	35.00	36.00	48.00	60.00	60.00	180,934
car value (log)	9.902	0.55	9.19	9.57	9.92	10.30	10.54	182,567
income (log)	10.262	0.81	9.39	10.04	10.24	10.69	11.18	128,028
income verified	0.327	0.47	0.00	0.00	0.00	1.00	1.00	182,567
non-performing or repurchased by seller	0.085	0.28	0.00	0.00	0.00	0.00	0.00	182,567
non-performing	0.042	0.20	0.00	0.00	0.00	0.00	0.00	182,567
arrears	0.041	0.20	0.00	0.00	0.00	0.00	0.00	182,567
default	0.004	0.06	0.00	0.00	0.00	0.00	0.00	182,567
redeemed	0.190	0.39	0.00	0.00	0.00	0.00	1.00	182,567

Panel b. non-EV loans

	mean	sd	p10	p25	p50	p75	p90	count
rate	4.949	2.46	2.00	3.50	4.99	6.00	8.50	15,068,693
LTV	82.964	24.09	48.00	70.00	90.00	100.00	100.00	14,398,559
maturity	47.126	14.60	36.00	36.00	48.00	49.00	60.00	15,017,068
car value (log)	9.626	0.61	8.86	9.28	9.66	10.04	10.34	15,068,693
income (log)	10.181	0.73	9.41	9.80	10.17	10.62	11.00	8,179,249
income verified	0.449	0.50	0.00	0.00	0.00	1.00	1.00	15,068,693
non-performing or repurchased by seller	0.075	0.26	0.00	0.00	0.00	0.00	0.00	15,068,693
non-performing	0.047	0.21	0.00	0.00	0.00	0.00	0.00	15,068,693
arrears	0.045	0.21	0.00	0.00	0.00	0.00	0.00	15,068,693
default	0.008	0.09	0.00	0.00	0.00	0.00	0.00	15,068,693
redeemed	0.388	0.49	0.00	0.00	0.00	1.00	1.00	15,068,693

Note.—This table presents summary statistics for our key explanatory and outcome variables. Panel a. includes EV loans and Panel b non-EV loans. The sample period is January 2010 to August 2021.

Table B.2: Warranty Summary

manufacturer	power type	after year	coverage	components	months	distance km
BMW	green - hybrid/electric	2022	powertrain - battery	Extensive Battery Warranty	96	160000
BMW	green - hybrid/electric	2022	powertrain - used	Powertrain Limited Warranty - Certified Pre-Owned Hybrid/Electric (from the vehicle in-service date)	60	unlimited
Ford	green - hybrid/electric	2022	powertrain	hybrid/electric unique components	96	160000
Honda	green - hybrid/electric	2022	powertrain	Hybrid system	36	60000
Honda	green - hybrid/electric	2022	powertrain	Hybrid system (some parts, see mannual p13-14)	96	160000
Hyundai	green - hybrid/electric	2019	powertrain	HEV and PHEV system	96	160000
Hyundai	green - hybrid/electric	2019	powertrain	EV system	96	160000
Lexus	green - hybrid/electric	NA	powertrain	Hybrid-related components	96	160000
Lexus	green - hybrid/electric	NA	powertrain - battery	Hybrid High Voltage battery	120	240000
Mercedes	green - hybrid/electric	NA	overall	EQB SUV	96	160000
Mercedes	green - hybrid/electric	NA	overall	EQE, EQS	120	250000
Peugeot	green - hybrid/electric	NA	powertrain - battery	traction battery	96	unlimited
Toyota	green - hybrid/electric	2023	powertrain	Hybrid-Related Components Warranty (includes Battery Control Module, Hybrid Control Module, Inverter with Converter)	96	160000
Toyota	green - hybrid/electric	2023	powertrain - battery	Hybrid Battery Warranty	120	240000
Toyota	green - hybrid/electric	2023	powertrain	BEV Specific Components Warranty (inlcudes Transaxle, Inverter with Converter)	96	160000
Toyota	green - hybrid/electric	2023	powertrain - battery	Electric Vehicle Battery Warranty	96	160000
Toyota	green - hybrid/electric	2023	powertrain - battery	Electric Vehicle Battery Capacity Warranty (applied to battery capacity below 70% of original capacity)	96	160000
Volkswagen	green - hybrid/electric	NA	overall	New Vehicle Limited Warranty (wear & tear items and adjustments excluded after initial 12 months / 20,000 km)	48	80000
Volkswagen	green - hybrid/electric	NA	powertrain	Mechanical Powertrain	60	100000
Volkswagen	green - hybrid/electric	NA	powertrain - battery	High Voltage System Limited Warranty	96	160000
Volvo	green - hybrid/electric	2022	powertrain - battery	any material defect of the hybrid Lithium battery pack (Loss of battery capacity due to or resulting from normal gradual capacity loss is not covered)	96	150000

Table B.2: Warranty Summary - Cont'd

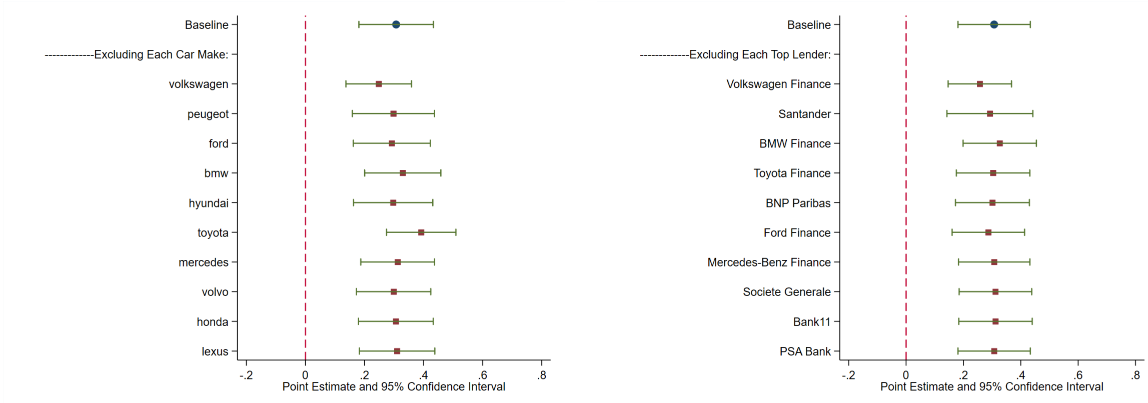
manufacturer	power type	after year	coverage	components	months	distance km
BMW	all	2022	overall	Basic New Vehicle Limited Warranty	48	80000
Ford	all	2022	overall	Basic New Vehicle Limited Warranty	36	60000
Ford	all	2022	powertrain	powertrain	60	100000
Ford	conventional - diesel	2022	powertrain	diesel engine	60	160000
Ford	conventional - diesel	2022	powertrain	diesel engine unique powertrain	60	160000
Honda	all	2022	powertrain	Powertrain	60	100000
Honda	all	2022	overall	basic new vehicle parts (distributor's warranty)	36	60000
Honda	all	2022	powertrain - battery	battery 100%	24	unlimited
Honda	all	2022	powertrain - battery	battery 50% retail price (excluding labor)	36	unlimited
Hyundai	all	2019	overall	Basic New Vehicle Limited Warranty	60	100000
Hyundai	all	2019	powertrain	Powertrain	60	100000
Hyundai	all	2019	powertrain - battery	battery	24	40000
Lexus	all	NA	overall	Comprehensive Coverage (any original Lexus part)	48	80000
Lexus	all	NA	powertrain	Powertrain & Safety Restraints	72	110000
Mercedes	all	2014	overall	Basic New Vehicle Limited Warranty	48	80000
Peugeot	all	NA	overall	Defective parts, except normal wear and tear	36	unlimited
Toyota	all	2023	overall	Basic New Vehicle Limited Warranty	36	60000
Toyota	all	2023	powertrain	Powertrain New Vehicle Limited Warranty (Hybrid Transaxle (w/motors) is covered by Powertrain Warranty)	60	100000
Volkswagen	conventional	2018	overall	New Vehicle Limited Warranty (wear & tear items and adjustments excluded after initial 12 months / 20,000 km)	48	80000
Volkswagen	conventional	2018	powertrain	Powertrain Limited Warranty	60	100000
Volvo	all	2022	overall	any component failure attributable to faulty materials or workmanship during manufacture	36	100000

C Additional Robustness Checks

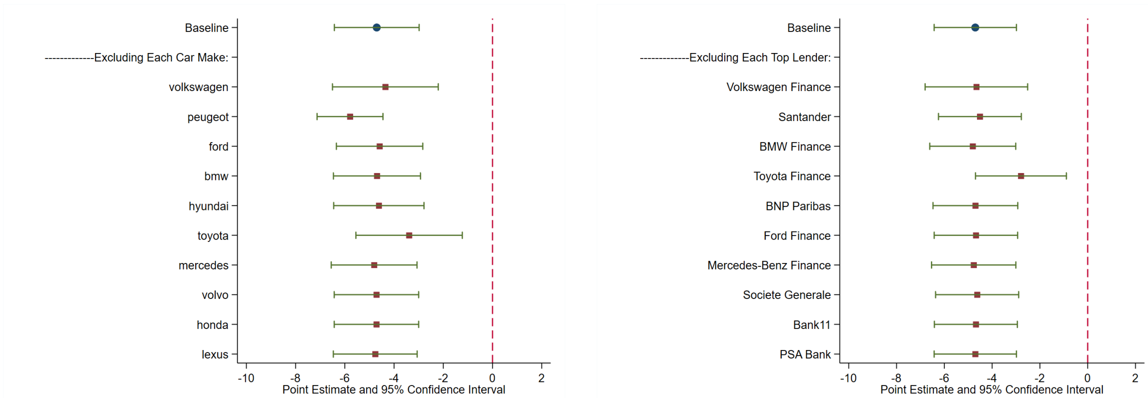
Figure C.1: Robustness Checks Across Makes and Lenders

Make **Lender**

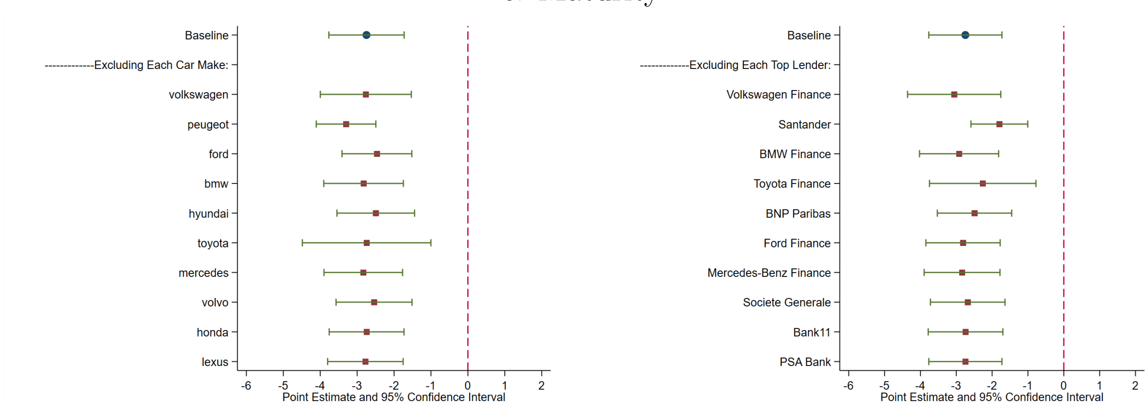
a. Interest Rate



b. LTV



c. Maturity



NOTE.—Figure C.1 presents the point estimates of the EV indicator using alternative regression samples, in which we exclude one significant car manufacturer or lender at a time. We study each of the following three outcome variables: interest rate (panel a), LTV (panel b), and maturity (panel c).

D Additional Measures of WTP and Macroeconomic Factors

Table D.1: WTP for EVs does not Explain the EV Spread: Vehicle Price

	interest rate		
	(1)	(2)	(3)
EV	0.157*	0.238**	0.280***
	(0.08)	(0.11)	(0.09)
EV × EV price premium	0.007		
	(0.04)		
EV × Overpay (family-year)		0.044	
		(0.04)	
EV × Overpay (family-year-NUTS3)			0.024
			(0.03)
lender FE	Y	Y	Y
deal FE	Y	Y	Y
family FE	Y	Y	Y
nuts3 × year FE	Y	Y	Y
borrower controls	Y	Y	Y
loan controls	Y	Y	Y
Observations	633,339	2,245,924	2,245,920
R-sq	0.839	0.792	0.792

NOTE.— This table shows that consumers' WTP for EVs do not explain the EV spread in financing terms. We interact various measures of WTP for the vehicles with the EV indicator. These measures include the average price difference between EV and non-EVs within the same model in a given year (column 1), the difference between the purchase price and average price of cars in the same family-engine-type combination in the same year (column 2), and the difference between the purchase price and average price of cars in the same family-engine-type combination in the same year and NUTS3-level region (column 3). To facilitate the interpretation of the coefficients, we divide these measures based on the quartiles and use the categorical values (0, 1, 2, 3). In all columns, we include lender-, deal-, car family-, NUT3×year- fixed effects, and control for car value (in log form), borrower income, and the verification status of income. We additionally control for LTV and term of the loan. The sample period is January 2010 to August 2021 in both panels. Standard errors double clustered by deal and NUTS3-level region are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table D.2: WTP for EVs does not Explain the EV Spread: Media Climate Change Concerns Index

	interest rate				
	(1)	(2)	(3)	(4)	(5)
EV	0.257**	0.268***	0.259***	0.253**	0.354***
	(0.10)	(0.09)	(0.09)	(0.11)	(0.06)
EV × MCCC index - aggregate	0.038				
	(0.04)				
EV × MCCC subindex - bus. impact		0.034			
		(0.03)			
EV × MCCC subindex - environ. impact			0.037		
			(0.04)		
EV × MCCC subindex - societal debate				0.041	
				(0.05)	
EV × MCCC subindex - research					−0.015
					(0.02)
lender FE	Y	Y	Y	Y	Y
deal FE	Y	Y	Y	Y	Y
family FE	Y	Y	Y	Y	Y
nuts3 × year FE	Y	Y	Y	Y	Y
borrower controls	Y	Y	Y	Y	Y
loan controls	Y	Y	Y	Y	Y
Observations	7,458,362	7,458,362	7,458,362	7,458,362	7,458,362
R-sq	0.728	0.728	0.728	0.729	0.728

NOTE.— This table shows that consumers' WTP for EVs do not explain the EV spread in financing terms. We measure WTP for EV using the Media Climate Change Concerns Index from Ardia et al. (2022). The MCCC index is a proxy for unexpected changes in climate change concerns computed from news articles. We interact various MCCC indexes with the EV indicator. From column 1 to column 5, we use the aggregate MCCC index, the subindexes based on the business impact theme, the environmental impact theme, the societal debate theme, and the research theme, respectively. To facilitate the interpretation of the coefficients, we divide these measures based on the quartiles and use the categorical values (0, 1, 2, 3). In all columns, we include lender-, deal-, car family-, NUT3×year- fixed effects, and control for car value (in log form), borrower income, and the verification status of income. We additionally control for LTV and term of the loan. The sample period is January 2010 to August 2021 in both panels. Standard errors double clustered by deal and NUTS3-level region are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table D.3: Macroeconomic Factors do not Explain the EV Spread

	interest rate					
	(1)	(2)	(3)	(4)	(5)	(6)
EV	0.434***	0.443***	0.303***	0.308***	0.326***	0.305***
	(0.09)	(0.09)	(0.05)	(0.06)	(0.07)	(0.11)
EV × T10Y3M	−0.108					
	(0.08)					
EV × AAAFF		−0.117				
		(0.09)				
EV × AAABAA			0.017			
			(0.02)			
EV × VIXCLS				0.013		
				(0.02)		
EV × SPXret					0.001	
					(0.01)	
EV × Crude Oil return						0.015
						(0.03)
lender FE	Y	Y	Y	Y	Y	Y
deal FE	Y	Y	Y	Y	Y	Y
family FE	Y	Y	Y	Y	Y	Y
nuts3 × year FE	Y	Y	Y	Y	Y	Y
borrower controls	Y	Y	Y	Y	Y	Y
loan controls	Y	Y	Y	Y	Y	Y
Observations	7,458,362	7,458,362	7,458,362	7,458,362	7,458,362	7,458,362
R-sq	0.728	0.728	0.728	0.728	0.728	0.728

Note.—This table shows that macroeconomic factors do not explain the EV spread. We interact various macroeconomic factors with the EV indicator. In all columns, we include lender-, deal-, car family-, NUT3×year- fixed effects, and control for car value (in log form), borrower income, and the verification status of income. We additionally control for LTV and term of the loan. The sample period is January 2010 to August 2021 in Panels a and b and January 2015 to August 2021 in Panel c. Standard errors double clustered by deal and NUTS3-level region are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

E Alternative Measures of Technological Risk

Table E.1: Battery Technological Risks and the EV Spread: Clean Patents Expanded

Panel A. The number of clean patents (in log form) - ADHMV2016 expanded

	interest rate			
	(1)	(2)	(3)	(4)
EV	−0.018	−0.014	−0.091	−0.079
	(0.11)	(0.12)	(0.11)	(0.13)
EV × number of clean patents (log)	0.221***	0.211***	0.210***	0.201***
	(0.04)	(0.04)	(0.04)	(0.04)
baseline FE, borrower&loan controls	Y	Y	Y	Y
EV × demographic controls		Y		Y
EV × competition controls			Y	Y
Observations	2,816,501	2,816,501	2,816,501	2,816,501
R-sq	0.805	0.805	0.805	0.805

Panel B. The share of clean patents - ADHMV2016 expanded

	interest rate			
	(1)	(2)	(3)	(4)
EV	−0.350**	−0.337**	−0.362**	−0.346**
	(0.14)	(0.16)	(0.15)	(0.17)
EV × share of clean patents	0.326***	0.315***	0.311***	0.301***
	(0.06)	(0.06)	(0.06)	(0.06)
baseline FE, borrower&loan controls	Y	Y	Y	Y
EV × demographic controls		Y		Y
EV × competition controls			Y	Y
Observations	2,816,501	2,816,501	2,816,501	2,816,501
R-sq	0.805	0.805	0.805	0.805

NOTE.— This table shows the role of technological risks in explaining the EV spread. We interact various measures of EV-related technological risks with the EV indicator. In Panel a. we measure the intensity of innovation in EV-related technologies using the number of clean patents (in log form), and in panel b using the share of clean patents relative to all the patents in the corresponding parent groups (subclasses). Both measures are derived using the *expanded* classification of clean patents in Aghion et al. (2016). To facilitate the interpretation of the coefficients, we divide these measures based on the quartiles and use the categorical values (0, 1, 2, 3). We include the interaction terms of EV indicator and demographic variables (population density, GDP per capita, median age) in column 2, the interaction term of that with competition (segment HHI ($loans)) in column 3, and both in column 4. In all columns, we include lender-, deal-, car family-, NUT3×year- fixed effects, and control for car value (in log form), borrower income, and the verification status of income. We additionally control for LTV and term of the loan. The sample period is January 2010 to August 2021 in both panels. Standard errors double clustered by deal and NUTS3-level region are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table E.2: Battery Technological Risks and the EV Spread: VC Investments

Panel A. The dollar amount of VC investment in the EV-related firms (in log form)

	interest rate			
	(1)	(2)	(3)	(4)
EV	0.301***	0.285***	0.181**	0.180**
	(0.06)	(0.07)	(0.07)	(0.09)
EV × VC investment in EV (log)	0.068***	0.066***	0.065***	0.063***
	(0.01)	(0.01)	(0.01)	(0.01)
baseline FE, borrower & loan controls	Y	Y	Y	Y
EV × demographic controls	N	Y	N	Y
EV × competition controls	N	N	Y	Y
Observations	2,816,501	2,816,501	2,816,501	2,816,501
R-sq	0.805	0.805	0.805	0.805

Panel B. The share of dollar amount of VC investment in the EV-related firms

	interest rate			
	(1)	(2)	(3)	(4)
EV	0.330***	0.311***	0.201***	0.198**
	(0.06)	(0.07)	(0.07)	(0.09)
EV × share of VC investment in EV	0.054***	0.053***	0.054***	0.054***
	(0.01)	(0.01)	(0.01)	(0.01)
baseline FE, borrower & loan controls	Y	Y	Y	Y
EV × demographic controls	N	Y	N	Y
EV × competition controls	N	N	Y	Y
Observations	2,816,501	2,816,501	2,816,501	2,816,501
R-sq	0.805	0.805	0.805	0.805

NOTE.— This table shows the role of technological risks in explaining the EV spread. We interact various measures of EV-related technological risks with the EV indicator. In Panel a. we measure the intensity of innovation in EV-related technologies using the dollar amount of VC investment in the EV-related firms (in log form), and in panel b using the share of dollar amount of VC investment in the EV-related firms relative to all firms. To facilitate the interpretation of the coefficients, we divide these measures based on the quartiles and use the categorical values (0, 1, 2, 3). We include the interaction terms of EV indicator and demographic variables (population density, GDP per capita, median age) in column 2, the interaction term of that with competition (segment HHI ($loans)) in column 3, and both in column 4. In all columns, we include lender-, deal-, car family-, NUT3×year- fixed effects, and control for car value (in log form), borrower income, and the verification status of income. We additionally control for LTV and term of the loan. The sample period is January 2010 to August 2021 in both panels. Standard errors double clustered by deal and NUTS3-level region are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

F The Role of EV Purchase Incentives

In this section, we consider the role of EV purchase incentives. We use hand-collected data on EV purchase tax credit and purchase subsidy to construct two indicators for the presence of EV purchase incentives. These indicators vary at the country-year level. Around 14% of the observations are subject to EV tax credit and 48% EV purchase subsidy.

In the tables below, we include the interaction terms between the EV indicators and the two purchase incentive indicators and find quantitatively similar results.

Table F.1: Technological Risks and the EV Spread: Intensity of Clean Patenting

Panel A. The number of clean patents (in log form) - ADHMV2016

	interest rate			
	(1)	(2)	(3)	(4)
EV	0.101	0.133	−0.000	0.072
	(0.10)	(0.08)	(0.10)	(0.09)
EV × number of clean patents ADHMV2016 (log)	0.162***	0.086***	0.156***	0.088***
	(0.03)	(0.02)	(0.03)	(0.02)
baseline FE, borrower & loan controls	Y	Y	Y	Y
EV × WTP controls	N	Y	N	Y
EV × competition controls	N	N	Y	Y
Observations	2,816,501	2,816,501	2,816,501	2,816,501
R-sq	0.805	0.805	0.805	0.805

Panel B. The share of clean patents relative to all auto patents - ADHMV2016

	interest rate			
	(1)	(2)	(3)	(4)
EV	0.039	0.128	−0.048	0.067
	(0.08)	(0.09)	(0.09)	(0.09)
EV × share of clean patents ADHMV2016	0.169***	0.078***	0.161***	0.080***
	(0.02)	(0.03)	(0.02)	(0.02)
baseline FE, borrower & loan controls	Y	Y	Y	Y
EV × WTP controls	N	Y	N	Y
EV × competition controls	N	N	Y	Y
Observations	2,816,501	2,816,501	2,816,501	2,816,501
R-sq	0.805	0.805	0.805	0.805

NOTE.— This table follows the same structure as Table 9, except that in Columns 2 and 4, we additionally includes the interaction of the EV indicator with the indicators for EV purchase incentives that vary at the country-year level. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table F.2: Technological Risks and the EV Spread: Dispersion in Battery Technology

Panel A. HHI of the unique bigrams in battery patent titles

	interest rate			
	(1)	(2)	(3)	(4)
EV	0.170**	0.150**	0.079	0.101
	(0.08)	(0.07)	(0.08)	(0.08)
EV × 1-HHI of battery bigrams (monthly)	0.136***	0.084***	0.129***	0.084***
	(0.02)	(0.02)	(0.02)	(0.02)
baseline FE, borrower & loan controls	Y	Y	Y	Y
EV × WTP controls	N	Y	N	Y
EV × competition controls	N	N	Y	Y
Observations	2,816,501	2,816,501	2,816,501	2,816,501
R-sq	0.805	0.805	0.805	0.805

Panel B. number of unqiue bigrams in battery patent titles

	interest rate			
	(1)	(2)	(3)	(4)
EV	0.074	0.158**	−0.010	0.099
	(0.09)	(0.08)	(0.10)	(0.08)
EV × number of battery bigrams (monthly)	0.180***	0.076***	0.170***	0.078***
	(0.03)	(0.02)	(0.03)	(0.02)
baseline FE, borrower & loan controls	Y	Y	Y	Y
EV × WTP controls	N	Y	N	Y
EV × competition controls	N	N	Y	Y
Observations	2,816,501	2,816,501	2,816,501	2,816,501
R-sq	0.805	0.805	0.805	0.805

NOTE.— This table follows the same structure as Table 10, except that in Columns 2 and 4, we additionally includes the interaction of the EV indicator with the indicator for EV purchase incentives that vary at the country-year level. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.