Do ESG investors care about carbon emissions? Evidence from securitized auto loans*

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January 30, 2024

Abstract

Securitized auto loans present a clean empirical setting to study the effects of ESG investing on equilibrium asset prices and quantities. I estimate that the convenience yield of ESG investments increased almost threefold from 0.14% in 2017 to 0.39% p.a. in 2022. However, I document that ESG mutual funds invest more in auto ABS whose issuers have higher ESG scores, even if those securities finance higher emissions vehicles. The market's focus on ESG scores instead of CO_2 emissions lowers the cost of capital for high-emission auto ABS by 6%; likely driven by the positive correlation of ESG scores and emissions. These findings raise questions about the effectiveness of ESG investing in addressing environmental externalities.

JEL classification: G12, G18, G20, G41, Q56

Keywords: Auto ABS, Asset-backed securities, Carbon Emissions, Climate Change, Climate Finance, Corporate Social Responsibility, Environmental, Social, and Governance, Green bonds, Greenium, Green Finance, Sustainable investing, Responsible Investing, SRI, CSR, ESG

*I thank Joe Aldy (discussant), Hunt Allcot, Jonathan Berk, Sebastian Bauer, Elaine Buckberg, Darrell Duffie, Alex Edmans, Lawrence Goulder, Lars Hansen, Sebastian Hanson, Ben Hébert, Mete Kılıç (discussant), Hanno Lustig, Adrien Matray, Amit Seru, Ľuboš Pástor, Edward Watts, Oliver Xie, Luigi Zingales, as well as seminar and conference participants at Stanford GSB Finance Brown Bag, GEA Winter Meeting 2022, Stanford Environmental Economics and Energy Workshop, Advanced Financial Technology Lab, MFR UChicago Conference "Assessing the Economic and Environmental Consequences of Climate Change", Harvard Climate Economics Pipeline Workshop, and USC Marshall for helpful comments. All errors remain my own. First version: October 01, 2022

1 Introduction

Over the last decade, financial assets managed by funds using environmental, social, and governance (ESG) criteria have increased tenfold. Money managers report that the leading ESG criteria are climate change, carbon dioxide emissions, and fossil fuel divestment.[1] The goal of many ESG investors is to change financing conditions by rewarding "green" assets with a lower cost of capital and penalizing "brown" assets by raising their cost of capital.

The high financing intensity of durable goods, such as automobiles, makes changing their cost of capital a potentially powerful tool to increase the cost of emitting CO_2 in the absence of a formal carbon pricing mechanism. However, estimating whether investors' non-pecuniary preferences lower the cost of capital of green assets[2] is challenging. A clean measurement must hold exposure to risk factors constant while varying greenness. It must also quantify the true environmental impact of an investment to differentiate green from brown securities.[3]

This paper sheds light on whether ESG investing lowers the cost of capital for green assets and increases the cost of CO_2 emissions by addressing these challenges. To do so, I compare the cost of capital across senior tranches of automobile asset-backed securities (auto ABS). Auto ABS are highly standardized debt instruments that securitize pools of consumer auto loans. They present a unique setting to study the effects of ESG investing on equilibrium asset prices and quantities. Only a few parameters distinguish auto ABS deals from each other besides their collateral pool. Senior tranches of auto ABS are considered safe assets, similar to US treasurys (Gorton, 2017). I exploit the safe asset nature of senior tranches together with variables derived from loan-level data to hold risk factors across securities constant. I then test if the greenness of the security influences its cost of capital and the decision of investors to invest in it, using the fact that there is substantial variation of CO_2 emissions across collateral pools. Further, I am able to test the often implicit assumption that a green premium increases the cost of emitting CO_2, by comparing the impact of ESG scores and CO_2 emissions on the pricing of auto ABS.

I leverage loan-level data on the collateral pools of all publicly traded consumer auto loan ABS.[4] The data covers 281 auto ABS deals from 2017 to 2022, backed by the collateral of 19 million consumer loans. The securities are issued by 22 issuers, which are either captive lenders of vehicle

[1] USSIF (2022): Sustainable Investing – Money Managers 2022

[2] E.g., as in Heinkel, Kraus, and Zechner (2001), Pástor, Stambaugh, and Taylor (2021), Berk and van Binsbergen (2021), Pedersen, Fitzgibbons, and Pomorski (2021), Oehmke and Opp (2020), or Zerbib (2022).

[3] On the paucity of objective and standardized measures of greenness see Berg, Fabisik, and Sautner (2020) and Berg, Koelbel, and Rigobon (2022).

[4] There are other types of auto ABS that finance dealer inventories, corporate vehicle fleets, or consumer leases. I exclude these types of auto ABS from my sample because of their different risk characteristics.

manufacturers, banks, non-bank finance companies, or vehicle retailers. By merging data about the collateral at make, model, and year level with data on CO_2 emissions from the Environmental Protection Agency, I estimate the lifetime emissions of each vehicle in a collateral pool. The loan-level data further allow me to control for the predictors and ex-post performance of the collateral pools.

Two unique features of the securitization market allow me to rule out confounders that affect both exposure to risk factors and greenness in my effort to identify the causal effect of ESG investing on asset prices.[5] First, the security design of auto ABS reduces the number of risk factors, as prepayment is the main risk factor for AAA-rated senior tranches of consumer auto loans. Second, consumer and loan characteristics determine prepayment risk rather than the collateral itself. In other words, borrowers with high interest rate loans are more likely to prepay when interest rates fall, regardless of the collateral they finance. This distinction, combined with detailed loan-level data, enables me to disentangle the effects of environmental considerations on equilibrium prices and quantities. Loan-level data allows me to control for both ex-ante determinants and ex-post realizations of prepayment risk. Controlling for both predictors and ex-post performance at issuance together with high-dimensional fixed effects removes as much unobserved heterogeneity as possible. This identification strategy allows me to answer the following questions: once an investor can be sure that the loan they extend will be paid back at the agreed time, does the greenness of the deal influence their choice to invest and is this choice reflected in equilibrium prices?

A potential threat to identification is that CO_2 emissions or ESG scores might correlate with exposure to risk factors or predictors of cash flow growth. For example, if high-emission pools were less exposed to prepayment risk, then this would provide a rationale for investors to require a lower cost of capital. I therefore verify that neither emissions nor ESG scores predict prepayment at the collateral pool or at loan-level. This supports my identifying strategy and increases confidence that differences in the cost of capital are driven by factors unrelated to risk compensation, such as investors' non-pecuniary preferences.

I show that ESG investing successfully lowers the cost of capital of auto ABS for issuers with high ESG scores. However, I show that ESG mutual funds, relative to non-ESG, invest more in auto ABS whose issuers have higher ESG scores, even if those securities have a higher CO_2 emission intensity. The market's focus on ESG scores instead of the collateral's actual CO_2 emission lowers the cost of capital for high-emission auto ABS. These findings seem to be driven by the

[5] I use "ESG investing" as a shorthand to refer to all investment strategies that aim to address environmental externalities. Other often used terms for such investment strategies are sustainable investing, green investing, socially responsible investments (SRI), ethical investing, or corporate social responsibility (CSR) investing.

facts that commonly used ESG scores are positively correlated with CO_2 emissions, do not reflect the variability of emissions across issuers, and fail to account for Scope 3 emissions.[6]

I start by documenting the large cross-sectional dispersion of CO_2 emissions across auto ABS. For example, Auto ABS issued by Ally Bank finance an average of 55tCO_2 per vehicle, while ABS issued by Ford Credit finance an average of 95tCO_2 per vehicle. This implies that similar to a motorist's choice to buy a high-emission or a low-emission vehicle, an investor has the choice to invest in an auto ABS that finances high-emission or relatively low-emission vehicles.

Neither ESG nor environmental pillar scores capture the large differences in CO_2 emissions of auto ABS pools. On the contrary, both have a strong positive correlation with collateral pool emissions when not adjusted for industry differences. After adjusting for industry differences in ESG scores, the correlation is still positive, but not statistically greater than zero. Decomposing the variance of ESG scores and CO_2 emissions among captive lenders of manufacturers shows that both ESG and environmental scores vary considerably less across issuers than their actual emissions footprint.[7] That ESG and environmental scores vary considerably less than CO_2 emissions and are positively correlated with CO_2 emissions make them bad proxies for the environmental impact of auto ABS.

Using cross-sectional dispersion in CO_2 emissions and ESG scores, I show that estimates of the effects on the cost of capital and conclusions about ESG investors' goal of raising the cost of emitting CO_2 depend on whether it is possible to account for heterogeneity and risk-exposure across securities. In a *naïve* specification that only accounts for market conditions at issuance, auto ABS with emissions below the median have statistically significant *lower* issuance spreads between 14.0% to 25.0%. At the same time, issuers with ESG scores above the median also see a significant reduction in their issuance spreads of 26.8%, indicating that ESG and carbon pricing are aligned. However, this naïve specification fails to account for differences in prepayment risk and thus delivers a biased picture.

Instead, in regressions that control for prepayment risk, I find that *higher*-emission collateral pools have a *lower* cost of capital. Auto ABS with emissions above the median have 5.9% lower issuance spreads. Moving from the 20th percentile of emissions per US dollar to the 80th (a 1.85 standard deviation distance equivalent to comparing Toyota to Ford) reduces issuance spreads by 6 basis points (bps). The magnitude of this difference is economically meaningful compared

[6] Scope 3 measures indirect emissions that occur in the firm's upstream and downstream supply chain. Scope 3 emissions usually account for more than 70% of a firm's carbon footprint (UN Global Compact). Among vehicle manufacturers, Scope 3 downstream emissions are on average 41 times the Scope 1 and 2 emissions of production.

[7] While it is unclear how ESG scores of diversified banks reflect emissions of vehicle loans, one might expect that environmental scores of vehicle manufacturers reflect vehicle emissions. However, I find that this is not the case.

against the mean issuance spread of 42 bps. At the same time, auto ABS of issuers with above median ESG scores still have 9.8% lower issuance spreads, which is consistent with the positive correlation of ESG scores and emissions. Moving from the 20th to the 80th percentile of ESG scores (a 1.80 sd distance) reduces issuance spread by 9 bps. The finding that issuers with high ESG scores that want to finance high-emission auto ABS have a lower cost of capital is robust to using alternative measures, tranches, specifications, and estimators.

The difference in spreads among high and low ESG assets translates into a convenience yield that an investor with non-pecuniary preferences derives from their ESG investment. Crucially, this ESG convenience yield is fundamentally different from a risk premium: it generates seigniorage to issuers of ESG assets rather than generating compensation for exposure to a risk factor. I find that investors, on average, earn an extra 0.28% p.a. in ESG convenience yields. The ESG convenience yield nearly tripled from 0.14% in 2017 to 0.39% p.a. in 2022.[8] This time pattern is consistent with the inflows into ESG funds which grew by roughly $1.1 trillion between 2017 and 2022 (Van der Beck, 2021).

Hong and Kacperczyk (2009) argue that norm-constrained investors, such as ESG mutual funds, are more likely to invest in green securities than unconstrained investors. I test this argument in the portfolio data of mutual funds. Mutual funds are key investors in the auto ABS market, and up to 85% of a senior tranche is held on their balance sheets. This makes them ideal for testing whether CO_2 emissions or ESG scores influence their investment decisions.

Using a stringent set of fixed effects, I measure ESG funds' preferences for greenness from variation in CO_2 emissions across multiple auto ABS deals held by ESG funds relative to non-ESG funds during the same reporting period. The specifications include fixed effects for the collateral pool and fund and thus absorb the characteristics and preferences of each mutual fund and the features of each auto ABS deal. By including these fixed effects, the model controls for as much of the unobserved heterogeneity across collateral pools and funds as possible. However, the relative difference in preferences for greener assets by ESG versus non-ESG funds remains identifiable.

I show that ESG funds (i) invest across the full distribution of CO_2 emissions and (ii) have larger portfolio shares in higher-emission auto ABS compared with non-ESG funds, even if those securities have a higher CO_2 emission intensity. ESG funds allocate approximately 20% less capital to auto ABS deals with emissions below the median than non-ESG funds. Both findings are difficult to reconcile with common ESG strategies that usually prescribe outright exclusion or

[8] Similar to my findings, Avramov, Lioui, Liu, and Tarelli (2023) estimate an ESG convenience yield for stocks between 0.37% and 0.66%, from 2007 to 2022. These magnitudes might be compared with other convenience yields. Krishnamurthy and Vissing-Jorgensen (2012) document an average convenience yields of 0.73% on US Treasurys.

best-in-class investment of brown securities.[9]

The positive correlation between the ESG scores and CO_2 emissions rationalizes these findings. As expected, ESG funds allocate more capital to auto ABS issued by firms with higher ESG scores than non-ESG funds. However, ESG funds' reliance on the ESG scores of auto ABS issuers tilts their portfolio toward higher emission pools compared with non-ESG funds.

I innovate in several ways over the literature. First, to the best of my knowledge, this paper is the first to study the effects of environmental externalities, ESG scores, and ESG investing on the pricing and holdings of asset-backed securities. I demonstrate that even in a market for safe assets, the cost of capital for otherwise identical green assets can be meaningfully different from that of brown assets. I exploit a unique setting that allows me to compare the impact of ESG scores *and* CO_2 emissions on the cost of capital for otherwise identical securities. My findings highlight the tension between the goals of ESG investing and the use of issuer-level ESG scores in this market.

Second, I am studying the pricing of Scope 3 emissions. Scope 3 emissions, which result from product usage, are the largest source of emissions for most firms and are the emissions most relevant to climate change. Prior studies on the effects of CO_2 emissions on asset prices have focused on Scope 1 and 2 emissions, which are emissions from the production process. For example, Bolton and Kacperczyk (2021) study the effect of Scope 1 and 2 emissions on the pricing of stocks.[10] Much less is known about Scope 3 (downstream) emissions. I document that investors do not take Scope 3 emissions into account when pricing auto ABS but focus on ESG scores which are positively correlated with financed CO_2 emissions.

Finally, I use *continuous* and *objective* measures of sustainability rather than discrete definitions or proxies such as "green" certifications. Other studies of the green premium in debt markets often focus on municipal and corporate bonds (e.g., Baker, Bergstresser, Serafeim, and Wurgler, 2022, Larcker and Watts, 2020). These bonds are either green if they fund "environmentally friendly" projects or not. However, there can be large qualitative and quantitative differences between green projects. Economists do not yet know how investors react to these differences. I address this problem by focusing on a single, continuous dimension of environmental relevance.[11]

The paper is organized as follows. The remainder of the introduction discusses the related literature. Section 2 describes the data. Section 3 provides a brief overview over the auto ABS

[9] There is an active debate about which strategy ESG investors should follow: *exit* (divestment or exclusion) versus *voice* (shareholder activism). Broccardo, Hart, and Zingales (2022) analyze the relative effectiveness those strategies. Edmans, Levit, and Schneemeier (2022) analyze whether exclusion or best-in-class investment is more effective.

[10] See also the critique by Aswani, Raghunandan, and Rajgopal (2023) and reply in the *Review of Finance*.

[11] Note that the auto ABS I study are inherently brown because they finance CO_2 emissions. However, the cross-sectional differences in their emissions, render some auto ABS deals much greener than others.

market and establishes stylized facts about the emissions content of auto ABS and the ESG scores of issuers. Section 4 outlines a simple green asset pricing model, discusses the identification strategy, and reports estimates of influence of ESG investors on the cost of capital of auto ABS. Section 5 studies mutual funds' holdings of green and brown auto ABS. Section 6 discusses. Section 7 concludes.

Related Literature The rise of ESG investing has sparked an active literature.[12] Theoretical contributions highlight that if the share of ESG investors is large, green assets have a lower cost of capital than brown assets. Heinkel et al. (2001) model an equilibrium in which the behavior of ESG investors raises the cost of capital of polluting firms and lowers the cost of capital for green firms. Oehmke and Opp (2020) characterize the conditions under which ESG investors impact firm behavior in a setting in which firm production generates social costs and is subject to financing constraints. Pástor et al. (2021) propose a model to study the impact of changes in sustainability preferences on asset prices by analyzing equilibrium implications of ESG investing. Berk and van Binsbergen (2021) study the theoretical effect of equity divestment in a single-period mean-variance environment.

Empirical studies of the green premium in debt markets find results which are *prima facie* similar to the results of this study. For example, Pástor, Stambaugh, and Taylor (2022) document that German government's green twin bonds relative to their non-green twin trade at 5 bps lower yields. Baker et al. (2022) estimate a green premium of 6 bps in a sample of over 2,000 U.S. municipal and corporate green bonds, Zerbib (2019) estimates a green premium of 2 bps.[13] However, my results highlight that this green premium does not necessarily increase the cost of emitting CO_2, which is often implicitly assumed.

Perhaps the paper most closely related is Hartzmark and Shue (2023). The authors show that if the ESG strategy of directing capital away from brown companies toward green companies succeeds in changing financing costs, such a strategy could be counterproductive as most green companies have little room to improve further while brown companies tend to become browner when financing conditions worsen. Instead of focusing on companies, I focus on the pricing of auto ABS which directly finance household's purchases of vehicles. Changes to the cost of capital in this market might be able to direct consumer demand away from brown products to green products.

This paper also contributes to the literature on auto loan securitization. Benmelech, Meisen-

[12] Both Gillan, Koch, and Starks (2021) and Hong and Shore (2023) provide excellent literature reviews.

[13] See also the studies of Goss and Roberts (2011), Chava (2014), Tang and Zhang (2020), Larcker and Watts (2020), Flammer (2021), Fatica, Panzica, and Rancan (2021), Huynh and Xia (2021), Seltzer, Starks, and Zhu (2022), Aswani and Rajgopal (2022).

Table 1: Summary Statistics of Issuance-Level Data (A-2 Tranches)

	Mean	SD	Median	Min	Max	N
Total Deal Size ($ m)	1,234.93	344.47	1,250.00	367.31	2,663.82	281
Tranche Size ($ m)	366.71	131.99	362.00	42.40	746.94	281
Weight. Avg. Life (years)	0.98	0.32	1.01	0.37	3.50	281
Spread (bps)	41.68	29.10	32.29	6.13	194.22	281
Coupon (%)	1.91	1.30	1.86	0.14	5.81	281
Subprime ABS	0.28	0.45	0.00	0.00	1.00	281
Captive Lender	0.44	0.50	0.00	0.00	1.00	281
Number of Loans	66,953	25,500	66,011	15,212	180,352	281
Avg. Loan-to-Value	0.92	0.04	0.92	0.80	0.98	281
Avg. Credit Score	706.20	74.85	738.43	564.98	788.46	281
Avg. Interest Rate (%)	7.64	5.86	4.46	1.38	21.35	281
Avg. % of Balance Outstanding	0.90	0.07	0.91	0.74	1.00	281
Avg. Warehousing Time (months)	9.54	4.38	9.19	1.33	21.07	281

Notes: Loan-level averages are weighted by outstanding loan balance.

zahl, and Ramcharan (2017) find that the disruption in ABS markets during the Financial Crisis reduced credit supply and thus vehicle sales. Klee and Shin (2020) study asymmetric information and signaling in the auto ABS market. Benetton, Mayordomo, and Paravisini (2021) analyze European auto ABS and find that the vertical integration of manufacturing and credit provision allows captive auto lenders to increase cash collected from vehicle sales through credit fire sales.

2 Data

This section describes the loan-level data used to construct the measures of greenness and provides information about the issuance level data I use in the empirical tests.

ABS deal data I collect information about the structure of each deal from prospectuses filed with the SEC (Form 424H, 424B5, and FWP). These contain information about the characteristics of each deal and its tranches, e.g., issue date, credit rating, coupon, spreads, issuance amounts, weighted average life (WAL), and book running banks. I calculate issuance spreads as the difference between the issuance yields and yield curve estimates of Filipović, Pelger, and Ye (2022) by matching the maturity against the WAL of a tranche. Table 1 shows the summary statistics for the A-2 tranches of each deal. The average deal size is $1.2bn, of which 30% is associated with the A-2 tranche. The average spread is 42 bps with a WAL of one year. Captive lenders issue around 42% of deals and around 28% are sub-prime deals. The average deal finances around 67,000 vehicles. A $100,000 investment finances 220tCO_2 over the remaining life of the collateral.

The average vehicle investors finance emits approximately 58tCO_2 .

Loan-level data The loan-level data are from the Securities and Exchange Commission (SEC) form ABS-EE. Form ABS-EE is part of the post-financial crisis reporting requirements under Regulation AB, that went into effect on November 23, 2016. Under the reporting requirement, all prospectuses for public offerings of asset-backed securities must submit loan-level information in electronic format. Furthermore, every month loan-level information about the performance of the loan pool are to be provided. I exploit this requirement to construct performance measures of collateral pools.

The loan-level data covers all public consumer auto ABS issued from 2017 to 2022, consisting of approximately 18.9 million unique loans from 281 ABS deals issued by 22 issuers.[14] The data contains information on the originator, borrower, and collateral of each loan. Appendix Table A2 presents the summary statistics of the loan-level data. The average borrower in my sample finances $26,000, at 90% loan-to-value, at a 7.6% interest rate for 67 months. Their credit score is 712 and their monthly payment to income ratio is 0.08. The vehicle the average borrower is financing is worth $27,733.

Emissions data Data on CO_2 emissions are from the EPA. This data is matched on make, model, and model year to the loan-level data. Estimates of survival-weighted vehicle miles traveled (SVM) by vehicle type are from the EPA Corporate Average Fuel Economy (CAFE) standard simulator. The SVM estimates vary by vehicle type and assume up to 40 years of useful life. The EPA estimates that trucks and SUVs have higher SVM than sedans and compact cars. Appendix Figure B2 plots SVM curves by vehicle type.

The average vehicle in my sample is driven for 202,963 miles, of which 162,450 miles are financed by the proceeds of the auto ABS. Over its total lifetime, the vehicle emits 79tCO_2 , of which 63tCO_2 is financed. There is considerable heterogeneity among emissions of the collateral because the sample includes fully-electric vehicles, compact cars, SUVs, pick-up trucks, and other high-emission vehicles.[15]

ESG scores and other data I collect ESG scores from Refinitiv and Standard and Poor's (S&P). Both providers create their scores on the basis of publicly available information and penalize com-

[14] These issuers are: Ally Financial, AmeriCredit, BMW Financial, Capital One Bank, CarMax, Carvana, Exeter Finance, Fifth Third Bank, Ford Credit, GM Financial, Honda Finance, Hyundai Capital, JM Family (WOART), JM Family (WOSAT), Mechanics Bank, Mercedes-Benz Financial Services, Nissan Finance, Santander Bank (DRIVE), Santander Bank (SDART), Toyota Motor Credit, USAA Federal Savings Bank, and Volkswagen Credit.

[15] The 10 most popular vehicles in my sample exemplify this heterogeneity. These are, in order, Toyota Camry (sedan, on average 60t of CO_2 emissions over full lifetime), Toyota RAV4 (SUV, 73t), Toyota Corolla (sedan, 53t), Nissan Rogue (SUV, 62t), Chevrolet Silverado (truck, 120t), Honda Civic (sedan, 51t), Nissan Altima (sedan, 59t), Honda CR-V (SUV, 65t), Honda Accord (sedan, 62t), and Ford F-150 (truck, 114t).

panies with limited reporting. The scores are updated annually and are available for 17 of the 22 originators in my sample. The choice of score providers is purely driven by data limitations. Refinitiv's and S&P's scores are available with consistent methodology for the entire sample period from 2017 to 2022. For example, the methodology of Sustainalytics changed in 2020.[16]

Credit ratings of auto ABS issuers are from S&P. I use the issuer's long-term credit rating at the time of issuance. The rating is available for 15 of the 22 originators in the sample.

I use firm-level data on scope 1, 2, and 3 emissions from Trucost. Scope 1 emissions are direct emissions from production. Scope 2 emissions are the indirect emissions associated with the purchase of electricity, steam, and heating. Scope 3 (downstream) emissions measure the emissions associated with the use of firm's products.

3 Securitized Auto Loans and their Emissions

This section provides a brief introduction to the market for securitized auto loans, explains key concepts, and establishes key stylized facts. I show that similar to a motorist's choice between a high-emission vehicle or a low-emission vehicle, an investor has the choice to invest in an auto ABS that finances high-emission vehicles or relatively low-emission vehicles. I further show that commonly used ESG and environmental pillar scores of issuers do not reflect emissions of the collateral pool of auto ABS or the production process of vehicles.

3.1 ABCs of Consumer Auto ABS

I focus on a set of homogeneous consumer loan auto ABS that finance the purchases of vehicles by individual consumers.[17] Auto ABSs were among the first consumer ABS to come to the market in the 1980s, when the securitization of consumer loans became popular. At the end of 2021, auto ABS accounted for around 18% of total outstanding auto loans in the US, with a value of approximately $220 billion.[18]

Issuers of consumer auto ABS come from several industries: vehicle manufacturers and their captive lending companies, specialty retailers, banks and non-bank finance companies. Table 2 shows the importance of the consumer loan securitization channel for these industries. The average company in my sample securitizes approximately 45% of its revenues, 10% of its total assets,

[16] The results are qualitatively and quantitatively unchanged when using Sustainalytics ESG scores from 2017 to 2019 as Appendix Table A7 and Appendix Table A6 show.

[17] There are other types of auto ABS that finance dealer inventories, corporate vehicle fleets, or consumer leases. I exclude these types of auto ABS from my sample because of their different risk characteristics.

[18] see SIFMA, U.S. ABS issuance and outstanding.

Table 2: Average Securitization Intensity per Year by Industry Groups

Firm-level averages by industry:	Banks	Captive Lenders	Retailers	All Industries
Vehicles Securitized per Year	278,569	231,265	261,850	248,870
Vehicles Securitized as Share of Units Sold		0.16	0.39	0.20[1]
Amount Securitized as Share of Revenue	0.83	0.32	0.24	0.45
Amount Securitized as Share of Assets	0.11	0.05	0.30	0.10

Notes: N=60 firm-years. Securitization include only consumer loans and exclude lease and dealer floor plan securitizations. Revenue and assets are for US vehicle lending segment when available, otherwise for overall US segment. Data from Compustat Segment files from 2016 to 2022, when available. US unit sales data of manufacturers from www.goodcarbadcar.net. [1]excludes banks.

or 20% of total unit sales per year. Since consumer loan securitizations are an important part of the financial value chain of these industries, small changes to financing conditions in the auto ABS market potentially have large effects on the supply of credit.

All 281 deals in my sample are structured as monthly amortizing with higher seniority tranches receiving repayments first. Appendix Figure B1 shows examples of auto ABS deal structures.[19] There are, on average, 10 new consumer auto loan ABSs with a total notional value of approximately $13 billion per quarter over my sample period from 2017 to 2022. The auto ABS market can be split into prime and sub-prime deals based on the creditworthiness of the underlying loans; sub-prime deals command higher issuance spreads.

Compared with corporate and municipal bond markets, the security design of the auto ABS market is highly standardized. Only a few parameters distinguish auto ABS deals from each other besides their collateral pool. The high levels of standardization in the auto ABS market and the safety of these securities make auto ABS highly liquid, as the low bid-ask spreads of $0.04 and immediate market impact estimates of $0.01 show. For comparison, this is a similar level of liquidity and a lower level of market risk than agency mortgage-backed securities that trade in the $200 billion daily volume to-be-announced market (He and Mizrach, 2017).

Prepayment is the main risk factor for investors in senior tranches of consumer auto ABS because time and risk tranching, high levels of over-collateralization, and other credit enhancements (e.g., reserve accounts or excess spreads) mitigate default risk. Prepayment risk can materialize in several ways, primarily as the early repayment of loans by consumers, but also if a borrower defaults on a loan and the vehicle is repossessed. This risk is measured and priced using a pre-

[19]For a description of the corporate bond underwriting process by investment banks, which is similar to the ABS underwriting process, see Siani (2022).

payment model.[20] Consumer loan auto ABS deals further have embedded clean-up call options, allowing the issuer to prematurely call the outstanding notes if the remaining pool balance drops below a certain percentage (most commonly 5% or 10%). Clean-up call options, however, are not relevant for most senior tranches because they are paid off before the pool balance reaches the cutoff point. While all of the auto ABS deals I analyze are registered securities and publicly traded, a considerable amount of auto ABS are privately placed under Rule 144A. Private placements do not disclose public loan-level information and are therefore excluded from my sample.

3.2 Stylized Facts about CO2 Emissions from auto ABS

My empirical analysis examines the effects of CO_2 emissions from vehicles that serve as collateral for asset-backed securities on issuance prices and quantities purchased by investors. Auto ABSs need to disclose granular loan-level data that allow me to calculate the financed CO_2 emissions for each ABS. By matching the vehicle collateral to emission data from the EPA, I can calculate the amount of financed emissions for each deal.

The amount of expected emissions that auto ABS collateral pool b is financing is given by the sum over each vehicle i as:

$$\begin{aligned} \mathbb{E}\left[\text{Financed CO}_2 \text{ Emissions}\right]_b = \sum_{i \in b} & \underbrace{\text{CO}_2 \text{ Emissions}_i \times \mathbb{E}\left[\text{Survival-Weighted Miles}\right]_i}_{\text{Expected Emissions}} \\ & \times \underbrace{\text{LTV}_i \times \text{Outstanding Balance Share}_i}_{\text{Financing Adjustment}} . \end{aligned} \tag{1}$$

The first term on the right-hand side of (1) is the CO_2 emissions of vehicle i measured in tons of CO_2 per mile driven. The second term is the expected survival-weighted vehicle miles traveled over the lifetime of the vehicle. The product of these terms is the total expected lifetime emissions of a new vehicle.[21] The loan-to-value (LTV) part of the financing adjustment of (1) reflects that not all of the expected CO_2 emissions are financed through a loan because many consumers make down-payments at the time of purchase. The financing adjustment also considers that loans have

[20] Prepayments on consumer auto ABS are measured relative to a prepayment standard or model. The model used in all 281 deals in my sample is the Absolute Prepayment Model (APS). APS assumes a constant rate of prepayment each month relative to the original number of receivables. APS further assumes that all of the receivables are the same size, amortize at the same rate, and that each receivable in each month of its life will either be paid as scheduled or be prepaid in full. For example, in a pool of receivables originally containing 10,000 receivables, a 1% APS rate shows that 100 receivables are expected to be prepaid each month.

[21] I adjust the survival-weighted vehicle miles traveled of used vehicles to reflect the remaining expected lifetime of the vehicle.

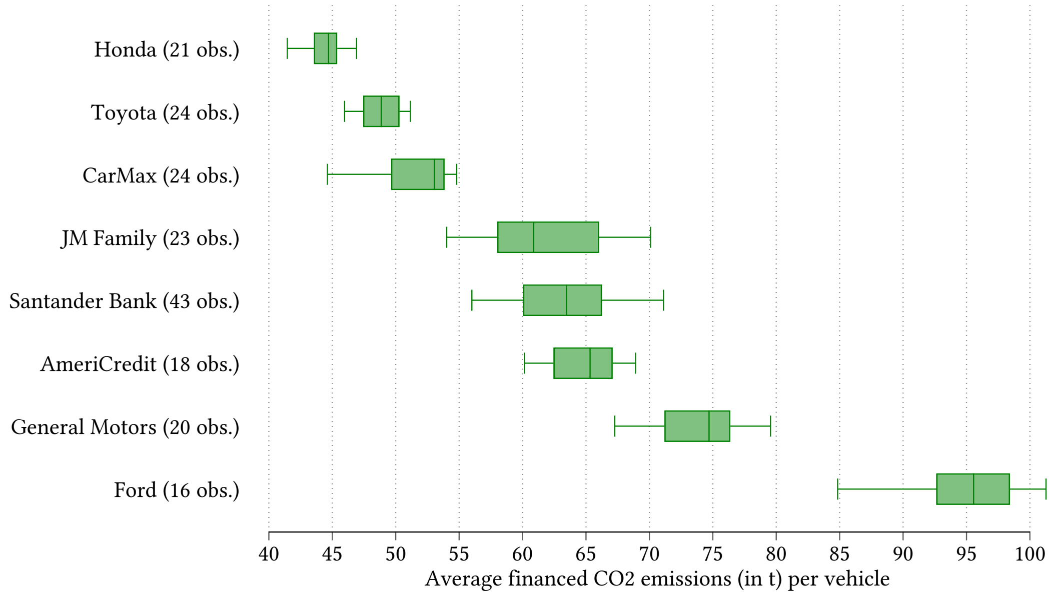


Figure 1: Dispersion of CO_2 emissions across all ABS pools of the eight largest issuers

different balances at the time of securitized.

I operationalize estimates of the financed tCO_2 emissions from (1) in two ways: (i) as tCO_2 per vehicle and (ii) as tCO_2 per \$100,000.[22] Both measures can be justified theoretically: per vehicle measures correspond to environmental impact per quantity of output, while per dollar measures correspond to environmental impact relative to the amount of capital invested. I remain agnostic as to which measure is preferable and report empirical results for both measures throughout.

The CO_2 emissions of ABS deals vary substantially across and within issuers. Figure 1 shows boxplots of the average financed tCO_2 emissions per vehicle across all collateral pools for auto ABS for the eight largest issuers.[23] The differences in emissions across deals are largely explained by the vehicle type composition of the collateral pool largely explains the differences in emissions across issuers and auto ABS deals. Appendix Table A1 shows that for each 1 percentage point increase in the truck share, the average amount of CO_2 per vehicle increases by 1.021 tons. The vehicle type composition for captive lenders is obviously related to the products offered by their manufacturing parents and consumer demand for them. The high share of trucks and the high

[22] These two intensity measures, while strongly positively correlated, are distinct. For example, compare an auto ABS that securitizes a single vehicle that costs \$100,000 and emits $100tCO_2$ with an auto ABS that securitizes three vehicles that each cost \$33,333 and each emit $33.3tCO_2$. Both have an emission intensity of $100tCO_2$ per \$100,000 while the first has an emission intensity of $100tCO_2$ per vehicle and the latter only $33.3tCO_2$ per vehicle.

[23] Note that the CO_2 emissions that are calculated from equation (1) are tailpipe emissions only. This measure reflects the emissions of the vehicle itself but does not include emissions from the production of the vehicle. However, appendix Figure B3 shows that including production emissions for captive auto lenders does not affect the relative rankings.

emissions of Ford's auto ABS reflect the fact that Americans have bought more F-Series trucks than any other vehicle for more than four decades.[24]

Figure 1 illustrates a striking fact: similar to a motorist's choice between a high-emission vehicle or a low-emission vehicle, an investor has the choice to invest in an auto ABS that finances high-emission vehicles or an auto ABS that finances low-emission vehicles. In the empirical exercises below, I exploit this fact to measure the effect of CO_2 emissions of the collateral on the cost of capital of auto ABS.

3.3 ESG scores of issuers and their relationship to CO2 emissions

ESG scores are a measure of a firm's the environmental, social, and governance performance. Advocates of ESG investing often claim that investors can use ESG scores to identify firms with low environmental impact and invest in their securities. The goal of many ESG investors is to change firm financing conditions by rewarding green firms with a lower cost of capital and penalizing brown firms by raising their cost of capital. Practitioners view this mechanism as a way to internalize environmental externalities such as CO_2 emissions. The success of ESG investing thus hinges on investors' ability to identify green firms, projects, and securities.

Table 3 provides summary statistics for ESG scores of issuer at the time of issuance as well as measures of the environmental impact of collateral pools of auto ABS. I report the usual summary statistics and additionally decompose the standard deviation in ESG scores into a between ($\overline{sd}_i$) and within ($sd_{it} - \overline{sd}_i + \overline{sd}$) component. The between component measures the cross-sectional variation in the ESG scores across the 22 issuers. The within component measures the time series variation in the ESG scores of issuers. I report ratios of between to within standard deviations. A ratio greater than 1 indicates that the cross-sectional variation in the ESG scores is larger than the individual time series variation.

While it is unclear how the ESG scores of diversified banks and finance companies reflect the emissions of vehicle loans, one might expect that the environmental scores of vehicle manufacturers reflect vehicle emissions. However, I find that this is not the case. Decomposing the standard deviation of ESG scores and CO_2 emissions among captive lenders of manufacturers shows that ESG and environmental scores vary considerably less across issuers than their actual emissions footprint.

ESG scores of captive lenders do not vary much, but CO_2 emission intensity does. Panel A in Table 3 shows that the standard deviations of ESG (0.06 to 0.07) among captive lenders are quite low. For example, the coefficient of variation for the Refinitiv ESG score is only 8%, indicating

[24] Kelley Blue Book: Ford F-150 Retakes Best-Selling Vehicle Crown

Table 3: ESG and CO2 Summary Statistics of Collateral Pools

	Mean	SD	$\frac{\text{Between SD}}{\text{Within SD}}$	Median	Min	Max	N
Panel A: ESG ratings of issuers at time of issuance:							
Refinitiv ESG score of issuer	0.73	0.18	4.99	0.79	0.22	0.94	243
- Captive Lenders	0.79	0.06	1.87	0.79	0.62	0.94	123
- Other Lenders	0.68	0.23	6.67	0.78	0.22	0.90	120
Refinitiv environmental score of issuer	0.69	0.31	5.95	0.85	0.00	0.97	243
- Captive Lenders	0.85	0.07	1.70	0.86	0.67	0.98	123
- Other Lenders	0.66	0.36	5.96	0.53	0.00	0.92	120
S&P ESG score of issuer	0.58	0.26	3.43	0.70	0.07	0.92	243
- Captive Lenders	0.63	0.17	1.63	0.67	0.27	0.86	123
- Other Lenders	0.53	0.32	9.27	0.75	0.07	0.92	120
S&P ESG environmental score of issuer	0.61	0.31	4.42	0.76	0.00	0.98	243
- Captive Lenders	0.70	0.16	1.71	0.76	0.34	0.98	123
- Other Lenders	0.53	0.39	9.82	0.79	0.00	0.95	120
Panel B: Measures of environmental impact of collateral pools:							
Financed tCO2 per vehicle	58.01	12.76	3.39	54.49	40.54	101.27	281
- Captive Lenders	58.58	17.24	4.98	50.48	41.33	101.27	123
- Other Lenders	57.75	7.55	2.00	58.46	40.73	71.11	156
Financed tCO2 per $100,000	219.58	40.08	1.77	211.15	107.10	311.78	281
- Captive Lenders	197.62	29.99	2.59	199.49	107.10	274.82	123
- Other Lenders	237.15	38.58	1.05	241.35	150.28	311.78	156
Expected tCO2 per $100,000	292.83	51.42	1.61	296.31	161.51	456.16	281
Expected tCO2 per vehicle	70.51	15.55	4.15	67.61	42.94	125.73	281
Average Miles-per-Gallon per vehicle	24.25	2.49	2.80	23.88	18.71	32.66	281
Average EPA GHG rating per vehicle	5.59	0.54	2.31	5.68	4.13	6.68	247

Panel C: Correlation between ESG scores of issuers and environmental impact of collateral pools:

	Refinitiv ESG score	Refinitiv Env. score	S&P ESG score	S&P Env. score	Fin. tCO2 per vehicle	Fin. tCO2 per USD	Avg. MPG
Refinitiv ESG score of issuer	1.00						
Refinitiv environmental score of issuer	0.87	1.00					
S&P ESG of issuer	0.73	0.69	1.00				
S&P environmental score of issuer	0.77	0.72	0.96	1.00			
Financed tCO2 per vehicle	0.41	0.27	0.31	0.28	1.00		
Financed tCO2 per USD	0.11	0.03	0.20	0.12	0.58	1.00	
Average MPG $\times(-1)$	0.23	0.07	0.08	0.07	0.80	0.44	1.00

Notes: Financed and expected tons of CO_2 of collateral pools calculated using (1). EPA GHG rating per vehicle as calculated by KBRA (2022). Spearman rank correlation among N=243 observations for which ESG scores of issuers are available. MPG is multiplied by (-1) such that higher values correspond to worse environmental performance.

that there is little variation. Furthermore, the standard deviation ratios (1.6 to 1.9) show that ESG scores for captive lenders vary almost as much in their individual time series than across issuers. Panel B of Table 3 shows that the standard deviations of CO_2 emissions vary 2.6 to 4.9 times more across issuers than within issuers. A fact that can also be gleaned from Figure 1. The coefficient of variation for financed CO_2 emissions ranges from 15% to 29%. The disconnect ESG and emissions variability is problematic if investors use ESG scores to screen green from brown auto ABS.

Panel C of Table 3 shows the correlations between the environmental impact of auto ABS and the ESG scores of the issuers. Reassuringly, the ESG scores of S&P and Refinitiv are positively correlated with each other. However, Panel C of Table 3 also shows that ESG scores are positively

Table 4: Regressions of ESG scores on CO2 Emissions

	(1) Refinitiv ESG score	(2) S&P ESG score	(3) Refinitiv Env. score	(4) S&P Env. score	(5) Refinitiv ESG score	(6) S&P ESG score	(7) Refinitiv Env. score	(8) S&P Env. score
Panel A: Auto ABS emissions intensity:								
Financed tCO2 per USD	0.0661	0.0896	0.00435	0.00780				
	(0.103)	(0.150)	(0.0738)	(0.125)				
Financed tCO2 per vehicle					0.152	-0.0570	0.0943	-0.0550
					(0.0994)	(0.185)	(0.0880)	(0.162)
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.583	0.447	0.587	0.473	0.604	0.446	0.596	0.476
Observations	243	243	243	243	243	243	243	243
Panel B: Firm-year emissions intensity from Trucost:								
Scope 1+2/Revenue	0.132	0.213	0.138	0.184				
	(0.158)	(0.238)	(0.160)	(0.219)				
Scope 3 Downstream/Revenue					0.0911	0.0895	0.148	0.0822
					(0.118)	(0.204)	(0.113)	(0.180)
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.487	0.317	0.501	0.372	0.539	0.307	0.524	0.366
Observations	99	99	99	99	83	83	83	83

Standard errors are clustered at issuer-level. + p<0.10, * p<0.05, ** p<0.01, *** p<0.001 Coefficients are standardized to unit variances.

correlated with CO_2 emissions from collateral pools. The positive correlation holds even for the environmental pillar scores.

The positive correlation between ESG and environmental pillar scores and pool-level emissions is not completely surprising. ESG scores are a composite *firm-level* measures of the overall societal impact of a firm whereas the CO_2 measures of auto ABS pools are *project-specific* measures of environmental impact. I therefore also provide results using the firm-level environmental pillar score, which should be most comparable to the CO_2 intensity of auto ABS. One potential explanation for the positive correlations could be that the project-specific environmental impact of the collateral pool is not reflective of the firm-level environmental impact of the issuer's overall business. Another potential explanation for the positive correlations is that the correlation matrix in Panel C of Table 3 fails to account for industry differences in ESG scores.

Table 4 explores both explanations for the positive correlation of ESG scores and environmental impact of auto ABS by regressing ESG and environmental pillar scores on firm-level and pool-level measures of carbon intensity while accounting for industry fixed effects. The results in Panel A of Table 4 show that the positive correlation between ESG scores and environmental impact of auto ABS is attenuated but are not driven by industry differences in ESG scores. Qualitatively similar results can be obtained when using sub-scores on which the environmental pillar score is based (e.g., emissions scores).

Panel B of Table 4 shows that even at the firm-level, ESG and environmental pillar scores are positively rather than negatively correlated to CO_2 emissions. Scope 1 and 2 emissions are positively correlated to ESG scores, even when controlling for industry fixed effects. Columns (1) to (4) show this for scope 1 and 2 emissions over revenue, while Columns (5) to (8) show this for scope 3 emissions over revenue. Notice further that the collateral pool tCO_2 per USD is directly related to Scope 3 downstream emission intensity of vehicle manufacturers.[25] This implies that the observed positive correlation between ESG and environmental pillar scores and CO_2 emissions of collateral pools is not just a data artifact but reflects that ESG and environmental pillar scores are uninformative about CO_2 emissions among auto ABS issuers, even at the firm-level.

4 Issuance Spreads, Cost of Capital, and Convenience Yields

This section develops the main results of the paper that both high-ESG and high-emission auto ABS are associated with lower issuance spreads and therefore lower the cost of capital for auto ABS issuers while earning the holders of those assets a convenience yield. I motivate the empirical specifications through the lens of a simple green asset pricing framework. I then present the identification strategy and the empirical results.

4.1 A simple green asset pricing framework

Kontz and Xie (2023) build an asset pricing model and derives pricing conditions for green assets that are implied by no-arbitrage. I present a simplified version of this model that conveys most of the intuition. I assume that the economy is populated by a single investor whose Euler equation is given by

$$\mathbb{E}_t\left[M_{t+1}R^i_{t+1}\right] = \exp(-\beta^i_t\lambda_t) \tag{2}$$

The expression on the left side of the equation is standard. On the right side, I allow the investor to derive a convenience yield $\lambda_t \geq 0$ from holding asset i of $\beta^i_t \in [0, 1]$ greenness. Higher values of β^i_t correspond to greener assets and earn a convenience yield of $\beta^i_t\lambda_t$. This convenience yield is asset-specific and hence cannot be folded into the SDF. For simplicity, assume that there are only two assets in the economy, a brown b security and a green g security where $\beta^g_t > \beta^b_t$. I assume that $m_t = \log M_t$ and $r^i_t = \log R^i_t$ are conditionally normal. Rewriting the Euler equation (2)

[25] Unreported regressions confirm the strong relationship between the collateral pool level CO_2 per USD I constructed and the scope 3 downstream emission intensity of vehicle manufacturers as reported by Trucost.

using log-normality, one finds

$$\mathbb{E}_t\left[m_{t+1}\right]+\frac{1}{2}\operatorname{Var}_t\left[m_{t+1}\right]+\mathbb{E}_t\left[r_{t+1}^i\right]+\frac{1}{2}\operatorname{Var}_t\left[r_{t+1}^i\right]+\operatorname{Cov}_t\left[m_{t+1},r_{t+1}^i\right]+\beta_t^i\lambda_t=0$$

and the following result:

Lemma 1. *The expected return in levels on a long position in an asset earned by the investor is decreasing in the convenience yield and in the greenness of the asset:*

$$\mathbb{E}_t\left[r_{t+1}^i\right]-r_{t+1}^f+\sigma_{i,t}^2/2=-\sigma_{i,m,t}-\beta_t^i\lambda_t \tag{3}$$

Using the Campbell and Shiller (1988) approximation, we can write the dividend yield of an asset with fixed maturity T in this economy as

$$\begin{aligned}
dp_t^i&=\sum_{j=0}^{T}\rho^j\mathbb{E}_t\left[r_{t+1+j}^i\right]-\sum_{j=0}^{T}\rho^j\mathbb{E}_t\left[\Delta d_{t+1+j}^i\right]-\kappa\frac{1-\rho^T}{1-\rho}\\
&=-\beta_t^i\lambda_t\frac{1-\rho^T}{1-\rho}+\sum_{j=0}^{T}\rho^j r_{t+1+j}^f-\sum_{j=0}^{T}\rho^j\left(\sigma_{i,m,t,t+j}+\sigma_{i,t,t+j}^2/2\right)-\sum_{j=0}^{T}\rho^j\mathbb{E}_t\left[\Delta d_{t+1+j}^i\right]-\kappa\frac{1-\rho^T}{1-\rho}.
\end{aligned} \tag{4}$$

where $\rho=\frac{1}{1-\exp\left(\overline{d-p}\right)}$ and $\kappa=-\log\left(\rho\right)-\left(1-\rho\right)\log\left(1/\rho-1\right)$. The first term in (4) shows that a higher non-pecuniary value derived from the greenness of an asset, lowers its dividend yield and thus raises the price of the asset. The differences in yields between two fixed maturity assets with different levels of greenness but otherwise identical payoffs and risk-characteristics is given by the difference of (4). I term this difference in yields the green basis.

Lemma 2. *The absolute level of the green basis is increasing in final maturity T, the convenience yield, and in the difference of greenness between the two assets:*

$$y_t^g-y_t^b=dp_t^g-dp_t^b=-(\beta_t^g-\beta_t^b)\lambda_t\frac{1-\rho^T}{1-\rho} \tag{5}$$

In the case of a one-period bond, the green basis simplifies to:

$$y_t^g-y_t^b=-(\beta_t^g-\beta_t^b)\lambda_t$$

However, as (4) shows one, needs to carefully account for potentially differences in risk-exposure and cash-flow growth of green and brown assets in order to infer the green basis. I therefore build an identification strategy in the next section, that exploits the unique features of the auto ABS market to isolate the green basis from risk and cashflow components across auto ABS.

4.2 Identification Strategy

Empirically studying whether green assets have a lower cost of capital is challenging for several reasons. Expected returns, and thus the cost of capital, are difficult to measure. For example, equity markets are volatile and realized returns may not equal expected returns. Inferring expected returns from yields in bond markets is also non-trivial because one must carefully account for expected cash flow growth and exposure to risk factors. Unobserved heterogeneity can create a spurious correlation between greenness and risk factors. For example, exposure to regulatory risk, such as carbon taxation, clearly correlates with greenness. This complexity is further compounded by the paucity of objective and standardized measures of greenness (Berg et al., 2022), making it challenging to quantify the environmental impact of an investment and differentiate between green and non-green securities.

I address these challenges by studying the effects of greenness on the cost of capital in the auto ABS market. I consider two measures of greenness: (i) ESG scores of issuers and (ii) CO_2 emissions of the collateral pool. The unique features of this market allow me to credibly identify if green assets have a lower cost of capital. Moreover, the setting allows me to test which dimension of greenness is more influential for the cost of capital. My identification strategy rests on three points.

First, high levels of standardization and the short-term, safe-asset nature of the securities make it unlikely that unobserved heterogeneity at the issuer or security level would contaminate my estimates. Moreover, the claims to the assets are held within special purpose vehicles that are set up to be bankruptcy remote from their sponsoring entity.[26] Even if the sponsor enters bankruptcy, holders of auto ABS and the collateral pools they finance are protected from claimants. This makes it unlikely that unobserved heterogeneity at the issuer level affects exposure to risk factors across auto ABS.

Second, the seniority structure and security design of auto ABS deals ensures that prepayment is the main risk factor for senior tranches. By allocating cash flows and credit risks of the underlying assets in a specific manner across tranches, the design of these deals limits other sources of risk, such as credit default or collateral performance, primarily to subordinate tranches. Time

[26] Technically, the special purpose vehicle (or owner trust) is the issuer of the auto ABS. The SPVs, however, do not have ESG scores and I therefore use the ESG scores of the sponsoring entity and with a slight abuse of terminology refer to them as the issuer's ESG score.

tranching involves dividing cash flows from underlying assets into different tranches based on payment priority, ensuring that senior tranches receive cash flows before subordinate tranches. While usual auto loans have a five-year duration, time tranching ensures that the senior A-2 tranches I study have a weighted average life of only one year. Risk tranching involves assigning different levels of credit risk to tranches, with senior tranches having lower default risk and subordinate tranches facing higher default risk.[27] My analysis focuses on senior tranches that are AAA-rated by at least two rating agencies. Due to risk tranching, the threshold at which pool-level credit losses would start to impact these tranches is approximately 50%, assuming zero percent recovery value. This makes it unlikely that any observed effects are due to exposure to credit risk.

Third, the granularity of the loan-level data allows me to control for both ex-ante determinants and ex-post realizations of prepayment risk. The ex-ante determinants of prepayment risk include borrower characteristics (e.g., creditworthiness), loan characteristics (e.g., loan-to-value ratio), and prevailing market conditions (e.g., interest rates). Importantly, borrower and loan characteristics determine prepayment risk is rather than the underlying collateral's greenness. In other words, borrowers with high interest rate loans are likely to prepay when interest rate fall, regardless of the greenness of the vehicle they purchased. I provide evidence that the measures of greenness that I consider do not predict prepayment. This implies that any observed impact on asset prices and financing costs can be attributed to a preference for the greenness of the collateral, rather than greenness being a proxy for a risk factor.

Empirical Specification I use the unique features of the auto ABS market to test whether green assets have a lower cost of capital using the following specification:

$$\log\left(\text{Issuance Spread}\right)_{bt} = \alpha\,\mathbb{1}[\text{Green} > p50]_b + \zeta' X_b + \gamma_t + \varepsilon_{bt} \tag{6}$$

for bond tranche b issued in year-month t. $\mathbb{1}[\text{Green} > p50]_b$ is an indicator variable equal to one if the greenness of the auto ABS deal is above the 50th percentile of all auto ABS deals and zero otherwise. The coefficient of interest is α, which reflects the premium investors are willing to pay for a green security. The specification in (6) is consistent with the literature on the green premium that uses a discrete definition of greenness (Zerbib, 2019, Larcker and Watts, 2020, Baker et al., 2022, e.g.,). In addition, I test the following specification that uses a continuous definition

[27] If a borrower in the collateral pool defaults on their loan, the vehicle gets repossessed and sold again. To holders of senior tranches the default, repossession, and subsequent recovery constitutes "involuntary" prepayment. The difference in outstanding balance and recovery value is born by the most junior tranche. Historic recovery values are around 60% and 45% for prime and subprime loans, respectively (Structured Finance Association).

of greenness:

$$\log\left(\text{Issuance Spread}\right)_{bt} = \beta \log\left(\text{Green}\right)_b + \zeta' X_b + \gamma_t + \varepsilon_{bt} \tag{7}$$

The coefficient of interest is β, which reflects the elasticity of issuance spreads with respect to greenness. Note that γ_t ensures that both α and β are identified using the within-month variation of greenness across auto ABS deals.

Vector X_b contains controls for market conditions on the issuance day, tranche characteristics, and collateral pool characteristics. To control for within-month market conditions, X_b includes estimates of the yield curve for maturity of 6 and 12 months from Filipović et al. (2022), the level of the VIX on the day of issuance, the standard deviation of the VIX in the 30 days before issuance, and the level of the 5-year breakeven inflation rate on the day of issuance.[28] The included tranche characteristics are weighted average life, default attachment point, and the issuance size. The vector X_b also contains collateral pool controls that are predictors and ex-post realizations of prepayment risk. These are the collateral pool averages of LTV, credit scores, remaining loan balance share, interest rate, warehousing time, realized difference to assumed APS, and the share of loans that are more than 30 days delinquent after 12 months. Collateral pool variables derived from individual loans are weighted by the outstanding loan amount. Collateral pool and tranche characteristic have individual slopes across subprime and prime issues to account for potentially different pricing relevance. All control variables are in logs to achieve a more symmetric and normally distributed data distribution. The specifications further control for subprime issue fixed effects and fixed effects for the assumed absolute prepayment speed (APS). I further interact the APS fixed effects with the weighted average life of the tranche to account for potential "ramp-up" periods in which prepayments increase and then level off to their assumed APS. Standard errors are clustered at the year-month level to account for common variation among spreads caused by market conditions.

Identifying Assumption The identifying assumption in both (6) and (7) is that the assignment of greenness is uncorrelated with the error term conditional on traditional risk factors: once prepayment risk is accounted for, the assignment of greenness is "as good as random." This identification assumption allows me to answer the following questions: once an investor can be sure that their loan will be paid back at the agreed time, does the greenness of the deal influence their choice to invest – and is this choice reflected in prices? A natural null hypothesis is that the greenness of the deal does not influence the cost of capital and therefore $\alpha = \beta = 0$. That is,

[28] Note that these variables are not subsumed by year-month fixed effects because they vary at daily frequency.

$\alpha < 0 < \beta$ is evidence that investors prefer greener auto ABS deals over comparable brown ones and are willing to accept lower yields because of this.

The identification assumption would be violated if the greenness of auto ABS deals is correlated with risk factors in and of itself. I can test the identifying assumption ex-post because auto ABS file monthly performance reports. I derive ex-post performance variables from these reports that measure the realization of prepayment risk. Specifically, I examine two measures that capture voluntary and involuntary prepayment at the pool-level: the average realized difference in monthly absolute prepayment speed (APS) compared with its prospectus assumption, and the average realized percentage of loans that are more than 30 days delinquent.

The greenness of an auto ABS deal does not predict prepayment. Appendix Table A3 shows estimates from regressions of ESG scores and CO_2 emissions on measures of voluntary and involuntary prepayment. The estimates show that neither CO_2 emissions nor ESG scores are predictors of pool-level performance. The estimates are noisy, close to zero, and switch signs across measures across columns. I take these results as evidence that the identifying assumption holds and proceed as if the assignment of greenness is “as good as random”.

4.3 Results

In this subsection, I document the main results that (i) if one does not carefully account for the risk factors that drive prices in the ABS market, greener securities and securities from high-ESG issuers seem to have a statistically significant lower cost of capital and thus one might falsely conclude that ESG and carbon pricing are aligned, (ii) this relationship flips around once I account for security design and prepayment risk, and (iii) the correlation between ESG scores and CO_2 emissions seems to be driving the elasticity between emissions and issuance spreads. These findings are robust to alternative specifications, samples, measures of greenness, and estimators.

Figure 2a shows a naïve pricing model that only controls for market conditions during the issuance month. The figures show that if one does not adjust for risk, ESG and carbon pricing seem to be aligned. From this, one might conclude that ESG scores are a useful tool for identifying environmentally friendly assets and that ESG investing is a helpful tool in climate change mitigation.

However, a risk-adjusted pricing model finds exactly the opposite. Figure 2b shows that once one controls for risk, the alignment disappears and actually flips around. This is because one needs to control for borrower and loan characteristics that determine prepayment risk that can correlate with the CO_2 emission of the collateral pool. For example, higher emission vehicles

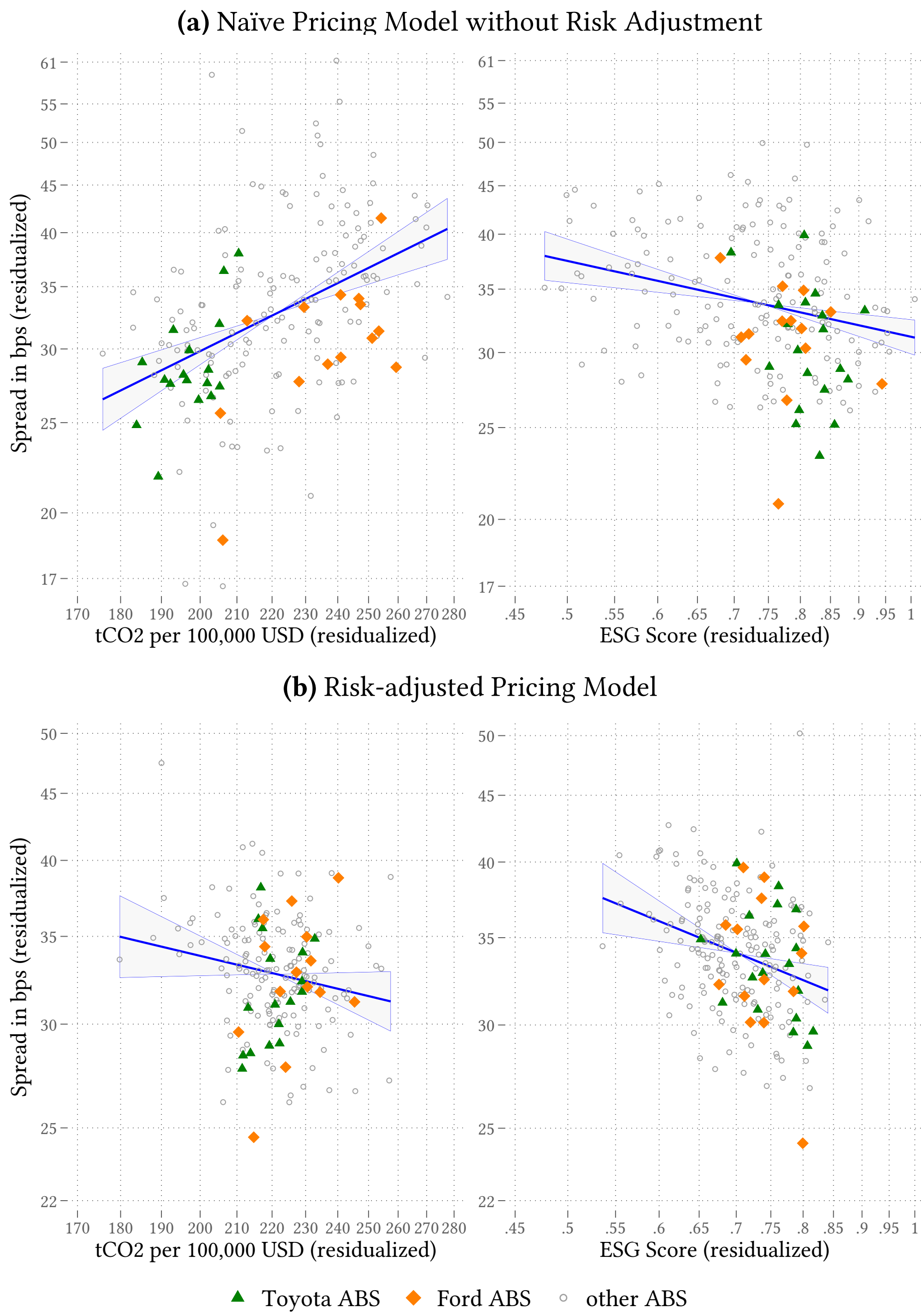


Figure 2: Residualized Scatter Plots and Line of Best Fit of Pricing Models Pricing models of (7) in Panel (a) and (b) both control for issuance-month fixed effects as well as the yield curve, VIX, and inflation expectations that vary within-month. Panel (b) additionally controls for the security design as well as ex-ante prepayment risk and ex-post realized prepayment. Issuance spreads, tCO2 per USD, and ESG scores are trimmed at the 5% and 95% level.

are more often associated with lower credit scores, as Appendix Table A4 shows. Once this correlation is taken into account we find that similar to ESG scores, higher CO_2 emissions are associated with lower issuance spreads.

Table 5 presents the main results using a risk-adjusted pricing model. Odd-columns controls for ex-ante predictors of prepayment risk, even-columns add controls for ex-post realizations of prepayment risk. Panel A shows estimates of the semi-elasticity of issuance spreads with respect to the high-ESG or low-emission indicator using the pricing model of equation (6). Panel B shows estimates of the elasticity of issuance spreads with respect to either ESG scores or CO_2 emissions using the pricing model of equation (7).

The results in Panel A indicate that high ESG scores lower issuance spreads by between 7.55% and 9.83%.[29] Panel A also shows that high CO_2 emissions lower issuance spreads by between 4.39% and 5.61%. Reassuringly, estimates that account for ex-post performance of collateral pools do not vary much from estimates that only control for ex-ante predictors of prepayment risk. This further supports the identifying assumption that neither ESG-scores nor CO_2 emissions are correlated with ex-post performance or used by the market as predictors of performance. These results are consistent with the hypothesis that investors prefer green assets and are willing to pay a premium for them. However, the results also show that investors are willing to pay a premium for brown assets. likely driven by the fact that common ESG scores positively correlate with the CO_2 emissions of auto ABS collateral pools.

Panel B reports similar results using the linear pricing model of equation (7). The estimates indicate that issuance spreads have an elasticity between -0.13 and -0.43 with respect to ESG scores and between -0.18 and -0.20 with respect to CO_2 emission intensity. I again find that estimates that control for ex-post performance of collateral pools are similar to estimates that only control for ex-ante predictors of prepayment risk, alleviating concerns that the results are driven by correlation between ESG and CO_2 measures with collateral pool performance.

The estimates in Panel C show the elasticity of issuance spreads while simultaneously controlling for both ESG scores and CO_2 emissions. When controlling for both ESG scores and CO_2 emissions, the elasticity of issuance spreads with respect to ESG scores remain close to the estimates in Panel B and statistically significant. However, the elasticity of issuance spreads with respect to CO_2 emissions is attenuated up to 50% and is often no longer statistically significant. This suggests that the effect of CO_2 emissions on issuance spreads is driven by correlation with ESG scores.

Figure 3 shows yearly estimates of the elasticity of issuance spreads with respect to CO_2

[29] $-9.83\% \approx 100(\exp\left(-0.103 - 0.0325^2/2\right) - 1)$, see Halvorsen and Palmquist (1980).

Table 5: Main result: Both high-ESG and high-emission auto ABS have a lower cost of capital

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
				Issuance Spread				
Panel A: Semi-Elasticity of Issuance Spreads with respect to High-ESG or Low-Emissions indicator								
High Refinitiv ESG (score>p50)	-0.103**	-0.0781**						
	(0.0325)	(0.0287)						
High S&P ESG (score>p50)			-0.0957*	-0.0852+				
			(0.0419)	(0.0437)				
Low Emissions (per USD<p50)					0.0571*	0.0574*		
					(0.0277)	(0.0275)		
Low Emissions (per vehicle<p50)							0.0551*	0.0433
							(0.0254)	(0.0260)
Year-month FE, daily market controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Prepayment speed FE, tranche controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Ex-ante prepayment controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Ex-post prepayment controls		Yes		Yes		Yes		Yes
Adj. R^2	0.971	0.975	0.969	0.974	0.965	0.970	0.965	0.969
Observations	235	235	235	235	276	276	276	276
Panel B: Elasticity of Issuance Spreads with respect to either ESG score or Carbon Emissions								
Refinitiv ESG Score	-0.430***	-0.337**						
	(0.113)	(0.105)						
S&P ESG Score			-0.131**	-0.135**				
			(0.0465)	(0.0469)				
Financed tCO2 per USD					-0.181	-0.238*		
					(0.118)	(0.119)		
Financed tCO2 per vehicle							-0.204**	-0.238**
							(0.0697)	(0.0721)
Year-month FE, daily market controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Prepayment speed FE, tranche controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Ex-ante prepayment controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Ex-post prepayment controls		Yes		Yes		Yes		Yes
Adj. R^2	0.972	0.976	0.970	0.975	0.965	0.970	0.966	0.971
Observations	235	235	235	235	276	276	276	276
Panel C: Elasticity of Issuance Spreads with respect to ESG score and Carbon Emissions								
Refinitiv ESG Score	-0.438***	-0.341**	-0.409**	-0.291*				
	(0.108)	(0.101)	(0.137)	(0.129)				
S&P ESG Score					-0.128**	-0.128**	-0.121*	-0.108*
					(0.0458)	(0.0455)	(0.0471)	(0.0458)
Financed tCO2 per USD	-0.123	-0.155			-0.0672	-0.106		
	(0.121)	(0.122)			(0.110)	(0.111)		
Financed tCO2 per vehicle			-0.0390	-0.0831			-0.127+	-0.117+
			(0.0911)	(0.0934)			(0.0659)	(0.0684)
Year-month FE, daily market controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Prepayment speed FE, tranche controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Ex-ante prepayment controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Ex-post prepayment controls		Yes		Yes		Yes		Yes
Adj. R^2	0.972	0.976	0.972	0.976	0.970	0.975	0.970	0.976
Observations	235	235	235	235	235	235	235	235

Notes: Standard errors in parentheses are clustered at year-month. + p<0.10, * p<0.05, ** p<0.01, *** p<0.001. Panel A shows estimates of (6) and Panel B and C show estimates of (7).

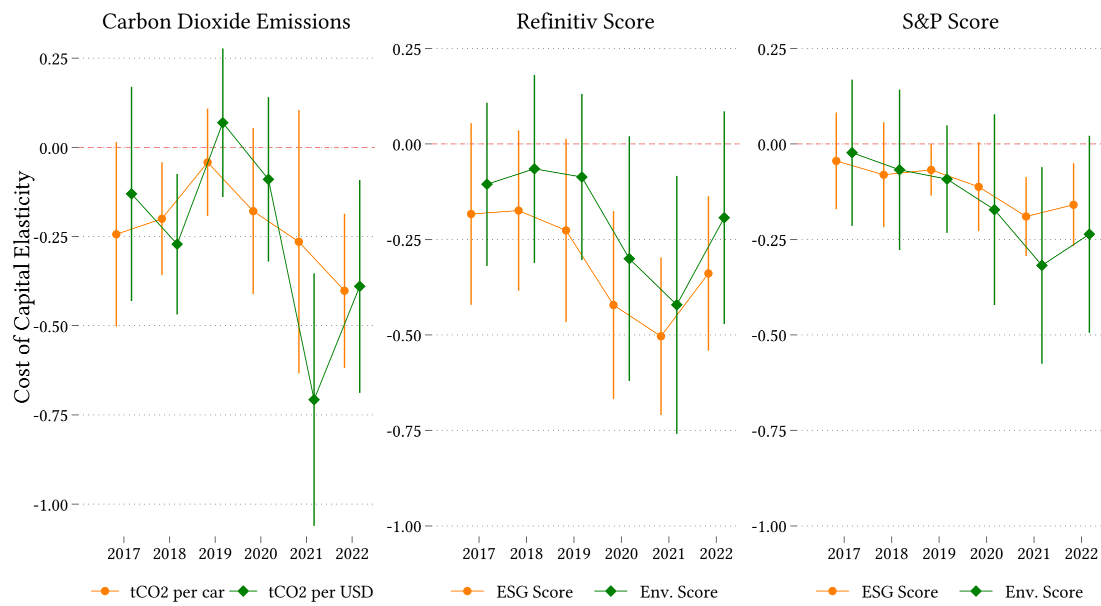


Figure 3: Elasticity of Cost of Capital with respect to CO_2, ESG score, and environmental score

emissions, ESG scores, and environmental pillar scores. The strength of the measured elasticities increases over time until 2021 and then attenuates in 2022. Van der Beck (2021) shows that returns from sustainable investing are strongly driven by price pressure from flows toward sustainable funds. The yearly estimates that Figure 3 shows closely follow the time trend of flows into ESG mutual funds (see Appendix Figure B4). Figure 3 also shows that estimates using the environmental pillar score of both S&P and Refinitiv follow the same time trend and deliver estimates that are close to the original estimates using ESG scores. This is consistent with the hypothesis that investors are primarily concerned with the environmental impact of their investments.

The results so far point toward the conclusion that investors are pricing in their non-pecuniary preferences using ESG or environmental pillar scores while neglecting the actual environmental impact as measured by the CO_2 intensity of collateral pools. However, there is a possibility that ESG investors are compensated for their exposure to CO_2 emissions through higher social and governance scores. To address this concern, I check whether deals that finance high-emission collateral differ along the social and governance scores. The covariate balance test in Appendix Table B1 splits the sample into Green and Brown auto ABS based on tCO_2 per vehicle and compares the ESG, E, S, and G scores for three score providers. The table shows that Brown auto ABS have on average slightly higher scores across all dimensions. However, most differences in means are less than 25% of a standard deviation and all but one are not statistically different from zero. This suggests that ESG investors do not perceive environmentally worse deals to be more

Table 6: Estimates of the ESG Convenience Yield over Time

		2017	2018	2019	2020	2021	2022	All
Difference in ESG score:	$\beta_t^g - \beta_t^b$	0.29	0.18	0.20	0.15	0.43	0.31	0.32
ESG basis spread in basis points:	$y_t^g - y_t^b$	-4	-2	-2	-5	-11	-12	-9
ESG convenience yield in basis points:	λ_t	14	11	10	34	26	39	28
Average spread of A-2 tranches in basis points:		40	38	31	47	22	72	41

Notes: Estimates of ESG basis spread based on Refinitiv ESG scores and yearly elasticity estimates (see Figure 3) using the risk-adjusted pricing model of (7). Differences in ESG scores evaluated at the 20th and 80th percentiles of ESG score per year.

desirable along S and G dimensions.

Translating yields spreads into convenience yields One can translate the estimated differences of issuance spreads induced by ESG scores (i.e., the green basis) into the convenience yield that an investor earns on their ESG investment by rewriting (5) as

$$\lambda_t = -\frac{y_t^g - y_t^b}{\beta_t^g - \beta_t^b} \tag{8}$$

where y^g and y^b are the yields on green and brown asset and β_t^g and β_t^b the perceived greenness of the security, respectively. Crucially, this ESG convenience yield is fundamentally different from a risk premium: it generates seigniorage to issuers of ESG assets rather than generating compensation for exposure to a risk factor.

Table 6 shows estimates of the ESG convenience yield based on the ESG scores of Refinitiv and elasticity estimates (see Figure 3) using the risk-adjusted pricing model of (7). My estimates indicate that, on average, investors receive an ESG convenience yield of 0.28% p.a. from their high-ESG investments. The convenience yield nearly tripled from 0.14% p.a. in 2017 to 0.39% p.a. in 2022.

Similar to my estimates of an ESG convenience yield of 0.28% in asset-backed securities, Avramov et al. (2023) estimate an ESG convenience yield for stocks between 0.37% and 0.66%, from 2007 to 2022. These magnitudes should be compared with other convenience yields, such as the convenience yields of US Treasurys. Krishnamurthy and Vissing-Jorgensen (2012) document an average convenience yields of 0.73% on US Treasurys. The ESG convenience yield in auto ABS that I document is smaller but of similar magnitude than those.

4.4 Robustness

The result that issuers with high ESG scores that finance high-emission auto ABS have a lower cost of capital is robust to using alternative measures, tranches, specifications, and estimators.

Lower cost of capital for brown and high-ESG auto ABS is robust to different estimators A potential concern of the empirical specifications in the main analysis is that the OLS estimators fail to accurately control for differences in covariates and thus falsely attribute differences in issuance spreads to differences in greenness or ESG scores. I address this concern using two alternative estimators.

First, I use the Propensity-Score Matching estimator described in Abadie and Imbens (2016). Appendix Table A12 shows that the results of the matching estimator for ESG scores are similar to those observed using the OLS specifications of Panel A in Table 5, whereas the matching estimator results for the low-emission indicator are larger in magnitude. The latter is likely due to the fact that the matching estimator selects a sample that is more similar in terms of covariates than the OLS estimator. My main results thus underestimate the effect of CO_2 emissions on issuance spreads. Appendix Figure A2 shows the usual diagnostics on the validity of the propensity score matching. The figure shows that the propensity score matching balances the covariates across auto ABS deals and that propensity scores have large areas of common support.

Second, I use the Double-Lasso estimator of Belloni, Chernozhukov, and Hansen (2014). Appendix Table A13 shows that the results of the Double-Lasso estimator are qualitatively and quantitatively similar results to the main results in Table 5, even when the set of potential controls contains over 850 variables. The estimator automatically selects control variables that are relevant to both the outcome and treatment via Lasso estimation.[30] The resulting treatment effect estimator provides inference that is uniformly valid over a large class of models.

Lower cost of capital for brown auto ABS is robust to alternative measures of greenness I perform a series of robustness tests using different measures of greenness for each auto ABS deal. The other measures of greenness are (i) expected tCO_2 per USD, (ii) expected tCO_2 per vehicle, (iii) average MPG of the vehicles in the collateral pool, (iv) average truck share in the collateral pool, and (v) an independently constructed measure of greenness by the Kroll Bond Rating Agency (KBRA).[31] The measures (i) to (v) are not perfectly correlated ($0.1 < |\rho| < 0.67$) with the

[30] The estimation procedure has three steps: (1) select a set of controls that are useful for predicting treatment via Lasso, (2) select a set of controls that predict the outcome via Lasso, and (3) estimate treatment effects by linear regressions while controlling for the union of the set of variables selected in (1) and (2).

[31] KBRA released free reports in March 2021 (KBRA, 2021) and July 2022 (KBRA, 2022) mapping the EPA's vehicle GHG scores to 247 auto ABS deals. The EPA's GHG scores, ranging from 1 to 10 with higher values indicating lower emissions, are displayed on window labels attached to each new vehicle in the US since 2013.

measure of financed tCO_2 from Table 5 and therefore provide an independent signal about the relative greenness of each auto ABS deal. While measures (ii) to (iv) are highly correlated with the KBRA measure ($|\rho| > 0.75$), the latter as a good robustness check because it is independently constructed, publicly available, and a salient feature of the US vehicle market.

Appendix Table A8 shows that the results do not change qualitatively when different measures of relative greenness are used. All specifications show that browner auto ABS have a lower cost of capital. Quantitatively, most estimates imply an elasticity of approximately -0.2, which is close to the estimates of the main results in Table 5.

Lower cost of capital of brown auto ABS holds across the capital structure The analysis above uses A-2 tranches because they all have similar characteristics across different deals; low credit risk, clean-up call options are non-binding, and have the highest observation count. However, the results are robust to the choice of other AAA-rated tranches. Appendix Table A9 reports results across all AAA-rated tranches. The table shows qualitatively and quantitatively similar results to the main results in Table 5. The estimated elasticities of issuance spreads with respect to emissions are also close to -0.2 in other tranches. This implies that the lower cost of capital for environmentally worse auto ABS is scaling through the entire capital structure of these deals.

Lower cost of capital for brown auto ABS is unrelated to credit quality A potential concern is that I use both prime and sub-prime auto ABS. Differences in CO_2 emissions may be correlated with unobserved characteristics related to loan-quality. For example, subprime borrowers more often buy used vehicles and likely find it harder to refinance their loans or trade in their vehicle than prime borrowers. Appendix Table A10 shows that the result is robust when using prime auto ABS deals only. The estimated elasticities of issuance spreads with respect to emissions are between 0.16 and 0.19 in prime auto ABS, similar to the main result in Table 5. This alleviates potential concerns that the unobserved heterogeneity along credit quality contaminates contaminates my estimates.

Lower cost of capital of brown auto ABS is not driven by a specific issuer Given the limited number of 281 deals issued by 22 issuers, one might be worried that a single issuer is driving the result. I therefore re-estimate (6) and (7) while dropping one issuer at a time from the estimation sample. Appendix Figure A1 shows standardized estimates of the leave-out exercise alongside the original estimate. The figure makes clear that no single issuer drives the result. The estimated elasticities are again close to the original estimates.

5 Auto ABS Holdings of ESG Mutual Funds

In seminal work, Hong and Kacperczyk (2009) argue that norm-constrained investors, such as ESG mutual funds, are more likely to invest in green securities compared with unconstrained investors. I therefore turn to portfolio holdings of mutual funds to analyze if the greenness of auto ABS influence ESG mutual funds' decision to invest.

I document two counterintuitive facts: ESG mutual funds (i) hold positions across the full distribution of CO_2 emissions and (ii) invest more in higher-emission deals relative to non-ESG funds. However, these findings are confounded by the fact that the ESG scores of auto ABS issuers are positively correlated with the CO_2 emissions of collateral pools. Once this confounding factor is taken into account, it emerges that ESG funds invest more in brown auto ABS whose issuers have high ESG scores. This finding highlights a consequence of the misalignment between the ESG scores of issuers and the actual greenness of the collateral pools.

ESG Mutual Funds' Approach to auto ABS Prospectuses of ESG mutual funds often detail their investment selection approach with regard to asset-backed securities. For example,

> "[...] When evaluating securitized debt securities [...], the Adviser generally considers the issuer's ESG rating along with ESG factors related to the underlying pool of assets, such as energy efficiency and environmental impact of the underlying assets"
>
> – ESG Mutual Fund Prospectus I

or

> "[...] Potential asset-backed securities are evaluated according to the manager's assessment of material ESG issues for the ABS sectors. The assessment utilizes sector specific metrics across ESG categories, insights from third-party data providers, our analysts' qualitative assessment and a sector-level risk evaluation. [...] Environmental assessment involves issues such as carbon emissions, pollution, and renewable energy"
>
> – ESG Mutual Fund Prospectus II

The fact that ESG mutual funds discuss both "environmental impact of the underlying assets" and the ESG scores of issuer suggests a test of which dimension actually influences an ESG funds choice to invest.

5.1 Data

I obtain mutual fund holdings from the SEC Form N-PORT from Q3 2019 to Q2 2022. I keep the first observation for that a mutual fund reports a position in a senior tranche of an auto ABS. I trim portfolio shares at the 1%-level to account for outliers and reporting errors.[32] Appendix

[32]The results are qualitatively similar to using 2%, 5%, or not trimming.

Table A11 provides summary statistics of the mutual fund holding data. I observe 266 individual auto ABS deals in the holding data.[33] Mutual funds are among the largest group of investors in auto ABS. Mutual funds hold an average of 23% of issuance per deal on their balance sheets. This share can reach 85% for some senior tranches. Other notable institutional investors in senior auto ABS include insurance companies, corporate treasuries, and local and state governments.

In the holding data, I identify ESG mutual funds in two ways: (i) by their name using key words[34] such as "sustainable", "ESG", or "climate" and (ii) using a list of "Sustainable Investment Mutual Funds and ETFs" offered by institutional member firms of "The Forum for Sustainable and Responsible Investing".[35] I identify 35 ESG funds (and 787 non-ESG funds) that hold at least one position in an auto ABS tranche over the sample period (32 ESG funds hold at least two positions). These ESG funds make up 25% of the 143 ESG-bond funds which I am able to identify in the N-PORT filings.

5.2 Identification Strategy

To test whether ESG funds tilt their portfolio toward greener auto ABS, I estimate a reduced form asset demand function in the spirit of Koijen and Yogo (2019). I use the following reduced form model for portfolio shares in tranche t of auto ABS deal b by mutual funds i in year-quarter r:

$$\log\left(\text{Portfolio Share}\right)_{itrb} = \alpha\left(\text{ESG Fund}_i \times \text{Green}_b\right) + \gamma_i + \gamma_b + \gamma_r + \zeta' X_t + \varepsilon_{itrb} \tag{9}$$

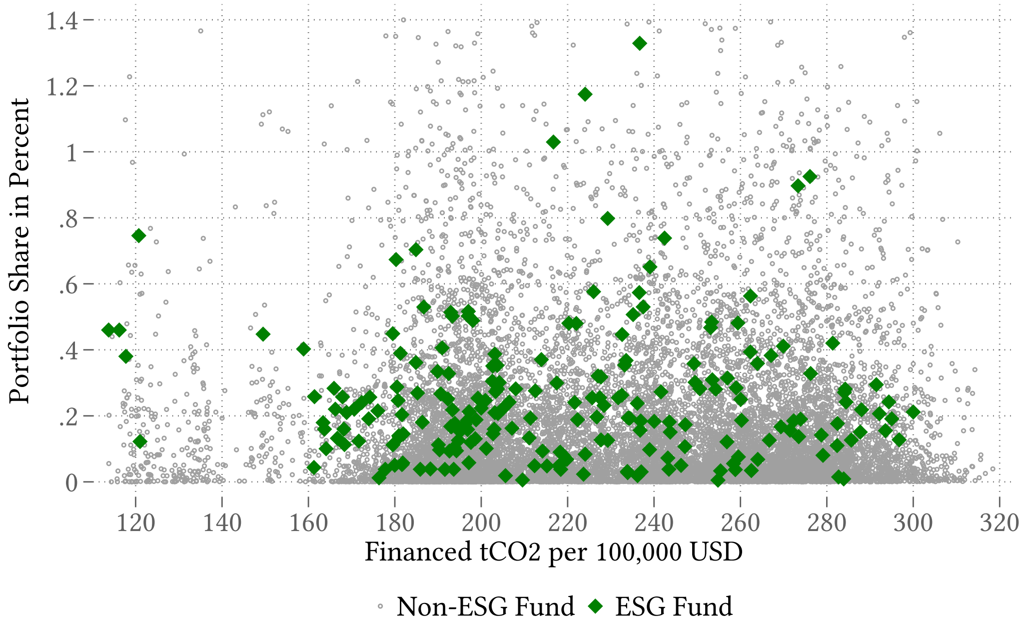
where Green_b is either a measure of environmental impact such as tCO_2 per vehicle, a measure of energy efficiency such as MPG, or the ESG score of the issuer; γ_i are fund fixed effects; γ_b are auto ABS deal fixed effects; and γ_r reporting year-quarter fixed effects. Vector X_t contains tranche characteristics that are allowed to have different slopes for subprime and prime issues. These characteristics are the weighted average life, size, and annualized yield of the tranche. The coefficient of interest is α which captures the effect of variation in greenness of the collateral on portfolio shares by ESG funds relative to non-ESG funds.

I leverage the fact that mutual funds hold positions in multiple auto ABSs to tightly identify whether ESG funds invest more capital in environmentally friendly auto ABS compared with non-ESG funds. Using a stringent set of fixed effects, I estimate ESG fund preferences from variation

[33]The discrepancy to the 281 auto ABS deals in Section 4.3 is explained by the shorter sample period for that N-PORT filings are available.

[34]The key word list contains the following words: "green", "climate", "esg", "sustainable", "environment", "responsible", "impact", "catholic", "social", "sri", "csr", "community", and "justice".

[35]https://charts.ussif.org/mfpc/



Note: X-axis is jittered with normally distributed noise for readability.

Figure 4: Portfolio Shares of Mutual Funds in Auto ABS

in greenness of multiple auto ABS deals held by ESG funds relative to non-ESG funds during the same reporting period. The empirical specifications include fixed effects for the collateral pool and fund and thus absorb the characteristics and preferences of each mutual fund and the specific features of each auto ABS deal. By including these fixed effects, the model effectively controls for as much of the unobserved heterogeneity across collateral pools and funds as possible. The relative difference in preferences for green assets by ESG versus non-ESG funds, however, remains identified. Standard errors are clustered at the fund-level to account for common variation at the fund-level.

5.3 Results

Figure 4 plots portfolio shares in auto ABS of mutual funds against financed CO_2 emissions per \$100,000. The graph shows that ESG mutual funds hold positions across the full distribution of CO_2 emissions. The fact that ESG funds have positions across the full distribution is surprising because common ESG strategies imply either outright exclusions of brown assets or best-in-class investment. Counterintuitive to best-in-class investment, Figure 4 also shows that ESG funds hold similar or higher shares in browner auto ABS.

Table 7 provides estimates of the relationship between greenness and ESG ownership using

Table 7: Reduced Form Demand of Mutual Fund for Auto ABS

Panel A: Measures of Environmental Impact of Investment

	(1) Portfolio Share	(2) Portfolio Share	(3) Portfolio Share	(4) Portfolio Share	(5) Portfolio Share	(6) Portfolio Share
ESG Fund=1 × Green (tCO2<p50)=1	-0.221*					
	(0.0911)					
ESG Fund=1 × Financed tCO2 per vehicle		0.162*				
		(0.0687)				
ESG Fund=1 × Financed tCO2 per vehicle			0.162*			
			(0.0687)			
ESG Fund=1 × Avg. MPG $\times(-1)$				0.206***		
				(0.0605)		
ESG Fund=1 × Truck Share					0.136	
					(0.138)	
ESG Fund=1 × Avg. GHG Rating (KBRA)$\times(-1)$						0.233**
						(0.0777)
Tranche controls	Yes	Yes	Yes	Yes	Yes	Yes
Fund FE, Deal FE	Yes	Yes	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Tranche FE	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.835	0.835	0.835	0.835	0.835	0.832
Observations	11,207	11,202	11,202	11,202	11,202	10,432

Panel B: ESG Scores versus Environmental Impact of Investment

	(1) Portfolio Share	(2) Portfolio Share	(3) Portfolio Share	(4) Portfolio Share	(5) Portfolio Share	(6) Portfolio Share
ESG Fund=1 × S&P ESG Score	0.171***	0.137**	0.166***			
	(0.0487)	(0.0508)	(0.0474)			
ESG Fund=1 × Refinitiv ESG Score				0.127**	0.0855+	0.121**
				(0.0448)	(0.0480)	(0.0453)
ESG Fund=1 × Financed tCO2 per car		0.0793			0.113	
		(0.0744)			(0.0788)	
ESG Fund=1 × Financed tCO2 per USD			0.0423			0.0445
			(0.0620)			(0.0683)
Fund FE	Yes	Yes	Yes	Yes	Yes	Yes
ABS Deal FE	Yes	Yes	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Tranche FE	Yes	Yes	Yes	Yes	Yes	Yes
Tranche controls	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.836	0.836	0.836	0.836	0.836	0.836
Observations	9987	9987	9987	9987	9987	9987

Notes: Coefficients are standardized to unit variances. Standard errors in parentheses clustered at fund-level (min K=639). + p<0.10, * p<0.05, ** p<0.01, *** p<0.001. MPG and GHG Rating are multiplied by (-1) such that higher values are environmentally worse.

the specification of equation (9). The estimated coefficients in Column (1) of Panel A of Table 7 indicate that the greenest 50% off auto ABS receive between 20% less capital from ESG funds relative to non-ESG funds. Column (2) to (6) present similar estimates using other measures of greenness. In all columns, the estimated coefficients are positive and of similar magnitude. The estimates in column (2) of Panel A imply that moving from the 10th percentile of average financed tCO_2 per vehicle to the 90th percentile (a 2.75 sd distance equivalent to comparing Honda to Ford auto ABS) results in 0.45 sd higher portfolio shares for a ESG funds than a non-ESG funds.

The correlation between ESG scores and CO_2 emissions is even stronger in the mutual fund holding data as Appendix Table B2 shows. Panel B of Table 7 therefore repeats the reduced form demand estimation of Panel A but controls for the ESG scores of auto ABS issuers. The estimates in columns (1) and (4) show that both the S&P and Refinitiv ESC scores are highly correlated with the differential demand by ESG funds relative to non-ESG funds. Moreover, columns (2), (3), (5), and (6) show that the differential demand for auto ABS by issuers with high ESG-scores attenuates the estimates of differential demand for high-emission auto ABS up to 50%.

The results indicate that ESG funds hold more auto ABS of issuers with high ESG-scores relative to non-ESG funds. This by itself is not surprising. However, the ESG scores of issuers are positively correlated with the CO_2 emissions of collateral. ESG funds therefore inadvertently hold higher portfolio shares of environmentally less friendly auto ABS than non-ESG funds.

6 Discussion

The goal of many ESG investors is to change firm financing conditions by rewarding green firms with a lower cost of capital and penalizing brown firms by raising their cost of capital. Practitioners view this mechanism as a way to internalize environmental externalities such as CO_2 emissions.[36]

I document that ESG investors are successful in lowering the cost of capital for auto asset-backed security deals of issuers with high-ESG scores. The observed effects translate into an ESG convenience yield of 0.28% p.a. that investors earn on their ESG investments. This convenience yield is economically meaningful and similar in magnitude to the convenience yield of US Treasurys.

However, my findings show that ESG investors are not necessarily investing in the most environmentally-friendly securities but in securities whose issuers have higher ESG scores, even

[36] Money managers report that the leading ESG criteria are climate change CO_2 emissions, and fossil fuel divestment (USSIF (2022): Sustainable Investing – Money Managers 2022).

if those securities have higher CO_2 emission intensity. This finding raises questions about the effectiveness of ESG investment strategies in addressing environmental externalities. Fund managers may need to re-evaluate their investment processes and methods to ensure that they are fulfilling their obligations to promote environmentally sustainable investing. Fund managers may also need to look for alternative investments that are better aligned with their ESG objectives and consider the environmental impact of their investments more closely to meet the expectations of their investors.

The findings further suggest that there may be a need for more clarity and transparency in ESG labeling and investment processes. Policymakers may need to provide greater guidance to the financial sector on what constitutes environmentally sustainable investing, and to ensure that ESG labels accurately reflect the environmental impact of investments.

ESG regulation in the United States is still in its infancy. The SEC has taken some steps to provide guidance to the financial industry to ensure that ESG labels accurately reflect the environmental impact of investments. The SEC has issued several statements and guidance documents related to ESG investing and has encouraged companies to provide more comprehensive and transparent disclosure of their ESG practices and impact. In Europe, there are similar efforts to ensure the accuracy of ESG labeling. The European Union has adopted the Sustainable Finance Disclosure Regulation (SFDR), that requires companies and market participants to provide more comprehensive and transparent disclosure of their sustainability risks, impacts, and objectives. Emiris, Harris, and Koulischer (2023) examine the impact of the SFDR on portfolio allocation and ESG fund flows. Their findings indicate that the regulation led to increased flows to ESG funds, particularly among investors with stronger environmental preferences, and that funds with higher initial uncertainty about their sustainability benefited the most from the disclosure.

7 Conclusion

This paper shows that ESG investing successfully lowers the cost of capital of auto ABS for issuers with high ESG scores. The observed differences in spreads imply that investors derive ESG convenience yields of 0.28% p.a., on average. This convenience yield nearly tripled from 0.14% in 2017 to 0.39% p.a. in 2022. However, the focus on issuer ESG scores instead of the collateral's CO2 emissions also lowers the cost of capital for high-emission auto ABS. This seems to be driven by the facts that commonly used ESG scores are positively correlated with CO2 emissions, do not reflect the variability of emissions across issuers, and fail to account for large Scope 3 emissions.

This paper also shows that ESG mutual funds invest more in auto ABS of issuers with high

ESG scores. However, the ESG scores of issuers are positively correlated with the CO_2 emissions of collateral pools. ESG funds therefore inadvertently hold higher portfolio shares in environmentally less friendly auto ABS than non-ESG funds.

These findings have implications for retail investors of ESG mutual funds, fund managers, and policy makers. The results suggest that commonly used ESG scores are uninformative about the environmental impact of certain securities and that ESG mutual funds are not investing in the most environmentally-friendly securities; raising questions about the effectiveness of ESG investment strategies in addressing environmental externalities.

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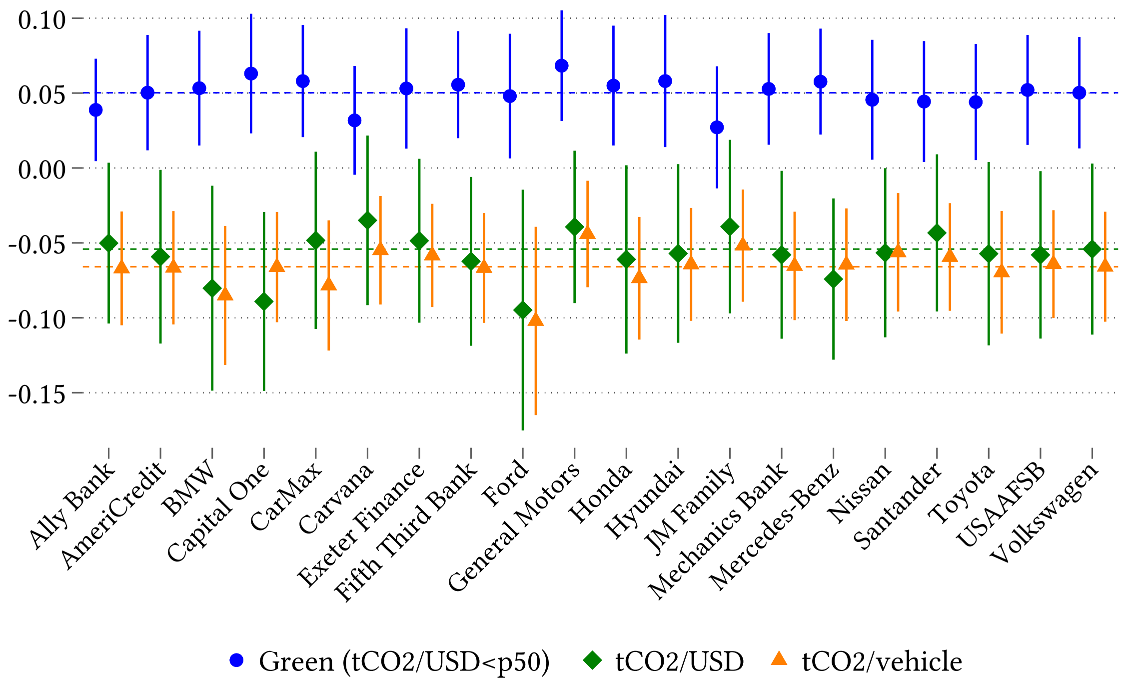
A Appendix

A.1 Appendix Figures



Note: Coefficients are standardized to unit variances. Dashed colored lines give original point estimate.

Figure A1: Leave-out estimates of (6) and (7) that drop one issuer at a time from the estimation sample.

A.2 Appendix Tables

Table A1: Regression of average tCO_2 emissions per vehicle on vehicle types

	Constant	Truck share	SUV share	Adj. R^2	N	Avg. tCO_2/vehicle
β	44.108***	1.019***	0.210***	0.746	281	70.514
(se) or sd	(1.879)	(0.036)	(0.040)			15.550

+ p<0.10, * p<0.05, ** p<0.01, *** p<0.001.

Table A2: Summary Statistics Loan-Level Data

	Mean	SD	Median	Min	Max	N
Original Interest Rate	7.62	6.95	4.99	0.00	30.00	18,863,466
Original Loan Amount ($)	26,154.45	12,488.05	23,925.29	518.03	248,681.95	18,863,467
Original Loan Term (months)	67.56	8.68	72.00	7.00	96.00	18,863,467
Credit Score	711.48	101.21	722.00	250.00	900.00	18,029,902
Payment-to-Income Ratio	0.08	0.05	0.08	0.00	0.79	18,644,373
Income Verified	0.09	0.29	0.00	0.00	1.00	18,863,467
Loan-to-Value	0.90	0.16	1.00	0.01	1.00	18,862,126
Outstanding Balance Ratio	0.83	0.24	0.93	0.00	1.00	18,863,463
Vehicle Value Amount ($)	27,723.22	13,358.86	25,251.00	0.00	1,084,455.00	18,863,464
Vehicle Age (Years)	2.69	2.53	2.00	0.00	35.00	18,863,467
Used Vehicle	0.46	0.50	0.00	0.00	1.00	18,863,467
SVM, Financed	162,526.16	39,846.07	173,251.82	254.15	240,728.61	18,863,467
SVM, Total	202,941.11	17,235.53	207,738.97	189,173.82	240,728.61	18,863,467
tCO2, total Lifetime	78.87	33.08	72.43	0.00	538.75	18,863,467
tCO2, remaining Lifetime	62.97	31.90	56.71	0.00	538.75	18,863,467
tCO2, financed remaining Lifetime	47.05	29.53	44.64	0.00	538.75	18,862,122

Table A3: Greenness and Ex-post Performance of Collateral Pools

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Δ Realized APS				Realized % loans delinquent 30d+			
Financed tCO2 per USD	0.0921				0.0226			
	(0.123)				(0.0280)			
Financed tCO2 per vehicle		-0.0322				-0.0305		
		(0.139)				(0.0207)		
Refinitiv ESG Score			-0.0663				0.0795	
			(0.159)				(0.0861)	
S&P ESG Score				0.0133				0.129
				(0.172)				(0.102)
Avg. Credit Score					-0.534**	-0.559***	-0.599*	-0.696*
					(0.140)	(0.146)	(0.277)	(0.301)
Subprime FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.0270	0.0193	0.00902	0.00540	0.899	0.899	0.902	0.905
Observations	281	281	243	243	281	281	243	243

Robust standard errors in parenthesis clustered at originator. + p<0.10, * p<0.05, ** p<0.01, *** p<0.001.
Coefficients are standardized to unit variances.

Table A4: Covariate Balance Test of *Green* and *Brown* auto ABS Deals

Variable	(1) Brown (CO2>=p50) Mean/(SE)	(2) Green (CO2<p50) Mean/(SE)	(1)-(2) Pairwise t-test Mean difference
Financed tCO2 per USD	251.861 (2.187)	187.059 (1.761)	64.802***
Yield Curve 6m	0.013 (0.001)	0.014 (0.001)	-0.001
Yield Curve 12m	0.014 (0.001)	0.016 (0.001)	-0.002
VIX	17.377 (0.577)	21.661 (0.593)	-4.284
5 Year Breakeven Inflation	1.863 (0.038)	2.202 (0.055)	-0.339
Attachment Point	0.504 (0.006)	0.463 (0.006)	0.041*
Weight. Avg. Life	0.930 (0.026)	1.030 (0.028)	-0.100
Tranche Size	336.219 (10.636)	397.411 (11.062)	-61.192
Loan-to-Value	0.927 (0.003)	0.909 (0.003)	0.017
Mean Credit Score	673.859 (6.297)	738.773 (5.018)	-64.913***
Mean Interest Rate	9.862 (0.506)	5.406 (0.403)	4.456*
Mean % of outstanding	0.923 (0.005)	0.873 (0.006)	0.049
Warehousing Time (Months)	8.185 (0.334)	10.909 (0.369)	-2.723
Number of observations	141	140	281

Note: Similar to the regression analysis the t-test include APS FE, subprime FE, and year-month FE. * p<0.05, ** p<0.01, *** p<0.001

Table A5: Correlation between environmental impact of auto ABS and ESG scores of Issuers

	Sustainalytics ESG score	Sustainalytics Env. score	S&P ESG score	S&P Env. score	Refinitiv ESG score	Refinitiv Env. score	Fin. tCO2 per vehicle	Fin. tCO2 per USD
Sustainalytics ESG score	1.00							
Sustainalytics Environmental score	0.86	1.00						
S&P ESG score	0.81	0.76	1.00					
S&P Environmental score	0.84	0.80	0.95	1.00				
Refinitiv ESG score	0.84	0.67	0.78	0.78	1.00			
Refinitiv Environmental score	0.74	0.63	0.67	0.63	0.67	1.00		
Financed tCO2 per vehicle	0.20	-0.10	0.17	0.16	0.48	0.07	1.00	
Financed tCO2 per USD	0.11	-0.04	0.21	0.12	0.25	-0.09	0.62	1.00

Notes: Spearman rank correlation among N=122 observations for which ESG scores of issuers are available.

Table A6: Regressions of Sustainalytics ESG scores on CO2 Emissions

	(1) Sustainalytics ESG score	(2) Sustainalytics Env. score	(3) Sustainalytics ESG score	(4) Sustainalytics Env. score
Financed tCO2 per USD	0.0425	0.0174		
	(0.287)	(0.297)		
Financed tCO2 per vehicle			0.169	-0.126
			(0.145)	(0.145)
Issuer Type FE	Yes	Yes	Yes	Yes
Adj. R^2	0.206	0.180	0.232	0.195
Observations	122	122	122	122

Standard errors in parentheses are clustered at issuer-level. + p<0.10, * p<0.05, ** p<0.01, *** p<0.001.
Coefficients are standardized to unit variances.

Table A7: Estimates using Sustainalytics ESG scores

	(1) Issuance Spread	(2) Issuance Spread	(3) Issuance Spread	(4) Issuance Spread	(5) Issuance Spread	(6) Issuance Spread	(7) Issuance Spread
High ESG (score>p50)	-0.0553						
	(0.0323)						
Sustainalytics ESG score		-0.304**		-0.389+		-0.388+	
		(0.0951)		(0.186)		(0.210)	
Sustainalytics Env. score			-0.112*		-0.146		-0.156
			(0.0518)		(0.166)		(0.155)
Year-month FE, daily market controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Prepayment speed FE, Tranche FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Other tranche characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Ex-ante prepayment controls	No	No	No	Yes	Yes	Yes	Yes
Ex-post prepayment controls	No	No	No	No	No	Yes	Yes
Adj. R^2	0.941	0.943	0.940	0.947	0.945	0.948	0.946
Observations	118	118	118	118	118	118	118

Standard errors in parentheses are double clustered at issuer and year-month. + p<0.10, * p<0.05, ** p<0.01, *** p<0.001

Table A8: Elasticity of issuance spreads with respect to different measures of *Greenness*

	(1) Issuance Spread	(2) Issuance Spread	(3) Issuance Spread	(4) Issuance Spread	(5) Issuance Spread	(6) Issuance Spread	(7) Issuance Spread	(8) Issuance Spread	(9) Issuance Spread	(10) Issuance Spread
Expected tCO2 per USD	-0.199^{+}	-0.245*								
	(0.110)	(0.108)								
Expected tCO2 per vehicle			-0.201**	-0.239**						
			(0.0700)	(0.0726)						
Avg. MPG$\times(-1)$					-0.201	-0.275*				
					(0.127)	(0.130)				
Avg. Truck Share							-0.209^{+}	-0.258*		
							(0.106)	(0.121)		
Avg. GHG Rating (KBRA)$\times(-1)$									-0.145	-0.232^{+}
									(0.125)	(0.137)
Year-month FE, daily market controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Assumed prepayment speed FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Other tranche characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Ex-ante prepayment controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Ex-post prepayment controls	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Adj. R^2	0.966	0.970	0.966	0.971	0.965	0.970	0.965	0.970	0.961	0.968
Observations	276	276	276	276	276	276	276	276	243	243

Standard errors in parentheses clustered at year-month (min K=71). + p<0.10, * p<0.05, ** p<0.01, *** p<0.001

Average MPG and GHG Rating are multiplied by (-1) such that higher values respond to worse environmental performance.

Table A9: Elasticity of issuance spreads with respect to emissions in other senior tranches

	(1) Issuance Spread	(2) Issuance Spread	(3) Issuance Spread	(4) Issuance Spread	(5) Issuance Spread	(6) Issuance Spread	(7) Issuance Spread	(8) Issuance Spread
	A-3 Tranche				A-4 Tranche			
Financed tCO2 per USD	-0.220**	-0.230**			-0.267***	-0.253**		
	(0.0795)	(0.0835)			(0.0704)	(0.0742)		
Financed tCO2 per vehicle			-0.124*	-0.177**			-0.150**	-0.112^{+}
			(0.0516)	(0.0639)			(0.0517)	(0.0628)
Year-month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Market condition controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Assumed prepayment speed FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Other tranche characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Ex-ante prepayment controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Ex-post prepayment controls	No	Yes	No	Yes	No	Yes	No	Yes
Adj. R^2	0.964	0.964	0.964	0.964	0.980	0.981	0.980	0.980
Observations	272	272	272	272	190	190	190	190

Standard errors in parentheses clustered at year-month.

+ p<0.10, * p<0.05, ** p<0.01, *** p<0.001

Table A10: Elasticity of issuance spreads with respect to emissions in prime auto ABS

	(1) Issuance Spread	(2) Issuance Spread	(3) Issuance Spread	(4) Issuance Spread	(5) Issuance Spread	(6) Issuance Spread	(7) Issuance Spread	(8) Issuance Spread
Financed tCO2 per USD	-0.139	-0.167^{+}						
	(0.0869)	(0.0877)						
Expected tCO2 per USD			-0.166*	-0.184*				
			(0.0818)	(0.0831)				
Financed tCO2 per vehicle					-0.117*	-0.154**		
					(0.0515)	(0.0571)		
Expected tCO2 per vehicle							-0.122*	-0.162**
							(0.0508)	(0.0562)
Year-month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Market condition controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Assumed prepayment speed FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Other tranche characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Ex-ante prepayment controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Ex-post prepayment controls	No	Yes	No	Yes	No	Yes	No	Yes
Adj. R^2	0.936	0.937	0.937	0.937	0.937	0.937	0.937	0.937

Standard errors in parentheses clustered at year-month (min K=70). + p<0.10, * p<0.05, ** p<0.01, *** p<0.001

Table A11: Summary Statistics of Holding Data

	Mean	SD	Median	Min	Max	N
Portfolio Share	0.17	0.22	0.09	0.00	1.40	11,325
Coupon Yield	1.90	1.21	1.92	0.00	6.51	11,325
Tranche Size ($m)	263.32	168.75	230.50	8.51	746.94	11,325
Weighted Average Life	2.35	0.99	2.38	0.11	5.06	11,325
Subprime ABS	0.41	0.49	0.00	0.00	1.00	11,325
Financed tCO2 per USD	227.80	37.88	226.88	118.20	311.78	11,325
Financed tCO2 per car	59.65	12.18	58.31	40.54	101.27	11,325

Table A12: Estimates using Propensity Score Matching

	(1) Issuance Spread	(2) Issuance Spread	(3) Issuance Spread
Green (tCO2<p50)	0.236***		
	(0.0616)		
Top-ESG (Refinitiv Score>p50)		-0.136*	
		(0.0590)	
Top-ESG (S&P Score>p50)			-0.128*
			(0.0563)
Time, Subprime, APS FE	Yes	Yes	Yes
Observations	84	174	198
Treated	50	93	77
Control	34	81	121
# Nearest Neighbors	2	2	2

+ p<0.10, * p<0.05, ** p<0.01, *** p<0.001

A.3 Matching Estimator

Appendix table A12 shows that one obtains qualitatively and quantitatively similar results to the main results when using a propensity score matching estimator. The "treated" (i.e., either low CO2 emissions or high ESG score) and "untreated" auto ABS are matched to their k=2 nearest neighbors.

Appendix Figure A2 provides diagnostics on the validity of the propensity matching. Panel (a) to (c) show that the propensity scores of CO2, Refinitiv's ESG, as well as S&P's ESG score have sufficient overlap to estimate a matching model. The red bars in panels (a) to (c) show propensity score restrictions imposed on the region of overlap when estimating the models of Appendix table A12. Panel (d) shows the standardized difference[37] between treated and untreated units. The standardized difference are all within or close the rule of thumb bands (± 0.25) depicted as red bars. This implies that a regression model adjusting for covariates would not be sensitive to model specification.

[37] $\Delta x = \frac{\bar{x}_{\text{treated}} - \bar{x}_{\text{untreated}}}{\sqrt{S^2_{\text{treated}} - S^2_{\text{untreated}}}}$

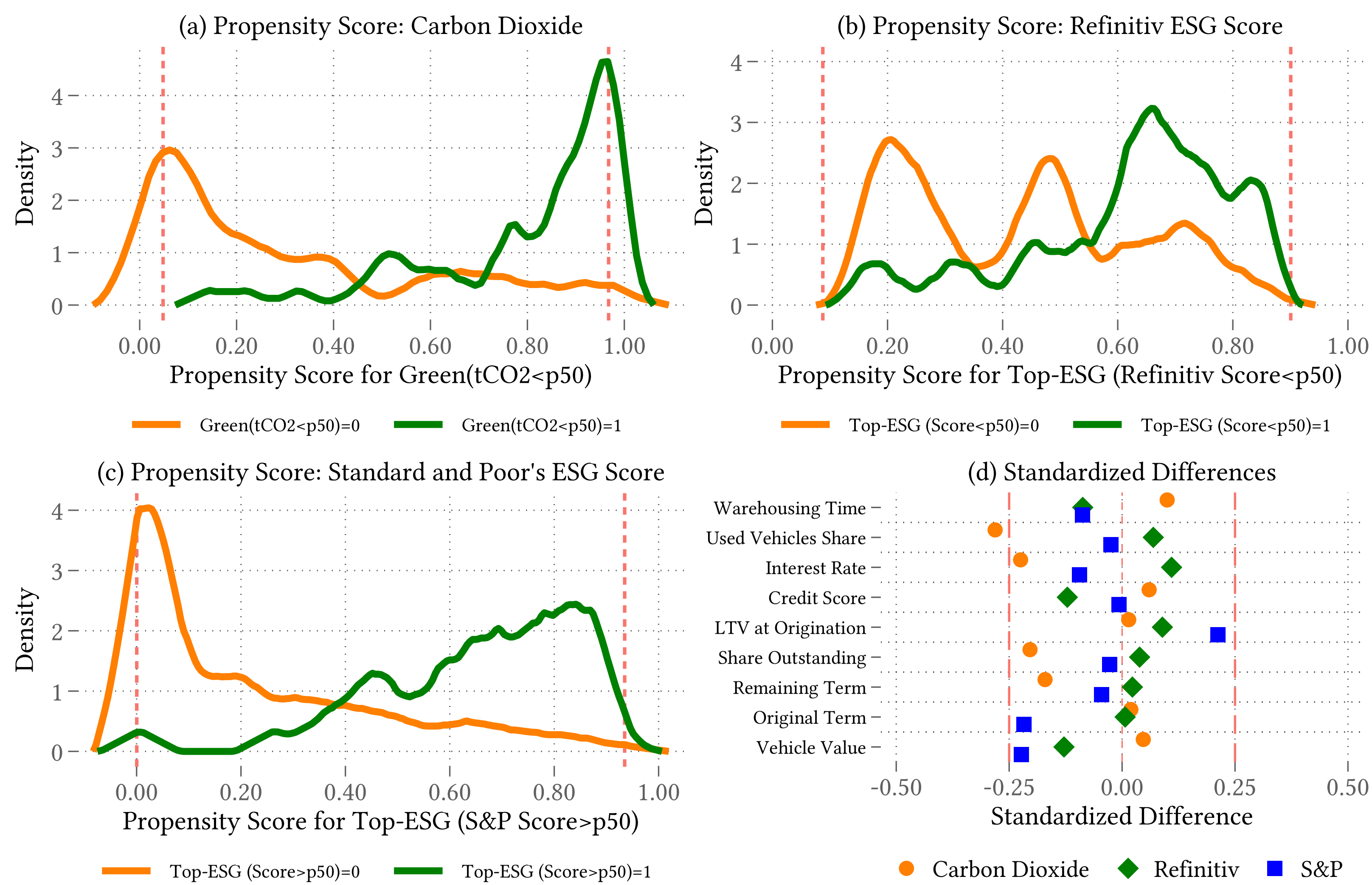


Figure A2: Propensity Score Matching: Diagnostics

A.4 Double-selection Lasso Estimator

Table A13: Estimates using Double-selection Lasso Estimator of Belloni et al. (2014)

	(1) Issuance Spread	(2) Issuance Spread	(3) Issuance Spread	(4) Issuance Spread	(5) Issuance Spread	(6) Issuance Spread
Refinitiv ESG Score	-0.511***	-0.379***	-0.374***			
	(0.0672)	(0.0879)	(0.0817)			
S&P ESG Score				-0.168***	-0.163***	-0.149***
				(0.0356)	(0.0424)	(0.0430)
Financed tCO2 per USD	-0.0729	-0.128	-0.102	-0.208+	-0.119	-0.194*
	(0.113)	(0.115)	(0.0855)	(0.111)	(0.114)	(0.0982)
Time, Subprime, APS, Tranche FE	Yes	Yes	Yes	Yes	Yes	Yes
No. of potential controls	38	290	858	38	290	858
No. of selected controls	11	15	15	11	17	15

Standard error clustered at year-month. + $p<0.10$, * $p<0.05$, ** $p<0.01$, *** $p<0.001$

Appendix Table A13 shows that one obtains qualitatively and quantitatively similar results to the main results when using the double-selection lasso estimator of Belloni et al. (2014).

The list of potential control variables for the lasso algorithm is the following: Level of VIX at issuance, standard deviation of VIX in the 30 days before issuance, inflation expectations (5-Year breakeven inflation rate) at issuance, 6 month and 12 month estimate of the treasury yield curve from Filipović et al. (2022), attachment point, weighted average life of tranche, issuance size of tranche, total issuance size, 30d+ delinquency rate, difference to assumed prepayment speed, average share of used cars, average interest rate of loans, average warehousing time, 25th percentile of warehousing time, 75th percentile of warehousing time, average credit score of borrowers, 25th percentile of credit score of borrowers, 75th percentile of credit score of borrowers, average loan-to-value ratio at issuance, 25th percentile of loan-to-value ratio at issuance, 75th percentile of loan-to-value ratio at issuance, average % of principal outstanding at time of securitization, 25th percentile of % of principal outstanding at time of securitization, 75th percentile of % of principal outstanding at time of securitization, average remaining term, 25th percentile of remaining term, 75th percentile of remaining term, average original term, 25th percentile of original term, 75th percentile of original term, average vehicle value at origination, 25th percentile of value at origination, 75th percentile of value at origination, captive FE, US issuer FE, as well as interaction term of these variables. I require the following fixed effects to be present in each (Lasso) regression: assumed absolute prepayment speed, year-month, and subprime fixed effects.

B Online Appendix (for online publication only)

(a) Santander SDRIVE 2021-4 Subprime Issue

Pricing $1.8bn Santander Drive Auto Receivables Trust 2021-4

Issuer: Santander Consumer USA
Lead Managers: Citi(str.), JPM, and SIS
DE&I Co-managers: AmeriVet Securities, Great Pacific Securities, Mischler Financial Group

Anticipated Capital Structure:

CL	OFF. AMT	WAL	F/M	L.FNL	BENCH	SPRD	YLD%	CPN	PX
A-1	$222.40	0.13	F1+/P-1	11/15/2022	Intl.	7	0.16802	0.16802	100.00000
A-2	$543.10	0.64	AAA/Aaa	08/15/2024	EDSF	20	0.380	0.37	99.99378
A-3	$292.37	1.43	AAA/Aaa	08/15/2025	EDSF	15	0.517	0.51	99.99081
B	$288.61	2.10	AA/Aaa	06/15/2026	IntS	30	0.887	0.88	99.98887
C	$243.48	2.80	A/Aa2	02/16/2027	IntS	47	1.271	1.26	99.97902
D	$241.38	3.58	BBB/Baa2	10/15/2027	IntS	70	1.685	1.67	99.98569
E	$131.18	3.97	NR/B2	<<NOT OFFERED>>					

(b) CarMax 2019-1 Prime Issue

$1.5bln CarMax (CARMX) 2019-1
JOINT BOOKRUNNERS : Credit Suisse (str), Barclays, Wells Fargo
CO-MANAGERS : MUFG, Scotia, SMBC, TD

CLS	$AMT(MM)	WAL	S&P/FITCH	P.WIN	L.FNL	BNCH	SPRD	YLD%
A1	277.000	0.28	A-1+/F1+	1-7	01/2020	IntL -	1	2.78007
A2A	412.000	1.16	AAA/AAA	7-22	07/2022	EDSF +	31	3.045
A2B	100.000	1.16	AAA/AAA	7-22	07/2022	1mL +	31	
A3	493.900	2.64	AAA/AAA	22-43	03/2024	IntS +	40	3.074
A4	107.910	3.84	AAA/AAA	43-48	08/2024	IntS +	65	3.283
B	42.170	3.98	AA/AA	48-48	11/2024	IntS +	85	3.479
C	39.910	3.98	A/A	48-48	01/2025	IntS +	115	3.779
D	27.110	3.98	BBB/BBB	48-48	08/2025	IntS +	145	4.079

* Exp. Settle: 01/23/19
* First Pay Date: 02/15/19
* Px Speed: 1.30% ABS to 10% Call
* Timing: PRICED
* Format: Public/SEC
* ERISA: Yes
* Min Denoms: $5k by $1k
* B&D: Credit Suisse

Figure B1: Examples of Typical auto ABS Deals

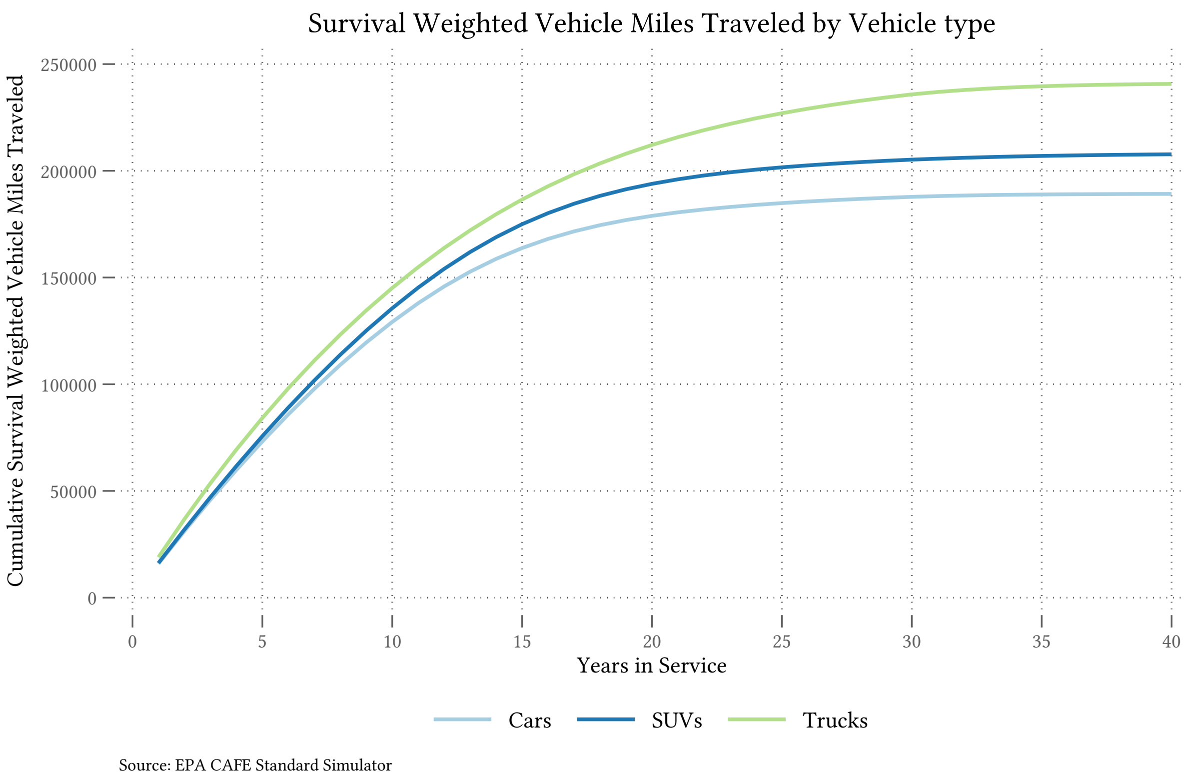
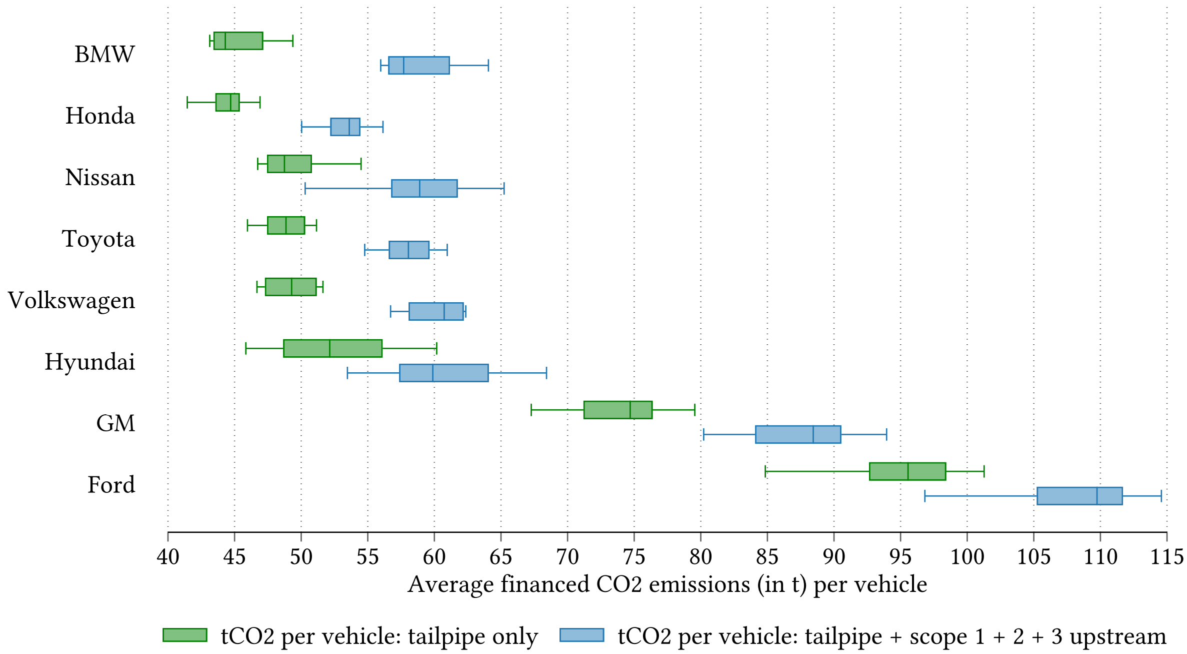


Figure B2: Survival-Weighted Vehicle Miles by Vehicle Type

(a) tCO_2 emissions per vehicle



(b) tCO_2 emissions per $100,000

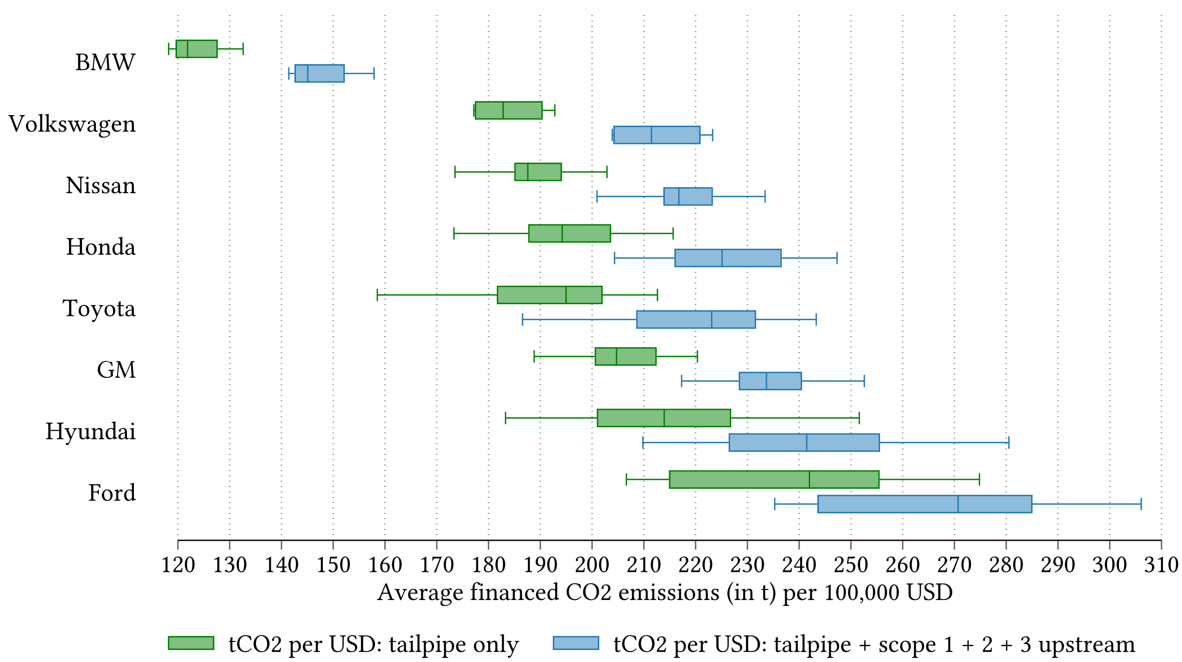


Figure B3: Dispersion of tailpipe and production CO_2 emissions across auto ABS pools of captive lenders

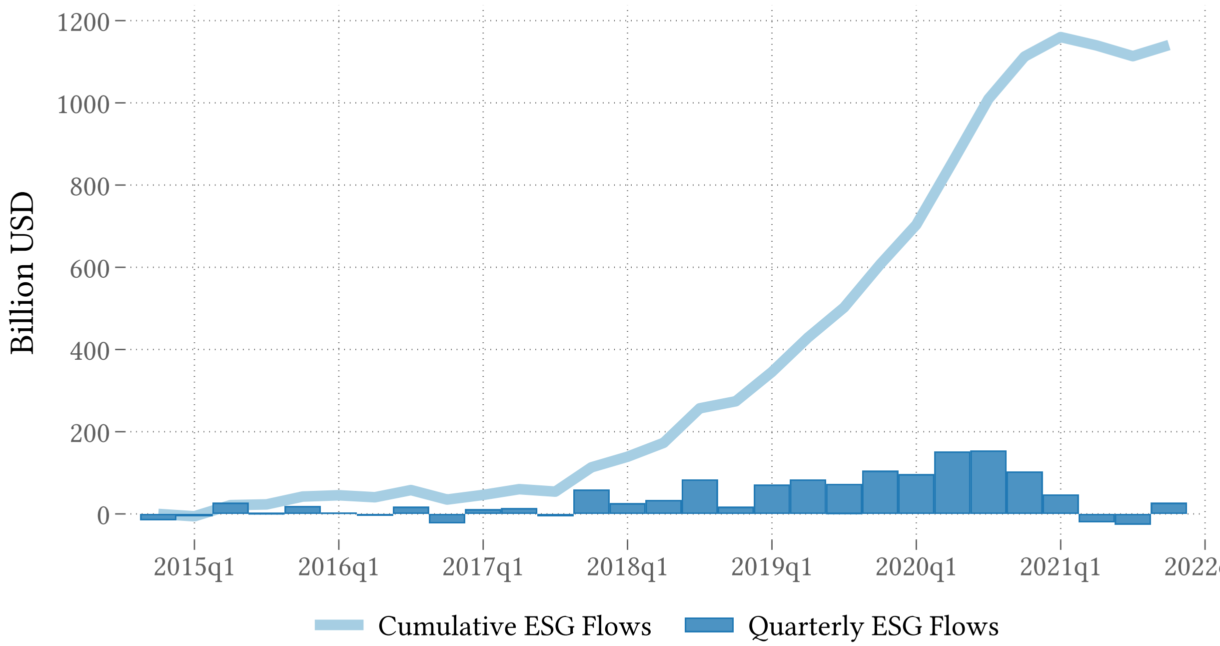


Figure B4: Total ESG Flow (Van der Beck, 2021). ESG flow for each 13F institution as the return-adjusted change in ESG-assets under management and then summed across all institutions. I report rolling 4-quarter averages and plot the cumulative sum of all flows since 2014.

Table B1: ESG Score Balance across Green (tCO2/vehicle<p50) and Brown (tCO2/vehicle>p50)

	(1)		(2)		(1)-(2)	
	Brown (tCO2/vehicle>p50)		Green (tCO2/vehicle<=p50)		Pairwise t-test	
Variable	N/Clusters	Mean/(SE)	N/Clusters	Mean/(SE)	N/Clusters	Mean difference
Refinitiv ESG Score	119	0.783	124	0.688	243	0.095
	13	(0.045)	11	(0.069)	17	
Refinitiv E Score	119	0.722	124	0.659	243	0.063
	13	(0.096)	11	(0.127)	17	
Refinitiv S Score	119	0.753	124	0.692	243	0.061
	13	(0.050)	11	(0.056)	17	
Refinitiv G Score	119	0.816	124	0.676	243	0.140
	13	(0.051)	11	(0.066)	17	
S&P ESG Score	119	0.614	124	0.552	243	0.062
	13	(0.082)	11	(0.101)	17	
S&P E Score	119	0.645	124	0.582	243	0.063
	13	(0.100)	11	(0.123)	17	
S&P S Score	119	0.590	124	0.542	243	0.048
	13	(0.096)	11	(0.112)	17	
S&P G Score	119	0.615	124	0.530	243	0.084
	13	(0.068)	11	(0.083)	17	
Sustainalytics ESG Score	64	0.604	58	0.589	122	0.015
	11	(0.032)	10	(0.030)	16	
Sustainalytics E Score	64	0.567	58	0.615	122	-0.048*
	11	(0.054)	10	(0.045)	16	
Sustainalytics S Score	64	0.650	58	0.557	122	0.093
	11	(0.028)	10	(0.043)	16	
Sustainalytics G Score	64	0.608	58	0.587	122	0.021
	11	(0.036)	10	(0.022)	16	

Notes: Pairwise t-tests adjust for industry fixed effects. Standard errors are clustered at issuer-level. * p<0.05, ** p<0.01, *** p<0.001.

Table B2: Correlation of ESG scores and measures of environmental impact in N-PORT holdings

	Refinitiv ESG Score	S&P ESG Score	Financed tCO2/car	Financed tCO2/USD	Avg. MPG	Truck %	GHG Rating
Refinitiv ESG Score	1.00						
S&P ESG Score	0.85	1.00					
Fin. tCO2/car	0.50	0.41	1.00				
Fin. tCO2/USD	0.36	0.34	0.54	1.00			
Avg. MPG	0.32	0.25	0.83	0.42	1.00		
Truck %	0.33	0.24	0.83	0.33	0.86	1.00	
GHG Rating	0.27	0.15	0.75	0.19	0.86	0.85	1.00

MPG and GHG Rating are multiplied by (-1) such that higher values are environmentally worse.