Do ESG Investors Care About Carbon Emissions? Evidence From Securitized Auto Loans*

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Abstract

The ESG convenience yield in auto loan securitizations rose from 0.03% in 2017 to 0.54% in 2022. Consumers financing vehicles through captive lenders benefit from lower borrowing costs. However, the focus on ESG scores also lowers the cost of capital for high-emissions vehicles. ESG funds allocate more capital to securitizations from issuers with high ESG scores even when they finance high-emissions vehicles. A model of subjective beliefs in which investors heuristically infer CO_2 emissions from ESG scores can explain the observed effects. These findings suggest that ESG investing affects real quantities but does not raise the cost of emitting CO_2.

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

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1 Introduction

Environmental, social, and governance (ESG) investing aims to raise the cost of emitting carbon dioxide (CO_2) by redirecting capital towards "green" and away from "brown" assets.[1] The hope is that a higher cost of capital reduces demand for high-emission activities and therefore mitigates climate change. However, estimating whether ESG investing successfully raises the cost of emitting CO_2 is challenging: a clean measurement must hold an asset's risk exposure constant while varying its greenness and must quantify the actual environmental impact of the investment.

This paper sheds light on whether ESG investing increases the cost of emitting CO_2 by addressing these challenges. I study the effect of ESG investing on the cost of capital of automobile asset-backed securities (ABS) and its pass-through to consumer interest rates. Auto loan securitizations finance over 20% of vehicle sales and serve as a critical link between consumer and financial markets. By changing the cost of capital for high-emission vehicles, ESG investing could shift consumer demand away from high-emission vehicles toward greener alternatives.[2] Figure A1 highlights the attention that ESG investing receives in the auto ABS market with examples from websites of issuers, investors, rating agencies, industry associations, and law firms.

Auto loan securitizations provide an ideal setting to study the impact of ESG investing on equilibrium asset prices and evaluate its real effects. The pooling and tranching of auto loans creates highly liquid securities with specified risk exposures (DeMarzo, 2005). I exploit the safe asset nature of senior tranches and use variables derived from loan-level data to hold risk exposure across securities constant. I then test whether the greenness of a securitization influences its cost of capital. I contrast two measures of greenness: (i) ESG scores, commonly used by the asset management industry, and (ii) the collateral pool's CO_2 emissions. By comparing the influence of ESG scores and CO_2 emissions, I test the often implicit assumption that a "green" premium is associated with a higher cost of emitting CO_2. Finally, I use granular loan-level data to estimate the pass-through of ESG investing to consumer interest rates and calculate the corresponding shift in consumer auto loan demand. This allows me to evaluate ESG investing's potential to shift consumer demand away from high-emissions vehicles and toward greener alternatives.

I collect data on 17.8 million vehicle loans that serve as collateral for all auto ABS issued by captive lenders of manufacturers, banks, non-bank finance companies, and retailers from 2017 to 2022. I estimate the lifetime CO_2 emissions of each vehicle loan by merging collateral data

[1] I use "ESG investing" as a shorthand for all investment strategies aimed at addressing environmental externalities. Asset managers rank climate change, CO_2 emissions, and fossil fuel divestment as the top ESG criteria (USSIF, 2022).

[2] Reducing vehicle emissions is a key policy goal to mitigate climate change. Transportation accounts for more than 35% of energy-related CO_2 emissions in the U.S. and became its leading source in 2017 (CBO, 2022).

at the make, model, and year level with CO_2 emissions data from the Environmental Protection Agency (EPA). This enables me to calculate the financed CO_2 emissions of each securitization and to quantify its environmental impact. Additionally, I collect issuer-level ESG scores from MSCI, Sustainalytics, Refinitiv, and S&P to analyze how ESG scores affect the cost of capital of auto ABS.

I start by documenting large cross-sectional differences in CO_2 emissions across auto ABS. For instance, auto ABS issued by Ally Bank finance an average of 55tCO_2 per vehicle, while those issued by Ford Credit finance an average of 95tCO_2 per vehicle. The large cross-sectional differences in CO_2 imply that, much like motorists choose between high- and low-emissions vehicles, investors have the choice between securities that finance high- or low-emissions vehicles. I exploit that auto ABS have large environmental differences but low and similar levels of risk exposure to test whether CO_2 emissions influence their cost of capital.

The ESG and environmental pillar scores of auto ABS issuers do not capture the large differences in CO_2 emissions. Both scores positively correlate with security-level CO_2 emissions. Decomposing the variance of ESG scores and CO_2 emissions shows that ESG and environmental scores vary significantly less across issuers than collateral pool emissions. The smaller variance and positive correlation with CO_2 emissions make ESG and environmental scores poor proxies for the actual environmental impact of auto ABS. The reasons for this discrepancy are that (a) environmental scores of banks and non-bank finance companies do not reflect the CO_2 emissions content of the loans they securitize, and (b) environmental scores among vehicle manufacturers do not capture CO_2 emissions from the usage of sold products (Scope 3 Category 11). However, emissions from the usage of sold vehicles are up to 1,000% larger than production emissions (Scope 1, 2, and 3 upstream).[3] Consequently, investors who rely on ESG scores to allocate capital may inadvertently subsidize CO_2 emissions. I use this fact to test whether a green premium based on ESG scores actually increases the cost of emitting CO_2.[4]

I next test whether ESG investing impacts equilibrium prices and quantities in the auto ABS market. I motivate my identification strategy with a stylized asset pricing model that features a green convenience yield in the spirit of Krishnamurthy and Vissing-Jorgensen (2012). The 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 asset prices?

[3]For example, the utilization emissions of a Volkswagen Passat are 626% larger at 47tCO_2 than its production emissions of 7.5tCO_2 (Buberger, Kersten, Kuder, Eckerle, Weyh, and Thiringer, 2022). Nissan (2024, p. 24) reports that their Scope 3 Category 11 emissions are 747% larger than their combined Scope 1, 2, and 3 upstream emissions.

[4]Amel-Zadeh and Serafeim (2018) report that 82% of surveyed investment firms, accounting for 43% of global institutional assets under management (AUM), consider ESG information when making investment decisions. More than 66% of their survey respondents use ESG information to screen investment opportunities or tilt their portfolio.

Two features of the securitization market allow me to rule out confounders in my effort to identify the causal effect of ESG investing. First, auto ABS are highly standardized debt instruments. Their senior tranches are considered safe assets similar to US Treasurys (Gorton, 2017). Only a few parameters distinguish auto ABS beyond their collateral pools. I exploit the safe asset nature of senior tranches and use variables derived from loan-level data to control for any remaining differences across securities. Second, the security design of auto ABS reduces the number of risk factors. The main risk factor for AAA-rated senior tranches of auto ABS is prepayment. Consumer and loan characteristics determine prepayment risk rather than the issuer identity or the collateral. Borrowers with high interest rate loans prepay when interest rates fall, regardless of ESG score of the issuer or the CO_2 emissions of collateral they finance. Moreover, the granularity of the loan-level data allows me to control for ex-post prepayments at the time of issuance. This alleviates concerns that investors use greenness to infer risky payoffs, as in Pedersen, Fitzgibbons, and Pomorski (2021), rather than to express their non-pecuniary preferences. Controlling for both predictors and ex-post performance together with fixed effects that capture security design removes as much unobserved heterogeneity as possible.

I find that issuers with high ESG or environmental pillar scores have significantly lower issuance spreads. Moving from 20th to 80th percentile of ESG scores reduces spreads by 8 bps (0.34 standard deviations), holding security design and risk exposure constant. However, I also find that *high-emissions* collateral pools have a *lower* cost of capital. Moving from 20th to 80th percentile of tCO_2 per USD (moving from Toyota to Ford) reduces issuance spreads by 4 bps, a 10% decrease compared to the mean issuance spread.

ESG scores, rather than CO_2 emissions, drive actual investor decisions and their impact on the cost of capital for auto ABS. A horse race between CO_2 emissions and ESG scores shows that ESG scores dominate emissions in explaining the cost of capital. The CO_2 coefficients shrink towards zero and lose statistical significance when ESG scores are included in the model. Coefficients on ESG scores, however, remain stable and statistically significant. This suggests that investors rely on ESG scores rather than actual CO_2 emissions to evaluate the environmental impact of auto ABS. The reliance on ESG scores, however, leads to a subsidy for high-emissions auto ABS since ESG scores and CO_2 emissions positively correlate.

I translate the observed differences in issuance spreads into an ESG convenience yield, motivated by my ESG asset pricing model. This ESG convenience yield provides seigniorage to issuers of ESG assets and lowers their borrowing cost. The ESG convenience yield rose from 0.03% in 2017 to 0.54% in 2022. The average ESG convenience yield over the sample period is 0.42% p.a., comparable to those documented in equity markets. For instance, Avramov, Lioui, Liu, and Tarelli

(2024) estimate an ESG convenience yield for stocks ranging from 0.37% to 0.66%, while Eskildsen, Ibert, Jensen, and Pedersen (2024) report a convenience yield of 0.5% per year.

Concerns about climate change drive the pricing of the ESG convenience yield into auto ABS issuance spreads. I test whether concerns about climate change drives the pricing of ESG scores by interacting ESG scores with the monthly Media Climate Change Concerns Indices of Ardia, Bluteau, Boudt, and Inghelbrecht (2023). I find strong evidence that media attention to societal debates about climate change and its environmental impact significantly influences ESG score pricing. In contrast, using both an index specific to the car industry's transition risk and the general transition risk index, I find no evidence that concerns about transition risks affects ESG score pricing. These results lend support to the hypothesis that non-pecuniary preferences for ESG investing are shaped by environmental concerns about climate change.

The more than $1.1 trillion of net flows into ESG funds over the past decade (Van der Beck, 2023) similarly drive the pricing of ESG scores into auto ABS issuance spreads.[5] Interacting ESG scores with flows into ESG funds, I find that a $100bn higher net inflow to ESG funds lowers issuance spreads for high-ESG issuers by 2 bps. I directly examine the portfolios of ESG mutual funds to test whether CO_2 emissions or ESG scores influence their portfolio choice. ESG funds invest more in auto ABS from issuers with high ESG scores compared to non-ESG funds. However, the portfolio analysis also shows that ESG funds hold higher portfolio shares in high-emissions auto ABS compared to non-ESG funds. ESG funds allocate approximately 20% less capital to auto ABS with emissions below the median than non-ESG funds. These findings are difficult to reconcile with common ESG strategies that usually prescribe outright exclusion or best-in-class investment of brown securities.[6]

The results documented above imply that ESG investors use ESG scores to express their non-pecuniary preferences over greenness. Relying on ESG scores inadvertently subsidizes CO_2 emissions due to a positive correlation between them. However, this does not imply that subsidizing CO_2 emissions is the intended effect of ESG investing. It is possible that ESG investors intend to raise the cost of emitting CO_2 by using ESG scores to allocate capital but have imperfect information about the CO_2 emissions of the collateral they finance.

I develop a stylized model of subjective (and potentially biased) beliefs of ESG investors and their intention to price CO_2 emissions in auto ABS. I model CO_2 emissions as latent variables

[5] Pastor, Stambaugh, and Taylor (2024) estimate that institutional ESG tilts grew from 10% to 22% over that time.

[6] There is a long-running debate about which strategy ESG investors should follow: exit (exclusion) or voice (activism) (Hirschmann, 1970). Broccardo, Hart, and Zingales (2022) analyze the relative effectiveness of these strategies, while Edmans, Levit, and Schneemeier (2022) examine whether exclusion or best-in-class investment is more effective.

over which ESG investors have subjective beliefs, informed by ESG scores.[7] Combining insights from the model with survey evidence from Haber, Kepler, Larcker, Seru, and Tayan (2022) allows me to back out implied subjective beliefs. Alternatively, assuming that investors use a representativeness heuristic (Gennaioli and Shleifer, 2010) to infer the relationship of CO_2 emissions and ESG scores, allows me to back out the intended effect of using ESG scores to proxy for CO_2 emissions when pricing auto ABS. Both approaches yield similar results.

The model calibration implies that ESG investors intended to demand 0.2% higher issuance spreads for a 1% higher CO_2 emissions intensity. Since auto ABS's CO_2 emissions are not directly observable, investors heuristically rely on ESG scores to express their non-pecuniary preferences for greenness. However, their subjective beliefs about the link between ESG scores and CO_2 emissions differ significantly from the actual relationship: subjective beliefs imply that a 1% higher ESG score corresponds to a 0.2% decrease in emissions intensity, while the true relationship is a 0.1% increase in emissions intensity.

Lastly, I test whether the ESG convenience yield affects consumer auto loan demand. The integration of the consumer loan market and financial markets via securitization provides an opportunity to study whether issuers who benefit from the ESG convenience yield pass on lower borrowing cost to consumers. The impact of ESG investing on consumer loan demand depends on the pass-through elasticity of issuance spreads in the ABS market to consumer rates and the price elasticity of consumer loan demand with respect to these rates. I estimate the endogenous pass-through elasticity using instrumental variables that isolate exogenous variation in common funding costs of auto loan lenders and rely on price elasticity estimates from the literature (e.g., Argyle, Nadauld, and Palmer, 2020). With estimates of pass-through and price elasticity in hand, one can translate the 8 bps difference in issuance spreads into a percentage change in consumer loan demand.

Consumers financing vehicles with loans from captive lenders benefit from the ESG convenience yield through lower borrowing costs. Estimates of the pass-through elasticity imply that a 8 bps decrease in auto ABS spreads translate into a 19 bps to 30 bps lower consumer rate due to the non-linear effect of loan subsidies. Manufacturers often use the vertical integration of credit provision to increase their sales by offering subsidized interest rates to consumers (Benetton, Mayordomo, and Paravisini, 2021).[8] The resulting changes in individual consumer loan demand

[7]Informal conversations with market participants confirm that investors did not have real-time access to collateral-pool CO_2 emissions data until after the end of my sample period. Appendix A.4 shows that even dedicated ESG mutual funds relied on ESG scores to assess the greenness of auto ABS.

[8]A 8 bps lower issuance spread increases the probability of receiving a subsidized rate (e.g., 0% APR) by a captive lender by 6.1 p.p. The expected decrease in the consumer interest rate conditional on subsidization is 23 bps.

range from 0.98% to 4.45%. This translates into an increase in demand of $324 to $1,469 for a $33,000 loan. Determining whether the ESG convenience yield results in a net reduction in CO_2 emissions hinges on the substitution effect between high- and low-emission vehicles. Assessing this requires a demand model that captures consumer preferences for vehicle emissions, prices, and financing—a task I leave for future research.

In summary, auto ABS issuers with high ESG scores who securitize high-emissions vehicles enjoy a lower cost of capital. The lower cost of capital for high-emissions ABS is unrelated to risk. Rather, heightened concerns about climate change and large capital flows into ESG funds over the past decade drive this lower cost of capital. ESG mutual funds allocate more capital to auto ABS of high-ESG issuers even when those finance high-emissions vehicles. A model of subjective beliefs in which investors use a representativeness heuristic to infer CO_2 emissions from ESG scores can explain these findings. Consumers financing through captive lenders benefit from the ESG convenience yield through lower borrowing costs. The results are robust across various measures of greenness, samples, specifications, and estimators. The findings contribute to the broader debate on whether ESG investing truly incentivizes environmental change or merely signals green preferences without substantive impact.

The paper is organized as follows. The remainder of the introduction discusses the related literature and contribution. Section 2 describes the data. Section 3 provides an overview of the auto ABS market. Section 4 outlines a stylized green asset pricing model, discusses the identification strategy, and estimates the influence that ESG investors have on the cost of capital. Section 5 explores the pass-through of the ESG convenience yield to consumer interest rates and calculates the implied changes in consumer loan demand. Section 6 provides a discussion of the findings. Section 7 concludes.

Related Literature The rise of ESG investing spurred extensive research.[9] Theoretical studies show that if ESG investors comprise a significant share, green assets will have a lower cost of capital. Heinkel, Kraus, and Zechner (2001) model an equilibrium in which ESG investors increases the cost of capital for polluting firms. Oehmke and Opp (2024) outline conditions under which ESG investors affect firm behavior, considering social costs and financing constraints. Pástor, Stambaugh, and Taylor (2021) examine how changes in ESG preferences impact asset prices. Berk and van Binsbergen (2025) study equity divestment in a single-period mean-variance model. I add by proposing a stylized asset pricing model featuring a green convenience yield in the spirit of Krishnamurthy and Vissing-Jorgensen (2012). I further highlight how subjective beliefs about the efficacy of ESG scores and representativeness heuristics (Gennaioli and Shleifer, 2010) can

[9] See Gillan, Koch, and Starks (2021) and Hong and Shore (2023) for excellent reviews.

lead to the unintended consequence that brown securities have a lower cost of capital.

This paper introduces several innovations to the empirical literature, being the first to study the effects of environmental externalities, ESG scores, and ESG investing on the pricing and holdings of asset-backed securities. I show that in a market for safe assets, the cost of capital for otherwise identical green assets can significantly differ from brown assets. My findings relate to other studies on the green premium in debt markets, such as Pástor, Stambaugh, and Taylor (2022), who report a 5 bps lower yield for Germany's green Bunds and Baker, Bergstresser, Serafeim, and Wurgler (2022) who estimate a 6 bps green premium in U.S. municipal and corporate bonds.[10] However, my results highlight a tension between ESG investors' goal and the use of misleading issuer-level ESG scores. I find that ESG investing can have a meaningful impact but it does not increase the cost of emitting CO_2.[11]

This paper also contributes to the literature on the real effects of captive finance and securitization. Benmelech, Meisenzahl, and Ramcharan (2017) find that the disruption in ABS markets during the Financial Crisis reduced credit supply and vehicle sales. Klee and Shin (2020) find that lenders signal private information in the auto ABS market by warehousing high-quality loans longer. Benetton et al. (2021) shows that vertical integration of manufacturing and credit provision allows manufacturers to increase cash collected from vehicle sales through credit fire sales. Hankins, Momeni, and Sovich (2022) show that captive lending creates a channel for trade policy to affect consumer credit. I measure the pass-through of the ESG convenience yield to consumer rates and explore the impact of ESG investing on consumer loan demand. By examining how differences in the cost of capital for ESG assets influence loan demand, I shed light on whether ESG preferences translate into tangible economic outcomes and their broader economic implications.

2 Data

This section describes the loan-level data I use to construct measures of greenness for each auto ABS and the issuance-level data I use in the empirical tests. The sample covers all publicly traded consumer loan auto ABS issued from 2017 to 2022, consisting of approximately 17.8 million

[10] See also Goss and Roberts (2011), Chava (2014), Zerbib (2019), Flammer (2021), Seltzer, Starks, and Zhu (2022), Aswani and Rajgopal (2022).

[11] Relatedly, Hartzmark and Shue (2023) argue that redirecting capital from brown to green companies may backfire due to limited improvement potential in green firms and deterioration in brown firms. In contrast, I focus on vehicle loans for which adjusting the cost of capital could shift consumer demand from brown to green products.

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

	Mean	SD	Median	Min	Max	N
Total Deal Size ($ m)	1,242.38	348.24	1,250.00	367.31	2,663.82	281
Tranche Size ($ m)	366.71	131.99	362.00	42.40	746.94	281
Weighted Average Life / Maturity (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 Receivables in Collateral Pool	63,031	21,302	62,886	15,329	136,860	281
Loan-to-Value	0.92	0.04	0.92	0.80	0.98	281
Average Credit Score	706.19	74.87	738.34	564.98	788.46	281
Average Interest Rate (%)	7.64	5.87	4.46	1.38	21.35	281
Average Remaining Balance	0.90	0.07	0.91	0.74	1.00	281
Warehousing Time (Months)	9.54	4.38	9.19	1.33	21.06	281
Expected tCO2 per $100,000	292.26	51.02	295.29	161.51	456.01	281
Expected tCO2 per Vehicle	70.23	14.76	67.61	42.94	125.57	281
Financed tCO2 per $100,000	219.14	39.96	211.08	107.10	311.78	281
Financed tCO2 per Vehicle	57.78	12.11	54.50	40.54	101.25	281
Average ESG Score of Issuer	0.58	0.15	0.62	0.15	0.76	243
Average Environmental Score of Issuer	0.62	0.24	0.68	0.01	0.89	243

Notes: This table reports summary statistics for the main variables. The first two columns report the mean and the standard deviation, and the third to fifth columns report the median, minimum, and maximum, respectively. The sample contains all A-2 tranches of publicly traded consumer loan auto ABS from 2017 to 2022.

unique loans from 281 ABS deals of 22 issuers.[12] I exclude vehicle lease and dealer floor plan securitizations from the sample due to their different risk characteristics.

ABS Deal Data I collect information about the structure of each deal from prospectuses filed with the SEC, which include details on the deal and its tranches, such as 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 to the WAL. Table 1 presents summary statistics for the A-2 tranches of each deal. The average deal size is $1.2 billion of which the A-2 tranche is 30%. The average spread is 42 bps with a WAL of one year. Captive lenders issue about 42% of deals and approximately 28% are subprime deals. The average deal finances around 63,031 vehicles. A $100,000 investment finances 219 tCO_2 over the remaining life of the collateral.

[12] 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.

Loan-level Data The loan-level data are from the SEC form ABS-EE. Form ABS-EE is part of the post-financial crisis reporting requirements under Regulation AB, that went into effect in November 2016.[13] This regulation mandates that all prospectuses for public offerings of asset-backed securities must submit loan-level information electronically, with monthly updates on loan pool performance. The data includes 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 the sample finances $25,822, at 90% loan-to-value, at a 7.84% interest rate for 67 months. Their credit score is 708 and their monthly payment to income ratio is 0.08. The vehicle the average borrower is financing is worth $27,341.

CO_2 Emissions Data Data on CO_2 emissions come from the EPA. I match these by make, model, and model year to the loan-level data. Estimates of survival-weighted vehicle miles traveled (SVM) by vehicle type come from the EPA Corporate Average Fuel Economy (CAFE) standard simulator. The average vehicle in the sample is driven 202,963 miles, with 162,450 miles financed. Emissions vary significantly among the collateral, which includes fully electric vehicles, compact cars, SUVs, pickup trucks, and other high-emissions vehicles.[14] The average vehicle will emit 62tCO_2 over its remaining lifetime with a standard deviation of 29.5tCO_2.

Issuer-level ESG Scores I collect issuer-level ESG scores of auto ABS issuers from MSCI, Sustainalytics, Refinitiv/LSEG, and Standard and Poor's (S&P). All providers create their scores on the basis of publicly available information and penalize companies with limited reporting. I use the average across available ESG and environmental pillar scores and report results using individual ESG and environmental pillar scores in the Appendix. The scores are available for 17 of the 22 issuers in the sample.[15]

3 Securitized Auto Loans and Their CO_2 Emissions

This section provides background on the market for securitized auto loans, presents key concepts and facts. I show that just as motorists choose between high- and low-emissions vehicles,

[13] Using ABS-EE data, Bena, Bian, and Tang (2023) find that EV loans have higher interest rates, lower loan-to-value ratios, and shorter terms due to the higher residual value risk from technological obsolescence, while Klee, Morse, and Shin (2023) find EV borrowers default 29% less than ICE borrowers.

[14] The 10 most common vehicles in the 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).

[15] Technically, a special purpose vehicle (SPV) issues the auto ABS. The SPVs do not have ESG scores. I use the ESG scores of the sponsor (e.g., Santander Bank) and with a slight abuse of terminology refer to them as the issuer.

Table 2: Average Securitization Intensity by Industry

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 percentage of units sold		16%	39%	20%[1]
Amount securitized as percentage of revenue	83%	32%	24%	45%
Amount securitized as percentage of assets	11%	05%	30%	10%

Notes: This table reports the average securitization intensity by industry for N=60 firm-years. Securitizations include only consumer loans and exclude lease and floor plan securitizations. Revenue and assets of US vehicle lending segment when available, otherwise for overall US segment (S&P Compustat Segment files from 2016 to 2022). Unit sales of manufacturers from www.goodcarbadcar.net. [1]excludes banks.

investors choose between auto ABS that finance high- or low-emissions.

The ABCs of Consumer Auto ABS Auto loan securitizations were among the first consumer ABS to come to market in the 1980s. By 2022, auto ABS provide capital for approximately 20% of all auto loans in the United States. The auto ABS market is divided into prime and subprime deals based on the creditworthiness of underlying loans. Issuers of auto ABS come from various industries, including vehicle manufacturers and their captive lenders, vehicle retailers, banks, and non-bank finance companies. Table 2 highlights the importance of consumer loan securitization for these industries. Companies in the sample securitize approximately 45% of their revenues, 10% of their total assets, or 20% of total unit sales annually. Auto loan securitization is a crucial part of the financial intermediation chain. Changes in financing conditions in the auto ABS market can significantly impact supply of credit and vehicle sales (Benmelech et al., 2017).

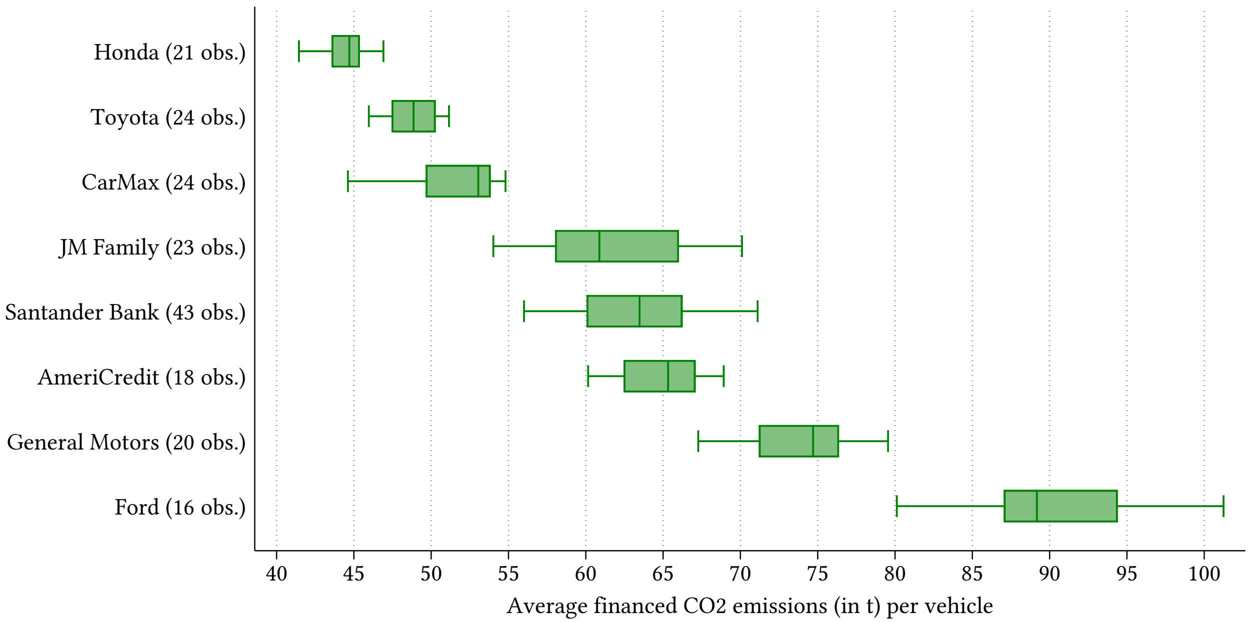
Compared with corporate and municipal bond markets, the security design of the auto ABS market is highly standardized. Only a few parameters distinguish auto loan securitizations from each other besides their collateral pool. All 281 deals in the sample are structured as monthly amortizing with higher seniority tranches receiving repayments first. The high levels of standardization in the auto ABS market and the safety of AAA-rated senior tranches make auto ABS highly liquid. He and Mizrach (2017) report that auto ABS have bid-ask spread as low as agency mortgage-backed securities that trade in the to-be-announced market.[16]

Prepayment is the main risk for investors in senior tranches of auto ABS since time and risk tranching, over-collateralization, and other credit enhancements mitigate credit risk. Prepayment risk arises from early loan repayment or borrower defaults leading to vehicle repossession.

Stylized Facts About CO_2 Emissions From Auto ABS The granular loan-level data which publicly traded auto ABSs need to disclose allow me to calculate the financed CO_2 emissions of each collateral pool. The CO_2 emissions that auto ABS b finances is the sum over the financed

[16]Online Appendix Figure B1 shows examples of auto ABS deal structures.

Figure 1: Dispersion of CO_2 Emissions Across all ABS Pools of the Eight Largest Issuers



Notes: This figure shows boxplots of the average financed CO_2 emissions per vehicle across all auto ABS for the eight largest issuers by number of deals from 2017 to 2022. Financed CO_2 emissions are defined in Eq. (1).

emissions of each vehicle i in its collateral pool:

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

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.[17] The loan-to-value (LTV) part of the financing adjustment of (1) reflects that not all expected CO_2 emissions are financed through a loan since many consumers make down-payments at the time of purchase. The financing adjustment also considers that loans have different outstanding balances at the time of securitization.

Figure 1 highlights that just as motorists choose between high- and low-emissions vehicles, investors choose between auto ABS that finance high- or low-emissions vehicles. Auto ABS of Honda and Toyota finance less than 50tCO_2, while those of Ford and General Motors finance

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

Table 3: Pairwise Correlations for Measures of Greenness: ESG, CO_2, and Miles-per-Gallon

	Average ESG Score	Average Env. Score	Fin. tCO2 per USD	Fin. tCO2 per Vehicle	Truck Share	MPG $\times$(-1)	EPA GHG Score $\times$(-1)
Average ESG Score	1.00						
Average Env. Score	0.94***	1.00					
Fin. tCO2 per USD	0.13**	-0.04	1.00				
Fin. tCO2 per Vehicle	0.20***	0.19***	0.18***	1.00			
Share of Trucks	0.05	-0.02	0.29***	0.84***	1.00		
MPG$\times$(-1)	0.12*	-0.02	0.40***	0.68***	0.74***	1.00	
EPA GHG Score$\times$(-1)	0.01	-0.06	0.09	0.78***	0.86***	0.82***	1.00

Notes: This table reports pairwise Pearson correlation coefficients between the average ESG scores, average environmental pillar scores, financed CO_2, share of trucks in collateral pool, negative of MPG, and negative of EPA GHG score. Average ESG and environmental scores are averages of MSCI, Sustainalytics, S&P, and Refinitiv. * p<0.10, ** p<0.05, *** p<0.01.

more than 75tCO_2 on average. The vehicle type composition of the collateral pool explains the large differences in emissions. Appendix Table A1 shows that a 1 percentage point increase in the share of trucks in the collateral pool raises the average CO_2 per vehicle by 1.02 tons.

Table 3 shows that ESG scores, commonly used by the asset management industry to assess environmental impacts of investments, positively correlate with CO_2 emissions and other measures of environmental friendliness. The positive correlation between ESG scores and CO_2 emissions creates problems if investors use ESG scores to screen green from brown auto ABS.

4 Issuance Spreads, ESG Basis, and ESG Convenience Yield

In this section, I develop a stylized asset pricing framework with ESG convenience yield. I use this framework to motivate my identification strategy for the ESG basis spread. Empirically, I find that higher ESG scores are robustly associated with lower issuance spreads. The pricing of ESG scores is driven by concerns about climate change and flows into ESG mutual funds and has increased steadily from 2017 to 2022. I use my stylized asset pricing framework to convert the ESG basis spread into an ESG convenience yield. However, I show that the positive correlation between ESG scores and CO_2 emissions also lowers the cost of capital for high-emissions securitizations. A model of subjective beliefs in which investors use a representativeness heuristic to infer CO_2 emissions from ESG scores can explain the observed effects. The findings are robust across specifications, samples, greenness definitions, and estimators.

4.1 A Stylized Green Asset Pricing Model

I build a stylized asset pricing model with an ESG convenience yield in the spirit of Krishnamurthy and Vissing-Jorgensen (2012) and derive the difference in yields between green and brown assets. The economy is populated by a single investor whose Euler equation is

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

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 $\beta^i_t\lambda_t$. The convenience yield is asset-specific and hence cannot be folded into the stochastic discount factor M_t. For simplicity, I assume that there are only two assets in the economy: a brown b asset and a green g asset with $\beta^g_t > \beta^b_t$. I assume that $m_t = \log M_t$ and $r^i_t = \log R^i_t$ are conditionally normal. Rewriting the Euler equation using log-normality, one finds

$$\mathbb{E}_t\left[m_{t+1}\right] + \frac{1}{2}\operatorname{Var}_t\left[m_{t+1}\right] + \mathbb{E}_t\left[r^i_{t+1}\right] + \frac{1}{2}\operatorname{Var}_t\left[r^i_{t+1}\right] + \operatorname{Cov}_t\left[m_{t+1}, r^i_{t+1}\right] + \beta^i_t\lambda_t = 0$$

and the following result:

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

$$\mathbb{E}_t\left[r^i_{t+1}\right] - r^f_{t+1} + \sigma^2_{i,t}/2 = -\sigma_{i,m,t} - \beta^i_t\lambda_t \tag{3}$$

Using the Campbell and Shiller (1988) approximation, one can write the dividend yield of an asset with maturity T as

$$\begin{aligned} dp^i_t &= \sum_{j=0}^{T}\rho^j\mathbb{E}_t\left[r^i_{t+1+j}\right] - \sum_{j=0}^{T}\rho^j\mathbb{E}_t\left[\Delta d^i_{t+1+j}\right] - \kappa\frac{1-\rho^T}{1-\rho} \\ &= -\beta^i_t\lambda_t\frac{1-\rho^T}{1-\rho} + \sum_{j=0}^{T}\rho^j r^f_{t+1+j} - \sum_{j=0}^{T}\rho^j\left(\sigma_{i,m,t,t+j} + \sigma^2_{i,t,t+j}/2\right) - \sum_{j=0}^{T}\rho^j\mathbb{E}_t\left[\Delta d^i_{t+1+j}\right] - \kappa\frac{1-\rho^T}{1-\rho}, \end{aligned} \tag{4}$$

with $\rho = \frac{1}{1-\exp\left(\overline{d-p}\right)}$ and $\kappa = -\log(\rho) - (1-\rho)\log(1/\rho - 1)$. The first term in Eq. (4) shows that a higher non-pecuniary value derived from the greenness of an asset, lowers the dividend yield and raises the price of the asset.

Taking the difference of Eq. (4) between a green and a brown asset with identical payoffs and risk one finds the ESG basis spread:

Lemma 2. *The absolute level of the ESG basis spread increases 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 ESG basis spread simplifies to:

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

Eq. (4) shows that to infer the ESG basis spread, one needs to carefully account for differences in risk-exposure and cash-flow growth of green and brown assets. Below, I build an identification strategy that exploits the features of the auto ABS market to isolate the ESG basis.

4.2 Identification Strategy for ESG Basis Spread

My identification strategy for the ESG basis rests on three points. First, high standardization and the short-term, safe-asset nature of the securities minimize the risk that unobserved heterogeneity affects the estimates. Second, the seniority structure and design of securitizations ensure that prepayment is the main risk factor for senior tranches. Allocating cash flows across tranches and time shifts credit risks to subordinate tranches. My analysis focuses on senior tranches rated AAA by at least two agencies. Credit losses would need to reach about 50%, assuming zero recovery value, to affect these tranches.[18] Third, borrower and loan characteristics determine prepayment risk, not the greenness of the issuer or the collateral. Borrowers with high interest rate loans prepay when interest rates fall, regardless of ESG score of the loan originator or the CO_2 emissions of collateral they finance. Moreover, the granularity of the loan-level data allows me to control for ex-post prepayments at the time of issuance. This alleviates concerns that investors use greenness to infer risky payoffs, as in Pedersen et al. (2021), rather than to express their non-pecuniary preferences.

[18] If a borrower defaults, the vehicle is repossessed and sold. For senior tranches, this process is an "involuntary prepayment". The most junior tranche bears the difference between the outstanding balance and recovery value, with historical recovery values around 60% for prime and 45% for subprime loans (Structured Finance Association).

Table 4: Ex-post Performance of Collateral Pools, ESG scores, and CO_2 Emissions

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Δ Realized to Assumed Prepayments				Realized % loans delinquent 30d+			
Financed tCO2 per USD	0.073				-0.022			
	(0.139)				(0.035)			
Financed tCO2 per Vehicle		-0.023				-0.043		
		(0.133)				(0.031)		
Average ESG Score			0.040				0.068	
			(0.137)				(0.069)	
Average Environmental Pillar Score				-0.020				0.044
				(0.155)				(0.095)
Subprime FE					✓	✓	✓	✓
Adj. R^2	0.005	0.001	0.002	0.000	0.912	0.913	0.913	0.912
Observations	281	281	243	243	281	281	243	243

Notes: This table reports results from a test of the identifying assumption that greenness is uncorrelated with traditional risk factors. Outcome variable in Column (1) to (4) is the difference of realized prepayment to assumed prepayment. Outcome variable in Column (5) to (9) is the realized delinquency rate to proxy for involuntary prepayment through default. Coefficients are standardized to unit variances. * p<0.10, ** p<0.05, *** p<0.01.

Empirical Specifications I estimate the ESG basis spread using the following specification:

$$\log\left(\text{Issuance Spread}\right)_b = \beta \log\left(\text{Green}\right)_b + \mathbf{X}_b'\zeta + \gamma_{p,t} + \varepsilon_b \tag{6}$$

for ABS b issued in year-month t.[19] The coefficient of interest, β, is the elasticity of issuance spreads with respect to greenness. The (sub)prime-by-year-month-fixed effect, $\gamma_{p,t}$, identifies β using variation in greenness across (sub)prime securitizations issued during the same month.

The main control variables in $\mathbf{X}_b$ are known predictors of prepayment risk. The predictors are collateral pool averages of LTV, credit scores, remaining loan balance, interest rate, and vehicle values. I further include the average time that loans have been warehoused on the lenders balance sheet before securitization. Klee and Shin (2020) show that lenders warehouse loans of unobservably higher quality longer to signal their private information to investors. To control for within-month variation in market conditions, I include the six month yield from Filipović et al. (2022), the level of the VIX on the day of issuance, and the standard deviation of the VIX in the 30 days before issuance in $\mathbf{X}_b$. All variables are in natural logarithms. The specifications include assumed absolute prepayment speed (APS) fixed effects, interacted with the tranche's weighted average life to allow for potential "ramp-up" periods in which prepayments increase before leveling off to their assumed APS. Appendix Table B4 shows that using the Lasso estimator of Belloni,

[19] I find consistent results using a specification with an indicator variable equal to one if the greenness is above the 50th percentile. See Online Appendix Table B2 for OLS and Table B3 for a propensity score estimator.

Chernozhukov, and Hansen (2014) to select from over 850 potential control variables yields similar results.

Identifying Assumption The identifying assumption in Eq. (6) is that the assignment of greenness is uncorrelated with the error term conditional on risk factors: once risk and security design are accounted for, the assignment of greenness is "as good as random". This identification assumption allows me to infer the ESG basis spread from variation in greenness across securitizations. The null hypothesis is that greenness does not affect issuance spreads, implying β=0. Evidence that β>0 indicates that investors accept lower yields because they prefer greener assets.

Auto ABS release monthly performance report after issuance which allow me to test whether greenness correlates with ex-post performance. Specifically, I examine two measures which capture voluntary and involuntary prepayment at the collateral pool-level: the realized difference in monthly prepayment speed compared with its prospectus assumption, and the average realized percentage of loans more than 30 days delinquent. Table 4 shows that neither CO_2 emissions nor ESG scores predict the performance of collateral pools. The estimates are noisy and close to zero. Although ultimately untestable, these results support the identification assumption: measures of greenness are not informative about the ex-post performance of auto ABS.

4.3 Results

Table 5 presents the results of the pricing model of Eq. (6). Odd-columns controls for predictors of prepayment risk only, even-columns add controls for ex-post realizations of prepayment risk. Panel A shows estimates of the elasticity of issuance spreads with respect to either ESG scores or CO_2 emissions using the pricing model of Eq. (6). Panel B runs a horse race between CO_2 emissions and ESG scores, comparing their effects on issuance spreads.

Panel A of Table 5 shows that both high ESG scores and high CO_2 emissions predict lower issuance spreads. The issuance spreads have an elasticity of -0.33 to -0.49 for ESG scores and -0.16 to -0.2 for CO_2 emissions intensity. I find similar results using individual ESG scores from MSCI, Sustainalytics, Refinitiv, and S&P instead of the average ESG score. Appendix Table A4 shows that all ESG and environmental pillar scores are associated with lower issuance spreads.

Panel B presents the results of a horse race between CO_2 and ESG in pricing auto ABS. The elasticity with respect to ESG scores remains stable and significant, but the elasticity of CO_2 emissions shrinks towards zero and loses statistical significance. This suggests that investors rely on ESG scores to identify and price green assets. However, CO_2 emissions and ESG scores positively correlate. Consequently, investors who rely on ESG scores to allocate capital inadvertently sub-

Table 5: The Pricing of Greenness in Auto Loan Securitizations

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
				Issuance Spread				
Panel A: Elasticity of Issuance Spreads With Respect to Either ESG Score or Carbon Emissions								
Average ESG Score	-0.332***	-0.381***						
	(0.113)	(0.111)						
Average Environmental Score			-0.416**	-0.485***				
			(0.163)	(0.154)				
Financed tCO2 per USD					-0.187*	-0.195*		
					(0.102)	(0.102)		
Financed tCO2 per Vehicle							-0.158*	-0.169*
							(0.088)	(0.088)
Year-month FE, daily market controls	✓	✓	✓	✓	✓	✓	✓	✓
Prepayment speed FE, tranche controls	✓	✓	✓	✓	✓	✓	✓	✓
Ex-ante prepayment controls	✓	✓	✓	✓	✓	✓	✓	✓
Ex-post prepayment controls		✓		✓		✓		✓
Adj. R^2	0.960	0.960	0.958	0.958	0.953	0.953	0.952	0.953
Observations	243	243	243	243	281	281	281	281
Panel B: Elasticity of Issuance Spreads With Respect to ESG Score and Carbon Emissions								
Average ESG Score	-0.337***	-0.381***	-0.331***	-0.376***				
	(0.109)	(0.107)	(0.110)	(0.108)				
Average Environmental Score					-0.384**	-0.447***	-0.384**	-0.448***
					(0.166)	(0.156)	(0.166)	(0.156)
Financed tCO2 per USD	-0.178	-0.167			-0.139	-0.127		
	(0.109)	(0.110)			(0.109)	(0.110)		
Financed tCO2 per Vehicle			-0.138	-0.127			-0.110	-0.098
			(0.093)	(0.094)			(0.094)	(0.095)
Year-month FE, daily market controls	✓	✓	✓	✓	✓	✓	✓	✓
Prepayment speed FE, tranche controls	✓	✓	✓	✓	✓	✓	✓	✓
Ex-ante prepayment controls	✓	✓	✓	✓	✓	✓	✓	✓
Ex-post prepayment controls		✓		✓		✓		✓
Adj. R^2	0.961	0.961	0.960	0.960	0.958	0.958	0.958	0.958
Observations	243	243	243	243	243	243	243	243

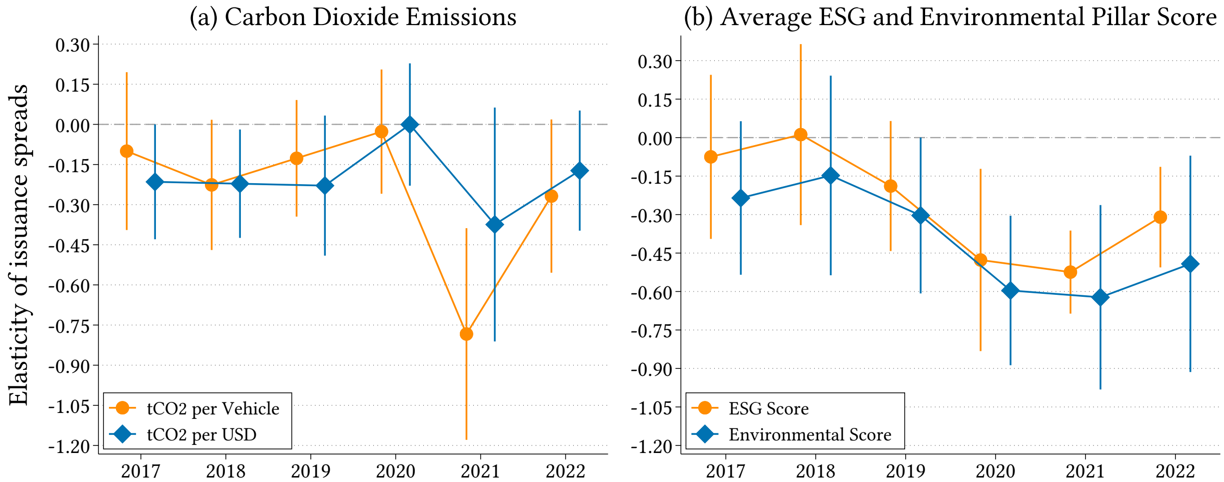
Notes: This table reports the effects of greenness on issuance spreads of auto ABS. Average of ESG and environmental pillar scores from MSCI, Sustainalytics, Refinitiv, and S&P. Panel A and B show coefficient estimates of Eq. (6). Daily market controls include 6 month yield from Filipović et al. (2022), the level of VIX on the issuance date, and the standard deviation of VIX in the 30 days before the issuance date. Ex-ante prepayment controls are collateral pool averages of LTV, credit scores, remaining loan balance share, interest rate, and vehicle values. Ex-post prepayment controls are the difference of realized prepayment to assumed prepayment and the realized 30d+ delinquency rate. All variables are in logs. Standard errors in parentheses clustered at year-month. * p<0.10, ** p<0.05, *** p<0.01.

sidize CO_2 emissions as Panel A shows.

Reassuringly, across both panels, estimates accounting for ex-post performance of collateral pools are similar to those controlling only for predictors of prepayment risk. This further supports the assumption that neither ESG scores nor CO_2 emissions predict performance of auto ABS.

Figure 2 shows yearly estimates of the elasticity of issuance spreads with respect to CO_2

Figure 2: Elasticity with Respect to CO_2, ESG, and Environmental Score From 2017 to 2022



Notes: This figure shows yearly elasticity estimates and 90% confidence intervals of the risk-adj. model of Eq. (6). Panel (a) shows elasticity estimates for CO_2 per vehicle and CO_2 per USD. Panel (b) shows elasticity estimates for the average of ESG and environmental pillar scores from MSCI, Sustainalytics, Refinitiv, and S&P.

emissions, average ESG score, and average environmental pillar score. The elasticities follow a similar time trend. They strengthen over time until 2021 and plateau in 2022. The elasticity of the average environmental score is similar or larger than elasticity estimates for composite ESG scores, supporting the hypothesis that investors prioritize "environmental" impact. The yearly elasticity estimates of CO_2 in Panel (a) of Figure 2 again shrink towards zero and become insignificant when controlling for ESG scores. This suggests that the pricing of CO_2 emissions is an accidental by-product of the pricing of ESG scores which positively correlate with emissions.

Translating the ESG Basis Spread into an ESG Convenience Yield The estimated differences in issuance spreads induced by high ESG scores (i.e., the ESG basis spread) translates into a convenience yield that an investor earns on their ESG investment. Rearranging Eq. (5) one finds that the ESG convenience yield is given by

$$\lambda_t = -\frac{y_t^g - y_t^b}{\beta_t^g - \beta_t^b} \tag{7}$$

in which $y^g - y^b$ is the ESG basis spread and $\beta_t^g - \beta_t^b$ the difference in ESG scores.

Table 6 shows estimates of the ESG convenience yield over time. The ESG convenience yield is close to zero and not statistically significant in the beginning of the sample. Starting in 2020, the ESG convenience yield becomes statistically significant. The average ESG convenience yield is 0.42% p.a. over the sample period. Similar to this estimate, Avramov et al. (2024) estimate an ESG convenience yield for stocks between 0.37% and 0.66%.

Table 6: Estimates of the ESG Convenience Yield From 2017 to 2022

		2017	2018	2019	2020	2021	2022	Avg.
Difference in Average ESG Score:	$\beta_t^g - \beta_t^b$	0.20	0.19	0.19	0.19	0.26	0.20	0.20
ESG Basis Spread (in basis points):	$y_t^g - y_t^b$	-0.6	1.3	-3.1	-10.3**	-8.6***	-10.8***	-8.4***
		(4.1)	(2.7)	(2.1)	(4.1)	(1.5)	(2.9)	(1.9)
ESG Convenience Yield (in basis points):	λ_t	2.9	-6.8	16.0	53.5**	32.9***	54.4***	41.8***
		(20.3)	(14.2)	(11.1)	(21.0)	(5.7)	(14.5)	(9.6)

Notes: This table reports estimates of the ESG convenience yield from 2017 to 2022. Differences in ESG scores and ESG basis spread evaluated at the 20th and 80th percentiles of average ESG scores. * p<0.10, ** p<0.05, *** p<0.01.

4.4 What Drives the Pricing of ESG Scores in the Auto ABS market?

Media Attention to Climate Change I interact ESG and environmental scores with the Media Climate Change Concerns (MCCC) Index of Ardia et al. (2023) to test whether concerns about climate change drives the pricing of ESG scores. The indices are constructed using news about climate change published by major U.S. newspapers and newswires. The data includes sub-indices that capture specific dimensions, such as societal concerns, environmental impact, and industry-specific transition risks. Ardia et al. (2023) find that increases climate change concerns are associated with an increase (decrease) in the discount rate of brown (green) stocks.

Table 7 shows that concerns about climate change drive the pricing of the ESG convenience yield into auto ABS issuance spreads. I find strong evidence that media attention to societal debates about climate change and its environmental impact significantly influences ESG score pricing. These results lend further support to the hypothesis that the pricing of non-pecuniary preferences are driven by concerns surrounding the environmental impact of climate change.

Importantly, media attention to transition risk does not drive the effects of ESG and environmental scores on issuance spreads, as shown in Appendix Table A5. To explore this, I utilize a sub-index specific to the car industry from Ardia et al. (2023) to test whether media attention to the car industry's transition risk influences the pricing of ESG scores. Additionally, I examine the general business impact/transition risk index. The results show no evidence that media attention to either the car industry's transition risk or general transition risk affect the pricing of ESG scores. In contrast, there is strong evidence that media attention to societal debates about climate change, its environmental impact, and climate change in general significantly influence the pricing of ESG scores into auto ABS.

Capital Flows Into ESG Funds Van der Beck (2023) reports that more than $1.1 trillion flowed into ESG funds over the past decade (see Online Appendix Figure B2). Similarly, Pastor et al. (2024) estimate that the typical institution's ESG tilt has grown from 12% to 22%. Even mutual funds without declared ESG objectives are affected by marketwide ESG concerns: Hartzmark and

Table 7: The Effects of ESG Capital Flows and Climate Change Concerns on Spreads of Auto ABS

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
				Issuance Spread				
Average ESG Score	-0.172	-0.199	-0.162	-0.165				
	(0.179)	(0.181)	(0.189)	(0.192)				
ESG Capital Flow ($100bn) × Avg. ESG Score	-0.045***	-0.047***						
	(0.014)	(0.014)						
Environmental Concerns × Avg. ESG Score			-0.392**	-0.477**				
			(0.188)	(0.198)				
Average Environmental Score					-0.572***	-0.588***	-0.253	-0.304
					(0.181)	(0.193)	(0.213)	(0.212)
ESG Capital Flow ($100bn) × Avg. Env. Score					-0.032**	-0.032***		
					(0.012)	(0.011)		
Environmental Concerns × Avg. Env. Score							-0.415*	-0.486**
							(0.224)	(0.231)
Year-month FE, daily market controls	✓	✓	✓	✓	✓	✓	✓	✓
Prepayment speed FE, tranche controls	✓	✓	✓	✓	✓	✓	✓	✓
Ex-ante prepayment controls	✓	✓	✓	✓	✓	✓	✓	✓
Ex-post prepayment controls		✓		✓		✓		✓
Adj. R^2	0.964	0.963	0.962	0.962	0.959	0.958	0.959	0.959
Observations	201	201	243	243	201	201	243	243

Notes: This table reports elasticity estimates with respect to ESG scores interacted with flows into ESG funds. ESG capital flows in units of $100bn. Flows into ESG funds from 2012 to 2021 from Van der Beck (2023). Environmental Concerns is a sub-index of the Media Climate Change Concerns Index of Ardia et al. (2023). Standard errors in parentheses are clustered at year-month. * p<0.10, ** p<0.05, *** p<0.01.

Sussman (2019) use the introduction of Morningstar's sustainability ratings for mutual funds to show that even being categorized either high or low sustainability by a third party results in large net capital flows.

I test whether flows into ESG funds drive the pricing of ESG scores. To do this, I interact ESG scores with the cumulative flow into ESG funds since 2012 from Van der Beck (2023). Table 7 shows that capital flows into ESG funds drive the pricing of ESG scores. Column (1) and (2) show that cumulative flows into ESG funds since 2012 explain a significant portion of the pricing of ESG scores: a $100bn higher net flow to ESG funds lowers issuance spreads by 2 bps.

Portfolio Holdings of ESG Mutual Funds I analyze the portfolios of ESG mutual funds to directly test whether greenness of auto ABS influences their investment decisions in Appendix A.4.

The portfolio data shows that ESG funds invest more in auto ABS from issuers with high ESG scores compared to non-ESG funds. While this is not surprising by itself, the positive correlation between ESG scores and CO_2 emissions of the collateral means that even dedicated ESG funds inadvertently invest more in high-emissions auto ABS compared with non-ESG funds. I document that ESG mutual funds hold positions across the full distribution of CO_2 emissions and invest more in high-emissions deals relative to non-ESG funds. However, similar to the findings in Table 5, the positive correlation between ESG scores and CO_2 emissions confounds these findings. Once I control for ESG scores, CO_2 emissions do not have explanatory power for the relative portfolio holdings of ESG mutual funds.

4.5 Does ESG Investing Raise the Cost of Emitting CO_2?

The results documented above imply that ESG investors use ESG scores to express their non-pecuniary preferences over greenness. This either implies investors care about ESG scores themselves (maybe for signalling purposes) or investors use ESG scores as a proxy for unobservable CO_2 emissions.[20] The fact that the effects of ESG scores on issuance spreads are larger during months with high concerns about environmental and societal impacts of climate change suggests that investors relied on ESG scores as a proxy for CO_2 emissions.

Relying on ESG scores inadvertently subsidizes CO_2 emissions due to a positive correlation between them. However, this does not imply that subsidizing CO_2 emissions is the intended effect of ESG investing. It is possible that ESG investors intend to raise the cost of emitting CO_2 by using ESG scores to allocate capital but have imperfect information about the CO_2 emissions of the collateral they finance. In this subsection, I develop a stylized model of subjective (and potentially biased) beliefs of ESG investors and their intention to price CO_2 emissions in auto ABS. I model CO_2 emissions as a latent variable over which ESG investors have subjective beliefs, informed by ESG scores. Combining insights from the model with additional information allows me to back out the implied subjective beliefs or the intended (subjective) effect of using ESG scores to proxy for CO_2 emissions.

I assume that the CO_2 emissions of auto ABS collateral pool are unobservable to investors. Instead, investors rely on ESG scores to proxy for CO_2 emissions and form subjective expectation $\mathbb{E}^{\star}\left[\cdot\right]$ about the relationship between CO_2 emissions and ESG scores as

$$\mathbb{E}^{\star}\left[\mathrm{CO}_2 \mid \text{ESG Score}\right] = \varphi^{\star} \times \ \text{ESG Score} \tag{8}$$

with $\varphi^{\star} < 0$, i.e., ESG investors expect high ESG scores to be associated with low CO_2 emissions. Using ESG scores as proxy variables for CO_2 emissions, the expected effect of CO_2 emissions on

[20]Informal conversations with market participants confirm that investors did not have real-time access to collateral-pool CO_2 emissions data until after the end of my sample period. Appendix A.4 shows that even dedicated ESG mutual funds relied on ESG scores to assess the greenness of auto ABS. Amel-Zadeh and Serafeim (2018) report that 66% of surveyed investment firms use ESG information to screen investment opportunities or tilt their portfolio.

Table 8: IV Estimates of δ Using ESG Scores as Instruments For CO_2 Emissions

	(1)	(2)	(3)	(4) Issuance Spread	(5)	(6)	(7)	(8)
$\mathbb{E}^\star$ [Fin. tCO2/USD|ESG] $/\varphi^0$	-0.441**	-0.470**			-0.512**	-0.567**		
	(0.221)	(0.235)			(0.254)	(0.275)		
$\mathbb{E}^\star$ [Fin. tCO2/Vehicle|ESG] $/\varphi^0$			-0.468**	-0.488**			-0.550**	-0.609**
			(0.219)	(0.228)			(0.270)	(0.294)
Instruments	ESG & Env.	ESG & Env.	ESG & Env.	ESG & Env.	Env.	Env.	Env.	Env.
Kleibergen-Paap F-stat.	8.9	8.0	6.3	5.6	16.5	13.1	11.4	9.2
Year-month FE, daily market con.	✓	✓	✓	✓	✓	✓	✓	✓
Prepay. speed FE, tranche con.	✓	✓	✓	✓	✓	✓	✓	✓
Ex-ante prepay. controls	✓	✓	✓	✓	✓	✓	✓	✓
Ex-post prepay. controls		✓		✓		✓		✓
Adj. R^2	0.343	0.333	0.326	0.317	0.320	0.298	0.289	0.257
Observations	231	231	231	231	231	231	231	231

Notes: This table reports IV estimates of Eq. (6) in which CO_2 emissions are instrumented with individual ESG and environmental pillar scores. Equations are estimated using Limited Information Maximum Likelihood (LIML) to account for potentially weak instruments. All variables are in logs. Observations are weighted by deal size. Standard errors in parentheses clustered at year-month. * p<0.10, ** p<0.05, *** p<0.01.

issuance spreads under the subjective expectations of ESG investors is

$$\begin{aligned} \mathbb{E}^\star\left[\text{Issuance Spread} \mid CO_2\right] &= \gamma^\star \times \ \mathbb{E}^\star\left[CO_2 \mid \text{ESG Score}\right] \\ &= \gamma^\star \times \varphi^\star \times \ \text{ESG Score} \\ &= \alpha^\star \times \ \text{ESG Score} \end{aligned} \tag{9}$$

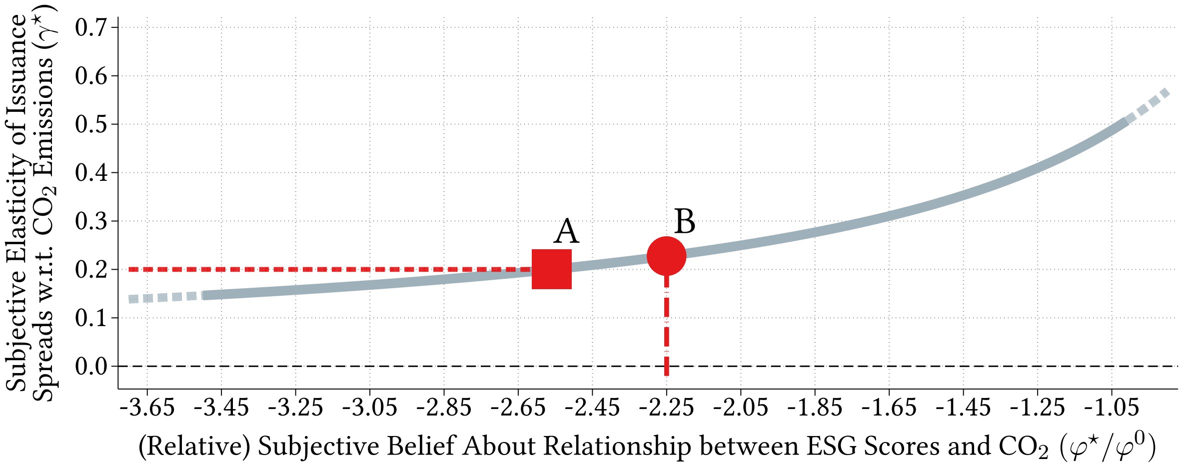
in which $\gamma^\star > 0$ and $\alpha^\star < 0$ reflect ESG investors' non-pecuniary preferences. Let φ^0 be the true relationship between CO_2 and ESG scores observed by the econometrician and define δ as

$$\delta \equiv \alpha^\star/\varphi^0 = \underbrace{\gamma^\star}_{\text{Intended Effect}} \times \underbrace{\varphi^\star/\varphi^0}_{\text{Subjective Beliefs}} . \tag{10}$$

This δ takes the Wald estimator form of an Instrumental Variable (IV) strategy using ESG scores to instrument for CO_2 emissions. Note that the IV estimate is not the causal effect of actual CO_2 emissions on issuance spreads. Instead, the IV estimates reflects the subjective intended effect of CO_2 emissions, $\gamma^\star$, scaled by the subjective efficacy of ESG scores, $\varphi^\star$, relative to the true relationship observed by the econometrician, φ^0.[21] Eq. (10) clarifies that the magnitude of this estimates is either due to a subjective beliefs about the efficacy of ESG scores ($\varphi^\star/\varphi^0$) to identify green securities or a (subjective) intended effect ($\gamma^\star$) of CO_2 emissions on issuance spreads. ESG investors either care a lot about CO_2 emissions ($\gamma^\star \gg 0$) or have subjective beliefs about the

[21] Formally, the data generating process is: Issuance Spread $= \beta \times CO_2 + \alpha^\star \times$ ESG $+ \varepsilon$ with β=0 and $\alpha^\star$<0. Instrumenting CO_2 emissions with ESG scores in the IV model recovers $\delta \equiv \beta^{IV} \xrightarrow{p} \beta + \alpha^\star/\varphi^0$, with φ^0 is the first stage regression coefficient of $CO_2 = \varphi^0 \times \text{ESG} + \nu$.

Figure 3: Curve of Intended Effect ($\gamma^\star$) as a Function of Subjective Beliefs ($\varphi^\star/\varphi^0$)



Notes: This figure shows in grey the curve of $\gamma^\star = \hat{\delta} \times \left(\varphi^\star/\varphi^0\right)^{-1}$ in which $\hat{\delta} \approx -0.51$ is from Column (5) of Table 8. Point A is the $\gamma^\star_A \approx 0.2$ implied by the subjective elasticity of wealth with respect to CO_2 emissions of investors surveyed in Haber et al. (2022). Point B is $\varphi^\star_B/\varphi^0 \approx -2.25$ implied by a representativeness heuristic (Gennaioli and Shleifer, 2010) that uses the average elasticity coefficients of firm-level CO_2 emissions with respect to firm-level ESG scores from Appendix Table A6. See section 4.5 for details.

efficacy of ESG scores that are much stronger than the true relationship between ESG scores and CO_2 emissions justifies ($|\varphi^\star/\varphi^0| \gg 1$).[22]

I recover $\hat{\delta}$ by instrumenting CO_2 emissions with ESG scores using the specification of Eq. (6). Table 8 shows that when investors use ESG scores to price the CO_2 emissions of auto loan securitization, it results in a lower cost of capital for high-emissions securitizations. The $\hat{\delta}$ coefficients are negative and statistically significant: a 1% higher CO_2 emissions intensity is associated with approximately 0.51% lower issuance spreads.

Figure 3 plots the curve that $\hat{\delta} \approx -0.51$ implies for ESG investor's intended effect of CO_2 emissions on issuance spreads as a function of their relative subjective beliefs about the efficacy of ESG scores. Given subjective beliefs about the relationship between ESG scores and CO_2 one can identify the intended effect of CO_2 emissions on issuance spreads. Or, vice versa, given the intended effect of CO_2 emissions on issuance spreads, one can infer subjective beliefs about the relationship between ESG scores and CO_2 emissions.

I gauge where on the curve ESG investors are using two complimentary approaches: First, I rely on the elasticity of wealth with respect to CO_2 emissions of investors surveyed in Haber et al. (2022) to infer the intended effect of CO_2 emissions on issuance spreads: 52% of investors are willing to give up 10% of their wealth to have the companies they are invested in change from industry-standard carbon emission levels to “net zero” by 2050. That is, the majority of surveyed

[22]The sign of δ depends on subjective beliefs about the relationship between ESG scores and CO_2, assuming $\gamma^\star > 0$.

investors are willing to give up 0.2% of their wealth to reduce CO_2 emissions by 1%.[23] I thus set $\gamma^\star_A \approx 0.2$, highlighted in Point A in Figure 3, which implies $\varphi^\star/\varphi^0 \approx -2.6$ under $\hat{\delta} \approx -0.51$.

Second, I estimate the subjective beliefs about the relationship between ESG scores and CO_2 emissions, $\varphi^\star$, and use them to back out the implied $\gamma^\star$. A natural way how ESG investors might form $\mathbb{E}^\star\left[CO_2 \mid \text{ESG Score}\right]$ is by relying on a representativeness heuristic (Tversky and Kahneman, 1974, Gennaioli and Shleifer, 2010): investors extrapolate from the firm-level CO_2-ESG relationship to auto ABS. This suggests that we can get an idea of $\varphi^\star$ by studying the elasticity of CO_2 emissions at the firm-level with respect to ESG and environmental scores. Appendix Table A6 shows elasticity estimates of firm-level CO_2 emissions intensity with respect to firm-level ESG scores. The average elasticity, using different definitions of emissions intensity, is $\hat{\varphi}^\star \approx -0.2$. Using this estimate heuristically implies that ESG investors believe that a 1% increase in ESG scores is associated with a 0.2% decrease in CO_2 emissions intensity at the auto ABS level. However, the true relationship, φ^0, is approximately $+0.09$. I thus set $\varphi^\star_B/\varphi^0 \approx -2.25$, highlighted in Point B in Figure 3, which implies $\gamma^\star \approx 0.23$ under $\hat{\delta} \approx -0.51$.

Both approaches deliver a consistent picture: ESG investors demand 0.2% higher issuance spreads for a 1% higher CO_2 emissions intensity. Since auto ABS collateral pool CO_2 emissions are not directly observable, investors heuristically rely on ESG scores to express their non-pecuniary preferences for greenness. However, their subjective beliefs about the link between ESG scores and CO_2 emissions differ significantly from the actual relationship: subjective beliefs imply that a 1% higher ESG score corresponds to a 0.2% decrease in emissions intensity, while the true relationship is a 0.09% increase in emissions intensity.

4.6 Robustness Tests

The result that issuers with high ESG scores that finance high-emissions auto loan securitizations have a lower cost of capital is robust to using alternative measures of greenness, tranches, specifications, and estimators. I find similar results using individual ESG scores and other measures of collateral greenness such as the average MPG of vehicles, share of trucks, and an independently constructed greenness measure by the Kroll Bond Rating Agency (KBRA, 2022). The results continue to hold when excluding deals with a high share of subprime loans. I find quantitatively similar results using propensity score matching and doubly-robust machine learning estimators. Appendix Section A.3 provides a detailed discussion of the robustness checks.

[23] Across sectors, U.S. companies analyzed in a recent S&P Global (2024) study are targeting an average 51% reduction in Scope 1 and 2 emissions as part of their "net zero" plans. I use this number as the %-definition of "net zero".

5 Pass-through of ESG Investing to Consumer Rates

ESG investing redirects capital towards "green" assets with the aim of raising the financing costs for "brown" activities. The hope is that a higher cost of capital reduces demand for high-emission activities and therefore mitigates climate change. By changing the cost of capital for high-emission vehicles, ESG investing could shift consumer demand away from high-emission vehicles toward greener alternatives. However, it is unclear whether changes in a lender's funding cost pass-through to consumer loan demand. The integration of the consumer loan market and financial markets via securitizations provides an ideal opportunity to study this question.

The impact of ESG investing on consumer loan demand depends on the pass-through of issuance spreads in the ABS market to consumer rates and the elasticity of consumer loan demand with respect to these rates. The percentage change in consumer loan demand is

$$\partial \log \text{Loan Demand} = \underbrace{\frac{\partial \log \text{Loan Demand}}{\partial \log \text{Consumer Rate}}}_{\text{Price Elasticity}} \times \underbrace{\frac{\partial \log \text{Consumer Rate}}{\Delta \text{ ABS Spreads}}}_{\text{Pass-through Elasticity}} \times \Delta \text{ ABS Spreads}, \tag{11}$$

in which the first term on the right-hand side is the price elasticity of consumer loan demand with respect to consumer interest rates, the second term is the pass-through (semi-)elasticity of issuance spreads to consumer interest rates, and the last term is the change in ABS issuance spreads.

Changes in ABS Spreads Table 6 reports that auto ABS of issuers with high ESG scores enjoyed 8 bps lower issuance spreads on average from 2017 to 2022. These magnitudes may seem low and their impact on real quantities negligible. However, the effect of changes in ABS spreads on consumer interest rates depend on the pass-through elasticity of changes in ABS spreads to changes in consumer interest rates. It is not immediately clear whether a ESG basis spread of 8 bps in senior tranches of auto ABS will result in a 8 bps change in consumer rates. The ESG basis spread represents a decrease in the average cost of funding for the safest tranche in a pool of thousands of loans, rather than the marginal cost decrease of funding for a marginal loan. Moreover, manufacturers with captive lenders jointly optimize lending and vehicle sales, which further complicate the pass-through (Benmelech et al., 2017, Benetton et al., 2021, Hankins et al., 2022). Manufacturers often use the vertical integration of credit provision to increase their sales by offering subsidized interest rates to consumers. Below, I show empirically that loan subsidies create an important non-linearity in pass-through.

Table 9: Estimates of the Pass-Through Elasticity from Issuance Spreads to Consumer Rates

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	within time across issuers				within issuer across time			
	Dependent variable: Log(Consumer Loan Rate)							
	OLS		IV		OLS		IV	
Spread t-1	0.517^{*}	0.461^{*}	0.194	0.016	0.021	0.004	-0.266^{*}	0.109^{+}
	(0.221)	(0.177)	(0.289)	(0.313)	(0.054)	(0.050)	(0.129)	(0.058)
Spread t-1 × Captive	1.740^{***}	1.670^{***}	0.906^{*}	0.707^{*}	1.219^{***}	1.286^{***}	0.970^{***}	0.654^{***}
	(0.264)	(0.230)	(0.342)	(0.319)	(0.193)	(0.189)	(0.281)	(0.120)
Total effect of Spread t-1 for Captive	2.256^{***}	2.131^{***}	1.100^{*}	0.723	1.240^{***}	1.290^{***}	0.704^{*}	0.763^{***}
	(0.267)	(0.241)	(0.452)	(0.445)	(0.193)	(0.188)	(0.294)	(0.128)
Origination Month × HDFE Set FE	Yes	Yes	Yes	Yes				
Originator × HDFE Set FE					Yes	Yes	Yes	Yes
Time × State FE					Yes	Yes	Yes	Yes
Linear Controls		Yes	Yes	Yes		Yes	Yes	Yes
Instrument			BofA	Others			BofA	Others
Kleibergen-Paap F-stat.			7.50	5.16			10.38	110.00
Adj. R^2	0.912	0.920	0.104	0.145	0.891	0.900	0.090	0.132
Sample	7,585,973	7,546,292	7,546,292	5,700,055	8,852,140	8,804,436	8,804,428	6,644,862

Notes: This table reports estimates of the pass-through semi-elasticity from auto ABS markets to consumer interest rates. Standard errors in parentheses double clustered at collateral pool and origination month. * p<0.10, ** p<0.05, *** p<0.01.

Estimating the Pass-through From Auto ABS to Consumer Rates I estimate the pass-through of ABS spreads to consumer rates using specifications of the form:

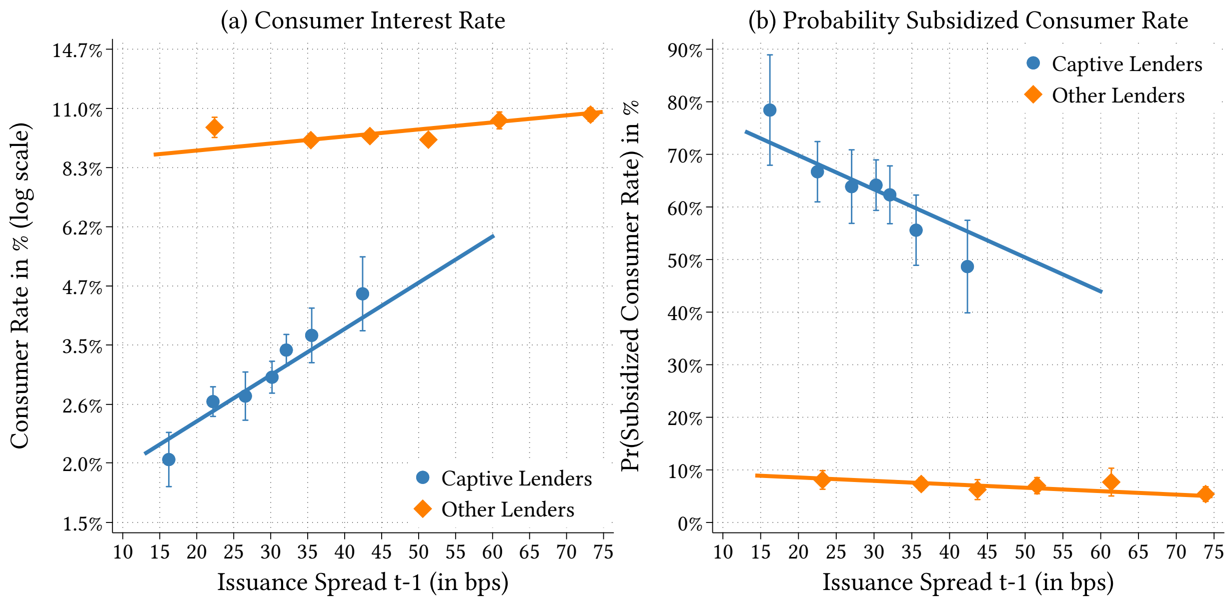
$$\log\left(\text{Consumer Loan Interest Rate}\right)_{i,o,t} = \beta \times \widehat{\text{ABS Spread}}_{o,t-1} + \mathit{HDFE} + \mathbf{X}_i'\zeta + \varepsilon_{i,o,t}$$

The coefficient of interest, β, measures the pass-through elasticity of ABS spreads to consumer loan interest rates in percent. The relationship between ABS spreads and consumer interest rates is obviously endogenous and determined by equilibrium conditions which connect the two markets through a financial intermediary. To address this endogeneity, I employ an instrumental variable approach using exogenous shifters of funding cost for auto loan lenders. I use two different instrument as proxies for shifts in funding cost of auto loan lenders: (i) ICE BofA US Corporate Index Option-Adjusted Spread and (ii) the leave-one-out mean of auto ABS spreads issued in the same month (excluding the originator itself). The idea behind these two instruments is to exploit common variation in funding markets which correlate with the actual funding cost of individual lenders.[24]

The specifications include a set of high-dimensional fixed effects (*HDFE*) that identify the

[24] See Berry and Haile (2021) who write "Noisy measures of a producer's actual cost shifters can also serve as instruments. For example, the average wage level in a producer's labor market may not perfectly track the producers' labor costs but is nonetheless likely to be highly correlated with those costs. Thus, such wage measures can serve as instruments as long as they are uncorrelated with demand shocks conditional on the exogenous variables [...]"

Figure 4: Relationship between Consumer Interest Rates and Auto ABS Issuance Spreads



Notes: This figure shows binned scatter plots of issuance spreads against consumer rates in Panel (a) and the probability of receiving a subsidized loan in Panel (b). The specifications include high-dimensional fixed effects which identify the relationships using loans with identical characteristics made by different lenders during the same month.

pass-through elasticity using loans with the same characteristics made either *across-issuers but within-time* or *across-time but within-issuer*. To be specific, the *within-time across issuer* specifications include (origination month $\times$ *HDFE Set*) fixed effects. The *within-issuer across time* specifications include (originator $\times$ *HDFE Set*) fixed effects. The *HDFE Set* is given by

$$\textit{HDFE Set} : \left\{ \begin{array}{l} \text{borrower state} \times \text{vehicle type} \times \text{vehicle used} \times \text{loan term quartile} \\ \times \text{ LTV quartile} \times \text{warehousing quartile} \times \text{credit score bin} \end{array} \right\}$$

in which credit score bins have a width of 50. The groups defined by *within-time across issuers* and *within-issuer across time* FE have on average 24 and 497 observations, respectively. The specifications further include a vector of controls at the loan level, $\mathbf{X}_i$, that linearly control for log-transformation of maturity-matched estimates of the real yield curve, LTV ratio, payment-to-income ratio, loan term, warehousing time, vehicle value, and vehicle age. The standard errors are double clustered at collateral pool and origination month.

Table 9 presents the estimates of the pass-through elasticity of auto ABS spreads to consumer interest rates. Several points are noteworthy. First, OLS estimates exhibit an upward bias compared to IV estimates. Second, the estimates for captive lenders are larger than those for non-captive lenders. In IV specifications, the pass-through elasticity is essentially zero for non-captive lenders but large and statistically significant for captive lenders.

Using within-time, across-issuer variation, the estimates of the pass-through (semi-)elasticity are 0.84% and 1.06%. Using within-issuer, across-time variation, the estimates are 0.65% and 0.80%. These estimates imply that a ESG basis spread of 8 bps in the auto ABS market translates into an consumer interest rates of 19 bps to 30 bps for the average loan by a captive lender.

The vertical integration of manufacturing and credit provision drives the large pass-through of the ESG convenience yield by captive lenders. Captive lenders frequently subsidize loans to increase car sales (Benetton et al., 2021). The most common form of subsidy is a reduced interest rate. Captive lenders often advertise 0% or 1.99% financing for new vehicles. Over 66% of captive lenders' subsidized loans have interest rates less than 2%.

Figure 4 shows that captive lenders increase their supply of subsidized loans when auto ABS issuance spreads are low. Specifically, a 8 bps decrease in issuance spreads is associated with a 6.1 percentage point increase in the probability of a loan interest rate being subsidized by a captive lender. The average difference between a subsidized loan and a non-subsidized from a captive lender is 369 bps. The increased probability of receiving a subsidized loan lowers consumer interest rates by 23 bps in expectation.

Price Elasticity I rely on the extensive literature on the price elasticity of consumer vehicle loan demand with respect to interest rates instead of directly estimating the elasticity. Argyle et al. (2020) report causal estimates for the price elasticity of -0.18, with estimates by FICO subgroup ranging from -0.22 to -0.07. Lukas (2017) estimate a loan price elasticity of -0.34. Attanasio, Koujianou Goldberg, and Kyriazidou (2008) report elasticity estimates ranging from -0.09 to -0.82 but cannot reject the null of zero elasticity. Given the considerable range of estimates for intensive margin price elasticities, I report results for elasticities from -0.18 to -0.5.

Implied Changes in Consumer Loan Demand Table 10 shows the implied changes in consumer loan demand for captive lenders associated with the ESG convenience yield. I provide a range of estimates based on the estimates of price elasticity of consumer loan demand and pass-through elasticity. The implied percentages changes in loan demand range from 0.98% to 4.45%. To illustrate, consider a $33,000 loan for a vehicle with a 3.34% interest rate. The results in column (1) imply that a 8 bps decrease in the auto ABS spread would result in a 0.98% increase in equilibrium loan demand, or about $324. Column (9) implies a change of about $1,469.

Changes in individual consumer loan demand do not directly equate to changes in vehicle demand. The estimated changes in loan demand in Table 10 are best understood as intensive margin changes affecting the loan amount for a given vehicle model purchase. This additional loan demand may be used for upgrades or accessories rather than for a higher priced vehicle model.

Table 10: Implied Changes in Individual Consumer Loan Demand for Captive Lenders

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$\frac{\partial \log \text{Loan demand}}{\partial \log \text{Consumer rate}}$		-0.18			-0.34			-0.50	
$\frac{\partial \log \text{Consumer rate}}{\Delta \text{ ABS spread}}$	0.65	0.80	1.06	0.65	0.80	1.06	0.65	0.80	1.06
$\partial \log$ Loan demand	0.98%	1.21%	1.60%	1.86%	2.28%	3.03%	2.73%	3.36%	4.45%
Δ Loan demand in USD	\$324	\$399	\$529	\$613	\$754	\$999	\$901	\$1,109	\$1,469

Notes: This table reports estimates of the implied change in consumer loan demand: $\partial \log \text{Loan Demand} = \frac{\partial \log \text{Loan Demand}}{\partial \log \text{Consumer Rate}} \times \frac{\partial \log \text{Consumer Rate}}{\Delta \text{ABS Spreads}} \times \Delta \text{ABS Spreads}$. The average change in ABS spread due to ESG pricing (ESG basis spread) is -8 bps, see Table 6. Intensive margin price elasticity of consumer vehicle credit demand are from Argyle et al. (2020), Lukas (2017), and Attanasio et al. (2008). The average loan amount for captive lenders is approximately \$33,000. The pass-through elasticity estimates are in percent per bps.

Depending on the elasticities, the implied changes in individual loan demand could finance a better sound system, set of winter tires, or an upgrade to four-wheel drive. However, manufacturers and captive auto lenders benefit from the cumulative increase in loan demand across all loans they extend, leading to a meaningful increase in product demand and profits for manufacturers with high ESG scores.

6 Discussion

I document that investors successfully lower the cost of capital for auto ABS of issuers with high issuer-level ESG scores. I estimate that investors earn an ESG convenience yield of 0.42% p.a. on their ESG investments. Importantly, this ESG convenience yield generates seigniorage for issuers of ESG assets and lowers their borrowing cost. Consumers financing vehicles with loans from captive lenders benefit from the ESG convenience yield through lower borrowing costs.

However, my findings also show that investors not necessarily invest in the most environmentally-friendly securities. Auto ABS investors reward issuers with higher ESG scores with a lower cost of capital, even if their securities have higher CO_2 emissions intensities. The market's focus on issuer-level ESG scores, rather than the collateral's CO_2 emissions, lowers the cost of capital for high-emissions vehicles. This raises questions about the effectiveness of ESG investment strategies in addressing environmental externalities.

These findings suggest a need for greater clarity and transparency in ESG labeling and investment processes. ESG fund managers may need to re-evaluate their investment processes to ensure they promote environmentally sustainable investing. Policymakers may need to provide more guidance to the financial sector on what constitutes environmentally sustainable investing and 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 issued guidance to ensure that ESG labels accurately reflect the environmental impact of investments, encouraging companies to provide comprehensive and transparent disclosures of their ESG practices and impacts. In Europe, similar efforts are underway with the adoption of the Sustainable Finance Disclosure Regulation (SFDR), which requires comprehensive and transparent disclosure of sustainability risks, impacts, and objectives. Emiris, Harris, and Koulischer (2023) examine the impact of the SFDR on portfolio allocation and ESG fund flows. The authors find that the regulation increased flows to ESG funds, particularly among environmentally-conscious investors, and that funds with higher initial uncertainty about their sustainability benefited most from the disclosure.

7 Conclusion

Many ESG investors want to raise the cost of emitting CO2 by rewarding "green" assets with a lower cost of capital and penalizing "brown" assets with higher capital costs. This paper shows that ESG investing successfully lowers the cost of capital for auto ABS issuers with high ESG scores. The pass-through of this green convenience yield to consumer interest rates can be significant for captive lenders, resulting in economically meaningful changes in loan demand.

However, the market's focus on issuer-level ESG scores, rather than the collateral's CO_2 emissions, also lowers the cost of capital for high-emissions securitizations; driven by the fact that ESG scores positively correlate with emissions. Consequently, investors who rely on ESG scores to allocate capital inadvertently subsidize CO_2 emissions. ESG mutual funds allocate more capital to auto ABS from issuers with high ESG scores even if those finance high-emissions vehicles. A model of subjective beliefs in which ESG investors use a representativeness heuristic to infer CO_2 emissions from firm-level ESG scores can explain the observed effects.

These findings highlight that while ESG investing can have meaningful impact, it does not increase the cost of emitting CO_2 and underscore the need for more accurate and comprehensive project-level ESG metrics that reflect environmental impact.

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A Appendix

A.1 Appendix Figures

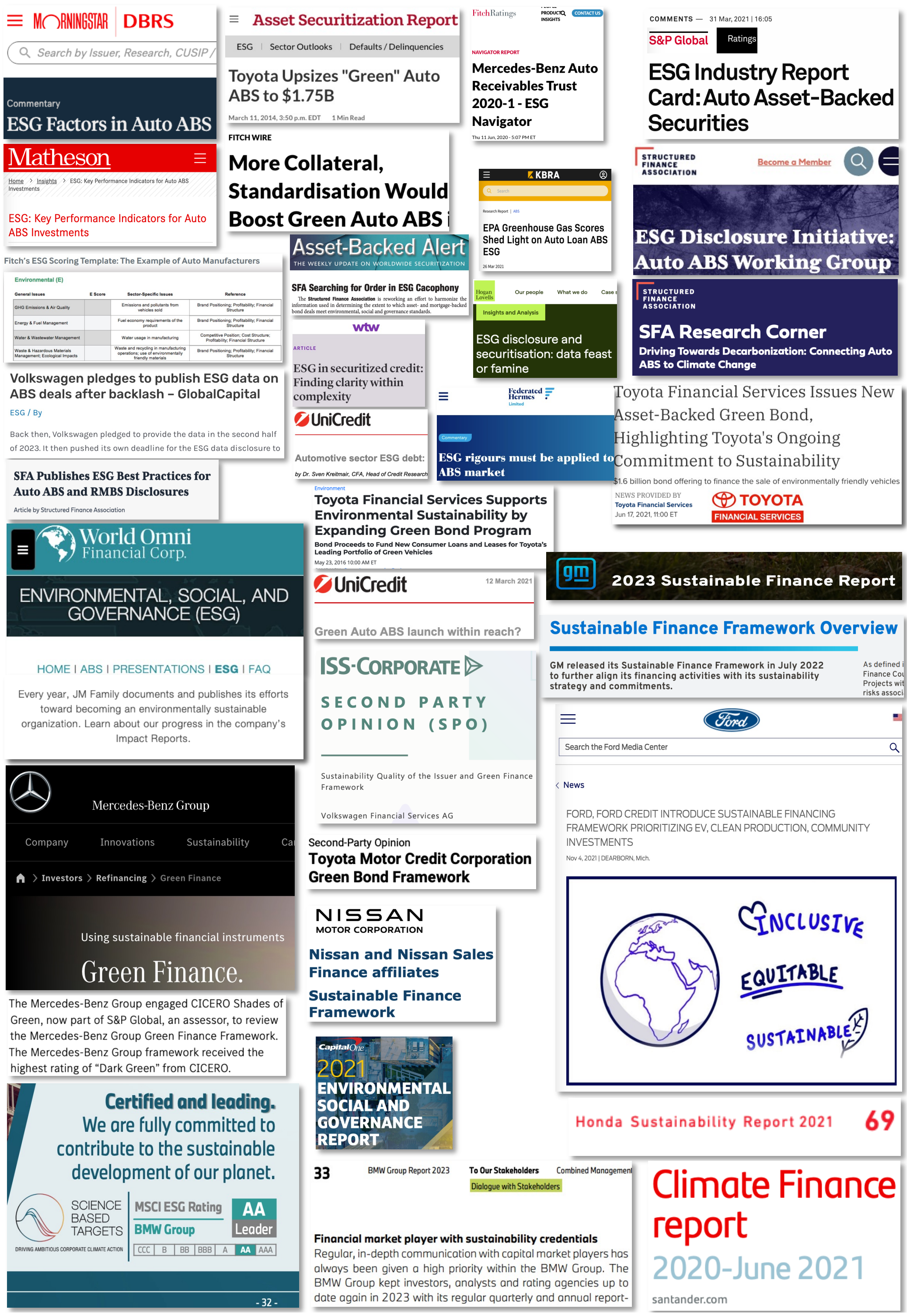


Figure A1: Clippings from ABS Issuers, Investors, Bond Rating Agencies, Industry Association, Law Firms, and News Outlets that Discuss the Importance of ESG Issues in the Auto ABS Market

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

Notes: This table reports coefficients from a regression of vehicles types on average tCO_2 emissions per vehicle. * p<0.10, ** p<0.05, *** p<0.01.

Table A2: Summary Statistics of Loan-Level Data

	Mean	SD	Median	Min	Max	Obs.
Original Interest Rate	7.84	7.00	5.25	0.00	30.00	17,823,551
Original Loan Amount ($)	25,822.58	12,251.91	23,650.84	518.03	248,681.95	17,823,552
Original Loan Term (months)	67.65	8.59	72.00	7.00	96.00	17,823,552
Credit Score	708.64	101.70	719.00	250.00	900.00	17,143,023
Payment-to-Income Share	0.08	0.05	0.08	0.00	0.79	17,700,290
Income Verified	0.09	0.29	0.00	0.00	1.00	17,823,552
Loan-to-Value	0.90	0.16	1.00	0.01	1.00	17,822,211
Outstanding Balance Share	0.83	0.24	0.93	0.00	1.00	17,823,548
Vehicle Value Amount ($)	27,341.46	13,177.32	24,998.00	0.00	1,084,455.00	17,823,549
Vehicle Age (Years)	2.74	2.56	2.00	0.00	35.00	17,823,552
Used Vehicle	0.48	0.50	0.00	0.00	1.00	17,823,552
SVM, Financed	161,660.73	40,008.49	171,346.10	254.15	240,728.61	17,823,552
SVM, Total	202,834.40	16,986.18	207,738.97	189,173.82	240,728.61	17,823,552
tCO2, total Lifetime	78.28	30.61	72.45	0.00	538.75	17,823,552
tCO2, remaining Lifetime	62.12	29.51	56.48	0.00	538.75	17,823,552
tCO2, financed remaining Lifetime	46.57	27.79	44.58	0.00	538.75	17,822,207

Notes: This table reports summary statistics for the loan-level data. Credit scores outside the FICO Auto Score range of 250 to 900 are set to missing.

Table A3: Summary Statistics of Mutual Fund Portfolio Data

	Mean	SD	Median	Min	Max	Obs.
Portfolio Share (%)	0.18	0.28	0.09	0.00	4.94	11,474
Coupon Yield (%)	1.95	1.19	1.95	0.00	6.51	11,474
Tranche Size ($m)	263.06	168.81	230.00	8.51	746.94	11,474
Weighted Average Life (years)	2.36	0.99	2.39	0.11	5.06	11,474
Subprime ABS	0.41	0.49	0.00	0.00	1.00	11,474
Financed tCO2 per USD	227.20	37.78	226.11	118.20	311.78	11,474
Financed tCO2 per Vehicle	59.39	11.52	58.31	40.54	101.25	11,474

Notes: This table reports summary statistics for the mutual fund portfolio data.

Table A4: Pricing Results Using Individual ESG Scores

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
				Issuance Spread				
Refinitiv ESG Score	-0.525***							
	(0.0539)							
Refinitiv Env. Score		-0.0900***						
		(0.0207)						
S&P ESG Score			-0.222***					
			(0.0284)					
S&P Env. Score				-0.581***				
				(0.0801)				
MSCI ESG Score					-0.225***			
					(0.0612)			
MSCI Env. Score						-0.198***		
						(0.0358)		
Sustainalytics ESG Score							-0.384***	
							(0.1036)	
Sustainalytics Env. Score								-0.201***
								(0.0501)
Year-month FE, daily market controls	✓	✓	✓	✓	✓	✓	✓	✓
Prepayment speed FE, tranche controls	✓	✓	✓	✓	✓	✓	✓	✓
Adj. R^2	0.951	0.925	0.940	0.944	0.966	0.957	0.884	0.885
Observations	243	243	243	243	231	231	122	122

Table A5: The Effects of Media Climate Change Concerns on Spreads of Auto ABS

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
				Issuance Spread				
Average ESG Score	-0.200	-0.253	-0.382**	-0.529***				
	(0.191)	(0.173)	(0.145)	(0.132)				
Aggregate Index × Avg. ESG Score	-0.462**							
	(0.226)							
Societal Debate × Avg. ESG Score		-0.354*						
		(0.186)						
Business Impact/Transition Risk × Avg. ESG Score			-0.189					
			(0.173)					
Car Industry Transition Risk × Avg. ESG Score				0.206				
				(0.172)				
Average Environmental Score					-0.327	-0.355	-0.471***	-0.542***
					(0.215)	(0.213)	(0.174)	(0.150)
Aggregate Index × Avg. Env. Score					-0.472*			
					(0.277)			
Societal Debate × Avg. Env. Score						-0.354		
						(0.235)		
Business Impact/Transition Risk × Avg. Env. Score							-0.209	
							(0.222)	
Car Industry Transition Risk × Avg. Env. Score								0.163
								(0.277)
Year-month FE, daily market controls	✓	✓	✓	✓	✓	✓	✓	✓
Prepayment speed FE, tranche controls	✓	✓	✓	✓	✓	✓	✓	✓
Ex-ante prepayment controls	✓	✓	✓	✓	✓	✓	✓	✓
Ex-post prepayment controls	✓	✓	✓	✓	✓	✓	✓	✓
Adj. R^2	0.962	0.962	0.961	0.961	0.959	0.958	0.957	0.957
Observations	243	243	243	243	243	243	243	243

Notes: This table reports elasticity estimates with respect to ESG scores interacted with the Media Climate Change Concerns Index of Ardia et al. (2023) Standard errors in parentheses are clustered at year-month. * p<0.10, ** p<0.05, *** p<0.01.

Table A6: Elasticity of CO_2 Emissions Intensity w.r.t to ESG Scores at Firm-Level in Compustat

	(1) $\frac{\text{Scope 1 + 2}}{\text{Sales}}$	(2) $\frac{\text{Scope 1 + 2}}{\text{COGS}}$	(3) $\frac{\text{Scope 1 + 2}}{\text{PPEGT}}$	(4) $\frac{\text{Scope 1 + 2}}{\text{Sales}}$	(5) $\frac{\text{Scope 1 + 2}}{\text{COGS}}$	(6) $\frac{\text{Scope 1 + 2}}{\text{PPEGT}}$
Average ESG Score ($\widehat{\varphi}^{\star}$)	-0.304**	-0.293**	-0.313**			
	(0.131)	(0.133)	(0.123)			
Average Env. Score ($\widehat{\varphi}^{\star}$)				-0.110***	-0.063**	-0.087***
				(0.036)	(0.029)	(0.023)
Constant	5.323***	5.897***	5.974***	4.392***	4.882***	4.964***
	(0.512)	(0.521)	(0.481)	(0.095)	(0.072)	(0.063)
NAICS-4 Industry $\times$ Year FE	✓	✓	✓	✓	✓	✓
Adj. R^2	0.758	0.735	0.492	0.747	0.718	0.487
Observations	5,172	5,121	5,121	5,506	5,503	5,235

Notes: This table shows coefficient estimates from Scope 1+2 CO_2 Emissions Intensity $= \beta_0 + \beta_1$ ESG Score $+ \varepsilon$. Scope 1+2 emissions from S&P Trucost from 2009 to 2022, excluding estimated data. Sales, cost of goods sold (COGS), and property, plant, and equipment (PPEGT) from S&P Compustat North America. Sales, COGS, and PPEGT trimmed at 2.5/97.5% (yearly) to remove outliers. All variables are in logs. Standard errors in parentheses clustered by firm and year. * p<0.10, ** p<0.05, *** p<0.01.

A.3 Robustness Tests

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

Table A7: Elasticity of Issuance Spreads with Respect to Emissions in Prime Auto ABS only

	(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	-0.183*	-0.222*						
	(0.099)	(0.109)						
Expected tCO2 per USD			-0.223**	-0.265**				
			(0.083)	(0.097)				
Financed tCO2 per Vehicle					-0.172*	-0.206**		
					(0.086)	(0.096)		
Financed tCO2 per Vehicle							-0.172*	-0.209**
							(0.085)	(0.095)
Year-month FE, daily market controls	✓	✓	✓	✓	✓	✓	✓	✓
Prepayment speed FE, tranche controls	✓	✓	✓	✓	✓	✓	✓	✓
Ex-ante prepayment controls	✓	✓	✓	✓	✓	✓	✓	✓
Ex-post prepayment controls		✓		✓		✓		✓
Adj. R^2	0.956	0.956	0.957	0.957	0.956	0.956	0.956	0.956
Observations	190	190	190	190	190	190	190	190

Notes: This table reports estimates of the risk-adjusted pricing model of Eq. (6) using prime auto ABS deals only. Standard errors in parentheses clustered at year-month. + p<0.10, * p<0.05, ** p<0.01, *** p<0.001

Lower Cost of Capital for Brown Auto ABS is Unrelated to Credit Quality A potential concern is that I use both prime and subprime 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 than prime borrowers. Appendix Table A7 shows that the results still hold when excluding subprime auto ABS. 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 the original estimates.

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	-0.198**	-0.223**								
	(0.093)	(0.091)								
Financed tCO2 per Vehicle			-0.163*	-0.175**						
			(0.084)	(0.082)						
Avg. MPG × (-1)					-0.239	-0.184				
					(0.196)	(0.204)				
Avg. Share of Trucks							-0.114	-0.157		
							(0.100)	(0.098)		
Avg. GHG Rating (KBRA) × (-1)									-0.319	-0.228
									(0.212)	(0.216)
Year-month FE, daily market controls	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Prepayment speed FE, tranche controls	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Ex-ante prepayment controls	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Ex-post prepayment controls		✓		✓		✓		✓		✓
Adj. R^2	0.952	0.953	0.952	0.952	0.951	0.951	0.951	0.952	0.943	0.943
Observations	234	234	234	234	234	234	234	234	205	205

Notes: This table reports estimates of the risk-adjusted pricing model of Eq. (6) with different measures of greenness. Average MPG and GHG Rating are multiplied by (-1) such that higher values are environmentally worse. Standard errors in parentheses clustered at year-month. + p<0.10, * p<0.05, ** p<0.01, *** p<0.001

Lower Cost of Capital for Brown Auto ABS is Robust to Alternative Measures I perform a series of robustness tests using different measures of greenness for each auto ABS deal: (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 greenness measure by the Kroll Bond Rating Agency (KBRA).[25]

Appendix Table A8 shows that the results remain qualitatively unchanged when different measures of relative greenness are used. All specifications indicate 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 in the main results of Table 5.

Lower Cost of Capital of Brown Auto ABS holds Across the Capital Structure The main analysis uses A-2 tranches due to their similar characteristics across different deals: low credit risk, non-binding clean-up call options, and the highest observation count. However, the results are robust to the choice of other AAA-rated tranches.

Appendix Table A9 reports results for all AAA-rated tranches, showing qualitatively and quantitatively similar outcomes 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, showing that the lower cost of capital scales through the entire capital structure of these deals.

Lower Cost of Capital for Brown and High-ESG Auto ABS is Robust to Different Estimators A potential concern with the main analysis is that OLS estimators may not accurately

[25] KBRA (2022) map the EPA's vehicle GHG scores (1 to 10, with higher values indicating lower emissions) to 247 auto ABS. GHG scores have been displayed on window labels of new vehicles in the US since 2013.

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	-0.207**	-0.253***			-0.271***	-0.298***		
	(0.081)	(0.078)			(0.062)	(0.066)		
Financed tCO2 per Vehicle			-0.175**	-0.222***			-0.245***	-0.265***
			(0.077)	(0.073)			(0.048)	(0.056)
Year-month FE, daily market controls	✓	✓	✓	✓	✓	✓	✓	✓
Prepayment speed FE, tranche controls	✓	✓	✓	✓	✓	✓	✓	✓
Ex-ante prepayment controls	✓	✓	✓	✓	✓	✓	✓	✓
Ex-post prepayment controls		✓		✓		✓		✓
Adj. R^2	0.935	0.937	0.935	0.937	0.965	0.964	0.965	0.964
Observations	230	230	230	230	190	190	190	190

Notes: This table reports estimates of the risk-adjusted pricing model of Eq. (6) in other senior tranches. Standard errors in parentheses clustered at year-month. + p<0.10, * p<0.05, ** p<0.01, *** p<0.001

control for differences in covariates and falsely attribute differences in issuance spreads to differences in greenness. I address this concern using two alternative estimators.

First, I use the Propensity-Score Matching estimator described by Abadie and Imbens (2016). Online Appendix Table B3 shows that the matching estimator results for ESG scores are similar to those from a dummy OLS specifications in Appendix Table B2, whereas the matching estimator results for the low-emissions indicator are larger. This likely occurs because the matching estimator selects a sample more similar in terms of covariates than the OLS estimator, suggesting that the main results underestimate the effect of CO_2 emissions on issuance spreads.

Second, I use the Double-Lasso estimator from Belloni et al. (2014). Online Appendix Table B4 shows that the Double-Lasso estimator results are qualitatively and quantitatively similar to the main results in Table 5, even when including over 850 potential control variables. The estimator automatically selects relevant control variables for both the outcome and treatment via Lasso estimation. This procedure involves three steps: (1) selecting controls that predict treatment via Lasso, (2) selecting controls that predict the outcome via Lasso, and (3) estimating treatment effects using linear regression while controlling for the union of the selected variables. This method provides inference that is uniformly valid over a large class of models.

A.4 The Auto ABS Holdings of ESG Mutual Funds

ESG Mutual Funds' Approach to Auto ABS Prospectuses of ESG mutual funds often detail their investment 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 [...] Environmental assessment involves issues such as carbon emissions, pollution, and renewable energy"

– ESG Mutual Fund Prospectus II

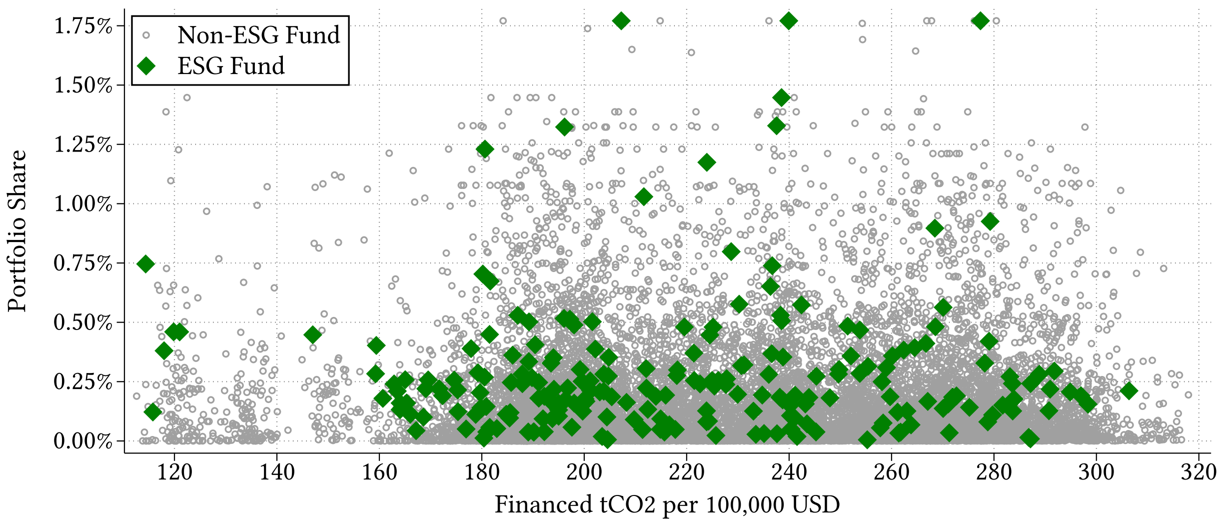
Mutual Fund Portfolio Data I obtain mutual fund holdings from the SEC Form N-PORT, starting from 2019-Q3 when they first became available. I keep the first observation in which a mutual fund reports a position in a senior tranche of an auto ABS. I identify ESG mutual funds by their name using key words such as "sustainable", "ESG", or "climate" and using a list of "Sustainable Investment Mutual Funds and ETFs" offered by institutional member firms of "The Forum for Sustainable and Responsible Investing".[26] Appendix Table A3 shows summary statistics of the mutual fund holding data.

I identify 35 self-declared ESG funds (and 787 non-ESG funds) that hold at least one position in an auto ABS tranche over the sample period. Note that this is a lower bound on the actual number of portfolios with ESG tilt. Van der Beck (2023) reports that net flows into portfolios with ESG tilts reached \$1.3 trillion in 2022, far exceeding the \$350 billion in net flows into labeled ESG mutual funds. Similarly, Pastor et al. (2024) estimate that the typical institution's ESG tilt has grown from 12% to 22% from 2017 to 2021. Even mutual funds without declared ESG objectives are affected by marketwide ESG concerns: Hartzmark and Sussman (2019) use the introduction of Morningstar's sustainability ratings to show that "[b]eing categorized as low sustainability resulted in net outflows of more than \$12 billion while being categorized as high sustainability led to net inflows of more than \$24 billion."

Identification Strategy I estimate a reduced form asset demand system in the spirit of Koijen and Yogo (2019) to test whether ESG funds tilt their portfolio toward greener auto ABS. I use the

[26] The key word list contains: "green", "climate", "esg", "sustainable", "environment", "responsible", "impact", "catholic", "social", "sri", "csr", "community", and "justice". List of Sustainable Mutual Funds from USSIF.

Figure A2: Portfolio Shares of Mutual Funds in Auto ABS



Notes: This figure shows portfolio shares of ESG and non-ESG mutual funds in auto ABS from 2019-Q3 to 2022-Q2. Portfolio shares are winsorized at 1% and 99%. X-axis is jittered with normally distributed noise for readability.

following specification for portfolio shares of fund j in year-quarter r in tranche t of auto ABS deal b issued by i:

$$\log\left(\text{Portfolio Share}\right)_{jtrb} = \alpha\left(\text{ESG Fund}_j \times \text{Green}_b\right) + \gamma_j + \gamma_b + \gamma_{i\times r} + \mathbf{X}_t'\zeta + \varepsilon_{jtrb} \qquad (12)$$

in which 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_j are fund fixed effects; γ_b are auto ABS deal fixed effects; and $\gamma_{i\times r}$ are issuer by reporting year-quarter fixed effects. The coefficient of interest, α, measures the preferences for greenness by ESG funds relative to non-ESG funds. The specifications control for the weighted average life, issuance size, and yield in $\mathbf{X}_t$

I estimate ESG fund preferences using variation in greenness across multiple auto ABS held by ESG and non-ESG funds during the same period. The specifications include fixed effects for the collateral pool and fund, thus absorbing the characteristics and preferences of each fund and the specific features of each auto ABS. This approach identifies the difference in preference for green assets between ESG and non-ESG funds while controlling for as much unobserved heterogeneity across collateral pools and funds as possible. Additionally, the specifications include issuer by period fixed effects that absorb time-varying issuer characteristics (e.g., issuer health).

Results Figure A2 plots mutual fund portfolio shares in auto ABS against financed CO_2 emissions per \$100,000. The graph shows that ESG mutual funds hold positions across the full distri-

Table A10: Reduced Form Asset Demand System 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	-0.226*					
	(0.095)					
ESG Fund=1 × Financed tCO2 per USD		0.154*				
		(0.069)				
ESG Fund=1 × Financed tCO2 per Vehicle			0.144**			
			(0.044)			
ESG Fund=1 × Avg. MPG ×(-1)				0.196***		
				(0.052)		
ESG Fund=1 × Truck Share					0.236*	
					(0.113)	
ESG Fund=1 × Avg. GHG Rating (KBRA)×(-1)						0.202**
						(0.063)
Fund FE	✓	✓	✓	✓	✓	✓
ABS Deal FE	✓	✓	✓	✓	✓	✓
Issuer × Year-Quarter FE	✓	✓	✓	✓	✓	✓
Tranche FE, Tranche controls	✓	✓	✓	✓	✓	✓
Adj. R^2	0.822	0.822	0.822	0.822	0.820	0.819
Observations	11,334	11,334	11,334	11,334	10,919	10,559

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 × Refinitiv ESG Score	0.157**	0.145*	0.115+			
	(0.060)	(0.059)	(0.066)			
ESG Fund=1 × S&P ESG Score				0.112*	0.102+	0.064
				(0.054)	(0.054)	(0.056)
ESG Fund=1 × Financed tCO2 per USD		0.107			0.120	
		(0.084)			(0.088)	
ESG Fund=1 × Financed tCO2 per Vehicle			0.086			0.120+
			(0.066)			(0.066)
Fund FE	✓	✓	✓	✓	✓	✓
ABS Deal FE	✓	✓	✓	✓	✓	✓
Issuer × Year-Quarter FE	✓	✓	✓	✓	✓	✓
Tranche FE, Tranche controls	✓	✓	✓	✓	✓	✓
Adj. R^2	0.821	0.821	0.821	0.821	0.821	0.821
Observations	10,111	10,111	10,111	10,111	10,111	10,111

Notes: This table reports coefficient estimates of Eq. (12). Sample from 2019-Q3 to 2022-Q2. Coefficients are standardized to unit variances. MPG and GHG Rating are multiplied by (-1) such that higher values are environmentally worse. Standard errors in parentheses clustered at fund-level. * p<0.10, ** p<0.05, *** p<0.01.

bution of CO_2 emissions. This is surprising since common ESG strategies typically involve either outright exclusions of brown assets or best-in-class investments. However, Figure A2 shows that ESG funds hold similar or higher shares in auto ABS with high-emissions intensity.

Table A10 reports estimates of the relationship between greenness and ESG ownership using Eq. (12). The coefficients in Column (1) of Panel A indicate that the greenest 50% of auto ABS receive 20.6% less capital from ESG funds compared to non-ESG funds. Columns (2) to (6) present similar estimates using other measures of greenness, all showing positive coefficients of similar magnitude. For example, moving from the 10th to the 90th percentile of average financed CO_2 per vehicle (moving from Honda to Ford) results in a 0.4 standard deviation higher portfolio share for ESG funds than for non-ESG funds.

Panel B of Table A10 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 ESG scores highly correlate with the differential demand by ESG funds. Columns (2), (3), (5), and (6) show that controlling for ESG scores shrinks the coefficients on CO_2 emissions shrinks towards zero and makes them insignificant.

In summary, ESG funds invest more in auto ABS from issuers with high ESG scores compared to non-ESG funds. The positive correlation between ESG scores and CO_2 emissions of the collateral means that ESG funds inadvertently invest more in high-emissions auto ABS compared with non-ESG funds.[27]

[27] Appendix Table B1 shows the positive correlation of ESG scores and CO_2 emissions in the mutual fund data.

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 Loan Securitizations

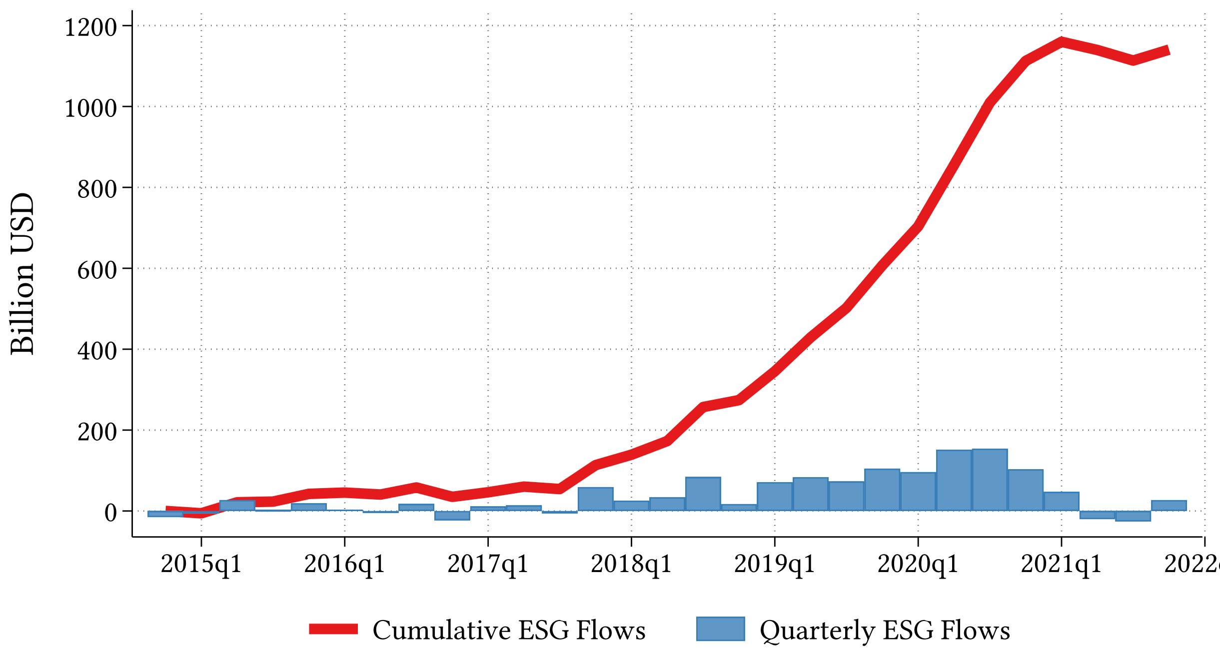


Figure B2: Total ESG Flow (Van der Beck, 2023). ESG flow for each 13F institution as the return-adjusted change in ESG-assets under management and then summed across all institutions. I report rolling 4-quarter averages and plot the cumulative sum of all flows since 2014.

Table B1: Correlation of Greenness Measures in Mutual Fund 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	0.86	1.00					
Fin. tCO2/car	0.54	0.42	1.00				
Fin. tCO2/USD	0.39	0.36	0.48	1.00			
Avg. MPG	0.32	0.25	0.85	0.40	1.00		
Truck %	0.38	0.25	0.83	0.24	0.89	1.00	
GHG Rating	0.27	0.16	0.78	0.19	0.87	0.90	1.00

Notes: This tables reports Spearman rank correlation coefficients across variables in the mutual fund portfolio data. MPG and GHG Rating are multiplied by (-1) such that higher values are environmentally worse.

B.1 Indicator Variable and Matching Estimator

Table B2: Semi-Elasticity with Respect to High-ESG or Low-Emissions indicator

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
			Issuance Spread					
High Refinitiv ESG (score>p50)	-0.108***	-0.082**						
	(0.030)	(0.027)						
High S&P ESG (score>p50)			-0.090+	-0.085+				
			(0.050)	(0.051)				
Low Emissions (USD<p50)					0.047	0.074*		
					(0.032)	(0.028)		
Low Emissions (Vehicle<p50)							0.055*	0.043
							(0.026)	(0.026)
Year-month FE, daily market controls	✓	✓	✓	✓	✓	✓	✓	✓
Prepayment speed FE, tranche controls	✓	✓	✓	✓	✓	✓	✓	✓
Ex-ante prepayment controls	✓	✓	✓	✓	✓	✓	✓	✓
Ex-post prepayment controls		✓		✓		✓		✓
Adj. R^2	0.953	0.959	0.950	0.957	0.946	0.953	0.947	0.952
Observations	235	235	235	235	276	276	276	276

Notes: All control variables are in logs. Standard errors in parentheses clustered at year-month. + p<0.10, * p<0.05, ** p<0.01, *** p<0.001.

Table B3: Semi-Elasticity Estimates using Propensity Score Matching

	(1) Issuance Spread	(2) Issuance Spread	(3) Issuance Spread
Low Emissions (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

Appendix table B3 shows that one obtains qualitatively similar results to the main results when using a propensity score matching estimator. The "treated" (i.e., either low CO_2 emissions or high ESG score) and "untreated" auto ABS are matched to their k=2 nearest neighbors.

B.2 Double-selection Lasso Estimator

Table B4: 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 B4 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.