Do ESG Investors Care About Carbon Emissions? Evidence from Securitized Auto Loans[*]

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Abstract

Securitized auto loans present a unique setting to measure the effects of ESG investing. I find that the ESG convenience yield almost quadrupled from 0.12% in 2017 to 0.46% in 2022. Consumers financing vehicles with loans from captive lenders benefit from the ESG convenience yield through lower borrowing costs. ESG mutual funds allocate more capital to securitizations from issuers with high ESG scores even if the securitizations finance high-emissions vehicles. The focus on ESG scores, rather than CO_2, lowers the cost of capital for high-emissions vehicles. The findings suggest that green premia affect real quantities but do not raise the cost of CO_2 emissions.

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

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1 Introduction

Many environmental, social, and governance (ESG) investors want to raise the cost of emitting CO_2 by rewarding "green" assets with lower cost of capital and penalizing "brown" assets with higher cost of capital.[1] Estimating whether ESG investors successfully lower the cost of capital of green assets is challenging. A clean measurement must hold risk exposure constant while varying greenness and quantify the true environmental impact.

This paper sheds light on whether ESG investors lower the cost of capital for green assets and increase the cost of CO_2 emissions by addressing these challenges. I compare the cost of capital across senior tranches of automobile asset-backed securities (auto ABS). The unique features of the auto loan securitization market allow me to study the impact of ESG investing on equilibrium asset prices and evaluate the real effects of green premia. I exploit the safe asset nature of senior tranches and use variables derived from loan-level data to hold risk exposure across auto ABS constant. I then test whether the greenness of a securitization influences its cost of capital. Asset managers commonly use ESG scores to assess the greenness of an investment. I use two measures of greenness: (i) the issuer's ESG score 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 green premia increase the cost of emitting CO_2. Lastly, I measure the pass-through of green premia to consumer rates and calculate the corresponding shift in consumer auto loan demand.

I collect data on 17.8 million vehicles loans that serve as collateral for all auto ABS issued by captive lenders of vehicle manufacturers, banks, non-bank finance companies, and vehicle retailers from 2017 to 2022. I estimate the lifetime emissions of each vehicle loan by merging information about the collateral at the make, model, and year level with data on CO_2 emissions from the Environmental Protection Agency. This allows me to calculate the financed CO_2 emissions and to quantify the environmental impact of each securitization. Additionally, I collect the issuer's ESG scores from several providers.

I start by documenting large cross-sectional differences in CO_2 emissions across auto ABS. For instance, auto ABS by Ally Bank finance an average of 55tCO_2 per vehicle, while those by Ford Credit finance an average of 95tCO_2 per vehicle. Just as a motorist chooses between high- and low-emissions vehicles, an investor chooses between loans that finance high- or low-emissions vehicles. The pooling and tranching of these loans creates highly liquid securities that are similar in risk exposure (DeMarzo, 2005). I exploit that auto ABS have large environmental differences and similarly low risk to test whether CO_2 emissions influence the cost of capital.

[1] Asset managers cite climate change, CO_2 emissions, and fossil fuel divestment as the top ESG criteria (USSIF, 2022).

The ESG and environmental pillar scores of auto ABS issuers do not capture the large differences in CO_2 emissions. Both firm-level 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 the actual emissions of their auto ABS. The smaller variance and positive correlation with CO_2 emissions make ESG scores poor proxies for the actual environmental impact of auto ABS. Consequently, investors who rely on ESG scores to allocate capital 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.

I build an identification strategy to estimate whether ESG investors' non-pecuniary preferences for green assets impact prices and quantities in the auto ABS market. I motivate the identification strategy with a stylized asset pricing model featuring 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?

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 collateral itself. Borrowers with high interest rate loans prepay when interest rates fall, regardless of the collateral they finance. The loan-level data allow me to control for predictors and ex-post realizations of prepayment. Controlling for both predictors and ex-post performance at issuance together with fixed effects removes as much unobserved heterogeneity as possible.

A correlation between CO_2 emissions or ESG scores and exposure to risk factors would pose a threat to identification. For example, if greenness reduces prepayment risk, it would lower the cost of capital, regardless of investors' non-pecuniary preferences. I therefore verify that neither CO_2 emissions nor ESG scores predict prepayment or default. Additionally, I report results that control for the ex-post performance of collateral pools. This supports the identifying strategy and increases confidence that investors' non-pecuniary preferences drive differences in the cost of capital.

I find that conclusions about whether ESG investors' archive their goal of raising the cost of CO_2 emissions depend on accounting for security design and risk exposure across securities. In a naïve specification that only accounts for market conditions, auto ABS with emissions below the median have 24.1% lower issuance spreads. Similarly, issuers with ESG scores above the median have 21.2% lower spreads. The naïve approach suggests an alignment between ESG scores and the goal of pricing CO_2. However, this naïve approach delivers a biased picture because it fails to account for differences in security design and risk which correlate with CO_2 emissions.

High-emissions collateral pools have a *lower* cost of capital when accounting for security design and risk. Moving from the 20th to the 80th percentile of tCO_2 per USD (moving from Toyota to Ford) reduces issuance spreads by 4 bps, an economically meaningful difference compared to the mean issuance spread of 42 bps. Consistent with the positive correlation of ESG scores and emissions, moving from the 20th to the 80th percentile of ESG scores reduces spreads by 10 bps.

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

The $1.1 trillion in capital that flowed into ESG funds over the past decade (Van der Beck, 2023) drive the effects of ESG scores on the cost of capital. Interacting ESG scores with flows into ESG funds, I find that a $200m inflow to ESG funds lowers issuance spreads by 3 bps. Both the contemporaneous flow into ESG funds and the cumulative stock of flows since 2012 lower issuance spreads for auto ABS of issuers with high-ESG scores. The interaction terms are statistically significant while coefficients on ESG scores alone are close to zero and not significant.

I next examine the portfolios of mutual funds to directly test whether CO_2 emissions or ESG scores influence their choice to investment in auto ABS. Mutual funds are key investors in the auto ABS market. Up to 85% of the issuance amount of senior tranches land on their balance sheets. I identify the relative preferences of ESG funds' for green assets from multiple auto ABS held by both ESG and non-ESG funds during the same period using stringent fixed effects.

The portfolio analysis shows that ESG funds (i) invest across the full distribution of CO_2 emissions and (ii) 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.[2] The positive correlation between firm-level ESG scores and CO_2 emissions explains these findings. 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 than non-ESG funds.

I translate the observed differences in issuance spreads into an ESG convenience yield, motivated by a stylized asset pricing model in the spirit of Krishnamurthy and Vissing-Jorgensen (2012). This ESG convenience yield provides seigniorage to issuers of ESG assets and lowers their borrowing cost. I estimate that investors earn an extra 0.24% p.a. in ESG convenience yield, on average. The ESG convenience yield nearly quadrupled from 0.12% in 2017 to 0.46% in 2022.

Lastly, I test whether the ESG convenience yield affects consumer loan demand. The integration of the consumer loan market and financial markets via securitizations provides a unique setting to study whether ESG issuers pass on lower borrowing cost. I estimate the pass-through of the ESG convenience yield to consumer rates and the resulting shift in consumer loan demand. Endogenous equilibrium conditions shape how funding markets and consumer markets interact. I address the endogeneity using instrumental variables (IV) that isolate exogenous variation in the funding cost of auto loan lenders.

Consumers financing vehicles with loans from captive lenders benefit from the ESG convenience yield through lower borrowing costs. The vertical integration of manufacturing and credit provision drives the pass-through of the ESG convenience yield by captive lenders. Captive lenders frequently subsidize loans to increase car sales (Benetton, Mayordomo, and Paravisini, 2021). The pass-through elasticities imply that a 10 bps decrease in auto ABS spreads translates into a 22 bps to 35 bps decrease in consumer rates due to loan subsidies. The resulting changes in consumer loan demand range from 1.17% to 5.30%. This translates into an increase in demand of \$386 to \$1,749 for a \$33,000 loan.

In summary, issuers of auto ABS with high ESG scores who securitize loans on high-emissions vehicles have a lower cost of capital. The finding is robust across various measures, samples, specifications, and estimators. The reduced cost of capital for high-emissions ABS exists throughout the capital structure and is unrelated to credit quality. The large flows into ESG funds over the past decade drive the lower cost of capital. ESG mutual funds allocate more capital to auto ABS of high-ESG issuers even when those finance high-emissions vehicles. Consumers financing through captive lenders benefit from the ESG convenience yield through lower borrowing costs.

[2] There is an ongoing debate about which strategy ESG investors should follow: exit (divestment/exclusion) or voice (shareholder activism). Broccardo, Hart, and Zingales (2022) analyze the relative effectiveness of these strategies, while Edmans, Levit, and Schneemeier (2022) examine if exclusion or best-in-class investment is more effective.

The paper is organized as follows. The remainder of this section 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 studies mutual funds' holdings of auto ABS. Section 6 explores the pass-through of the ESG convenience yield to consumer interest rates and calculates the implied changes in consumer loan demand. Section 7 discusses the results. Section 8 concludes.

Related Literature The rise of ESG investing spurred extensive research.[3] 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 where 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 (forthcoming) 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).

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. This finding aligns with 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.[4] However, my results highlighting a tension between ESG investors' goal and the use of potentially misleading firm-level ESG scores. I find that green premia can have a meaningful impact but they do not increase the cost of emitting CO_2.[5]

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

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

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

[5]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. I focus on consumer vehicle loans where adjusting the cost of capital could effectively shift consumer demand from brown to green products.

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 loan demand. By examining how differences in the cost of capital for ESG assets influence loan demand, I provide insights into the broader economic implications of ESG investing. This analysis helps to understand whether ESG preferences can translate into tangible economic behaviors and outcomes.

2 Data

This section describes the loan-level data I use to construct greenness measures 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 unique loans from 281 ABS deals of 22 issuers.[6] 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 sub-prime deals. The average deal finances around 63,031 vehicles. A \$100,000 investment finances 219 tCO_2 over the remaining life of the collateral.

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. 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

[6]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.

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
Weight. Avg. Life (years)	0.98	0.32	1.01	0.37	3.50	281
Spread (bps)	41.68	29.10	32.29	6.13	194.22	281
Coupon (%)	1.91	1.30	1.86	0.14	5.81	281
Subprime ABS	0.28	0.45	0.00	0.00	1.00	281
Captive Lender	0.44	0.50	0.00	0.00	1.00	281
Number of Loans Receivable	63,031	21,302	62,886	15,329	136,860	281
Avg. Loan-to-Value	0.92	0.04	0.92	0.80	0.98	281
Avg. Credit Score	706.19	74.87	738.34	564.98	788.46	281
Avg. Interest Rate (%)	7.64	5.87	4.46	1.38	21.35	281
Avg. Fraction of Original Loan Outstanding	0.90	0.07	0.91	0.74	1.00	281
Avg. Warehousing Time (Months)	9.54	4.38	9.19	1.33	21.06	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
Refinitiv/LSEG ESG Score of Issuer	0.73	0.18	0.79	0.22	0.94	243
S&P ESG Score of Issuer	0.58	0.26	0.70	0.07	0.92	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.

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.[7] The average vehicle will emit 62tCO_2 over its remaining lifetime with a standard deviation of 29.5tCO_2.

Firm-level ESG Scores I collect firm-level ESG scores of auto ABS issuers[8] from Refinitiv/LSEG and Standard and Poor's (S&P). Both providers create their scores on the basis of publicly available

[7]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).

[8]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 share of units sold		0.16	0.39	0.20[1]
Amount securitized as share of revenue	0.83	0.32	0.24	0.45
Amount securitized as share of assets	0.11	0.05	0.30	0.10

Notes: This table reports the average securitization intensity by industry for N=60 firm-years. Securitization 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.

information and penalize companies with limited reporting. The scores are available for 17 of the 22 originators in the sample. The average firm-level issuer ESG scores from Refinitiv/LSEG and S&P are 0.73 and 0.58, respectively.

3 Securitized Auto Loans and their CO_2 Emissions

This section introduces the market for securitized auto loans, presents key concepts and facts. I show that just as a motorist can choose between high- and low-emissions vehicles, an investor can choose between auto ABS that finance high- or low-emissions.

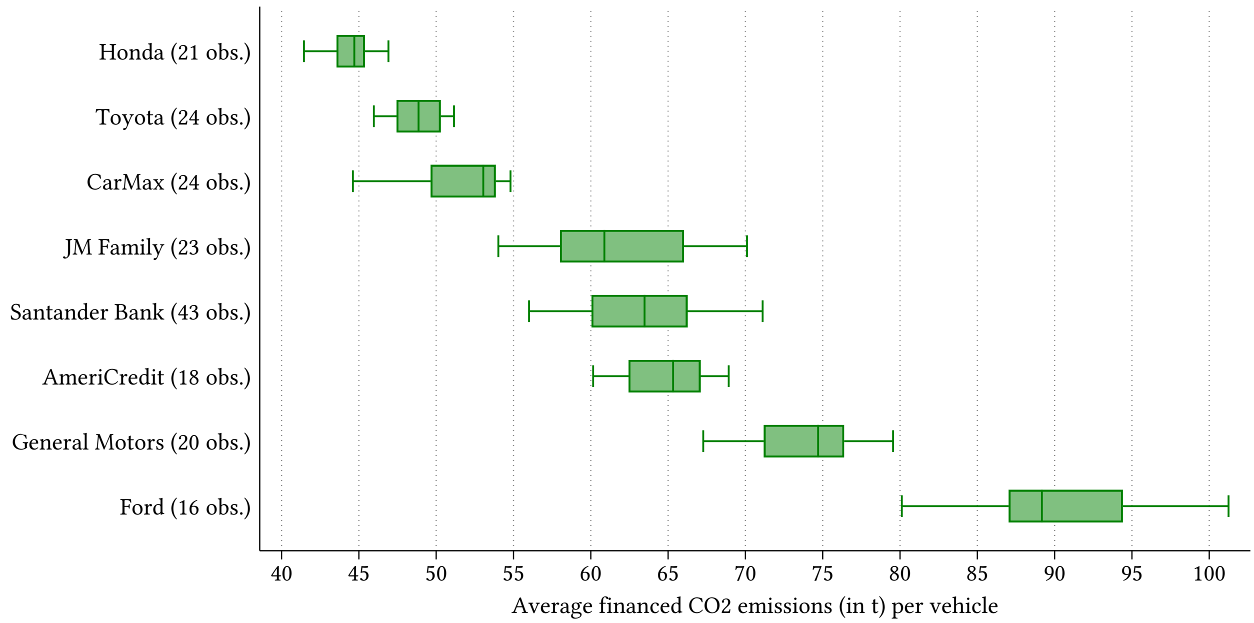
The ABCs of Consumer Auto ABS Auto loan securitizations were among the first consumer ABS to enter the market in the 1980s. In 2021, the $220 billion in auto ABS accounted for approximately 18% of outstanding auto loans in the United States.[9] The auto ABS market is divided into prime and sub-prime deals based on the creditworthiness of underlying loans, with sub-prime deals commanding higher issuance spreads.

Issuers of consumer auto ABS come from various industries, including vehicle manufacturers and their captive lending companies, vehicle retailers, banks, and non-bank finance companies. Table 2 highlights the importance of consumer loan securitization for these industries. On average, 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

[9]SIFMA, U.S. ABS issuance and outstanding.

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.

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 (Gorton, 2017). He and Mizrach (2017) show that auto ABS have bid-ask spread as low as agency mortgage-backed securities that trade in the to-be-announced market.[10]

Prepayment is the main risk for investors in senior tranches of consumer auto ABS since time and risk tranching, high levels of over-collateralization, and other credit enhancements mitigate default risk (DeMarzo, 2005). Prepayment risk arises from early loan repayments by consumers or borrower defaults leading to vehicle repossession. Consumer auto loan securitizations have clean-up call options, allowing issuers to call outstanding notes if the pool balance drops below a certain percentage (typically 5% or 10%). However, these options are irrelevant for most senior tranches as they are paid off before reaching the cutoff.

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 for each collateral pool. The emissions that auto ABS b finances is the sum over the financed

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

Table 3: Correlation Matrix for Measures of Greenness: ESG, CO_2, and Miles-per-Gallon

	Refinitiv ESG Score	Refinitiv Env. Score	S&P ESG Score	S&P Env. Score	Exp. tCO2 per Vehicle	Fin. tCO2 per Vehicle	Avg. MPG × (-1)
Refinitiv ESG Score	1.00						
Refinitiv Env. Score	0.92	1.00					
S&P ESG Score	0.79	0.75	1.00				
S&P Env. Score	0.84	0.84	0.97	1.00			
Exp. tCO2 per Vehicle	0.35	0.27	0.10	0.10	1.00		
Fin. tCO2 per Vehicle	0.37	0.28	0.17	0.17	0.89	1.00	
Avg. MPG × (-1)	0.18	-0.03	0.02	-0.01	0.68	0.71	1.00

Notes: This table reports Pearson correlation coefficients between the ESG scores, environmental pillar scores, average expected and financed CO_2 per vehicle, and average MPG.

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.[11] 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 a motorists choose between high- and low-emissions vehicles, investors choose between auto ABS that finance high- or low-emissions vehicles. 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 pools raises the average CO_2 per vehicle by 1.02 tons.

Table 3 shows that ESG scores, which the asset management industry commonly uses to assess the environmental impact of an investment, positively correlate with CO_2 emissions. Appendix A.4 documents that firm-level ESG scores of auto ABS issuers are poor proxies for the environmental impact of auto ABS. The positive correlation between ESG scores and CO_2 emissions creates problems if investors use ESG scores to screen green from brown auto ABS.

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

4 Issuance Spreads, Cost of Capital, and Convenience Yield

This section develops the main results: (i) without accounting for differences in security design and risk, securities with lower CO_2 emissions and those from high-ESG issuers appear to have a significantly lower cost of capital, incorrectly suggesting alignment between ESG and carbon pricing; (ii) this relationship reverses when accounting for security design and risk; (iii) the correlation between ESG scores and CO_2 emissions confounds the elasticity between emissions and issuance spreads; and (iv) flows into ESG funds drive the pricing of ESG scores. 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 a green convenience yield in the spirit of Krishnamurthy and Vissing-Jorgensen (2012) and derive the difference in yields between green and brown assets. I populate the economy with 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 SDF. For simplicity, I assume that there are only two assets in the economy: a brown b asset and a green g asset where $\beta^g_t > \beta^b_t$. I assume that $m_t = \log M_t$ and $r^i_t = \log R^i_t$ are conditionally normal. Rewriting the Euler equation using log-normality, one finds

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

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, we can write the dividend yield of an asset with fixed maturity T in this economy as

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

where $\rho = \frac{1}{1-\exp\left(\overline{d-p}\right)}$ and $\kappa = -\log(\rho) - (1-\rho)\log(1/\rho - 1)$. 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 green basis spread:

Lemma 2. *The absolute level of the green basis 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 green basis simplifies to:

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

To infer the green basis, one needs to carefully account for potentially differences in risk-exposure and cash-flow growth of green and brown assets. I build an identification strategy in the next section that exploits the unique features of the auto ABS market to isolate the green basis.

4.2 Identification Strategy

The identification strategy 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 prepayment is the main risk factor for senior tranches. Allocating cash flows across tranches and time shifts credit risks to subordinate tranches (DeMarzo, 2005). 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. This makes credit risk an unlikely factor in observed effects.[12] Third, the granularity of the loan-level data allow me to control for both predictors and ex-post realizations of prepayment. Borrower and loan characteristics drive prepayment risk, not the greenness of the collateral.

Empirical Specifications I test whether green assets have a lower cost of capital using the following specification:

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

for bond tranche b issued in year-month t. $\mathbb{1}[\text{Green} > p50]_b$ is an indicator variable equal to one if the greenness of the auto ABS deal is above the 50th percentile of all securitizations and zero otherwise. α is the premium investors are willing to pay for a security with above median greenness. The specification is consistent with the literature on green premia that uses a discrete definition of greenness.

I additionally test the following specification that uses a continuous definition of greenness:

$$\log\left(\text{Issuance Spread}\right)_b = \beta\log\left(\text{Green}\right)_b + \mathbf{X}_b'\zeta + \gamma_t + \varepsilon_b. \tag{7}$$

The coefficient of interest, β, is the elasticity of issuance spreads with respect to greenness. The time-fixed effect, γ_t, identifies both α and β using variation in greenness across securitizations issued during the same month. To control for within-month market conditions, I include the six month yield from Filipović et al. (2022), the level of the VIX on the day of issuance, the standard deviation of the VIX in the 30 days before issuance, and the 5-year breakeven inflation rate in $\mathbf{X}_b$.

I include predictors and ex-post realizations of prepayment risk in $\mathbf{X}_b$. The predictors are collateral pool averages of LTV, credit scores, remaining loan balance share, interest rate, and warehousing time. The ex-post realizations are the realized difference to assumed prepayment speed and the share of loans more than 30 days delinquent (both measured 12 months after issuance). I also include the following tranche characteristics: weighted average life (WAL), default attachment point, and the issuance size. All controls are in logs and allowed to have different slopes across subprime and prime deals.

The specifications include subprime and assumed absolute prepayment speed (APS) fixed effects. I interact the APS fixed effects with the WAL to allow for potential "ramp-up" periods in

[12] 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 Prepayment				Realized % Delinquent Loans (30d+)			
Financed tCO2 per USD	0.073				0.025			
	(0.139)				(0.029)			
Financed tCO2 per Vehicle		-0.023				-0.030		
		(0.133)				(0.024)		
Refinitiv ESG Score			-0.031				0.077	
			(0.152)				(0.081)	
S&P ESG Score				0.044				0.127
				(0.153)				(0.099)
Subprime FE					✓	✓	✓	✓
Adj. R^2	0.005	0.001	0.001	0.002	0.899	0.899	0.902	0.905
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, *** p<0.001.

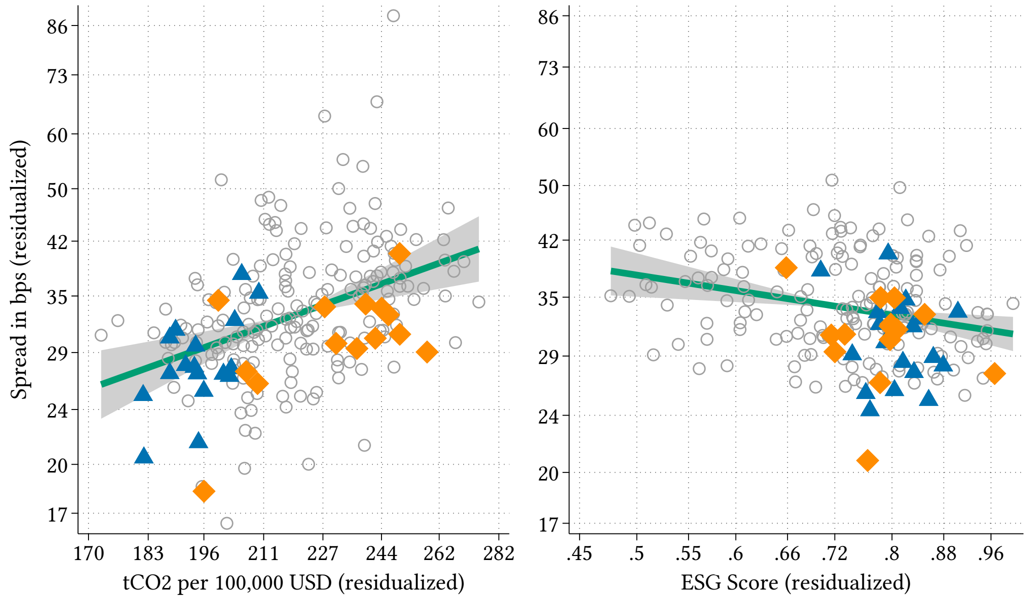
which prepayments increase and before leveling off to their assumed APS.

Identifying Assumption The identifying assumption in both Eq. (6) and Eq. (7) is that the assignment of greenness is uncorrelated with the error term conditional on risk factors: once prepayment risk is accounted for, the assignment of greenness is "as good as random." This identification assumption allows me to answer whether the greenness of a securitization affects its cost of capital. The null hypothesis is that greenness does not affect the cost of capital, implying $\alpha = \beta = 0$. Evidence that $\alpha < 0 < \beta$ indicates that investors accept lower yields because they prefer greener assets.

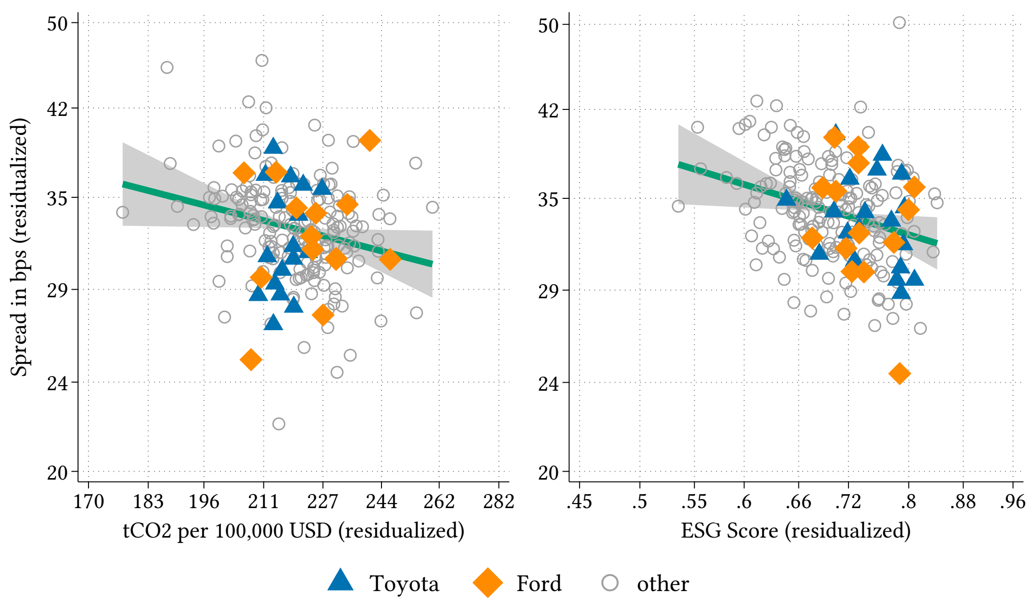
A correlation between CO2 emissions or ESG scores and exposure to risk factors would pose a threat to identification. I test whether greenness correlates with prepayment risk using data on the ex-post performance of auto ABS from monthly reports. Specifically, I examine two measures that capture voluntary and involuntary prepayment at the pool-level: the average realized difference in monthly absolute prepayment speed (APS) compared with its prospectus assumption, and the average realized percentage of loans more than 30 days delinquent. Table 4 reports that neither CO_2 emissions nor ESG scores predict collateral pool-level performance. The estimates are noisy and close to zero. These results support the identification assumption and allow me to treat the assignment of greenness effectively as "as good as random."

Figure 2: Residualized Scatter Plots and Line of Best Fit of Pricing Models

(a) Naïve Pricing Model without Risk Adjustment



(b) Risk-adjusted Pricing Model



Notes: This figure shows pricing models of Eq. (7) in Panel (a) and (b). Regressions in both panels control for issuance-month fixed effects as well as the yield curve, VIX, and inflation expectations which vary within-month. Panel (b) additionally controls for the security design, predictors of prepayment risk, and ex-post realized prepayment. All variables are in logarithms. Issuance spreads, tCO_2 per USD, and ESG scores are trimmed at the 5% and 95% level.

4.3 Results

Figure 2a shows that a naive pricing model, controlling only for market conditions, suggests an alignment between ESG and carbon pricing. This implies that ESG investing identifies environmentally friendly assets, rises the price of CO_2 emissions and thus aids climate change mitigation. However, Figure 2b reveals the opposite when using a risk-adjusted model when accounting for prepayment risk and security design. Appendix Table A4 shows that high-emissions vehicles have lower credit scores. Accounting for this, I find that *high*-emissions auto ABS have *lower* issuance spreads.

Table 5 presents the main results using the risk-adjusted pricing model. Odd-columns controls for predictors of prepayment risk, even-columns add controls for ex-post realizations of prepayment risk. Panel A shows estimates of the semi-elasticity of issuance spreads with respect to the high-ESG or low-emissions indicator using the pricing model of Eq. (6). Panel B shows estimates of the elasticity of issuance spreads with respect to either ESG scores or CO_2 emissions using the pricing model of Eq. (7). Panel C runs a horse race between CO_2 emissions and ESG scores, comparing their effects on issuance spreads.

The results in Panel A indicate that high ESG scores lower issuance spreads by between 7.9% and 10.3%.[13] These results are consistent with the hypothesis that investors are willing to pay a premium for green assets. However, Panel A also shows that high CO_2 emissions lower issuance spreads by 4.2% to 7.2%. This is inconsistent with the hypothesis that investors are trying to raise the cost of CO_2 emissions. Panel B, using the linear pricing model from Eq. (7), reports similar results. Issuance spreads have an elasticity of -0.13 to -0.44 for ESG scores and -0.17 to -0.25 for CO_2 emissions intensity.

Panel C 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. 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 subsidize CO_2 emissions as Panel A and B show.

Figure 4 reports yearly estimates of the elasticity of issuance spreads with respect to CO_2 emissions, average ESG score, and average environmental pillar score. The elasticities follow a similar 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.

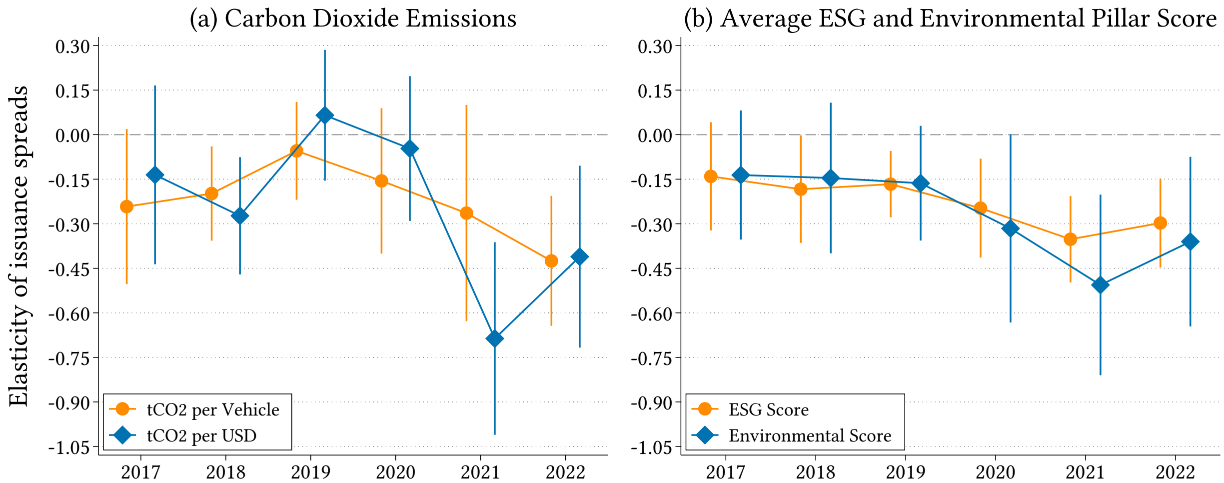
[13] $-10.3\% \approx 100(\exp\left(-0.108 - 0.030^2/2\right) - 1)$

Table 5: The Pricing of Greenness in Auto Loan Securitizations

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
				Issuance Spread				
Panel A: Semi-Elasticity of Issuance Spreads with respect to High-ESG or Low-Emissions indicator								
High Refinitiv ESG (score>p50)	-0.108***	-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
Panel B: Elasticity of Issuance Spreads with respect to either ESG score or Carbon Emissions								
Refinitiv ESG Score	-0.438***	-0.342**						
	(0.112)	(0.105)						
S&P ESG Score			-0.125**	-0.130**				
			(0.047)	(0.047)				
Financed tCO2 per USD					-0.174	-0.238^{+}		
					(0.121)	(0.122)		
Financed tCO2 per Vehicle							-0.216**	-0.253**
							(0.073)	(0.076)
Year-month FE, daily market controls	✓	✓	✓	✓	✓	✓	✓	✓
Prepayment speed FE, tranche controls	✓	✓	✓	✓	✓	✓	✓	✓
Ex-ante prepayment controls	✓	✓	✓	✓	✓	✓	✓	✓
Ex-post prepayment controls		✓		✓		✓		✓
Adj. R^2	0.954	0.960	0.951	0.959	0.947	0.953	0.948	0.954
Observations	235	235	235	235	276	276	276	276
Panel C: Elasticity of Issuance Spreads with respect to ESG score and Carbon Emissions								
Refinitiv ESG Score	-0.452***	-0.351***	-0.414**	-0.293*				
	(0.106)	(0.100)	(0.133)	(0.126)				
S&P ESG Score					-0.122*	-0.123**	-0.114*	-0.101*
					(0.046)	(0.046)	(0.047)	(0.046)
Financed tCO2 per USD	-0.136	-0.166			-0.057	-0.105		
	(0.123)	(0.122)			(0.116)	(0.114)		
Financed tCO2 per Vehicle			-0.051	-0.096			-0.138^{+}	-0.129^{+}
			(0.093)	(0.094)			(0.069)	(0.072)
Year-month FE, daily market controls	✓	✓	✓	✓	✓	✓	✓	✓
Prepayment speed FE, tranche controls	✓	✓	✓	✓	✓	✓	✓	✓
Ex-ante prepayment controls	✓	✓	✓	✓	✓	✓	✓	✓
Ex-post prepayment controls		✓		✓		✓		✓
Adj. R^2	0.955	0.960	0.954	0.960	0.951	0.959	0.952	0.959
Observations	235	235	235	235	235	235	235	235

Notes: This table reports the effects of greenness on issuance spreads of auto ABS. Panel A shows coefficient estimates of Eq. (6) and Panel B and C show estimates of Eq. (7). All variables are in logarithms. Standard errors in parentheses clustered at year-month. + p<0.10, * p<0.05, ** p<0.01, *** p<0.001.

Figure 3: Elasticity of Spreads with Respect to CO_2, ESG, and Environmental Score Over Time



Notes: This figure shows yearly elasticity estimates and 90% confidence intervals of the risk-adj. model of Eq. (7). Panel (a) shows elasticity estimates for CO_2 per vehicle and CO_2 per USD. Panel (b) shows elasticity estimates for the equal weighted average of ESG and environmental pillar scores from Refinitiv/LSEG and S&P.

Effects of Capital Flows into ESG Funds on Spreads Over \$1.1 trillion capital flowed into ESG funds over the past decade (see Online Appendix Figure B2). I test whether flows into ESG funds drive the pricing of ESG scores. I interact ESG scores with (i) flows into ESG funds in the issuance quarter, and (ii) the cumulative flow into ESG funds since 2012 from Van der Beck (2023).

Table 6 shows that capital flows into ESG funds drive the pricing of ESG scores. Both the contemporaneous flow into ESG funds as well as the cumulative flow into ESG funds since 2012 lower issuance spreads for auto ABS of issuer with high-ESG scores. The elasticity in Column (1) implies that a \$200m inflow to ESG funds lowers issuance spreads by 3 bps. Column (2), (4), and (6) show that cumulative flows into ESG funds since 2012 explain a significant portion of the pricing of ESG scores. The interaction terms are statistically significant while the coefficients on ESG scores alone are insignificant and close to zero. The results are again stronger using the environmental pillar score instead of the composite ESG score.

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

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

Table 6: The Effects of Capital Flows into ESG Funds on Spreads of Auto Loan Securitizations

	(1)	(2)	(3)	(4)	(5)	(6)
			Issuance Spread			
Average ESG Score	-0.241*	-0.043				
	(0.101)	(0.130)				
ESG Flow ($100m) × Average ESG Score	-0.050*					
	(0.022)					
Cum. ESG Flow ($100m) × Average ESG Score		-0.023*				
		(0.009)				
Average Environmental Pillar Score			-0.260	-0.135		
			(0.185)	(0.191)		
ESG Flow ($100m) × Average Env. Score			-0.077*			
			(0.033)			
Cum. ESG Flow ($100m) × Average Env. Score				-0.034**		
				(0.012)		
Refinitiv ESG Score					-0.433***	-0.191
					(0.108)	(0.132)
ESG Flow ($100m) × Refinitiv ESG Score					-0.071*	
					(0.035)	
Cum. ESG Flow ($100m) × Refinitiv ESG Score						-0.039**
						(0.013)
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	0.954	0.955	0.959	0.960
Observations	194	194	194	194	194	194

Notes: This table reports estimates of the elasticity of issuance spreads with respect to ESG scores interacted with flows into ESG funds. Issuance spreads and ESG scores are in logarithms. ESG flow variables in units of $100m. Flows into ESG funds from 2012 to 2021 estimated by Van der Beck (2023). Observations are weighted by tranche size. Standard errors in parentheses are clustered at year-month. + p<0.10, * p<0.05, ** p<0.01, *** p<0.001

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

Table 7 shows estimates of the ESG convenience yield based on yearly elasticity estimates from Figure 4. The ESG convenience yield nearly quadrupled from 0.12% p.a. in 2017 to 0.46% p.a. in 2022. The average ESG convenience yield is 0.24% p.a. over the sample period. Similar to this estimates, Avramov, Lioui, Liu, and Tarelli (2024) estimate an ESG convenience yield for stocks between 0.37% and 0.66%. These magnitudes are comparable to the 0.73% convenience yield on U.S. Treasurys documented by Krishnamurthy and Vissing-Jorgensen (2012).

Table 7: Estimates of the ESG Convenience Yield over Time

		2017	2018	2019	2020	2021	2022	Avg.
Difference in ESG Score:	$\beta_t^g - \beta_t^b$	0.42	0.36	0.36	0.33	0.53	0.45	0.43
ESG Basis Spread in Basis Points:	$y_t^g - y_t^b$	-5	-4	-4	-7	-12	-21	-10
ESG Convenience Yield in Basis Points:	λ_t	11.6	12.3^{+}	10.5^{*}	22.3^{*}	22.2^{***}	46.2^{**}	24.2^{***}
		(9.1)	(7.4)	(4.3)	(9.1)	(5.6)	(14.1)	(6.3)
Weighted Average Spread of auto ABS in Basis Points:		48	47	38	58	32	83	51

Notes: This table reports estimates of the ESG convenience yield from 2017 to 2022. Estimates of ESG basis spread based on estimates from Figure 4. Differences in ESG scores and ESG basis spread evaluated at the 20th and 80th percentiles of average ESG scores.

4.4 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, tranches, specifications, and estimators. The results continue to hold when excluding deals with a high share of subprime loans. I find similar results using other measures of greenness such as the average MPG of vehicles in the collateral pool, average share of truck in the collateral pool, and an independently constructed greenness measure by the Kroll Bond Rating Agency (KBRA, 2022). The lower cost of capital of high-emissions auto loan securitizations holds across the capital structure and also affects other senior tranches. I find quantitatively and qualitatively similar results using propensity score matching and doubly-robust machine learning estimators. Appendix Section A.2 provides a detailed discussion of the robustness checks.

5 The Auto ABS Holdings of ESG Mutual Funds

I analyze the portfolios of mutual funds to directly test whether the greenness of auto ABS influences their investment decisions. I document two facts: ESG mutual funds (i) hold positions across the full distribution of CO_2 emissions and (ii) invest more in high-emissions deals relative to non-ESG funds. The positive correlation between the ESG scores of issuers and the CO_2 emissions of collateral pools confounds these findings. 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 ESG funds inadvertently invest more in high-emissions auto ABS compared with non-ESG 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

5.1 Mutual Fund Portfolio Data

I obtain mutual fund holdings from the SEC Form N-PORT from 2019-Q3 to 2022-Q2. I keep the first observation where a mutual fund reports a position in a senior tranche of an auto ABS. Appendix Table A3 provides summary statistics of the mutual fund holding data. I observe 266 individual auto ABS in the holding data. I identify ESG mutual funds in two ways: (i) by their name using key words[14] such as “sustainable”, “ESG”, or “climate” and (ii) using a list of “Sustainable Investment Mutual Funds and ETFs” offered by institutional member firms of “The Forum for Sustainable and Responsible Investing”.[15] I identify 35 ESG funds (and 787 non-ESG funds) that hold at least one position in an auto ABS tranche over the sample period and 32 ESG funds holding at least two positions.

5.2 Identification Strategy

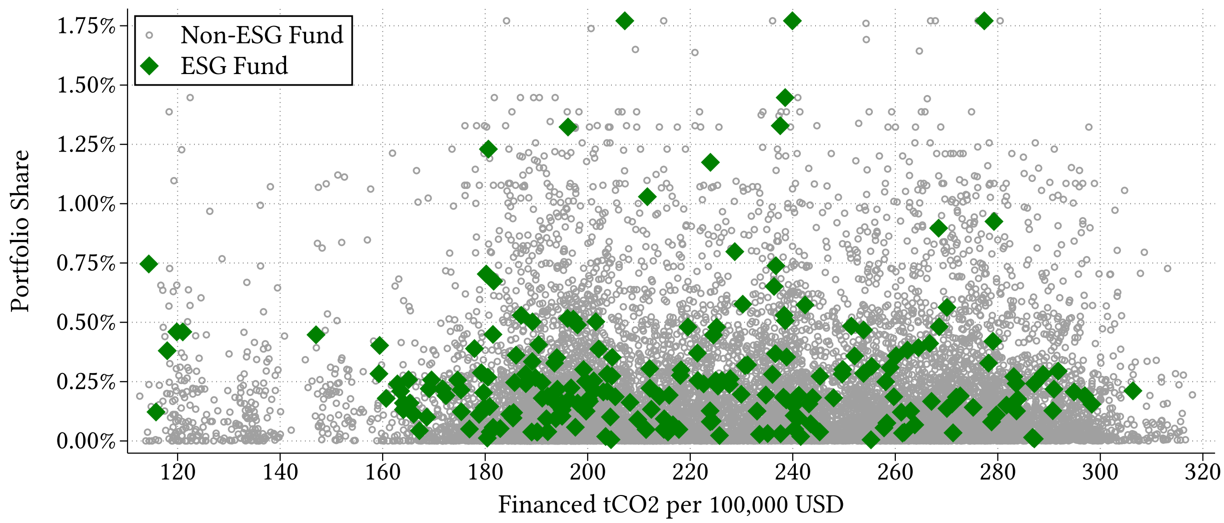
I estimate a reduced form asset demand system in the spirit of Koijen and Yogo (2019) to test whether ESG funds tilt their portfolio toward greener auto ABS. I use the following specification for portfolio shares of fund j in year-quarter r in tranche t of auto ABS deal b issued by i:

$$\log\left(\text{Portfolio Share}\right)_{jtrb} = \alpha\left(\text{ESG Fund}_j \times \text{Green}_b\right) + \gamma_j + \gamma_b + \gamma_{i\times r} + \mathbf{X}_t'\zeta + \varepsilon_{jtrb} \qquad (9)$$

where Green_b is either a measure of environmental impact such as tCO_2 per vehicle, a measure of energy efficiency such as MPG, or the ESG score of the issuer; γ_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.

[14] The key word list contains the following words: “green”, “climate”, “esg”, “sustainable”, “environment”, “responsible”, “impact”, “catholic”, “social”, “sri”, “csr”, “community”, and “justice”.
[15] https://charts.ussif.org/mfpc/

Figure 4: 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.

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).

5.3 Results

Figure 4 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 distribution 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 4 shows that ESG funds hold similar or higher shares in auto ABS with high-emissions intensity.

Table 8 reports estimates of the relationship between greenness and ESG ownership using the specification from Eq. (9). 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

Table 8: 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. (9). 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, *** p<0.001.

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 8 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.[16]

6 Pass-through of ESG to Consumer Rates and Real Effects

Many ESG investors aim to redirect capital towards greener assets to raise the financing costs for environmentally harmful activities, such as carbon emissions. Higher financing costs should reduce the demand for these activities and help mitigate climate change. Changing the cost of capital for vehicles could be a powerful way to increase the cost of emitting CO_2. However, it is unclear whether altering the funding cost of lenders in financial markets effectively impacts consumer loan demand. The integration of the consumer loan market and financial markets via securitizations provides a unique setting 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

$$\partial \log \text{Loan Demand} = \frac{\partial \log \text{Loan Demand}}{\partial \log \text{Consumer Rate}} \times \frac{\partial \log \text{Consumer Rate}}{\Delta \text{ ABS Spreads}} \times \Delta \text{ ABS Spreads}, \quad (10)$$

where 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 7 reports that auto ABS of issuers with high ESG scores have 10 bps lower issuance spreads. 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

[16] Appendix Table B2 shows the positive correlation of ESG scores and CO_2 emissions in the mutual fund data.

on the pass-through elasticity of changes in ABS spreads to changes in consumer interest rates. It is not immediately clear whether a green basis spread of 10 bps in senior tranches of auto ABS will result in a 10 bps change in consumer rates. The green 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). Loan subsidies create an important non-linearity in pass-through. Consequently, typical pass-through formulas which suggest a 1-for-1 pass-through of changes in marginal cost to consumer prices in competitive markets, do not apply.

Measuring the Pass-Through Elasticity Endogenous equilibrium conditions shape how funding markets and consumer markets interact. I address this endogeneity using instrumental variables (IV) that isolate exogenous variation in the funding cost of auto loan lenders. The instruments include: (i) the 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. These instruments leverage common variations in funding markets that correlate with individual lenders' actual funding costs. The IV regressions include high-dimensional fixed effects which identify the pass-through elasticity using loans with the same characteristics made either *within-time across-issuers* or *within-issuer across-time*. Appendix A.3 provides further details.

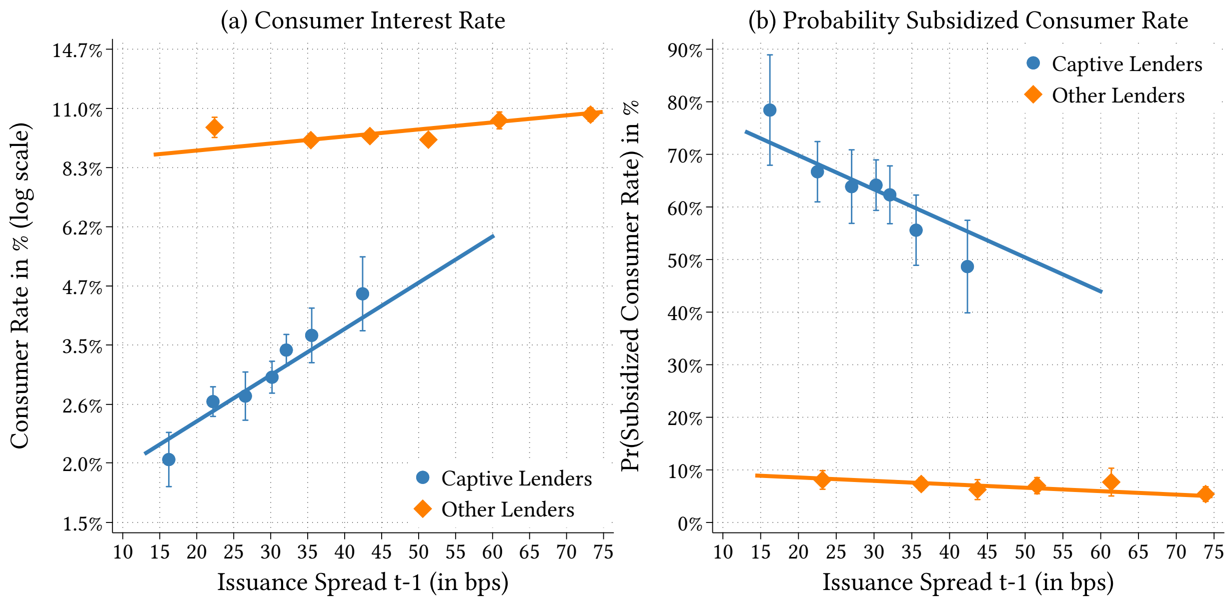
Appendix Table A8 presents the estimates of the pass-through elasticity of auto ABS spreads to consumer interest rates. Several points are noteworthy. First, OLS estimates exhibit an upward bias compared to IV estimates. Second, the estimates for captive lenders are larger than those for non-captive lenders. In IV specifications, the pass-through elasticity is essentially zero for non-captive lenders but large and statistically significant for captive lenders only.

Using within-time, across-issuer variation, the estimates of the pass-through 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 green basis spread of 10 bps in the auto ABS market translates into an decrease in consumer interest rates of 22 bps to 35 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 loans that are subsidized by captive lenders have interest rates less than 2% in the sample.

Figure 5 shows that captive lenders increase their supply of subsidized loans when auto ABS

Figure 5: 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 coefficients using loans with identical characteristics made by different lenders during the same month.

issuance spreads are low. Specifically, a 10 bps decrease in issuance spreads is associated with a 7.2 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 27 bps.

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, Nadauld, and Palmer (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.

Changes in Consumer Loan Demand Table 9 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 1.17% to 5.30%. To illustrate, consider a $33,000 loan for a vehicle with a 3.34% interest rate. The results in column (1)

Table 9: 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	1.17%	2.21%	3.25%	1.44%	2.72%	4.00%	1.91%	3.60%	5.30%
Δ Loan demand in USD	$386	$729	$1,072	$475	$898	$1,320	$630	$1,189	$1,749

Notes: This table reports estimates of the implied change in consumer loan demand: $\partial \log \text{Loan Demand} = \frac{\partial \log \text{Loan Demand}}{\partial \log \text{Consumer Rate}} \times \frac{\partial \log \text{Consumer Rate}}{\Delta \text{ABS Spreads}} \times \Delta$ABS Spreads. The average change in ABS spread due to ESG pricing is 10 bps, see Table 7. 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.

imply that a 10 bps decrease in the auto ABS spread would result in a 1.17% increase in equilibrium loan demand, or about $386. Column (9) implies a change of about $1,749.

Changes in individual consumer loan demand do not directly equate to changes in vehicle demand. The estimated changes in loan demand in Table 9 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. 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 in they make, potentially leading to a meaningful increase in product demand and profits for manufacturers with high ESG scores.

7 Discussion

I document that investors successfully lower the cost of capital for auto ABS of issuers with high firm-level ESG scores. I estimate that investors earn an ESG convenience yield of 0.24% p.a. on their ESG investments. Importantly, this ESG convenience yield generates seigniorage for issuers of ESG assets and lowers their borrowing cost. The pass-through of this ESG convenience yield to consumer interest rates is large for captive lenders. 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 but in those whose issuers have higher ESG scores even if these securities have higher CO_2 emissions intensities. The market's focus on issuer-level ESG scores, rather than the collateral's CO2 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.

8 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 firm-level ESG scores, rather than the collateral's CO_2 emissions, also lowers the cost of capital for high-emissions auto ABS; 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.

These findings highlight that while green premia have meaningful impact, they do 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 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, *** p<0.001.

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: Covariate Balance Test of *Green* and *Brown* auto ABS

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

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

A.2 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 A5: 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	-0.160	-0.180						
	(0.107)	(0.111)						
Expected tCO2 per USD			-0.191^{+}	-0.205^{+}				
			(0.104)	(0.107)				
Financed tCO2 per Vehicle					-0.164^{*}	-0.214^{**}		
					(0.066)	(0.071)		
Financed tCO2 per Vehicle							-0.166^{*}	-0.219^{**}
							(0.066)	(0.071)
Year-month FE, daily market controls	✓	✓	✓	✓	✓	✓	✓	✓
Prepayment speed FE, tranche controls	✓	✓	✓	✓	✓	✓	✓	✓
Ex-ante prepayment controls	✓	✓	✓	✓	✓	✓	✓	✓
Ex-post prepayment controls		✓		✓		✓		✓
Adj. R^2	0.955	0.955	0.956	0.955	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. (7) 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 sub-prime auto ABS. Differences in CO_2 emissions may be correlated with unobserved characteristics related to loan-quality. For example, subprime borrowers more often buy used vehicles and likely find it harder to refinance their loans than prime borrowers. Appendix Table A5 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 A6: 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	-0.211^{+}	-0.266*								
	(0.112)	(0.110)								
Financed tCO2 per Vehicle			-0.214**	-0.256**						
			(0.0726)	(0.0762)						
Avg. MPG × (-1)					-0.202	-0.280*				
					(0.128)	(0.133)				
Avg. Share of Trucks							-0.215^{+}	-0.276*		
							(0.109)	(0.128)		
Avg. GHG Rating (KBRA) × (-1)									-0.131	-0.228^{+}
									(0.122)	(0.134)
Year-month FE, daily market controls	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Prepayment speed FE, tranche controls	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Ex-ante prepayment controls	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Ex-post prepayment controls		✓		✓		✓		✓		✓
Adj. R^2	0.947	0.954	0.949	0.955	0.947	0.953	0.947	0.953	0.938	0.949
Observations	276	276	276	276	276	276	276	276	243	243

Notes: This table reports estimates of the risk-adjusted pricing model of Eq. (7) 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).[17] These measures are not perfectly correlated ($0.1 < |\rho| < 0.67$) with the financed CO_2 measure from Table 5, providing independent signals about the relative greenness of each auto ABS deal. While measures (ii) to (iv) are highly correlated with the KBRA measure ($|\rho| > 0.75$), the KBRA measure is a good robustness check because it is independently constructed and publicly available.

Appendix Table A6 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 A7 reports results for all AAA-rated tranches, showing qualitatively and quantitatively similar outcomes to the main results in Table 5. The estimated elasticities of is-

[17] 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 A7: 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	-0.197*	-0.212*			-0.255***	-0.267***		
	(0.084)	(0.087)			(0.070)	(0.070)		
Financed tCO2 per Vehicle			-0.120*	-0.179*			-0.077	-0.132*
			(0.054)	(0.073)			(0.051)	(0.061)
Year-month FE, daily market controls	✓	✓	✓	✓	✓	✓	✓	✓
Prepayment speed FE, tranche controls	✓	✓	✓	✓	✓	✓	✓	✓
Ex-ante prepayment controls	✓	✓	✓	✓	✓	✓	✓	✓
Ex-post prepayment controls		✓		✓		✓		✓
Adj. R^2	0.948	0.947	0.948	0.947	0.965	0.965	0.963	0.963
Observations	272	272	272	272	190	190	190	190

Notes: This table reports estimates of the risk-adjusted pricing model of Eq. (7) in other senior tranches. Standard errors in parentheses clustered at year-month. + p<0.10, * p<0.05, ** p<0.01, *** p<0.001

suance 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 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 the OLS specifications in Panel A of Table 5, 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, Chernozhukov, and Hansen (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.

Table A8: 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	
Issuance Spread t-1	0.469*	0.424*	0.0819	-0.0288	-0.00294	-0.0199	-0.315*	0.102+
	(0.217)	(0.172)	(0.279)	(0.307)	(0.0514)	(0.0480)	(0.127)	(0.0558)
Issuance Spread t-1 × Captive	1.651***	1.509***	0.979**	0.872**	1.194***	1.261***	0.962***	0.702***
	(0.263)	(0.237)	(0.313)	(0.290)	(0.186)	(0.182)	(0.272)	(0.121)
Total effect for Captive	2.120***	1.933***	1.061*	0.843*	1.192***	1.241***	0.647*	0.803***
	(0.266)	(0.246)	(0.403)	(0.406)	(0.185)	(0.180)	(0.281)	(0.128)
Origin. Month × HDFE Set FE	Yes	Yes	Yes	Yes				
Originator × HDFE Set FE					Yes	Yes	Yes	Yes
Year × State FE					Yes	Yes	Yes	Yes
Linear Controls		Yes	Yes	Yes		Yes	Yes	Yes
Instrument			BofA	Others			BofA	Others
Kleibergen-Paap F-stat.			7.30	5.40			10.89	111.87
Adj. R^2	0.916	0.924	0.107	0.152	0.896	0.905	0.093	0.135
Sample	7,801,359	7,758,215	7,758,215	5,804,920	9,017,159	8,966,592	8,966,578	6,723,651

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, *** p<0.001.

A.3 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.[18]

[18] 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 [...]"

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

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

where 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 A8 reports estimates of the pass-through from auto ABS spreads to consumer rates. Several things are noteworthy. First, OLS estimates are upward biased relative to IV estimates. Second, estimates for captive lenders are larger than estimates for non-captive lenders. In IV specifications, the pass-through elasticity is essentially zero for non-captive lenders but large and statistically significant for captives. The IV specifications of Columns (3) and (4) use within-time across-issuer variation and show that a 1 bps decrease in ABS spreads results in an decrease in consumer interest rates between 0.84% and 1.06% for captive lenders. The IV specifications of Columns (7) and (8) use within-issuer across-time variation and show that a 1 bps decrease in ABS spreads results in an decrease in consumer interest rates between 0.65% and 0.80%.

A.4 Auto ABS Issuers' ESG Scores and CO_2 Emissions

ESG scores measure a firm's environmental, social, and governance performance. Advocates of ESG investing claim that these scores help investors identify firms with low environmental impact to invest in their securities. The goal of many ESG investors is to alter firm financing conditions by rewarding green firms with lower capital costs and penalizing brown firms with higher costs, thereby internalizing the cost ofCO_2 emissions. The success of ESG investing depends on investors' ability to accurately identify green firms, projects, and securities.

Appendix Table A9 provides summary statistics for ESG scores of issuers at the time of issuance, as well as measures of the environmental impact of auto ABS collateral pools. The table includes standard summary statistics and decomposes the standard deviation in ESG scores into between and within components. The between component measures the cross-sectional variation in ESG scores across the 22 issuers, while the within component measures the time series variation in ESG scores for individual issuers. Ratios of between to within standard deviations are reported, with a ratio greater than 1 indicating that cross-sectional variation in ESG scores is larger than individual time series variation.

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

ESG scores of captive lenders exhibit low variation, while CO_2 emissions intensity does not. Panel A in Table A9 shows that the standard deviations of ESG scores (0.06 to 0.07) among captive lenders are quite low, with the coefficient of variation for the Refinitiv ESG score being only 8%. Additionally, standard deviation ratios (1.6 to 1.9) indicate that ESG scores for captive lenders vary almost as much within individual time series as they do across issuers.

In contrast, Panel B of Table A9 shows that the standard deviations of CO_2 emissions vary 2.6 to 4.9 times more across issuers than within issuers. The coefficient of variation for financed CO_2 emissions ranges from 15% to 29%, a fact also illustrated in Figure 1.

Panel C of Table A9 presents the correlations between the environmental impact of auto ABS and the ESG scores of the issuers. While the ESG scores of S&P and Refinitiv are positively correlated with each other, they are also positively correlated with CO_2 emissions from collateral pools, even for the environmental pillar scores.

This positive correlation between ESG and environmental pillar scores and pool-level emissions is not entirely surprising. ESG scores are composite firm-level measures of the overall

Table A9: ESG and CO_2 Summary Statistics of Collateral Pools

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

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

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

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

societal impact of a firm, whereas the CO_2 measures of auto ABS pools are project-specific measures of environmental impact. I also provide results using the firm-level environmental pillar score, which should be more comparable to the CO_2 intensity of auto ABS.

One potential explanation for the positive correlations is that the project-specific environmental impact of the collateral pool does not reflect the firm-level environmental impact of the issuer's overall business. Another explanation could be that the correlation matrix in Panel C of Table A9 fails to account for industry differences in ESG scores.

Table A10 explores the positive correlation between ESG scores and the environmental impact of auto ABS by regressing ESG and environmental pillar scores on firm-level and pool-level measures of carbon intensity while accounting for industry fixed effects. The results in Panel A

Table A10: Regressions of ESG scores on CO_2 Emissions

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

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

show that the positive correlation between ESG scores and the environmental impact of auto ABS is attenuated but not driven by industry differences in ESG scores. Qualitatively similar results are obtained when using sub-scores on which the environmental pillar score is based, such as emissions scores.

Panel B shows that even at the firm level, ESG and environmental pillar scores are positively correlated with CO_2 emissions. Scope 1 and 2 emissions are positively correlated with ESG scores, even when controlling for industry fixed effects. Columns (1) to (4) show this for scope 1 and 2 emissions over revenue, while Columns (5) to (8) show this for scope 3 emissions over revenue. Additionally, the collateral pool CO_2 per USD is directly related to the scope 3 downstream emissions intensity of vehicle manufacturers.[19]

This implies that the observed positive correlation between ESG and environmental pillar scores and CO_2 emissions of collateral pools is not just a data artifact but indicates that ESG and environmental pillar scores are uninformative about CO_2 emissions among auto ABS issuers, even at the firm level.

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

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

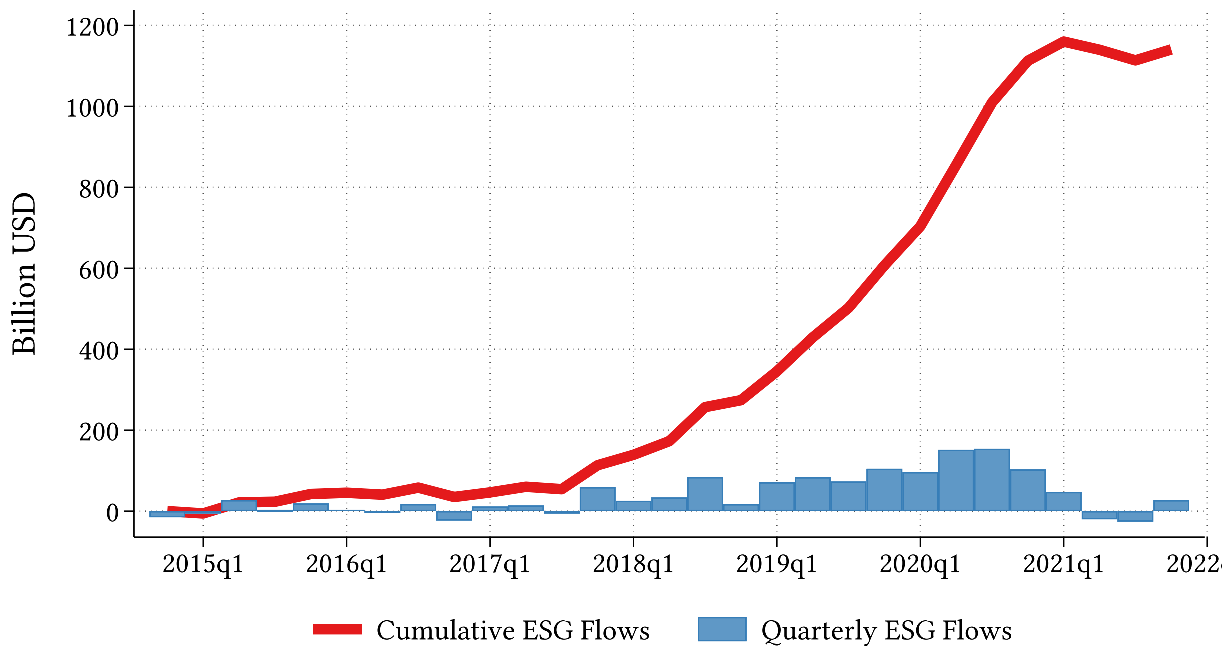

Figure B2: Total ESG Flow (Van der Beck, 2023). ESG flow for each 13F institution as the return-adjusted change in ESG-assets under management and then summed across all institutions. I report rolling 4-quarter averages and plot the cumulative sum of all flows since 2014.

Table B1: ESG Score Balance across Green (tCO_2 /vehicle<p50) and Brown (tCO_2 /vehicle>p50)

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

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

Table B2: Correlation of 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 Matching Estimator

Table B3: Estimates using Propensity Score Matching

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

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

Appendix table B3 shows that one obtains qualitatively and quantitatively similar results to the main results when using a propensity score matching estimator. The "treated" (i.e., either low 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.