



Investigating the role of passive funds in carbon-intensive capital markets: Evidence from U.S. bonds

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ABSTRACT

Capital flows in primary markets are key to the low-carbon transition, as capital raised can finance low or high-carbon assets. Yet, fund-level climate-related disclosures have focused on portfolio holdings, reducing the ability of investors to evaluate the impact of capital flows. In particular, as passive funds grow, there is a risk that capital is channelled into carbon-intensive assets through primary markets. To track carbon-intensive portfolio holdings and primary market transactions, and the role of passive funds within them, we construct a dataset of daily holdings for passive U.S. corporate bond exchange-traded funds (ETFs) from 2016 to 2021. We find that the carbon exposure and carbon intensity of ETF primary market transactions are associated with existing ETF portfolio holdings. We also find that the share of secondary market holdings and primary market transactions accounted for by passive ETFs is higher for fossil fuel bonds, and increases with bond-level carbon intensity. These findings indicate that the continued growth in passive funds could support carbon-intensive capital flows.

1. Introduction

To date, banks and investors with over \$130 trillion in assets have pledged net zero portfolios and loan books by 2050 (GFANZ, 2021). This requires financial institutions to increase low-carbon financing and reduce high-carbon financing (UNEP FI, 2021). As a result, these commitments have the potential to contribute to the implementation of Article 2c of the Paris Agreement, namely for capital flows to be “consistent with a pathway towards low greenhouse gas emission and climate-resilient development” (United Nations, 2015). Achieving this goal is critical, as limiting rises in global temperatures to 1.5 °C will require \$2.3 trillion of annual investment in electricity systems over 2023–2052 (IPCC, 2022).

Primary markets are key to delivering this investment. When securities are issued, financial capital flows from the financial system to the real economy, which can fund productive capital, such as low-carbon energy assets (Best, 2017). However, sustainable finance has historically focused on existing stocks of financial capital in portfolio holdings, and on secondary markets, where existing securities are traded between financial institutions (Urban and Wójcik, 2019). This focus is expected, as sustainable investing is most prevalent in equities (Morningstar, 2020), where primary market issuance is limited relative to bonds (SIFMA, 2021). Furthermore, environmental, social, and governance

(ESG) integration, the most common form of sustainable investing (GSIA, 2020), requires a focus on portfolio holdings to manage ESG risks.

However, a focus on primary markets is critical for generating investment impact with respect to environmental goals (Busch et al., 2021; Caldecott et al., 2022). While capital allocation in both primary and secondary markets affects the cost of capital, which influences the ability of firms to invest in low- or high-carbon technologies (Helms et al., 2020), the cost of capital is most material for firms in need of external finance (Baker et al., 2003). This makes primary markets a potential point of maximum impact generation (Brest et al., 2018). Yet, asset managers only disclose climate-related metrics for portfolio holdings, not for primary market transactions, limiting the ability of asset owners to assess impact. Therefore, by using passive funds, the first objective of this paper is to examine the relationship between portfolio holdings and primary market transactions in the context of impact generation.

Passive investing is reshaping the investment landscape. In the U.S., passive funds accounted for 48% of equity and 30% of bond mutual fund AUM in 2020, up from <5% in 1995 (Anadu et al., 2020). While the number of ESG passive funds is growing, they represent <1% of passive AUM (Mercereau et al., 2019), meaning the majority of passive AUM does not consider environmental impact (Harmes, 2011). In contrast,

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active investors have been shown to reduce their exposure to carbon-intensive assets¹ in response to climate risks and impacts (Boermans and Galema, 2019), with investors worth \$40 trillion divesting from fossil fuels (Divestment Database, 2022). As passive funds automatically “steer” capital into index constituents (Petry et al., 2021), for carbon-intensive assets, passive funds could become “holders of last resort” (Jahnke, 2019). Therefore, the second objective of this paper is to investigate the role of passive funds in carbon-intensive capital markets.

To conduct our analysis, passive U.S. corporate bond ETFs are used. ETFs disclose daily holdings, enabling primary market transactions and holdings to be extracted. We focus on bonds, as primary market issuance is orders of magnitude larger than equities (SIFMA, 2021). U.S. ETFs are used, as passive ownership is highest in the U.S. (Sushko and Turner, 2018) and the U.S. corporate bond market is the largest globally (ICMA, 2020). We use the CRSP U.S. Mutual Fund Holdings Dataset and construct a novel dataset of daily holdings from Bloomberg for 2016–2021. To our knowledge, this study is the first to use daily holdings to track primary market financing. Using these datasets, two stages of analysis are conducted.

First, we calculate climate-related metrics for both primary market transactions and portfolio holdings, allowing us to examine the relationship between the two. To do this, Primary Market Carbon Exposure (PMCE) and Secondary Market Carbon Exposure (SMCE) are defined as the allocation to fossil fuel and carbon-intensive sectors, in primary market transactions and portfolio holdings respectively. Primary Market Carbon Intensity (PMCI) and Secondary Market Carbon Intensity (SMCI) are defined as the weighted average Scope 1 and 2 carbon intensity of these carbon exposures. At the ETF level, we find that primary market metrics are higher for ETFs with high secondary market metrics in the previous year. This demonstrates how changes in portfolio holdings can affect future primary market financing, and therefore, impact generation. This adds an important nuance to the divestment versus engagement debate, which has focused on equities and secondary markets (Ansar et al., 2013; Braungardt et al., 2019).

In the second stage of analysis, the growing role of passive funds is examined in carbon-intensive assets. To do this, using U.S. issued bonds we calculate the proportion of primary market transactions and secondary market holdings accounted for by passive ETFs. We find that ETF participation is higher in fossil fuel sectors, and increases in both primary and secondary markets as bond-level carbon intensity increases. This holds in all sectors and for fossil fuel and carbon-intensive sectors. These results build on Boermans and Galema (2019), who find a negative relationship between active share and portfolio carbon intensity, and provide evidence that passive funds support carbon-intensive assets (Jahnke, 2019). This adds to the literature on passive investing and sustainability, which has focused on equities and secondary markets (Appel et al., 2016; Petry et al., 2021). It also raises important questions for future research, as passive funds could affect the pricing of climate risk, with passive demand shown to reduce the cost of capital (Dannhauser, 2017; Dathan and Davydenko, 2018).

This study is structured as follows. Section 2 explores the existing literature. Section 3 details the data and methods used. Section 4 presents results from descriptive and empirical analysis. Section 5 discusses the implications of our findings. Finally, Section 6 concludes.

2. Literature review

2.1. Impact generation through capital allocation

Kölbel et al. (2020) define investor impact as “the change that investor activities achieve in company impact”, and company impact as

“the change that company activities achieve in social and environmental parameters”. They identify capital allocation as a mechanism for impact generation, as the cost of capital affects the ability of firms to access finance (Frank and Shen, 2016), which affects low- and high-carbon investment (Fattouh et al., 2019; Schmidt, 2014). For example, in bond secondary markets, index eligibility increases valuations as investors allocate capital accordingly (Ottonello, 2018), while in bond primary markets, higher demand reduces new issue spreads (Bessembinder et al., 2020; Dathan and Davydenko, 2018). In the context of climate change, changes in capital allocation due to divestment can hit share prices (Dordi and Weber, 2019; Rohleder et al., 2022) and reduce capital flows to fossil fuels (Cojoianu et al., 2020).

While the cost of capital is the most material for firms raising finance in primary markets (Baker et al., 2003), secondary market conditions affect primary market issuance (Barry et al., 2008). For example, expected liquidity in secondary markets affects the cost of capital in primary markets, as underwriters take on inventory risk (Goldstein et al., 2019). Furthermore, secondary markets are a benchmark for primary market pricing, with new issues priced at a discount to seasoned offerings (Fridson and Gao, 1996; Mola and Loughran, 2004). This new issue premium (NIP) discount compensates investors for information asymmetry and liquidity risk (Cai et al., 2007). The size of NIPs is limited by demand from investors looking to capture underpricing, with dealers and hedge funds “flipping” new issues in secondary markets (Cestau et al., 2013). To mitigate selling pressure from “flippers”, when allocating new issues syndicates may prioritise long-term buy-and-hold investors such as passive funds (Jenkinson and Jones, 2004).

While primary and secondary markets are closely linked, it is important to differentiate between the two in the context of impact generation. For example, when considering if divestment or engagement is optimal (Braungardt et al., 2019). Equity primary markets enable early-stage companies to capitalise on future growth, but for established companies, debt provides the majority of financing. As shown in Fig. 1, equities accounted for 4.5% of fossil fuel financing in 2021, compared to 42.7% for bonds. While in the U.S., corporate bond issuance was 5.8 times that of equities in 2020, yet the value of outstanding equities was 3.9 times that of bonds (SIFMA, 2021). These differences in stocks and flows underscore the argument that to maximise impact, investors should “deny debt” to companies that do not decarbonise but continue to engage via equities to change corporate behaviour (Murray, 2022; Quigley, 2019).

Yet, while funds report climate metrics for portfolio holdings, none do so for capital flows. For example, portfolio temperature alignment scores (CDP, WWF, 2020), portfolio carbon accounting measures (PCAF, 2020), and weighted average carbon intensity (Hunt and Weber, 2019) all look at portfolio holdings. This makes it challenging for asset owners to evaluate impact through primary markets. For example, if asset owners invest in funds holding fossil fuels, does this result in the financing of fossil fuels? Similarly, if asset owners invest in an ESG alternative, does this decarbonise capital flows?

To shed light on these questions, we adapt carbon exposure and carbon intensity metrics for primary markets. Using these metrics, we conduct ETF-level analysis, testing how capital allocation in secondary markets affects primary market financing. We expect a close link, as issuers held within portfolios re-finance bonds through primary markets, and in passive ETFs, portfolio managers need to ensure that primary market trades do not increase tracking error. As part of our ETF-level analysis, we also test how the investment strategies of ETFs affect climate metrics. For example, whether ESG ETFs have lower carbon exposure and carbon intensity. We also test if climate metrics are affected by the credit risk of bonds held, given the link between climate and financial risk (Bui et al., 2020; Chava, 2014).

2.2. Passive funds and carbon-intensive assets

Passive funds are increasingly driving capital allocation in financial

¹ Carbon-intensive assets refer to those with high carbon intensity, defined as firms’ carbon usage relative to an operational business metric (Hoffmann and Busch, 2008).

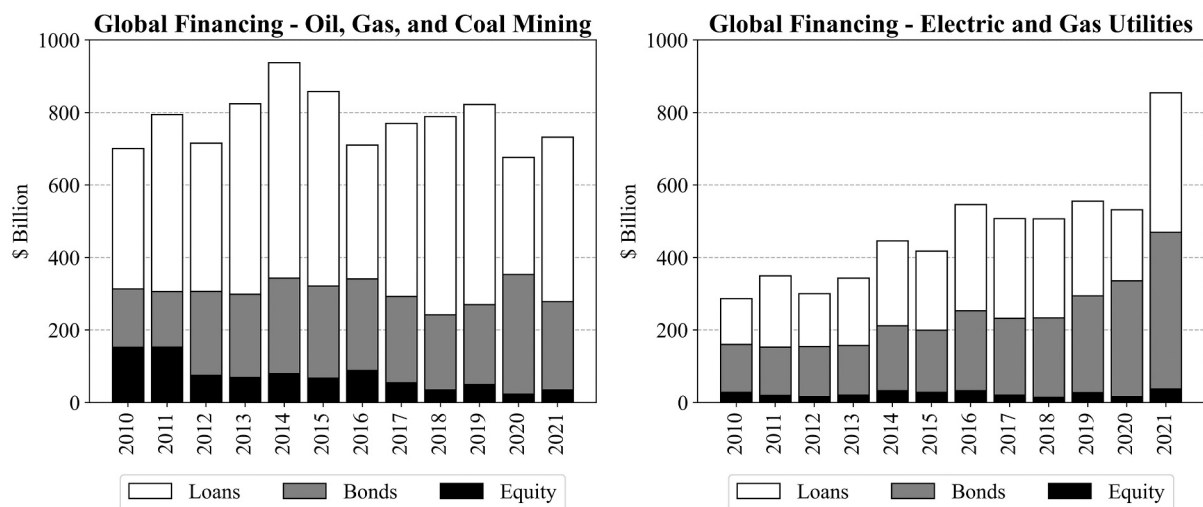


Fig. 1. Fossil fuel financing.

Fig. 1 shows total new financing from equities, corporate bonds, and syndicated loans in fossil fuel sectors. Data is from Eikon. TRBC Activity Classifications are used to identify companies in fossil fuel sectors, defined in Table A.1 in Appendix A.

markets. As shown in Fig. 2, U.S. passive fund ownership of U.S. equities is now greater than active ownership, with the gap closing for investment grade bonds. Several factors have driven this growth. First, running an ETF includes fixed costs (Adams et al., 2018). Due to economies of scale, an increase in AUM does not lead to a corresponding increase in costs (Bebchuk and Hirst, 2019), enabling ETF providers to lower fees as AUM grows, attracting inflows (Malkiel, 2013; Sushko and Turner, 2018). Second, trading ETFs has transaction costs, but larger ETFs are more liquid, lowering these costs. This creates a network effect and a first-mover advantage (Bebchuk and Hirst, 2019). Finally, active investing has underperformed passive investing (Fama and French, 2010).

These dynamics lead to high market concentration, with passive investing dominated by the “Big Three”: BlackRock, State Street Global Advisors, and Vanguard (Bebchuk and Hirst, 2019). This concentration is unique to passive investing, with the top 10 asset managers controlling 95% of passive ETF AUM, relative to 27% of active AUM in 2016 (Haberly et al., 2019). As a result, a select number of indices and passive funds channel capital into select groups of securities (Petry et al., 2021). When indices change, passive funds follow to minimise tracking error, causing a “non-fundamental” demand shock (Claessens and Yafeh, 2013). In response to this demand, firms issue more bonds, and at a lower cost of capital (Sushko and Turner, 2018).

While passive investing grows, investors are taking steps to decarbonise portfolios, for example, through divestment (Egli et al., 2022; Mésonnier and Nguyen, 2021). Indeed, the more “active” an investor is, as measured by deviation from their benchmark, the lower their carbon intensity (Boermans and Galema, 2019). Institutional investors are shown to underweight carbon-intensive assets (Bolton et al., 2021) and decarbonise portfolios over time (Choi et al., 2020c). In contrast, 88–99% of the fossil fuel holdings of the Big Three are in passive funds (Greenfield, 2019), with BlackRock stating that passive divestment is not possible (Mooney et al., 2018). Even though passive ESG funds have grown in number, incumbent non-ESG ETFs dominate,² due to the dynamics outlined. Therefore, growth in passive funds could offset the portfolio decarbonisation of investors, by continuing to allocate capital to carbon-intensive assets.

Therefore, we test how the role of passive funds changes for fossil

fuel and carbon-intensive sectors, and with bond-level carbon intensity. Given that investors are shown to reduce their carbon exposure, we expect passive funds to play a greater role in carbon-intensive bonds. We expect this in both primary and secondary markets, given the linkages outlined in Section 2.1.

3. Methodology and data

3.1. Data

To conduct analysis, two datasets are used. First, from the CRSP U.S. Mutual Fund Database containing quarterly and annual holdings we extract holdings for 180 passive corporate bond ETFs,³ holding 55,615 unique corporate bonds. The approach used to select ETFs is detailed in Appendix B. A time period of 1st January 2016 to 31st December 2021 is used, providing six years after the 2015 Paris Agreement. As CRSP provides quarterly holdings, it cannot track primary market trades. For this, daily holdings are manually extracted from Bloomberg Portfolio Risk & Analytics (PORT) for 2016–2021. Given manual limitations, holdings are obtained only for the largest 35 ETFs, split into 23 IG and 12 HY ETFs, holding 15,999 unique corporate bonds.⁴ From daily holdings, primary market transactions are extracted, showing that ETFs purchase newly issued bonds before index inclusion (see Appendix B for details).

3.2. ETF-level analysis

Having extracted ETF primary market (PM) trades and secondary market (SM) portfolio holdings, climate-related metrics are calculated. **Primary Market Carbon Exposure (PMCE)** is defined as the proportion of ETF primary market transactions occurring in selected sectors over a time period. Following Eq. (1), $PMCE_{i,t}$ is calculated for ETF i in year t as the sum of primary market transactions in USD of each bond j in selected sectors, divided by the sum of transactions in all sectors. **Secondary Market Carbon Exposure (SMCE)** is defined as the proportion of USD

² For example, using the CRSP U.S. Mutual Fund Database, in 2021, 8% of U.S. corporate bond ETFs have an ESG strategy but account for 0.8% of AUM.

³ As shown in Figure 1, loans consist of an even larger proportion of capital flows than bonds, providing an alternative to bonds for raising debt capital. However, while ETFs investing in loans exist, the size and number of these ETFs is considerably smaller than for corporate bond ETFs.

⁴ Vanguard ETFs are not selected, as daily holdings are not disclosed in Bloomberg.

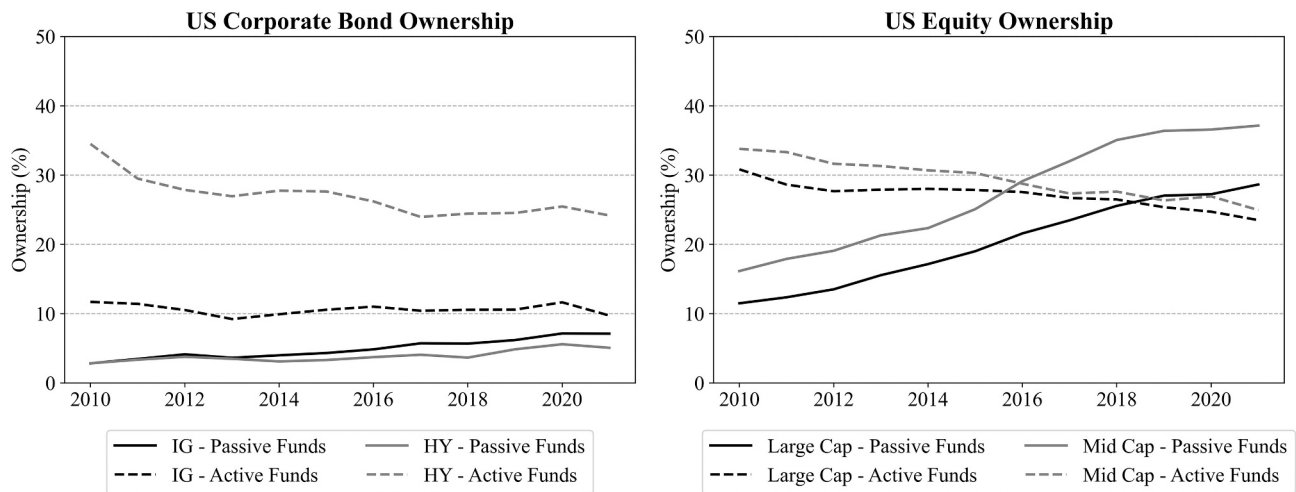


Fig. 2. Ownership of bonds and equities by U.S. mutual funds.

Fig. 2 shows the average level of passive and active ownership of equities and bonds by U.S. mutual funds in the CRSP Mutual Fund Database. Passive funds are identified as index-based or pure index funds. Investment grade (IG) bonds are selected from the iShares iBoxx \$ Investment Grade Corporate Bond ETF tracking the Market iBoxx USD Liquid Investment Grade Index. High yield (HY) bonds are selected from the iShares iBoxx \$ High Yield Corporate Bond ETF tracking the Market iBoxx USD Liquid High Yield Index. Large-cap equities are selected from the iShares Core S&P 500 UCITS ETF tracking the S&P 500 Index. Mid-cap equities are selected from the iShares Core S&P Mid-Cap ETF tracking the S&P MidCap 400 Index.

holdings of an ETF in selected sectors at a point in time (Eq. (2)).

Two groups of sectors are used to calculate PMCE and SMCE. First, **fossil fuel sectors** are defined as coal mining, oil & gas, and non-renewable electric and gas utilities (TCFD, 2020). Fossil fuels are a focus, given the high climate risks and impacts.⁵ Second, **carbon-intensive sectors** are defined according to sectors identified by the Intergovernmental Panel on Climate Change (IPCC) as significant sources of emissions⁶ (Krey et al., 2014). This definition used by Choi et al. (2020a, 2020b) encompasses transport, buildings, industry, agriculture, forestry, and other land use (AFOLU). In addition to fossil fuel energy, this definition includes “hard-to-abate” sectors such as cement, steel, and plastics with significant environmental impact.⁷ The Refinitiv Business Classifications (TRBC) is used to identify firms in scope (see Appendix A).

$$PMCE_{i,t} = \frac{\sum_{j=1}^n Carbon\ PM\ Trade\ Value_{j,i,t}}{\sum_{k=1}^m PM\ Trade\ Value_{k,i,t}} \quad (1)$$

⁵ Climate-related divestment activity is concentrated in fossil fuel sectors (Bolton et al., 2021), with the largest 90 “carbon majors”, of which over 90% are fossil fuel companies, responsible for 63% of global cumulative carbon emissions between 1751 and 2010 (Heede, 2013). These sectors also face substantial climate risks, as limiting global temperature rises requires a sharp curtailment in fossil fuel usage (IPCC, 2022), resulting in climate risk in the form of stranded assets (Fofrich et al., 2020).

⁶ We use this definition of carbon-intensive sectors as the IPCC is the leading scientific body on climate change. It also includes emissions from forestry and agriculture, in addition to energy and other industries. Finally, the level of granularity provided allows us to identify relevant TRBC Industries that fall into scope (Appendix A). Alternative definitions of carbon-intensive sectors also exist that have been deployed by researchers, for example, Climate Policy Relevant Sectors defined in Battiston et al. (2017).

⁷ These hard-to-abate sectors account for 22% of global carbon emissions (Bataille, 2020). These sectors are technically challenging to decarbonise, given a lack of low-carbon commercial alternatives and process-based emissions, meaning that the proportion of global emissions is set to rise as energy is decarbonised. This makes these sectors critical to meeting the goals of the Paris Agreement (Energy Transitions Commission, 2018).

$$SMCE_{i,t} = \frac{\sum_{j=1}^n Carbon\ Holdings_{j,i,t}}{\sum_{k=1}^m Holdings_{k,i,t}} \quad (2)$$

Next, value-weighted average carbon intensity is calculated (Boermans and Galema, 2019). **Primary Market Carbon Intensity (PMCI)** is defined as the carbon intensity of primary market transactions over a time period. Carbon intensity is defined as issuer Scope 1 and 2 CO₂ emissions in tonnes divided by revenues in USD million (Boermans and Galema, 2019; Egli et al., 2022), using reported data from Eikon.⁸ Carbon intensity measures firm-level use of carbon (Hoffmann and Busch, 2008), and therefore, indicates the level of climate risk and impact. Following Eq. (3), $PMCI_{i,t}$ is calculated for ETF i for year t as the sum of carbon intensity CI of each bond j weighted by w , the trade value in j relative to all trades in period t . **Secondary Market Carbon Intensity (SMCI)** is defined as the carbon intensity of portfolio holdings at a point in time (Eq. (4)).

PMCI and SMCI are calculated for both fossil fuel and carbon-intensive sectors. As shown in Fig. 3, these have low weights in ETFs, but the highest carbon intensity. A limitation is the omission of Scope 3 emissions, which understates carbon intensity, especially in fossil fuel energy, where most emissions are downstream (Hertwich and Wood, 2018). Metric summary statistics are displayed in Table C.2 in Appendix C.⁹ As carbon emissions are not reported in Eikon for 2021 at the time of analysis, the sample is limited to 2016–2020 for PMCI and SMCI.

$$PMCI_{i,t} = \sum_{j=1}^n (w_{j,i,t} \times CI_{j,t}) \quad (3)$$

$$SMCI_{i,t} = \sum_{j=1}^n (w_{j,i,t} \times CI_{j,t}) \quad (4)$$

⁸ When calculating ETF carbon intensity metrics, weights are adjusted to reflect that not all bond issuers have emissions data available in Eikon.

⁹ ETFs with <200 primary market trades are excluded to ensure a large enough sample to calculate PM metrics. Similarly, ETFs with <200 corporate bond holdings per year are excluded for SM metrics. This results in the exclusion of six Bloomberg ETFs and 49 CRSP ETFs.

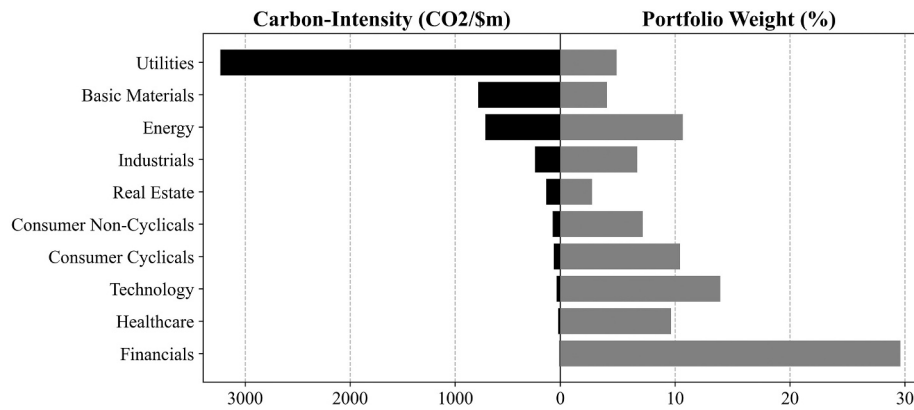


Fig. 3. Sector carbon intensity.

Carbon intensity and portfolio weight by TRBC Economic Sector are averaged across the selected Bloomberg ETFs for 2016–2020.

To explore the drivers of PM and SM metrics, and the relationship between them, descriptive analysis is used. To do this, we show trends in metrics over time for Bloomberg ETFs and compare them to the broader U.S corporate bond market. Next, we examine how differences in SM metrics between ETFs are associated with differences in PM metrics. To do this, a pooled OLS model is used, which captures cross-sectional variation within the panel.¹⁰ Given the small sample size used, with N below 30, results should be interpreted with caution, providing an indication of association rather than causation. First, we regress PM metrics on lagged SM metrics. This is performed for PMCE and PMCI in fossil fuel and carbon-intensive sectors, using SMCE and SMCI as the explanatory variables X in Eqs. (5) and (6) respectively. Next, we examine how ETF characteristics affect PM metrics, using portfolio-weighted averages of bond rating, size, and time to maturity, as well as ETF AUM and number of holdings as explanatory variables X in Eqs. (5) and (6). Year dummies, shown as $Year$ in Eqs. (5) and (6), are added to control for omitted variables that may affect PM metrics, such as the valuations of different sectors and market conditions affecting primary market issuance. As PM metrics capture capital flows over a year, rather than stocks at the end of a year, all explanatory variables are lagged to avoid simultaneity. In Appendix C, definitions of explanatory variables are shown in Table C.1. with ETF-level summary statistics displayed in Table C.2.

$$PMCE_{i,t} = B_0 + B_1X_{i,t-1} + B_2Year_t + e_{i,t} \quad (5)$$

$$PMCI_{i,t} = B_0 + B_1X_{i,t-1} + B_2Year_t + e_{i,t} \quad (6)$$

Next, we focus on SM metrics. Using the CRSP and Bloomberg ETFs, we test the effect of the ETF characteristics (bond rating, size, time to maturity, ETF AUM and number of holdings) on SMCI and SMCE, using a pooled OLS model to examine differences between ETFs (Eqs. (7) and

(8)). Out of the 180 CRSP ETFs, 17 ESG ETFs are identified,¹¹ enabling us to test if their SM metrics differ. To do this, we include a dummy variable for ESG ETFs as an additional explanatory variable in X alongside the other ETF characteristics.

$$SMCE_{i,t} = B_0 + B_1X_{i,t} + B_2Year_t + e_{i,t} \quad (7)$$

$$SMCI_{i,t} = B_0 + B_1X_{i,t} + B_2Year_t + e_{i,t} \quad (8)$$

3.3. Bond-level analysis

The second stage of analysis examines how passive ETF participation changes in carbon-intensive assets. To do this, we denote our dependent variable ETF Share. In primary markets, PM ETF Share is defined as the proportion of issuance bought by passive ETFs. Following Eq. (9), PM ETF Share _{i} is calculated for bond i as the summed value bought by each ETF j , divided by the face value of bond i at issuance. In secondary markets, SM ETF Share is defined as the amount of the bond outstanding held by passive ETFs (Eq. (10))

$$PM\ ETF\ Share_i = \frac{\sum_{j=1}^n PM\ Trade\ Value_{j,i}}{Face\ Value\ Issued_i} \quad (9)$$

$$SM\ ETF\ Share_{i,t} = \frac{\sum_{j=1}^n Holdings_{j,i,t}}{Face\ Value\ Issued_i} \quad (10)$$

For PM ETF Share, the Bloomberg sample is used, and for SM ETF Share, both Bloomberg and CRSP datasets are used. This mitigates the risk that findings only apply to the largest ETFs. Table C.3 in Appendix C shows summary statistics for ETF Share by year. In 2020, ETFs in the CRSP sample held 5.3% of corporate bonds on average, larger than the 2.2% held by ETFs in the Bloomberg sample. In primary markets, selected Bloomberg ETFs account for almost 1% of demand. In each instance, ETF Share increases over time.

Using these definitions, a pooled OLS model is used to see if bonds in fossil fuel and carbon-intensive sectors have a higher ETF Share. In Eq. (11), X_t represents explanatory variables and $Year$ represents time fixed effects that control for time-varying omitted variables constant across bonds, such as changes in the size of the ETF market that could affect ETF Share. This specification is run with a dummy variable equal to 1 for fossil fuel bonds, and then with a dummy equal to 1 for bonds in carbon-intensive sectors. Control variables in X include bond size, coupon, time-

¹⁰ To examine whether cross-sectional differences in ETF SM metrics are associated with PM metrics, a pooled OLS model is used to enable us to capture between-variation in ETFs, with standard errors clustered at the ETF level to account for the panel data structure. In line with Rees and Rodionova (2015), we compare results to a between-effects model and obtain almost identical results, showing that between-ETF variation drives the explanatory power of the pooled OLS model. However, we retain the panel structure to control for yearly differences (Rees and Rodionova, 2015). A fixed effects model is not appropriate in this instance as it only captures within-variation. A pooled OLS model does, however, have limitations, and our results should be interpreted as providing an indication of association and not causation. For example, the small sample size with $N < 30$ could bias the robust clustered standard errors used in the pooled OLS model (Angrist and Pischke, 2019). To address this, we compare results without robust standard errors and find no difference in the significance of results.

¹¹ To identify ESG ETFs a key word search is performed on ETF names using the terms ESG, climate, green bond, sustainable, impact, SDG, clean, transition, Paris, carbon, responsible, and renewable.

to-maturity, callability, rating score, issuer revenue, issuer operating profit margin, and issuer leverage. In Appendix C, variable definitions are shown in Table C.1 and summary statistics in Table C.4. The inclusion of control variables is key as ETFs deploy stratified sampling to select bonds within indices, meaning that certain bonds may be favoured. Furthermore, active investors may favour certain types of bonds, affecting passive ownership. In all specifications, standard errors are clustered at the issuer level. The model is run on USD bonds issued by U.S. public firms, allowing us to obtain issuer carbon intensity and accounting data from Eikon.¹² Additional criteria include a fixed vanilla fixed coupon, over a year until maturity, non-perpetual and not convertible. For the CRSP dataset, 6824 bonds with data meet the criteria. For Bloomberg holdings and primary market datasets, 6469 and 2819 bonds meet the criteria respectively.

$$ETF\ Share_{i,t} = B_0 + B_1 X_{i,t} + B_2 Year_t + e_{i,t} \quad (11)$$

Next, to test how bond-level carbon intensity affects ETF Share, a fixed effects panel OLS model is used. First, regressions with only year effects are used, showing between-variation in the panel. Next, issuer fixed effects are added to exploit within-variation, showing how changes in bond-level carbon intensity affect bond-level ETF Share.¹³ To check the suitability of a fixed effects model, a series of tests are conducted.¹⁴ The final model is shown in Eq. (12) with *Year* and *Firm* fixed effects, and *X* explanatory variables including carbon intensity and the control variables used in Eq. (11). From the CRSP dataset, 4899 bonds with data meet the criteria. For Bloomberg holdings and primary market datasets, 4686 and 1865 bonds meet the criteria respectively. To improve the robustness of the results, sub-sample analysis is conducted, first by splitting the sample into IG and HY bonds. This is key, as passive ownership differs in IG and HY markets (Fig. 2). Next, the sample is limited to carbon-intensive and then fossil fuel sectors. This is important, as we predict that passive ownership rises with carbon intensity, but in sectors with very low carbon intensity, this may not occur, as climate risks and impacts are not as material. Lastly, financial bonds are excluded, in line with previous studies examining the impact of carbon intensity (Busch et al., 2022).

$$ETF\ Share_{i,t} = B_0 + B_1 X_{i,t} + B_2 Year_t + B_3 Firm_i + e_{i,t} \quad (12)$$

The next stage of robustness checks addresses potential endogeneity from selection bias. In the explanatory variables, certain firms do not report carbon emissions, with data unavailable in Eikon. In the CRSP dataset, out of bonds with data for all other control variables, 72% have carbon intensity data. For the Bloomberg holdings and primary market datasets, it is 72% and 66%. Issuers more likely to disclose emissions may have certain characteristics, such as a larger size or higher credit rating, that also affect ETF Share. Therefore, to address selection bias in emissions disclosure, a two-stage Heckman model is used (Bui et al.,

2020; Kleimeier and Viehs, 2021). There is also potential selection bias in the dependent variable, ETF Share. As ETFs deploy stratified sampling rather than full replication, certain bonds in indices may be excluded. In this instance, ETF Share is not missing but is 0%. Therefore, a two-part model is used, which treats zeros as true zeros. This differs from the Heckman model, which treats zeros as missing values (Camba-Mendez et al., 2014). Finally, to correct for potential endogeneity in explanatory variables, in line with Kleimeier and Viehs (2021), propensity score matching is used to obtain a robust sample of treatment and control bonds. Further details for these robustness tests are provided in Appendix E.

4. Results

4.1. ETF level analysis

Having extracted ETF primary market trades and secondary market holdings, we examine the drivers of PM and SM metrics, and the relationship between them. First, we show high-level descriptive analysis. Using the Bloomberg sample of 35 ETFs, the upper panel of Fig. 4 displays the change in total primary market financing over time, with financing in all sectors trending upwards in line with AUM. In 2021 relative to 2016, total financing grew by 168%, while financing for IPCC carbon-intensive sectors and fossil fuels grew by 123% and 45% respectively. Over this time period, AUM grew by 107%. Furthermore, the issuance of U.S. USD bonds grew by 50.4% over the same period, providing more opportunities in primary markets.

While total financing increased with AUM, in 2021, this change was less pronounced for fossil fuels and carbon-intensive sectors, as shown by the fall in PMCE (Fig. 4 middle panel). After a surge in non-financial bond issuance during the Covid-19 induced economic shock (Halling et al., 2020), non-financial issuance fell sharply in 2021 (S&P Global, 2021), reducing PMCE. This relationship between ETF carbon exposure and the broader market is also seen over time. From 2016 to 2020, ETF PMCE remained stable at around 14%, before falling sharply in 2021 to 7.7%, while SMCE remained stable at around 15%. Carbon-intensive PMCE also moved in line with the U.S. market, increasing to 31.3% in 2020, before falling sharply in 2021 to 19.3%.

However, for both fossil fuels and carbon-intensive sectors, the average ETF SMCE is lower than the U.S. market. This is explained by the higher proportion of bonds in these sectors falling below index size thresholds. Using Bloomberg Barclays index inclusion thresholds of \$300 million for IG and \$150 million for HY, in 2016, 22.0% of outstanding fossil fuel bond value and 18.7% of carbon-intensive bond value fell below these thresholds, whereas in other sectors, this was 11.1% and 9.9%. By 2021, these values fell to 15.3% and 11.5%, leading to a convergence between ETFs and the broader market, with a difference in SMCE of 1.4% for carbon-intensive sectors and 0.7% for fossil fuel sectors remaining.

While on average ETF metrics in the Bloomberg sample trend with the broader U.S. bond market, at the ETF level, funds characteristics drive differences in carbon exposure and carbon intensity. For example, the average PMCE over 2016–2021 for fossil fuels was 10.4% for IG ETFs vs 21.0% for HY ETFs. For carbon-intensive sectors, this was 24.7% vs 44.8%. This reflects that the average allocation to financials is 19.4% higher for IG ETFs than HY ETFs. Furthermore, within these exposures, carbon intensity differs, with an average PMCI over 2016–2020 for fossil fuels of 1337 for IG vs 1767 for HY, and 704 vs 927 for carbon-intensive sectors. These differences are also reflected in SM metrics.

Extending the descriptive analysis, pooled OLS models are used to explore the drivers of PM and SM metrics, and the relationship between them. Table 1 shows the results of regressions where PM metrics are regressed on lagged SM counterparts. For PMCE, the coefficients on lagged SMCE variables are close to 1 and statistically significant at the 1% level with an adjusted R-squared above 0.30 (specifications 1 and 3). This indicates that ETFs with higher secondary market exposures have

¹² To avoid misclassifying bonds issued by subsidiaries, accounting, carbon, and sector classification data from the parent is used if the issuers parent is a guarantor of the bond.

¹³ As noted previously, by excluding Scope 3 emissions, the ability of our carbon intensity measure to accurately track changes in a company's climate risks and impacts is limited.

¹⁴ First, a panel regression F-test is used to compare the suitability of a fixed effects model compared to a pool OLS model. This test produces *p*-values below 0.05 across specifications, demonstrating that fixed effects are preferred. Second, the Breusch-Pagan Lagrange Multiplier Test is used to test the suitability of a random effects model relative to a pooled OLS model. This test produces *p*-values below 0.05 across specifications, demonstrating that random effects are preferred. Lastly, we conduct a Hausman test to compare the use of fixed effects to a random effects model. Across all specifications we reject the null with *p*-values below 0.05, indicating that a fixed effects model is suitable. These tests support our use of a fixed effects model. After conducting a Wald test, we find the presence of heteroskedasticity, which we account for through robust standard errors.

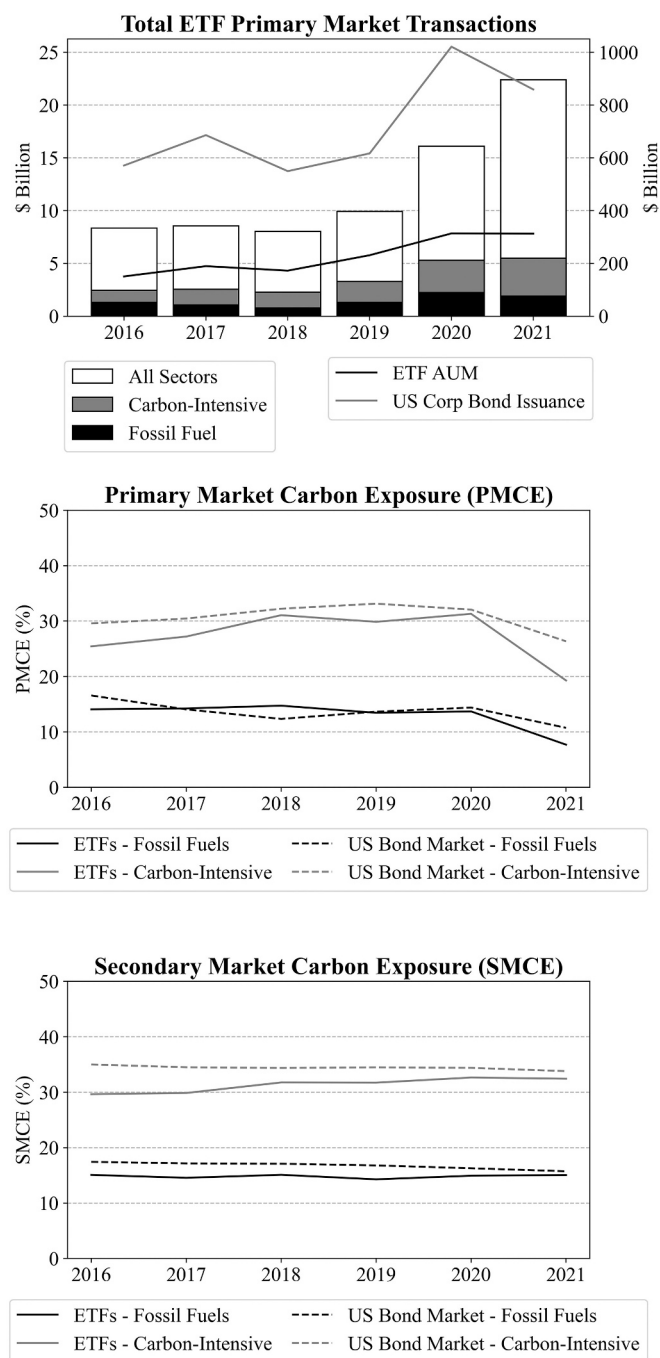


Fig. 4. ETF financing and carbon exposures.

The top panel displays bar charts of the total value of primary market trades by selected Bloomberg ETFs in All Sectors, Carbon-Intensive sectors, and Fossil Fuel sectors, shown on the primary y-axis. In addition to fossil fuel energy, Carbon-Intensive includes activities within transport, buildings, and industry as defined in Appendix A. Given overlaps between these three groupings, only additional financing is shown. For example, in 2019, total primary market financing in all sectors was \$10 billion. The secondary y-axis charts the total AUM of these ETFs and the issuance of U.S. USD corporate bonds. Using USD bonds issued by U.S. firms, the middle and bottom panel chart average PMCE and SMCE of Bloomberg ETFs, compared to the U.S. USD corporate bond market.

higher primary market carbon exposure in the following period. Lagged SMCI is also a statistically significant indicator regarding higher PMCI at the 5% and 1% level (specifications 5 and 8), with an adjusted R-squared

of 0.10 and 0.13. Lower explanatory power is expected, as issuers vary year-on-year and carbon intensity varies within sectors.

Table 1 also shows how ETF characteristics affect PM metrics. In line with IG and HY averages, a higher weighted average bond credit rating has a significant negative relationship with carbon exposure at the 1% level. For carbon intensity, rating has a statistically significant negative relationship with carbon-intensive PMCI, but not fossil fuel PMCI. We observe that weighted average bond size has a significant negative relationship with carbon exposure, but not carbon intensity, and that weighted average time to maturity has a significant positive relationship with carbon exposure and a significant negative relationship with fossil fuel carbon intensity. Finally, we see no consistent relationship between ETF AUM or N Holdings with PMCE or PMCI.

Next, Table 2 shows how ETF characteristics affect SM metrics in the CRSP dataset. In line with Table 1, rating score has a significant negative relationship with carbon exposure and carbon intensity but is only significant in specifications 2–4. Issue size has a significant negative relationship with carbon exposure at the 1% level and a positive significant relationship with time to maturity at the 1% level. While the results are similar to Table 1, the predictive power is higher, with adjusted R-squared ranging from 0.51 to 0.80. This is expected, as bond holdings change less each year than primary market transactions. In Appendix F, we also show similar results for SM metrics in the Bloomberg dataset. As the larger CRSP dataset contains ESG ETFs, a dummy variable for these 17 ETFs is added, showing a lower fossil fuel and carbon-intensive SMCE, but not SMCI. To investigate further, we identify five ESG ETFs with a matched non-ESG equivalent and display SMCE for these in Fig. 5, showing how ESG alternatives can have reduced carbon exposure.

4.2. Bond-level analysis

In the second stage of analysis, we examine how passive ETF participation changes in carbon-intensive assets. First, Table 3 tabulates the results of pooled OLS regressions in the CRSP and Bloomberg datasets, examining how ETF Share changes for bonds in fossil fuel and carbon-intensive sectors. For bonds issued in fossil fuel sectors, we observe a positive relationship with ETF Share across specifications and a significant relationship at the 5% level in the Bloomberg sample, showing an increase in SM ETF Share and PM ETF Share of 0.16% and 0.21% respectively. However, for carbon-intensive bonds, we observe a statistically insignificant negative relationship for SM ETF Share and an insignificant positive relationship for PM ETF Share. This indicates that while fossil fuel bonds may have a higher ETF Share, there is no evidence of this in carbon-intensive sectors more broadly. This could be due to the fact that while investors have reduced their exposure to fossil fuels, Bolton et al. (2021) do not find evidence of this in other sectors.

Next, Table 4 tabulates the results of fixed effects OLS regressions, examining how carbon intensity affects ETF Share in CRSP and Bloomberg datasets. With only time fixed effects, CO2 Intensity has a positive but insignificant relationship with SM ETF Share and a significant positive relationship with PM ETF Share at the 5% level, indicating that bonds with a higher carbon intensity have higher ETF Share in primary markets. With issuer fixed effects, CO2 Intensity has a positive significant relationship at the 1% level across specifications. In economic terms, for the CRSP dataset with issuer fixed effects a one standard deviation increase in CO2 Intensity is associated with a 0.34% increase in SM ETF Share. For the Bloomberg dataset, it is 0.23% and 0.34% for SM ETF Share and PM ETF Share respectively. This is large relative to average levels of ETF Share. Over the time period studied, the average CRSP SM ETF Share was 4.32%, while for Bloomberg SM ETF Share and PM ETF Share it was 1.75% and 0.93% respectively. In summary, there is evidence that SM ETF Share and PM ETF Share increase for bonds as their carbon intensity rises. Consistency across both datasets demonstrates that findings are not limited to the largest ETFs in the Bloomberg sample.

Table 1
Determinants of primary market metrics – Bloomberg ETFs.

	Primary market carbon exposure (PMCE)				Primary market carbon intensity (PMCI)			
	Fossil fuels		Carbon-intensive		Fossil fuels		Carbon-intensive	
	1	2	3	4	5	6	7	8
L.SMCE	1.074*** (0.173)		0.930*** (0.200)					
L.SMCI					0.260** (0.120)		0.900*** (0.260)	
L.Bond Rating Score		−1.056*** (0.316)		−1.952*** (0.317)		−2.042 (47.99)		−76.59*** (22.02)
L.Bond Issue Size		−7.558*** (2.074)		−19.38*** (3.130)		−66.16 (492.6)		95.74 (121.9)
L.Bond Time to Maturity		0.571*** (0.0719)		0.961*** (0.0928)		−31.80*** (8.455)		−5.128 (4.723)
L.AUM		−0.0117 (0.0331)		−0.0263 (0.0248)		1.423 (5.864)		−0.0767 (2.574)
L.N Holdings		−0.918*** (0.236)		−0.314 (0.472)		−100.2 (74.30)		−18.36 (17.42)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R ²	0.301	0.411	0.340	0.495	0.1000	0.141	0.128	0.120
N	136	134	138	136	105	104	110	108

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$ denote statistical significance at the 10%, 5% and 1% level, respectively. Standard errors clustered at the ETF level are shown in parentheses. All explanatory variables are lagged by one year. Bond Issue Size, Rating Score and Time to Maturity are calculated as a portfolio weighted average. AUM represents assets under management and N Holdings represents the number of corporate bond holdings. Specifications 1–4 show regressions on PMCE metrics for Fossil Fuel and Carbon-Intensive sector groups for 2016–2021. Specifications 5–8 show regressions on PMCI metrics for 2016–2020. All specifications apply to ETFs from Bloomberg. In addition to fossil fuel energy, Carbon-Intensive includes activities within transport, buildings, and industry as defined in Appendix A.

Table 2
Determinants of secondary market metrics – CRSP ETFs.

	Secondary market carbon exposure (SMCE)		Secondary market carbon intensity (SMCI)	
	Fossil fuels	Carbon-intensive	Fossil fuels	Carbon-intensive
	1	2	3	4
Bond Rating Score	−0.171 (0.132)	−1.707*** (0.201)	−223.4*** (40.77)	−59.27*** (10.42)
Bond Issue Size	−9.463*** (1.960)	−16.68*** (2.547)	518.5 (344.3)	65.22 (108.6)
Bond Time to Maturity	0.582*** (0.0730)	0.880*** (0.0638)	−14.75* (8.734)	−3.525 (3.441)
AUM	0.0200 (0.0138)	0.0149 (0.0200)	−2.165 (3.416)	−0.936 (0.961)
N Holdings	−0.273 (0.187)	−0.436* (0.226)	47.66* (24.51)	18.16 (11.41)
ESG Dummy	−6.157*** (1.465)	−5.251*** (1.319)	836.8 (654.5)	24.09 (90.78)
Year FE	Yes	Yes	Yes	Yes
Adjusted R ²	0.575	0.809	0.565	0.469
N	474	474	325	368

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$ denote statistical significance at the 10%, 5% and 1% level, respectively. Standard errors clustered at the ETF level are shown in parentheses. Bond Issue Size, Rating Score and Time to Maturity are calculated as a portfolio weighted average. AUM represents assets under management and N Holdings represents the number of corporate bond holdings. ESG Dummy indicates if an ESG or climate-related strategy is followed by the ETF. Specifications 1–2 show regressions of ETF characteristics on SMCE metrics for Fossil Fuel and Carbon-Intensive sector groups for 2016–2021. Specifications 3–4 show regressions of ETF characteristics on SMCI metrics for 2016–2020. All specifications apply to ETFs from CRSP. In addition to fossil fuel energy, Carbon-Intensive includes activities within transport, buildings, and industry as defined in Appendix A.

With regard to control variables, Issue Size has a positive relationship with SM ETF Share. Larger bonds are more liquid, which is beneficial for ETFs when conducting stratified sampling. However, this switches for PM ETF Share, with a negative significant relationship shown. Coupon is negatively related to ETF Share across all specifications and significant at the 1% level except for specification 5. As high-coupon bonds attract investors searching for yield (Ammer et al., 2018), this could explain lower ETF Share. Callability shows a positive significant relationship with SM ETF Share at the 1% to 5% level, but a significant negative relationship at the 1% level with PM ETF Share. Time to Maturity shows a negative relationship with ETF Share across all specifications at the 1% to 10% level. Active investors searching for yield may favour high-duration bonds with higher interest rate risk. For example, foreign investors favour high-duration U.S. bonds when

domestic interest rates fall (Ammer et al., 2018) and pension funds with long-term liabilities demand long-dated bonds (Greenwood and Vissing-Jorgensen, 2018). Rating score is negatively related to SM ETF Share at the 1% level with issuer fixed effects, indicating that passive ETF ownership is higher as issuer risk increases. However, for PM ETF Share, there is no significant relationship after controlling for issuer fixed effects.

To check the robustness of these findings, a sub-sample analysis is conducted. First, the sample is split into IG and HY bonds (Tables D.1 and D.2 in Appendix D). For IG bonds, representing approximately 90% of the datasets, CO2 Intensity has a positive significant relationship across all specifications with issuer fixed effects. In the smaller HY subsample, CO2 Intensity has a significant positive relationship with issuer fixed effects for the Bloomberg dataset but not CRSP. Next, the

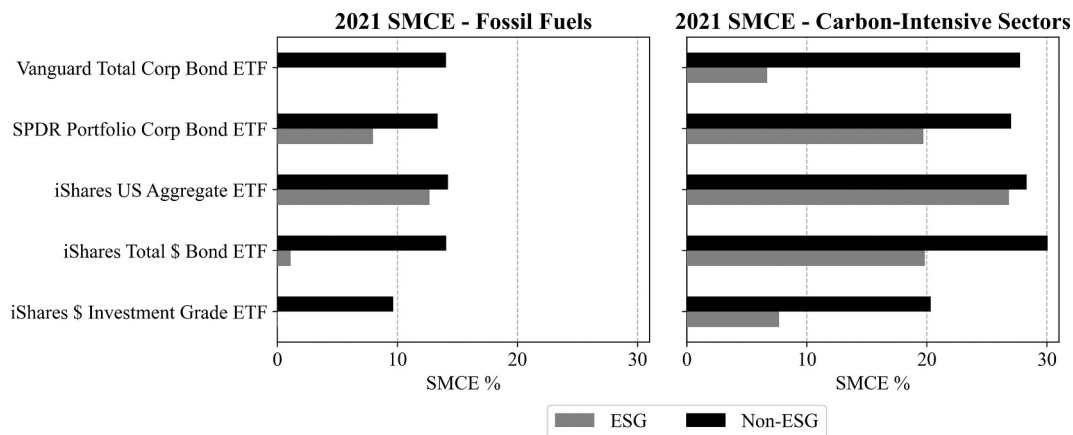


Fig. 5. SMCE comparison of ESG ETFs.

Fossil Fuel and Carbon-Intensive SMCE are compared for ESG and non-ESG ETFs in 2021. Vanguard ESG US Corporate Bond ETF is matched to the Vanguard Total Corporate Bond ETF. SPDR Bloomberg SASB Corporate Bond ESG Select ETF is matched to SPDR Portfolio Corporate Bond ETF. iShares ESG Aware US Aggregate Bond ETF is matched to iShares Core US Aggregate Bond ETF. iShares ESG Advanced Total USD Bond Market ETF is matched to iShares Core Total USD Bond Market ETF. iShares ESG Advanced Investment Grade Corp Bond ETF is matched to iShares iBoxx \$ Investment Grade Corporate Bond ETF. In addition to fossil fuel energy, Carbon-Intensive includes activities within transport, buildings, and industry as defined in Appendix A.

Table 3

Determinants of ETF share - fossil fuel and carbon-intensive sectors.

	CRSP ETFs		Bloomberg ETFs			
	SM ETF Share		SM ETF Share		PM ETF Share	
	1	2	3	4	5	6
Fossil Fuel Bond	0.117 (0.101)		0.166** (0.0837)		0.211** (0.0828)	
Carbon-Intensive Bond		−0.0856 (0.0700)		−0.0693 (0.0673)		0.0407 (0.0552)
Issue Size	0.404*** (0.110)	0.397*** (0.110)	0.439*** (0.112)	0.432*** (0.112)	−0.132*** (0.0416)	−0.136*** (0.0416)
Coupon	−0.470*** (0.0274)	−0.466*** (0.0270)	−0.0913*** (0.0217)	−0.0851*** (0.0214)	−0.0254 (0.0312)	−0.0218 (0.0322)
Callable	0.349*** (0.0711)	0.372*** (0.0701)	0.132* (0.0717)	0.158** (0.0705)	−0.457*** (0.0674)	−0.451*** (0.0681)
Time to Maturity	−0.0925*** (0.00459)	−0.0920*** (0.00457)	−0.0370*** (0.00256)	−0.0366*** (0.00258)	−0.0184*** (0.00242)	−0.0185*** (0.00246)
Rating Score	0.0538*** (0.0161)	0.0549*** (0.0159)	−0.160*** (0.0190)	−0.157*** (0.0188)	−0.0532*** (0.0137)	−0.0500*** (0.0132)
Revenue	0.00116 (0.000735)	0.000960 (0.000704)	0.00247*** (0.000653)	0.00225*** (0.000644)	0.00179*** (0.000463)	0.00175*** (0.000469)
Operating Profit Margin	−0.00244 (0.00162)	−0.00316* (0.00169)	−0.000164 (0.00149)	−0.00102 (0.00150)	0.00140 (0.00306)	0.00110 (0.00311)
Leverage	0.00295 (0.00184)	0.00297 (0.00183)	0.00637*** (0.00235)	0.00643*** (0.00233)	0.00137 (0.00154)	0.00143 (0.00153)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Issuer FE	No	No	No	No	No	No
Adjusted R ²	0.379	0.379	0.243	0.242	0.110	0.105
N	19,851	19,851	18,730	18,730	2816	2816

*p < 0.10, ** p < 0.05, *** p < 0.01 denote statistical significance at the 10%, 5% and 1% level, respectively. Standard errors clustered at the issuer level are shown in parentheses. Specifications 1–2 apply to bonds held by the 180 ETFs selected from CRSP. Specifications 3–4 apply to bonds held by the 35 ETFs selected from Bloomberg. SM ETF Share represents the percentage of a bond outstanding held by ETFs, while PM ETF Share represents the proportion of primary market issuance purchased by ETFs. All specifications apply to 2016–2020. Fossil Fuel Bond and Carbon-Intensive Bond represent dummy variables equal to one when bonds are issued in the respective relevant sectors. Definitions of fossil fuel and carbon-intensive sectors are shown in Appendix A. In addition to fossil fuel energy, carbon-intensive sectors include activities within transport, buildings, and industry.

sample is restricted to bonds in carbon-intensive sectors, covering approximately 37% of the datasets, with results consistent with Table 4 (Table D.3). Next, the sample is restricted to only fossil fuel bonds, covering approximately 11% of the datasets. Results are consistent for the Bloomberg dataset, but not the CRSP dataset, with the coefficient positive but insignificant (Table D.4). Finally, financial issuers at excluded, with results consistent with the full sample (Table D.5). Additional tests are conducted to ensure robustness to potential selection bias and endogeneity (Appendix E). Table E.1 controls for selection

bias in carbon emission disclosure by using a Heckman selection model and Table E.2 controls for selection bias in ETF Share. In both, CO2 Intensity is significant across specifications with issuer fixed effects, indicating that endogenous sample selection does not affect results. Finally, to ensure robustness to potential endogeneity between explanatory variables, regression results using a propensity score matched sample are displayed in Table E.3, with results consistent with the original specification. A more detailed interpretation of these additional tests is provided in Appendix E.

Table 4
Determinants of ETF share – carbon intensity.

	CRSP ETFs		Bloomberg ETFs			
	SM ETF Share		SM ETF Share		PM ETF Share	
	1	2	3	4	5	6
CO2 Intensity	0.00000461 (0.0000321)	0.000428*** (0.0000974)	0.0000101 (0.0000506)	0.000292*** (0.0000651)	0.0000484** (0.0000227)	0.000381*** (0.0000840)
Issue Size	0.288*** (0.100)	0.140* (0.0739)	0.339*** (0.102)	0.178*** (0.0677)	−0.128** (0.0514)	−0.0899 (0.0752)
Coupon	−0.526*** (0.0301)	−0.509*** (0.0379)	−0.115*** (0.0234)	−0.173*** (0.0204)	−0.0565 (0.0369)	−0.179*** (0.0637)
Callable	0.336*** (0.0822)	0.519*** (0.103)	0.181*** (0.0696)	0.239*** (0.0590)	−0.448*** (0.0761)	−0.440*** (0.104)
Time to Maturity	−0.0920*** (0.00563)	−0.0922*** (0.00666)	−0.0332*** (0.00281)	−0.0238*** (0.00264)	−0.0158*** (0.00266)	−0.00602 (0.00378)
Rating Score	0.000735 (0.0182)	−0.169*** (0.0505)	−0.138*** (0.0264)	−0.130*** (0.0390)	−0.0487*** (0.0160)	0.0348 (0.0752)
Revenue	0.00125** (0.000614)	0.00174 (0.00188)	0.00204*** (0.000651)	−0.000109 (0.00107)	0.00150*** (0.000444)	0.00712* (0.00430)
Operating Profit Margin	−0.00355 (0.00260)	−0.00337 (0.00281)	−0.00256 (0.00189)	−0.00227 (0.00205)	−0.00182 (0.00191)	−0.00460 (0.00319)
Leverage	−0.00000717 (0.00224)	0.00328 (0.00501)	0.00371* (0.00198)	0.00309 (0.00364)	0.00174 (0.00190)	0.0000188 (0.00837)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Issuer FE	No	Yes	No	Yes	No	Yes
Adjusted R ²	0.409	0.491	0.231	0.508	0.109	0.289
N	13,225	13,225	12,599	12,599	1865	1865

*p < 0.10, **p < 0.05, ***p < 0.01 denote statistical significance at the 10%, 5% and 1% level, respectively. Standard errors clustered at the issuer level are shown in parentheses. Specifications 1–2 apply to bonds held by the 180 ETFs selected from CRSP. Specifications 3–4 apply to bonds held by the 35 ETFs selected from Bloomberg. SM ETF Share represents the percentage of a bond outstanding held by ETFs, while PM ETF Share represents the proportion of primary market issuance purchased by ETFs. All specifications apply to 2016–2020.

5. Discussion

In this paper, we study passive ETF transactions first at the fund level and second at the bond level. At the fund level, we show how ETFs systematically partake in primary market transactions, purchasing bonds before index inclusion at month end (Appendix B). Then for each ETF, we calculate carbon exposure and carbon intensity metrics for primary market transactions and portfolio holdings. We find that metrics for primary market transactions are higher for ETFs with higher lagged portfolio holding metrics.

While limited by the small sample size and lack of casual analysis, these findings are informative for asset owners. As funds only provide climate-related disclosures for portfolio holdings, our findings show that these disclosures provide an indication of the impact of primary market transactions. For asset owners, this underscores the importance of selecting ETFs that track indices in line with their climate-related objectives, such as minimising fossil fuel financing, or financing companies that are decarbonising.¹⁵ This is particularly important for passive bond funds as carbon exposure has remained high due to the capital intensity of fossil fuel and carbon-intensive sectors (Fig. 6). In contrast, carbon exposure in equities has fallen in line with fossil fuel valuations (Sanzillo, 2020).

By analysing the relationship between ETF holdings and primary market transactions, we differentiate between capital stocks and flows within the context of impact generation. This builds on Kölbel et al. (2020) who identify capital allocation as a mechanism for impact

generation. This separation of flows and stocks is important within the context of divestment. Researchers have argued that divestment through secondary markets has a limited impact, as effects on asset prices are temporary (Braungardt et al., 2019). As non-ETF funds do not disclose daily holdings, we are not able to study the effect of actual divestment decisions on primary market transactions. However, in fixed income portfolios, our findings indicate that a lower allocation to fossil fuels in portfolio holdings is associated with lower financing of fossil fuels through primary markets. This is in line with Cojoianu et al. (2020), who find that country-level divestment activity reduces capital flows to fossil fuel sectors. By focusing on fixed income, and differentiating between capital stocks and flows, this paper brings a new perspective to the divestment versus engagement debate.

In this paper, we analyse the role of ETFs in carbon-intensive and fossil fuel bonds. Using descriptive analysis, we outline how ETF primary market financing of these sectors has grown as ETF AUM has risen, and how the carbon exposure of ETF holdings and primary market financing trends with the broader U.S. corporate bond market. This sector-agnostic capital allocation indicates that if passive ETF AUM continues to rise, so too will total primary market financing of bonds in fossil fuel and carbon-intensive sectors. Building on this, through empirical analysis we then test whether ETF Share (the share of primary market transactions and secondary market holdings accounted for by passive ETFs) changes depending on bond-level characteristics. While rising passive ETF AUM would result in a higher ETF Share for all assets, we demonstrate that ETF Share is higher for fossil fuel sectors and increases as bond-level carbon intensity increases. A potential explanation is the decarbonisation of institutional investor portfolios, which has been documented in multiple studies (Bolton et al., 2021; Choi et al., 2020c). As passive funds grow, they could gradually replace these investors as the holders of carbon-intensive assets (Jahnke, 2019). However, we use this interpretation with caution given two limitations in this study. First, as our data is limited to passive ETFs, we do not model the direct relationship between institutional investor decarbonisation and ETF Share, and therefore do not show causation. Second, given limited data availability, Scope 3 emissions are excluded from our measure of

¹⁵ While ESG indices can provide a reduced exposure to fossil fuels, as shown in Figure 5, index providers such as FTSE Russell offer indices that exclude fossil fuels entirely (FTSE Russell, 2022). Index providers also provide “transition indices” that weight companies within sectors according to their carbon intensity and readiness for the low-carbon transition. For example, MSCI transition indices consider emission reduction targets of companies and their opportunities related to the low-carbon transition (MSCI, 2019). In theory, by tracking such an index, investors will provide more capital to companies that will use it to decarbonise.

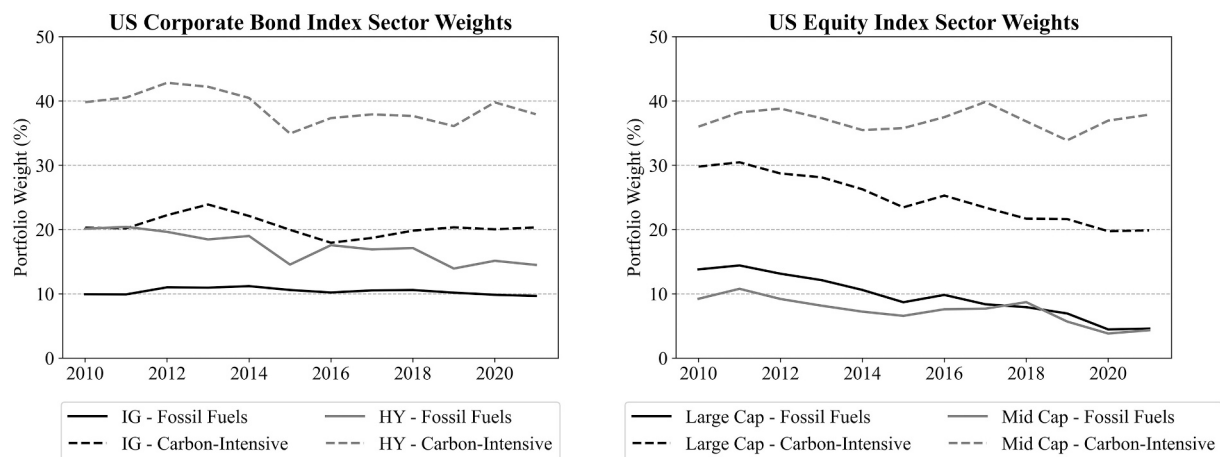


Fig. 6. Carbon exposure of U.S. equity and bond passive funds.

Fig. 6 shows the weight of Fossil Fuel and Carbon-Intensive sectors in U.S. indices. In addition to fossil fuel energy, Carbon-Intensive includes activities within transport, buildings, and industry as defined in Appendix A. IG index weights are represented by the iShares iBoxx \$ Investment Grade Corporate Bond ETF, tracking the Markit iBoxx USD Liquid Investment Grade Index. HY index weights are represented by the iShares iBoxx \$ High Yield Corporate Bond ETF (HYG) tracking the Markit iBoxx USD Liquid High Yield Index. Large-cap equity index weights are represented by the iShares Core S&P 500 UCITS ETF tracking the S&P 500 Index. Mid-cap equity index weights are represented by the iShares Core S&P Mid-Cap ETF tracking the S&P MidCap 400 Index.

carbon intensity. As a result, we omit a large proportion of an issuer's carbon footprint that institutional investors are likely to consider when evaluating a company to decarbonise portfolios.

Together, the findings of this study indicate that ETFs are set to support fossil fuels through primary market financing. This has implications for both asset managers and policymakers. For policymakers, passive funds could limit the efficacy of sustainable finance policies. To date, sustainable finance policy has focused on the provision of climate-related disclosures (European Commission, 2020; HM Treasury, 2020; TCFD, 2020). Such disclosures are intended to allow markets to price climate risks (Thomä and Chenet, 2017) and allocate capital accordingly (Christophers, 2017; Cullen, 2018). However, the efficacy of these policies could be limited if ETF Share increases with carbon intensity, as non-ESG passive funds are “permanent owners” of assets (Baines and Hager, 2022) and do not respond to environmental risks and impacts in the same manner as active funds (Harmes, 2011; Tarim, 2022).

These policies focused on climate-related disclosures are also limited by the ability of markets to correctly price the severe, complex, and radically uncertain risks associated with climate change. Instead, Chenet et al. (2021) outline that a market-shaping approach is needed to guide markets towards an optimal scenario where climate risks are mitigated. To shape capital flows within the context of passive investing, policymakers could require asset owners such as pension funds to offer funds tracking low-carbon indices as the default option for savers, requiring an opt-out rather than an opt-in. This would reduce capital flows from passive funds to companies with negative climate impacts. Another option would be to require fund-level climate-related disclosures for primary market transactions. The advantage is that, unlike other disclosure policies, markets are not relied upon to price risks. Instead, asset owners would be better able to select funds with capital flows aligned with their climate-related objectives.

For large asset managers offering active and passive funds, the sharp growth in passive AUM has resulted in fossil fuel holdings being concentrated within passive funds (Greenfield, 2019). With some of these asset managers committed to supporting net zero by 2050,¹⁶ they have taken steps to reduce their exposure to fossil fuels. However, these

have applied to active rather than passive funds. For example, BlackRock committed to divest from coal but excluded passive funds from this policy (Jolly, 2021), while Vanguard excludes all passive funds from its net zero commitment (Vanguard, 2022). ETF providers state that decarbonisation or divestment in passive funds is not possible due to the impact on tracking error (Mooney et al., 2018), yet de Jong and Nguyen (2016) show how a 50% reduction in carbon exposure has little impact on tracking error or returns. Furthermore, ETF providers advertise their ability to be selective in primary markets to buy bonds before index inclusion,¹⁷ as shown in Appendix B. Therefore, active security selection could partly decarbonise ETF primary market transactions.

Ultimately, ETF providers need to work with asset owners to increase the proportion of passive assets tracking low-carbon indices. A challenge in achieving this is the high fees of ESG ETFs vs non-ESG ETFs. For example, for the matched ETFs in Fig. 5, fees in the form of expense ratios are on average 2.9 times higher for ESG ETFs. Another concern is performance. While divestment in equities has been shown to have a limited impact on returns (Hunt and Weber, 2019; Plantinga and Scholtens, 2021; Trinks et al., 2018), few studies have focused on bonds. However, ESG-focused corporate bond portfolios are shown to outperform, indicating that switching to a lower-carbon alternative could occur without a negative impact on returns (Bahra and Thukral, 2020; Fridson et al., 2021; Polbennikov et al., 2016).

6. Conclusion

In sum, by differentiating between capital stocks and flows, this study builds on the literature on investor impact and provides a new perspective on the divestment versus engagement debate by establishing a link between portfolio holdings and primary market financing. There is, however, scope to build on this analysis, which was limited by the small sample size and U.S. focus. As passive investing is most developed in the U.S., our findings may not apply to other regions. Access to a larger global database of daily holdings, encompassing active and

¹⁶ BlackRock and State Street are signatories to the Net Zero Asset Managers Alliance, which commits them to “support investing aligned with net zero emissions by 2050 or sooner” (Net Zero Asset Managers, 2022).

¹⁷ In 2020, the Head of Bond Indexing at Vanguard wrote: “Take the new issue market, for example. Issuers often offer concessions to entice investors to buy a new bond, with no transaction costs. The question is, do you buy the bond at the time of issue, taking advantage of any concessions and lower costs? Or do you wait for it to be included in the index at the end of the month, by which point it might have gained (or lost) value?” (Whitbread, 2020)

passive investors, would enable researchers to examine the direct effect of decisions to decarbonise portfolios on primary market transactions. An additional limitation is the exclusion of Scope 3 emissions from carbon intensity due to low coverage, which limits our ability to accurately track changes in a company's climate-related risks and impacts. As standard setters such as The International Sustainability Standards Board (ISSB) work towards mandatory Scope 3 disclosure (IFRS, 2022), researchers could more accurately estimate issuer and ETF carbon intensity.

By analysing the role of passive ETFs in carbon-intensive and fossil fuel bonds, we make an important contribution to the literature on passive investing in sustainable finance, which to date has focused on equity markets and shareholder engagement (Appel et al., 2016; Jahnke, 2019; Petry et al., 2021). These findings raise important questions for future research. While we showed an increased role of passive ETFs as bond-level carbon intensity increased, we did not examine whether this alters the cost of capital or the pricing of climate risks. Furthermore, if passive investing continues to grow rapidly, it will also be important for researchers to consider policies that harness the power of passive investing for climate-related objectives.

Finally, it is important to keep in mind that while this study focuses on passive funds, capital flows from active funds are also important for impact generation within the context of the low-carbon transition.

Similarly, while primary market issuance in equities is a fraction of that in bonds, the importance of equity financing should not be forgotten.

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Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The authors do not have permission to share data.

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Appendix A. Sector classifications

Table A.1

Fossil fuel sector definition.

TRBC industry group	TRBC industry	TRBC activity
Coal	Coal	Coal (NEC), Coal Wholesale, Coal Mining Support
Oil & Gas	Integrated Oil & Gas	Integrated Oil & Gas
	Oil & Gas Exploration and Production	Oil & Gas Exploration and Production (NEC), Oil Exploration & Production - Onshore, Oil Exploration & Production - Offshore, Natural Gas Exploration & Production - Onshore, Natural Gas Exploration & Production - Offshore, Unconventional Oil & Gas Production
Oil & Gas Related Equipment and Services	Oil & Gas Refining and Marketing	Oil & Gas Refining and Marketing (NEC), Petroleum Refining, Gasoline Stations, Petroleum Product Wholesale
	Oil & Gas Drilling	Oil & Gas Drilling (NEC), Oil Drilling - Onshore, Gas Drilling - Onshore, Oil Drilling - Offshore, Gas Drilling - Offshore, Unconventional Oil & Gas Drilling
	Oil Related Services and Equipment	Oil Related Services and Equipment (NEC), Oil Related Services, Oil Related Equipment, Oil Related - Surveying & Mapping Services
Electrical Utilities & IPPs	Oil & Gas Transportation Services	Oil & Gas Transportation Services (NEC), LNG Transportation & Storage, Natural Gas Pipeline Transportation, Oil Pipeline Transportation, Sea-Borne Tankers, Oil & Gas Storage
	Electric Utilities	Electric Utilities (NEC), Fossil Fuel Electric Utilities
Natural Gas Utilities	Independent Power Producers	Independent Power Producers (NEC), Fossil Fuel IPPs
	Natural Gas Utilities	Natural Gas Utilities (NEC), Natural Gas Distribution

The table shows the scope of the fossil fuel sector definition using The Refinitiv Business Classification (TRBC).

Table A.2

Carbon-intensive sector definition.

TRBC code	TRBC industry group	IPCC code	IPCC industry name
Energy			
50,101	Coal	1A2f4	Mining and Quarrying
59,101	Electrical Utilities & IPPs	1A1a1, A1ax	Electricity & Heat Generation
50,102	Oil & Gas	1A3e, 1B2	Petroleum Refining, Fuel Production and Transport
59,102	Natural Gas Utilities	1A3e, 1B2	Fuel Production and Transport, Indirect N ₂ O Emissions from Transport
50,103	Oil Equip. & Services	1A1bc, 1B2, 1A3e	Petroleum Refining, Fuel Production and Transport, Indirect N ₂ O Emissions from Transport

(continued on next page)

Table A.2 (continued)

TRBC code	TRBC industry group	IPCC code	IPCC industry name
Transport			
52,406	Passenger Transportation Services	1A3a, 1A3b, 1A3c, 1A3d, 1C1, 1C2	Aviation, Road Transportation, Rail Transportation, Navigation, Aviation, International Shipping
52,405	Freight & Logistics Services	1A3a, 1A3b, 1A3c, 1A3d, 1C1, 1C2	Aviation, Road Transportation, Navigation, Rail Transportation, Navigation, International Aviation, International Shipping
Buildings			
51,202	Construction Materials	2A1	Cement Production
52,201	Construction & Engineering	1A2f6	Construction
53,203	Homebuilding & Construction Supplies	1A4a, 1A4b	Commercial, Residential
Industry			
51,201	Metals & Mining	1A1, 1A2, 2C, 1A2f4	Ferrous and Non-ferrous Metals, Mining and Quarrying
53,101	Automobiles & Auto Parts	1A2f2	Transport Equipment
51,101	Chemicals	1A2	Chemicals
52,102	Machinery, Tools, Heavy Vehicles, Trains & Ships	2F7a, 2F8a, 1A2f2, 1A2f3	Semiconductor Manufacture, Electrical Equipment Manufacture, Transport Equipment, Machinery
54,102	Food & Tobacco	1A2e1, A4c3, 4A, 4B, 4C, 4Dr, 4F	Food and Tobacco, Livestock, Rice Cultivation, Direct Soil, Fuel Combustion Emissions
51,301	Paper & Forest Products	1A2d	Pulp and Paper
52,203	Professional & Commercial Services	6A, 6B, 6C, 6D	Landfill & Waste Incineration, Wastewater Treatment

The table is adapted from Choi et al. (2020a, 2020b) and shows the TRBC Industry classifications used for IPCC carbon-intensive sectors. AFOLU sectors are not shown as a separate section, as relevant sectors are captured by Food & Tobacco under Industry.

Appendix B. Data collection

B.1. ETF selection

Using the CRSP Mutual Fund Database, the following steps are used to select relevant ETFs. First, “et_flag” is used to identify funds classified as ETFs. Second, “index_fund_flag” is used to identify passive funds, selecting index-based funds and pure index funds. Then, funds with over 5% of AUM in corporate bonds are retained, using the “per_corp” field, which details the percentage of assets held in corporate bonds. Finally, ETFs following multi-asset, equity, emerging market, and ex-U.S. strategies are removed to retain funds investing in U.S. corporate bonds, by selecting the following Lipper Objectives under “lipper_class_name”: Inflation Protected Bond Funds, Short High Yield Funds, Global High Yield Funds, High Current Yield Funds, Core Plus Bond Funds, General Bond Funds, Intermediate Investment Grade Debt Funds, Short-Intermediate Investment Grade Bond Funds, Short Investment Grade Bond Funds, Core Bond Funds, High Yield Funds, Corporate Debt Funds BBB-Rating, Corporate Debt Funds A Rated, and Global Income Funds. Following this, the relevant “crsp_fundno” codes are extracted as fund identifiers and used to access yearly portfolio holdings for 2016–2021, including the CUSIPs of assets held and their market value.

In November 2020, all fixed income ETFs were extracted from Bloomberg, using the “ETF” function. These are filtered to keep those tracking a broad-based U.S. investment grade (IG) or high-yield (HY) index. First, we exclude ETFs limited to a single sector or bond type, such as floating rate, or convertible bonds using “fund_strategy”. Similarly, bonds investing in a single maturity (“fund_maturity_band_focus”) and a single rating (“fund_rtg_class_focus”) are removed. Next, from the “ETF” function, weights by asset class and geography are extracted. To estimate the allocation to U.S. corporate bonds, the allocation to corporate bonds is multiplied by the allocation to the US. To select the largest ETFs, those with over \$500 m in U.S. corporate bonds are retained,¹⁸ leaving 35 ETFs with an AUM of \$180 billion, covering 38% of total ETF AUM before filtering. Using the Bloomberg Portfolio & Risk Analytics function, daily holdings are downloaded for 2016–2021, including the ISINs of assets held and the number of holdings. In both datasets, certain ETFs hold types of bonds other than corporate bonds. However, these holdings are discarded during analysis.

B.2. Extracting primary market trades

Using Bloomberg ETF data, a trade is identified when a new bond is held. To identify primary market trades, the ETF trade date is compared to the bond’s issuance date, with business days between defined as Days After Issuance (DAI). In our sample, within 10 days after issuance, 47% and 40% of ETF trades occur at DAI 0 and DAI 1 respectively. To compare this to the broader market, we extract trade data from TRACE for relevant U.S. bonds, showing that on average 73% and 7% of trades occur on 0 DAI and 1 DAI respectively. While the sum of DAI 0 and DAI 1 is similar, the split between the ETF sample and TRACE differs (Fig. B.1). This occurs as ETFs disclose holdings at the end of the trading day when Net Asset Value is calculated, at 16:00 Eastern when the New York Stock Exchange closes (ICI, 2014). TRACE indicates that on average 25% of primary market trades occur after this time, which wouldn’t be reported at DAI 0. Therefore, to include these trades, we count both DAI 0 and DAI 1 trades as primary market trades. Furthermore, holdings are reported differently depending on the ETF provider, with State Street reporting trades only at DAI 1 (Fig. B.1). Using this approach, 35,531 primary market trades are identified in 7397 bonds. A limitation is that primary market trade value is overestimated by approximately 7% according to TRACE, as secondary market trades on DAI 0 and DAI 1 are misclassified.

All indices tracked by Bloomberg ETFs rebalance at the end of the month when new issues are included. By identifying primary market trades, we

¹⁸ Vanguard ETFs are excluded as they do not report daily holdings in Bloomberg.

show that ETFs systematically buy new bonds before index inclusion. Fig. B.2. tracks the trading activity of ETFs in bonds issued within the past quarter, showing an uptick of total trading activity towards month end when indices are rebalanced. However, primary market trades occur throughout the month, accounting for an average of 44% of trades in new bonds. This shows that ETFs frequently purchase bonds in the primary market before index inclusion, as stated by Vanguard (Whitbread, 2020).

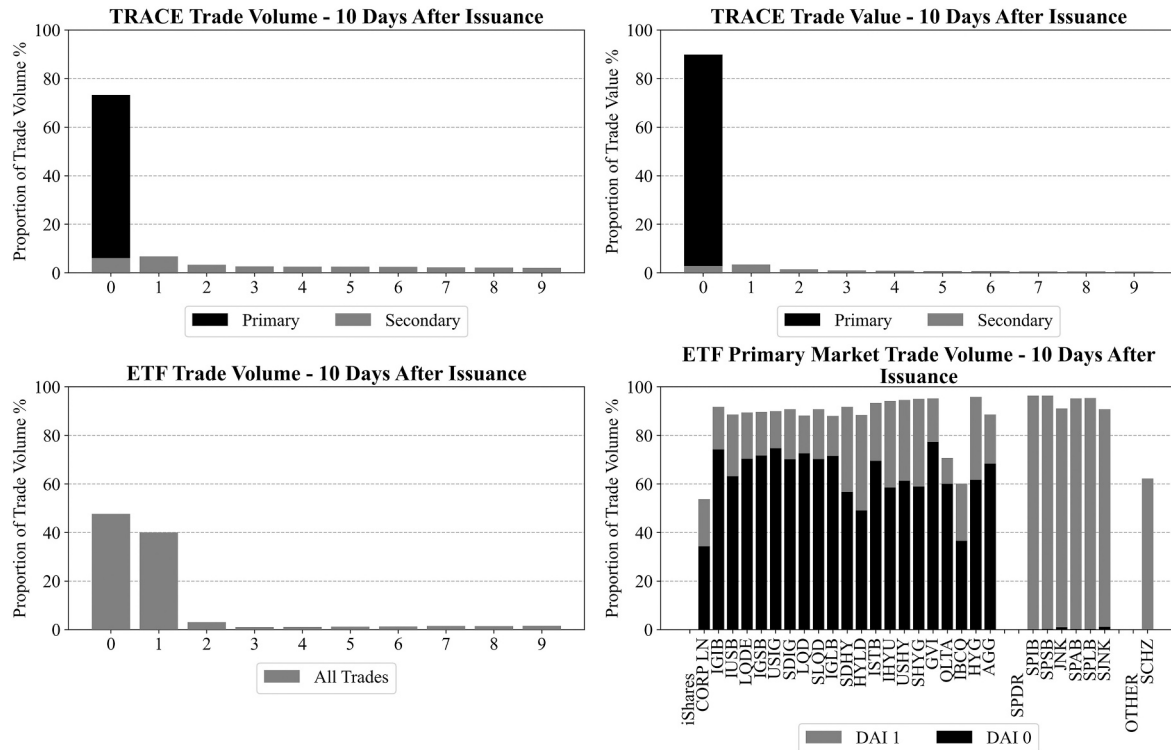


Fig. B.1. TRACE and ETF trade distribution.

The top-left panel shows the distribution of trade frequency in TRACE Enhanced occurring within 10 days of issuance for U.S. corporate bonds. This is split between transactions tagged as primary market (P1) and secondary market (S1) trades. Only sell trades to customers are used (non-FINRA members such as institutional investors). The top-right panel shows the distribution of trade value. The bottom-left panel shows the distribution of trade frequency of the selected ETFs in the Bloomberg sample. The bottom-right panel shows the proportion of ETF trades occurring on DAI 0 and DA 1 within the first 10 days after issuance, grouped by ETF provider, with only ETFs with over 200 primary market trades shown.

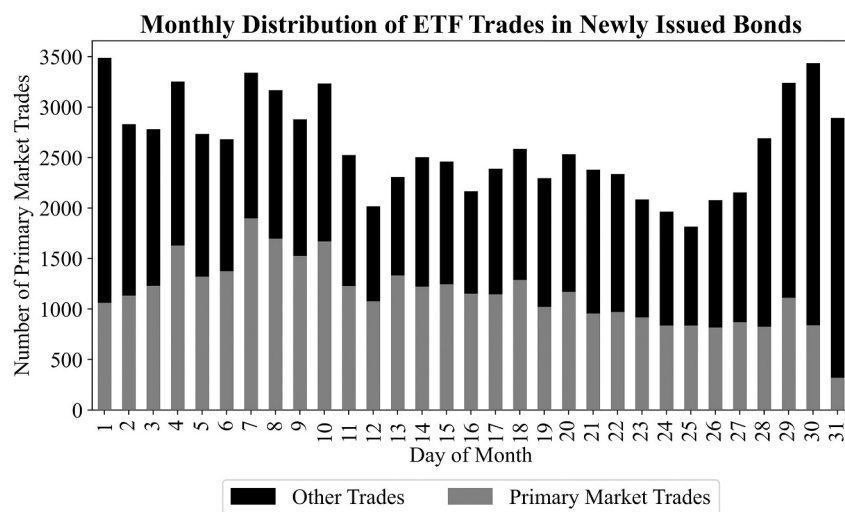


Fig. B.2. Monthly distribution of new issue trades.

The chart shows the monthly distribution of selected Bloomberg ETF trades in newly issued bonds, defined as those issued within the past quarter (65 working days). This is aggregated over the total sample period of 2016–2021. These trades are separated into primary market trades, that occur on DAI 0 or 1, and other trades, which occur after DAI 1.

Appendix C. Additional summary statistics

Table C.1

Variable definitions.

Variable	Definition
ETF-Level Variables	
Primary Market Carbon Exposure (PMCE)	The proportion of primary market trade value that occurs in selected sectors over a period of time (Eq. (1))
Secondary Market Carbon Exposure (SMCE)	The proportion of portfolio holdings held in selected sectors at a point in time (Eq. (2)).
Primary Market Carbon Intensity (PMCI)	The weighted sum carbon intensity of primary market transactions in selected sectors over a period of time (Eq. (3)).
Secondary Market Carbon Intensity (SMCI)	The weighted sum of portfolio holdings in selected sectors at a point in time (Eq. (3)).
N Holdings	The number of ETF corporate bond holdings.
AUM	Assets under management in USD billions.
Bond Issue Size	The portfolio weighted average of bond face value in USD billions.
Bond Rating Score	The portfolio weighted average of bond rating scores.
Bond Time to Maturity	The portfolio weighted average of bond time to maturity.
ESG Dummy	A dummy variable indicating if an ETF follows an ESG-related investment strategy.
Bond-Level Variables	
PM ETF Share	The proportion of primary market demand accounted for by ETFs (Eq. (9))
SM ETF Share	The proportion of secondary market holdings accounted for by ETFs (Eq. (10))
CO2 Intensity	Scope 1 and 2 emissions in tons of CO2 divided by revenue in USD Millions.
Rating Score	Credit ratings are ranked from 22 representing AAA to 1 representing default. Scores are then averaged for Moody's and Fitch ratings.
Issue Size	Bond face value at issuance in USD Billions.
Coupon	Bond coupon measured as a percentage of face value at issuance.
Time to Maturity	Bond time to maturity in years.
Revenue	Bond issuer total revenue in USD Billions.
Operating Profit Margin	Bond issuer operating profit margin defined as operating income to total revenue expressed as a percentage.
Leverage	Bond issuer leverage defined as total debt to total assets expressed as a percentage.

Table C.2

ETF summary statistics.

	Mean	SD	p25	p75
Bloomberg ETFs				
Fossil Fuel PMCE	13.45	7.34	9.02	17.06
Fossil Fuel SMCE	14.72	3.80	11.63	16.64
Carbon-Intensive PMCE	30.44	10.95	21.13	41.19
Carbon-Intensive SMCE	30.79	7.90	23.39	39.20
Fossil Fuel PMCI	1460.18	400.76	1266.40	1741.30
Fossil Fuel SMCI	1313.70	479.34	1019.15	1503.88
Carbon-Intensive PMCI	767.28	162.36	683.90	837.48
Carbon-Intensive SMCI	733.34	199.85	595.35	847.64
N Primary Market Transactions	1646.00	1133.37	801.00	1919.00
N Holdings	2672.04	1954.77	1306.92	3426.67
AUM	7.26	11.84	1.65	5.78
Bond Issue Size	1.37	0.27	1.16	1.53
Bond Rating Score	14.11	3.05	10.06	16.07
Bond Time To Maturity	8.59	5.64	3.86	11.62
CRSP ETFs				
Fossil Fuel SMCE	13.20	4.87	10.22	15.67
Carbon-Intensive SMCE	29.01	9.71	21.48	37.70
Fossil Fuel SMCI	1338.38	977.35	795.56	1454.07
Carbon-Intensive SMCI	562.40	457.27	347.49	625.28
N Holdings	755.77	854.42	237.80	1113.60
AUM	3.44	10.62	0.10	1.80
Issue Size	1.37	2.72	1.20	1.48
Rating Score	13.29	2.83	12.27	15.18
Time To Maturity	7.90	5.29	3.72	10.99
ESG Dummy	0.07	0.27	0	0

PMCI and SMCI are for 2016–2020 only, due to a lack of carbon intensity data for 2021. The remaining summary statistics are shown for 2016–2021. N Primary Market Transactions show the total number of ETF-level transactions, with all other summary statistics averaged over the time period. Bond Issue Size, Rating Score and Time to Maturity are calculated as a portfolio weighted average. Issue Size and AUM is shown in USD billions. Mean, standard deviation (SD), 25th percentile (p25), and 75th percentile (p75) is shown.

Table C.3
Summary statistics - ETF share and carbon intensity by year.

	Percentage	ETF share	CO2 intensity
CRSP – SM ETF Share			
2016	15.06	3.37	331.45
2017	17.60	4.07	292.27
2018	18.87	3.96	294.65
2019	22.50	4.37	297.72
2020	25.97	5.26	292.25
Total	100.00	4.32	299.84
Bloomberg – SM ETF Share			
2016	14.95	1.35	335.69
2017	17.30	1.67	291.66
2018	19.03	1.48	295.79
2019	22.68	1.79	303.89
2020	26.03	2.21	297.08
Total	100.00	1.75	303.21
Bloomberg – PM ETF Share			
2016	15.12	0.82	386.71
2017	15.50	0.92	299.87
2018	12.98	0.94	338.27
2019	20.70	0.96	344.56
2020	35.71	0.96	329.19
Total	100.00	0.93	337.70

The Percentage column shows the proportion of the sample occurring in each year. ETF Share shows the average of PM ETF Share or SM ETF Share by year. CO2 Intensity shows the average Scope 1 and 2 carbon intensity of bonds by year.

Table C.4
Variable summary statistics.

	Mean	SD	p25	p75
CRSP ETFs – SM Holdings				
SM ETF Share	4.32	2.41	2.57	5.92
CO2 Intensity	299.84	800.65	10.32	145.80
Rating Score	15.19	2.54	14.00	16.50
Issue Size	0.99	0.88	0.50	1.25
Coupon	4.17	1.47	3.20	4.95
Callable	0.63	0.48	0.00	1.00
Time to Maturity	11.57	9.86	4.00	19.00
Revenue	53.10	71.15	9.66	71.42
Operating Profit Margin	15.65	17.60	7.64	25.54
Leverage	35.23	17.44	24.07	45.10
N	13,225			
Bloomberg ETF – SM Holdings				
SM ETF Share	1.75	1.37	0.67	2.44
CO2 Intensity	303.21	804.38	10.20	147.54
Rating Score	15.24	2.52	14.00	16.50
Issue Size	1.00	0.88	0.50	1.25
Coupon	4.12	1.44	3.15	4.88
Callable	0.64	0.48	0.00	1.00
Time to Maturity	11.53	9.70	4.00	19.00
Revenue	53.48	71.67	9.66	71.86
Operating Profit Margin	15.77	17.69	7.66	25.60
Leverage	35.23	17.37	24.01	45.11
N	12,599			
Bloomberg ETFs – PM Trades				
PM ETF Share	0.93	0.97	0.23	1.28
CO2 Intensity	337.70	886.44	11.92	160.21
Rating Score	15.24	2.65	14.00	17.00
Issue Size	1.01	0.78	0.50	1.25
Coupon	3.37	1.41	2.50	4.10
Callable	0.85	0.35	1.00	1.00
Time to Maturity	12.56	10.06	5.00	11.00
Revenue	51.58	75.77	8.50	65.12
Operating Profit Margin	14.68	20.63	7.00	24.92
Leverage	36.25	16.87	26.24	45.90
N	1865			

Variable summary statistics are shown for the 180 CRSP ETFs and 35 Bloomberg ETFs, for both secondary market (SM) holdings and primary market (PM) transactions where CO2 Intensity is available. Mean, standard deviation (SD), 25th percentile (p25), and 75th percentile (p75) is calculated for 2016–2020.

Appendix D. Sub-sample analysis

Table D.1

Subsample analysis - investment grade bonds.

	CRSP ETFs		Bloomberg ETFs			
	SM ETF Share		SM ETF Share		PM ETF Share	
	1	2	3	4	5	6
CO2 Intensity	−0.0000465 (0.0000387)	0.000451*** (0.000134)	−0.00000509 (0.0000327)	0.000265*** (0.0000790)	0.0000113 (0.0000279)	0.000301** (0.000131)
Issue Size	0.247** (0.0974)	0.125* (0.0719)	0.292*** (0.0868)	0.165** (0.0658)	−0.111** (0.0542)	−0.0637 (0.0763)
Coupon	−0.543*** (0.0324)	−0.551*** (0.0387)	−0.202*** (0.0156)	−0.209*** (0.0187)	−0.189*** (0.0530)	−0.195*** (0.0699)
Callable	0.339*** (0.0870)	0.451*** (0.107)	0.0763 (0.0499)	0.130** (0.0535)	−0.375*** (0.0858)	−0.440*** (0.105)
Time to Maturity	−0.0912*** (0.00580)	−0.0882*** (0.00657)	−0.0194*** (0.00184)	−0.0176*** (0.00201)	−0.00854*** (0.00305)	−0.00493 (0.00397)
Rating Score	−0.0620*** (0.0194)	−0.176*** (0.0573)	−0.0124 (0.0132)	−0.0563* (0.0297)	−0.0215 (0.0167)	0.114 (0.0844)
Revenue	0.00200*** (0.000600)	0.00139 (0.00188)	0.00143*** (0.000494)	0.000128 (0.000875)	0.00129*** (0.000495)	0.00760* (0.00429)
Operating Profit Margin	0.00172 (0.00238)	0.00225 (0.00256)	0.000274 (0.00148)	0.00158 (0.00143)	0.00100 (0.00197)	−0.00301 (0.00507)
Leverage	0.00140 (0.00233)	−0.0000219 (0.00563)	0.00184 (0.00168)	0.00602* (0.00320)	0.000367 (0.00200)	0.00244 (0.00822)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Issuer FE	No	Yes	No	Yes	No	Yes
Adjusted R ²	0.424	0.488	0.276	0.410	0.128	0.268
N	12,136	12,136	11,610	11,610	1701	1701

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$ denote statistical significance at the 10%, 5% and 1% level, respectively. Standard errors clustered at the issuer level are shown in parentheses. Regressions are limited to investment grade (IG) bonds. Specifications 1–2 apply to bonds held by the 180 CRSP ETFs. Specifications 3–4 apply to bonds held by the 35 Bloomberg ETFs. Secondary Market (SM) ETF Share represents the percentage of a bond outstanding held by the ETFs, while Primary Market (PM) ETF Share represents the proportion purchased by ETFs in the sample. All specifications apply to 2016–2020.

Table D.2

Subsample analysis - high yield bonds.

	CRSP ETFs		Bloomberg ETFs			
	SM ETF share		SM ETF share		PM ETF share	
	1	2	3	4	5	6
CO2 Intensity	0.0000772 (0.0000588)	0.0000638 (0.000137)	−0.0000127 (0.0000623)	0.000313* (0.000162)	0.000125** (0.0000541)	0.000653* (0.000392)
Issue Size	1.191*** (0.322)	0.592* (0.319)	1.413*** (0.374)	0.742** (0.360)	−0.230 (0.188)	−0.494 (0.330)
Coupon	−0.308*** (0.0925)	−0.173** (0.0871)	−0.156* (0.0885)	−0.113 (0.0945)	−0.106 (0.0774)	−0.320** (0.134)
Callable	0.0164 (0.278)	1.182*** (0.314)	0.220 (0.297)	1.302*** (0.347)	−0.765* (0.422)	−0.212 (0.402)
Time to Maturity	−0.161*** (0.0204)	−0.179*** (0.0214)	−0.233*** (0.0180)	−0.210*** (0.0248)	−0.0562* (0.0300)	−0.0243 (0.0351)
Rating Score	0.323*** (0.0681)	0.144** (0.0680)	0.244*** (0.0758)	0.0754 (0.0723)	−0.0352 (0.0972)	0.0147 (0.224)
Revenue	0.000188 (0.00639)	−0.00606 (0.00869)	−0.00680 (0.00861)	0.00400 (0.0171)	0.00138 (0.00411)	0.0738 (0.105)
Operating Profit Margin	−0.0141*** (0.00489)	−0.0102*** (0.00333)	−0.000129 (0.00350)	0.00291 (0.00676)	−0.00476 (0.00458)	−0.0369 (0.0358)
Leverage	0.00435* (0.00253)	0.0215*** (0.00617)	0.00125 (0.00297)	0.0180** (0.00867)	0.00176 (0.00365)	0.0401 (0.0405)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Issuer FE	No	Yes	No	Yes	No	Yes
Adjusted R ²	0.363	0.612	0.319	0.580	0.0514	0.162
N	1089	1089	989	989	164	164

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$ denote statistical significance at the 10%, 5% and 1% level, respectively. Standard errors clustered at the issuer level are shown in parentheses. Regressions are limited to high yield (HY) bonds. Specifications 1–2 apply to bonds held by the 180 CRSP ETFs. Specifications 3–4 apply to bonds held by the 35 Bloomberg ETFs. Secondary Market (SM) ETF Share represents the percentage of a bond outstanding held by the ETFs, while Primary Market (PM) ETF Share represents the proportion purchased by ETFs in the sample. All specifications apply to 2016–2020.

Table D.3

Subsample analysis - carbon-intensive sectors.

	CRSP ETFs		Bloomberg ETFs			
	SM ETF share		SM ETF share		PM ETF share	
	1	2	3	4	5	6
CO2 Intensity	0.0000583 (0.0000375)	0.000343*** (0.0000964)	0.0000786* (0.0000466)	0.000324*** (0.0000719)	0.0000578** (0.0000259)	0.000426*** (0.000126)
Issue Size	0.704*** (0.180)	0.565*** (0.156)	0.844*** (0.135)	0.607*** (0.113)	-0.257*** (0.0755)	-0.00387 (0.106)
Coupon	-0.541*** (0.0510)	-0.478*** (0.0717)	-0.136*** (0.0371)	-0.145*** (0.0363)	-0.0182 (0.0510)	-0.186** (0.0785)
Callable	0.366** (0.161)	0.614*** (0.210)	0.298** (0.124)	0.254** (0.104)	-0.629*** (0.154)	-0.438*** (0.159)
Time to Maturity	-0.0808*** (0.0110)	-0.0879*** (0.0141)	-0.0340*** (0.00440)	-0.0271*** (0.00399)	-0.0174*** (0.00390)	-0.00928** (0.00422)
Rating Score	0.0235 (0.0357)	-0.156** (0.0754)	-0.228*** (0.0373)	-0.0875* (0.0448)	-0.0476 (0.0307)	-0.0119 (0.105)
Revenue	-0.000240 (0.00183)	0.00823 (0.00509)	0.00501** (0.00237)	0.00100 (0.00229)	0.00196 (0.00166)	0.0146* (0.00761)
Operating Profit Margin	-0.00786** (0.00331)	-0.00509 (0.00421)	-0.00372 (0.00258)	-0.00168 (0.00289)	-0.00481 (0.00361)	-0.00992 (0.00621)
Leverage	-0.0000297 (0.00455)	-0.00179 (0.00817)	0.00360 (0.00577)	-0.00426 (0.00540)	0.00434 (0.00449)	-0.0160 (0.0129)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Issuer FE	No	Yes	No	Yes	No	Yes
Adjusted R ²	0.378	0.469	0.311	0.551	0.158	0.343
N	4496	4496	4240	4240	671	671

*p < 0.10, ** p < 0.05, *** p < 0.01 denote statistical significance at the 10%, 5% and 1% level, respectively. Standard errors clustered at the issuer level are shown in parentheses. Regressions are limited to bonds issued by companies in TRBC Activities falling within scope of IPCC carbon-intensive sectors shown in Appendix A. Specifications 1–2 apply to bonds held by the 180 CRSP ETFs. Specifications 3–4 apply to bonds held by the 35 Bloomberg ETFs. Secondary Market (SM) ETF Share represents the percentage of a bond outstanding held by the ETFs, while Primary Market (PM) ETF Share represents the proportion purchased by ETFs in the sample. All specifications apply to 2016–2020.

Table D.4

Subsample analysis - fossil fuel sectors.

	CRSP ETFs		Bloomberg ETFs			
	SM ETF Share		SM ETF Share		PM ETF Share	
	1	2	3	4	5	6
CO2 Intensity	-0.0000410 (0.0000514)	0.000153 (0.000116)	0.0000616 (0.0000692)	0.000223*** (0.0000778)	0.0000221 (0.0000466)	0.000535*** (0.000147)
Issue Size	0.680*** (0.183)	0.834*** (0.270)	0.905*** (0.156)	0.829*** (0.199)	-0.509*** (0.148)	-0.279** (0.161)
Coupon	-0.441*** (0.0780)	-0.267** (0.103)	-0.0752 (0.0762)	-0.0953 (0.0731)	-0.0228 (0.0838)	-0.304** (0.113)
Callable	0.538** (0.220)	1.073*** (0.247)	0.639*** (0.195)	0.367** (0.179)	-0.613*** (0.198)	-0.539** (0.246)
Time to Maturity	-0.0953*** (0.00829)	-0.113*** (0.0103)	-0.0412*** (0.00817)	-0.0303*** (0.00712)	-0.0220** (0.00826)	0.00370 (0.00725)
Rating Score	-0.0227 (0.0613)	-0.234** (0.0918)	-0.242*** (0.0573)	-0.149 (0.0935)	-0.0361 (0.0463)	-0.108 (0.134)
Revenue	-0.00149 (0.00231)	0.000865 (0.00219)	0.00436* (0.00233)	-0.000932 (0.00199)	0.00475*** (0.00174)	0.0157** (0.00655)
Operating Profit Margin	-0.00648 (0.00451)	-0.00782* (0.00461)	-0.00414 (0.00370)	-0.00261 (0.00343)	-0.00599 (0.00581)	0.00725 (0.00967)
Leverage	-0.0122 (0.0101)	0.0139 (0.0125)	-0.0102 (0.0107)	0.00493 (0.0120)	0.0135 (0.00847)	-0.0327 (0.0255)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Issuer FE	No	Yes	No	Yes	No	Yes
Adjusted R ²	0.392	0.471	0.322	0.524	0.172	0.371
N	1423	1423	1366	1366	222	222

*p < 0.10, ** p < 0.05, *** p < 0.01 denote statistical significance at the 10%, 5% and 1% level, respectively. Standard errors clustered at the issuer level are shown in parentheses. Regressions are limited to bonds issued by companies in TRBC fossil fuel sectors shown in Appendix A. Specifications 1–2 apply to bonds held by the 180 CRSP ETFs. Specifications 3–4 apply to bonds held by the 35 Bloomberg ETFs. Secondary Market (SM) ETF Share represents the percentage of a bond outstanding held by the ETFs, while Primary Market (PM) ETF Share represents the proportion purchased by ETFs in the sample. All specifications apply to 2016–2020.

Table D.5
Subsample analysis - ex-financials.

	CRSP ETFs		Bloomberg ETFs			
	SM ETF share		SM ETF share		PM ETF Share	
	1	2	3	4	5	6
CO2 Intensity	0.0000791 (0.0000353)	0.000381*** (0.000110)	0.0000282 (0.0000530)	0.000279*** (0.0000701)	0.0000533** (0.0000234)	0.000377*** (0.0000883)
Issue Size	0.226** (0.102)	0.124 (0.0792)	0.316** (0.123)	0.180** (0.0788)	-0.121** (0.0587)	-0.0650 (0.0830)
Coupon	-0.538*** (0.0345)	-0.512*** (0.0440)	-0.107*** (0.0283)	-0.167*** (0.0239)	-0.0552 (0.0380)	-0.200*** (0.0715)
Callable	0.412*** (0.0934)	0.586*** (0.117)	0.216*** (0.0817)	0.277*** (0.0644)	-0.572*** (0.0928)	-0.484*** (0.121)
Time to Maturity	-0.0898*** (0.00646)	-0.0936*** (0.00776)	-0.0350*** (0.00306)	-0.0264*** (0.00292)	-0.0137*** (0.00268)	-0.00485 (0.00398)
Rating Score	0.00545 (0.0190)	-0.114** (0.0508)	-0.135*** (0.0290)	-0.107*** (0.0407)	-0.0559*** (0.0171)	0.0283 (0.0825)
Revenue	0.00124** (0.000592)	0.00232 (0.00187)	0.00222*** (0.000707)	0.0000347 (0.00109)	0.00157*** (0.000482)	0.00828** (0.00415)
Operating Profit Margin	-0.00517* (0.00270)	-0.00488* (0.00284)	-0.00336 (0.00206)	-0.00279 (0.00213)	-0.00199 (0.00205)	-0.00594* (0.00310)
Leverage	0.00218 (0.00309)	0.00634 (0.00500)	0.00570* (0.00290)	0.00404 (0.00383)	0.00171 (0.00228)	-0.00186 (0.00928)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Issuer FE	No	Yes	No	Yes	No	Yes
Adjusted R ²	0.406	0.486	0.225	0.511	0.120	0.296
N	10,839	10,839	10,276	10,276	1603	1603

*p < 0.10, **p < 0.05, ***p < 0.01 denote statistical significance at the 10%, 5% and 1% level, respectively. Standard errors clustered at the issuer level are shown in parentheses. Regressions are limited to bonds in the Financials TRBC Economic Sector. Specifications 1–2 apply to bonds held by the 180 CRSP ETFs. Specifications 3–4 apply to bonds held by the 35 Bloomberg ETFs. Secondary Market (SM) ETF Share represents the percentage of a bond outstanding held by the ETFs, while Primary Market (PM) ETF Share represents the proportion purchased by ETFs in the sample. All specifications apply to 2016–2020.

Appendix E. Robustness tests

E.1. Heckman selection model

The Heckman Selection Model is used to control for selection bias when carbon emissions are not disclosed. In the first stage “selection equation”, a probit regression is used to estimate the probability that carbon emissions are disclosed. In this stage, the bond and issuer-level control variables from Eq. (12) are used with year and sector fixed effects. For the dependent variable, a dummy variable is used equal to 1 when emissions are disclosed and zero otherwise. The Heckman Correction Factor, known as the Inverse Mills Ratio (IMR) is then calculated, representing the probability of disclosure. In the second stage “outcome equation”, the IMR is included in the original OLS model shown in Eq. (12) as an additional explanatory variable within X, first with only year fixed effects, and second with year and firm fixed effects. As the IMR incorporates information from the full sample, including firms that do and do not disclose, we can control for the likelihood of carbon emission disclosure. Results from the second stage are shown in Table E.1, with the Mills Ratio statistically significant only in specification 2 at the 10% level. CO2 Intensity remains significant across specifications with issuer fixed effects, and also for PM ETF Share with time fixed effects. These results are consistent with results from the original specification shown in Table 4, indicating that endogenous sample selection in emissions does not affect results.

E.2. Two-part model

The Two-Part model is used to control for selection bias within ETF Share. In the first part, a probit model predicts the probability of ETF Share being non-zero, using control variables from Eq. (12) and year fixed effects. In the second part, an OLS regression predicts the level of the dependent variable conditional on it being greater than zero (Belotti et al., 2015), using the original specification in Eq. (12), first with year fixed effects, and second with year and issuer fixed effects. In line with Cohen et al. (2020) and Faddy (2019), who use two-part models to address selection bias in energy investment, the results are shown as marginal effects combining both model parts. Marginal effects are interpreted as the effect of a change in explanatory variables on the probability that ETF Share is non-zero and the level of ETF Share given it is non-zero. These marginal effects are tabulated in Table E.2, with results consistent with the original specification shown in Table 4.

E.3. Propensity score matching

To account for potential endogeneity within explanatory variables, propensity score matching is used. Propensity scores are calculated via a probit model using control variables from the original specification Eq. (12), with the dependent variable equal to 1 for the treatment group and 0 for the control group. The treatment and control samples are generated by taking bonds with carbon intensity in the top 66th and bottom 33rd percentile respectively, by TRBC Economic Sector and year. Propensity scores provide a single number, between 0 and 1, indicating the probability that a bond is in the treatment group. Using these scores, matching between treatment and control groups is performed, within the same year and sector, using

Nearest Neighbour Matching with common support restrictions. After matching on propensity scores, the sample size is reduced by approximately 50%. The OLS specification in Eq. (12) is then run on the matched sample, first with only year fixed effects, and then with year and issuer fixed effects. Results are consistent with the original specification, showing a significant relationship between CO2 Intensity and SM ETF Share at the 5% level and for PM ETF Share at the 1% level with issuer fixed effects.

Table E.1

Selection bias in carbon intensity disclosure - Heckman selection model.

	CRSP ETFs		Bloomberg ETFs			
	SM ETF Share		SM ETF Share		PM ETF Share	
	1	2	3	4	5	6
CO2 Intensity	0.0000172 (0.0000338)	0.000490*** (0.0000999)	0.0000107 (0.0000526)	0.000335*** (0.0000731)	0.0000465* (0.0000261)	0.000395*** (0.0000819)
Mills Ratio	−0.274 (0.226)	−1.173* (0.663)	−0.00982 (0.250)	−0.823 (0.578)	0.0336 (0.185)	−0.247 (0.745)
Issue Size	0.266** (0.105)	0.0977 (0.0795)	0.338*** (0.113)	0.149** (0.0715)	−0.124** (0.0552)	−0.101 (0.0820)
Coupon	−0.517*** (0.0307)	−0.481*** (0.0416)	−0.115*** (0.0236)	−0.154*** (0.0237)	−0.0575 (0.0382)	−0.175*** (0.0675)
Callable	0.376*** (0.0893)	0.639*** (0.134)	0.183** (0.0786)	0.323*** (0.0859)	−0.452*** (0.0781)	−0.414*** (0.130)
Time to Maturity	−0.0936*** (0.00586)	−0.0973*** (0.00763)	−0.0333*** (0.00302)	−0.0274*** (0.00365)	−0.0156*** (0.00289)	−0.00701 (0.00517)
Rating Score	−0.0109 (0.0189)	−0.223*** (0.0555)	−0.138*** (0.0279)	−0.168*** (0.0390)	−0.0473*** (0.0181)	0.0213 (0.0846)
Revenue	0.00103* (0.000625)	0.00226 (0.00197)	0.00203*** (0.000671)	0.000287 (0.00111)	0.00152*** (0.000466)	0.00731* (0.00431)
Operating Profit Margin	−0.00349 (0.00256)	−0.00164 (0.00287)	−0.00255 (0.00189)	−0.00110 (0.00210)	−0.00185 (0.00193)	−0.00427 (0.00336)
Leverage	0.000109 (0.00220)	0.00295 (0.00484)	0.00371* (0.00198)	0.00284 (0.00349)	0.00174 (0.00190)	−0.0000499 (0.00840)
1st Step: Pseudo R ²	0.209	0.209	0.209	0.209	0.209	0.209
1st Step: N	25,323	25,323	25,323	25,323	25,323	25,323
2st Step: Year FE	Yes	Yes	Yes	Yes	Yes	Yes
2st Step: Issuer FE	No	Yes	No	Yes	No	Yes
2st Step: Adjusted R ²	0.409	0.491	0.231	0.508	0.108	0.289
2st Step: N	13,225	13,225	12,599	12,599	1865	1865

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$ denote statistical significance at the 10%, 5% and 1% level, respectively. Standard errors clustered at the issuer level are shown in parentheses. In the first stage, the Mills Ratio is calculated from a probit model, regressing the control variables with year and sector fixed effects on a dummy variable equal to 1 when CO2 emissions are disclosed. In the second stage, the Mills Ratio is included in the original specification. For brevity, regression coefficients and standard errors are only shown for the second stage. Specifications 1–2 apply to bonds held by the 180 CRSP ETFs. Specifications 3–4 apply to bonds held by the 35 Bloomberg ETFs. Secondary Market (SM) ETF Share represents the percentage of a bond outstanding held by the ETFs, while Primary Market (PM) ETF Share represents the proportion purchased by ETFs in the sample. All specifications apply to 2016–2020.

Table E.2

Selection bias in ETF share - two-part model.

	CRSP ETFs		Bloomberg ETFs			
	SM ETF Share		SM ETF Share		PM ETF Share	
	1	2	3	4	5	6
CO2 Intensity	0.000000373 (0.0000260)	0.000346*** (0.0000789)	0.00000779 (0.0000391)	0.000225*** (0.0000503)	0.00000571** (0.00000269)	0.0000450*** (0.0000100)
Issue Size	0.573*** (0.124)	0.448*** (0.110)	0.421*** (0.0878)	0.295*** (0.0641)	0.00470 (0.00835)	0.00593 (0.00988)
Coupon	−0.589*** (0.0279)	−0.573*** (0.0334)	−0.173*** (0.0185)	−0.217*** (0.0170)	−0.0563*** (0.00585)	−0.0627*** (0.00786)
Callable	0.541*** (0.0866)	0.685*** (0.0995)	0.272*** (0.0599)	0.314*** (0.0519)	0.0462*** (0.0114)	0.0310** (0.0144)
Time to Maturity	−0.0789*** (0.00500)	−0.0790*** (0.00576)	−0.0274*** (0.00238)	−0.0201*** (0.00223)	0.000587 (0.000409)	0.00134*** (0.000485)
Rating Score	0.0605*** (0.0173)	−0.0774* (0.0418)	−0.0747*** (0.0206)	−0.0691** (0.0303)	−0.0124*** (0.00249)	−0.00143 (0.00911)
Revenue	0.000147 (0.000819)	0.000554 (0.00166)	0.00118** (0.000594)	−0.000470 (0.000882)	0.000131 (0.000827)	0.000802 (0.000512)
Operating Profit Margin	−0.00367 (0.00225)	−0.00352 (0.00241)	−0.00218 (0.00150)	−0.00196 (0.00162)	−0.000386 (0.000268)	−0.000685* (0.000394)
Leverage	0.00362* (0.00219)	0.00623 (0.00423)	0.00466*** (0.00162)	0.00417 (0.00286)	0.000677** (0.000278)	0.000397 (0.000991)
1st Part: Pseudo R ²	0.168	0.168	0.178	0.178	0.128	0.128
1st Part: N	25,323	25,323	25,323	25,323	25,323	25,323
2st Part: Year FE	Yes	Yes	Yes	Yes	Yes	Yes
2st Part: Issuer FE	No	Yes	No	Yes	No	Yes

(continued on next page)

Table E.2 (continued)

	CRSP ETFs		Bloomberg ETFs			
	SM ETF Share		SM ETF Share		PM ETF Share	
	1	2	3	4	5	6
2st Part: Adjusted R ²	0.409	0.491	0.231	0.508	0.109	0.289
2st Part: N	13,225	13,225	12,599	12,599	1865	1865

*p < 0.10, ** p < 0.05, *** p < 0.01 denote statistical significance at the 10%, 5% and 1% level, respectively. Standard errors clustered at the issuer level are shown in parentheses. Following a two-part model, in the first part, a probit model is used to predict ETF Share being non-zero. In the second part, an OLS regression is used to predict the level of ETF Share, contingent on it being above zero. Marginal effects are then calculated, with coefficients and standard errors shown above. Coefficients and standard errors from the first two parts are not shown for brevity. Specifications 1–2 apply to bonds held by the 180 CRSP ETFs. Specifications 3–4 apply to bonds held by the 35 Bloomberg ETFs. Secondary Market (SM) ETF Share represents the percentage of a bond outstanding held by the ETFs, while Primary Market (PM) ETF Share represents the proportion purchased by ETFs in the sample. All specifications apply to 2016–2020.

Table E.3

Propensity score matching - carbon intensity 66th percentile.

	CRSP ETFs		Bloomberg ETFs			
	SM ETF share		SM ETF share		PM ETF share	
	1	2	3	4	5	6
CO2 Intensity	0.0000530 (0.0000327)	0.000457** (0.000193)	0.0000280 (0.0000606)	0.000298** (0.000129)	0.0000548** (0.0000246)	0.000462*** (0.000163)
Issue Size	0.337*** (0.100)	0.253** (0.127)	0.388*** (0.0766)	0.247*** (0.0634)	−0.133** (0.0622)	−0.236*** (0.0883)
Coupon	−0.537*** (0.0469)	−0.529*** (0.0626)	−0.124*** (0.0292)	−0.155*** (0.0287)	0.00633 (0.0510)	−0.0466 (0.0841)
Callable	0.426*** (0.125)	0.554*** (0.160)	0.141 (0.0928)	0.389*** (0.0828)	−0.440*** (0.122)	−0.385** (0.155)
Time to Maturity	−0.0884*** (0.0113)	−0.0867*** (0.0132)	−0.0336*** (0.00393)	−0.0277*** (0.00455)	−0.0177*** (0.00388)	−0.0129*** (0.00464)
Rating Score	0.0179 (0.0297)	−0.211*** (0.0627)	−0.197*** (0.0331)	−0.152*** (0.0566)	−0.0230 (0.0287)	0.115 (0.134)
Revenue	0.00174 (0.00114)	−0.000257 (0.00454)	0.00101 (0.000968)	−0.000712 (0.00254)	0.00139 (0.000898)	0.00457 (0.0119)
Operating Profit Margin	−0.00734** (0.00368)	−0.00320 (0.00403)	−0.00269 (0.00225)	−0.00252 (0.00254)	−0.00298 (0.00279)	−0.00157 (0.00415)
Leverage	0.000600 (0.00295)	0.0136* (0.00785)	0.00319 (0.00294)	0.0136** (0.00667)	0.00241 (0.00309)	0.0133 (0.0151)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Issuer FE	No	Yes	No	Yes	No	Yes
Adjusted R ²	0.405	0.493	0.248	0.504	0.113	0.267
N	5709	5709	5436	5436	818	818

*p < 0.10, ** p < 0.05, *** p < 0.01 denote statistical significance at the 10%, 5% and 1% level, respectively. Standard errors clustered at the issuer level are shown in parentheses. Treatment and control groups are generated based on the 66th and 33rd percentile of CO2 Intensity by year and sector. Propensity scores are calculated for CO2 Intensity using control variables. Matching on these scores between the treatment and control groups is conducted using Nearest Neighbour Matching with the common support restriction. Specifications 1–2 apply to bonds held by the 180 CRSP ETFs. Specifications 3–4 apply to bonds held by the 35 Bloomberg ETFs. Secondary Market (SM) ETF Share represents the percentage of a bond outstanding held by the ETFs, while Primary Market (PM) ETF Share represents the proportion purchased by ETFs in the sample. All specifications apply to 2016–2020.

Appendix F. Regression on Bloomberg ETF secondary market metrics

Table F.1

Determinants of secondary market metrics – Bloomberg ETFs.

	Secondary market carbon exposure (SMCE)		Secondary market carbon intensity (SMCI)	
	Fossil fuels	Carbon-intensive	Fossil fuels	Carbon-intensive
	1	2	3	4
Bond Rating Score	−0.711*** (0.250)	−1.991*** (0.367)	−164.6*** (30.11)	−67.57*** (12.20)
Bond Issue Size	−1.501 (3.705)	−6.654 (5.372)	151.8 (266.9)	93.77 (133.8)
Bond Time to Maturity	0.448*** (0.0667)	0.715*** (0.0937)	−1.094 (5.164)	−1.889 (2.224)
AUM	0.00683 (0.0303)	0.0166 (0.0386)	−0.220 (1.771)	−0.110 (0.820)
N Holdings	−0.262 (0.240)	−0.327 (0.399)	59.73* (29.66)	21.02* (12.30)
Year FE	Yes	Yes	Yes	Yes
Adjusted R ²	0.552	0.800	0.506	0.570
N	166	166	138	138

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$ denote statistical significance at the 10%, 5% and 1% level, respectively. Standard errors clustered at the ETF level are shown in parentheses. Bond Issue Size, Rating Score and Time to Maturity are calculated as a portfolio weighted average. AUM represents assets under management and N Holdings represents the number of corporate bond holdings. Specifications 1–2 show regressions of ETF characteristics on SMCE metrics for Fossil Fuel and Carbon-Intensive sector groups for 2016–2021. Specifications 3–4 show regressions of ETF characteristics on SMC metrics for 2016–2020. All specifications apply to ETFs from Bloomberg. In addition to fossil fuel energy, Carbon-Intensive includes activities within transport, buildings, and industry as defined in Appendix A.

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