ESG and bond market resilience: Evidence from the Covid crisis

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Abstract

We document a decline in CDS-bond basis and lower selling pressure during the COVID crisis for bonds issued by firms with high environmental and social (E&S) scores relative to bonds issued by low E&S firms. Bonds of high E&S firms experience lower selling pressure due to lower investor outflows from sustainability focused funds rather than fund managers discriminating among which bonds to sell. Our results highlight how the performance of bonds during a crisis is influenced not only by shifts in firm fundamentals but also by investor trading behavior and net flows into mutual funds.

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1. Introduction

The Covid-19 crisis has drawn further attention to the relevance of environmental and social (E&S) factors in investors' performance. Several studies show that high E&S firms suffered lower equity losses (see, for example, Albuquerque, Koskinen, and Santioni, 2020; Ding, Levine, Lin, and Xie, 2021; Mahmoud and Meyer, 2020). There has also been a tremendous increase in net flows into sustainable equity funds[1] consistent with investment performance being a key driver for investing in sustainability (Amel-Zadeh and Serafeim, 2018). However, there is limited evidence on how a firm's E&S scores impacted its bond market returns during the Covid-19 crisis. In this paper, we show that bonds of high E&S firms experienced lower losses and lower selling pressure than bonds issued by low E&S firms. This was mainly due to the lower investor outflows experienced by sustainability-focused funds.

While investment outperformance generates demand for sustainable investments, it is not yet clear what drives this outperformance. In this paper, we study the pricing of bonds during the outbreak of the Covid-19 crisis. We evaluate whether and why there were pricing discrepancies among bonds with different E&S scores.[2] The relative performance of stocks based on E&S status during crises and, in particular, during the Covid-19 crisis is well-studied (e.g., Albuquerque, Koskinen, and Santioni, 2020; Bae, El Ghoul, Gond, and Guedhami, 2021; Cheema-Fox, LaPerla, Serafeim, and Wang, 2021). However, the relative performance of bonds is understudied.[3]

We find that the widening of bond spreads during the Covid-19 crisis was mitigated for high E&S firms not only due to a lower increase in default risk for these firms but also due to factors beyond shifts in firm fundamentals. Bonds of issuers with low E&S scores were exposed to greater selling pressure and, therefore, E&S status may have possibly acted as a selective factor in their decision as to which assets to sell for liquidity, thereby likely contributing to the underperformance of bonds with low E&S scores. Finally, studying bond market responses during the Covid-19 outbreak provides us with the ideal set up to evaluate whether non-fundamental market factors drive the performance of bonds.

We use daily prices of bonds for a significant fraction of U.S. firms with bonds outstanding during the period from January to August 2020. We evaluate the relation between

[1] Hale, J. (2021) "A Broken Record: Flows for U.S. Sustainable Funds Again Reach New Heights". *Morningstar*. See also, Hale, J. (2020). "Despite the Downturn, U.S. Sustainable Funds Notch a Record Quarter for Flows". *Morningstar*.

[2] We focus on E&S as they are likely to channel stakeholder responses to a shock more cleanly than G.

[3] An exception is Amiraslani, Lins, Servaes, and Tamayo (2023) who attribute lower bond spreads enjoyed by high E&S firms during the 2008 crisis to social capital, and the trust that comes with, because it moderates default risk.

credit spreads (computed relative to treasury yields) and firm E&S scores using the Refinitiv ESG (formerly ASSET4) database. We estimate difference-in-differences regressions with continuous treatment using the Covid-19 outbreak as an exogenous shock. This strategy allows us to provide causal evidence on the role of sustainability on bond performance. For identification, we use E&S scores before the unexpected outbreak and add the battery of controls that are standard determinants of credit spreads.[4] In alternative specifications, we also consider firm and day fixed effects to control for other unobservable variables and to rule out that our results are due to, for example, more attractive firms or firms with more capable managers investing more in E&S and, therefore, better during the crisis.

We document that credit spreads increased substantially after the Covid-19 outbreak, but the increase was moderate for more sustainable firms. A one standard deviation higher E&S score was associated with 28 basis points lower credit spreads during the Covid-19 period. The lower expansion of credit spreads for high E&S firms translates into a lower price drop and return outperformance *vis-à-vis* low E&S firms. This result is consistent with the findings of Amiraslani, Lins, Servaes, and Tamayo (2023) who estimate a similar model around the 2008 financial crisis. Further, this result also confirms the narrative of investment professionals, although it does not inform us about possible channels that may lead to return discrepancies.

Why would the E&S status of a bond serve as a mitigating factor during a crisis in general or during the Covid-19 outbreak in particular? Amiraslani, Lins, Servaes, and Tamayo (2023) examine one potential mechanism. They argue that high E&S scores mitigate increases in fundamental default risk. In contrast, we delve into an alternative channel explaining why firms with high E&S scores experienced a lower expansion of credit spreads during the Covid-19 crisis as compared to firms with lower E&S scores. The crisis represents a shock to default risk, leading to an increase in credit spreads, but it also represents a shock to investors' asset holdings as it triggers a demand for liquidity and the need to rebalance portfolios (Haddad, Moreira, and Muir, 2021; Falato, Goldstein, and Hortaçsu, 2021).[5] In such a context, pure investor preferences could also explain the positive relation between high E&S firms and moderated increases in credit spreads. Pure investor preferences for high E&S bonds could trigger a discriminated sale of low E&S bonds, as investors become selective in what assets to keep. This behavior, in turn, would put significant downward pressure on prices of low E&S

[4] To deal with endogeneity concerns, we use pre-crisis levels of E&S scores as it is unlikely that firms chose E&S level in anticipation of the Covid-19 crisis.
[5] Halling, Yu, and Zechner (2021) explain that ESG scores can also provide information about extra demand from investors with socially responsible preferences well beyond a context of crisis.

bonds, leading to increases in credit spreads. This highlights a selling pressure channel through which E&S scores can impact credit spreads and, consequently, bond performance.

To distinguish whether the differential evolution of bond spreads – depending on E&S status – is driven by selling pressure beyond worsening firm fundamentals, we estimate the CDS-bond basis. The CDS-bond basis, computed as the difference between the CDS spread and the credit spread, proxies for the non-default component in credit spreads (Longstaff, Mithal, and Neis, 2005). To understand the role of selling pressure, we then study the relationship between the CDS-bond basis and the firm's E&S score. Empirical evidence shows that the CDS-bond basis was significantly negative during the Covid-19 outbreak as well as during the global financial crisis (GFC) of 2008 (Fontana, 2012; Bai and Collin-Dufresne, 2018). This means that credit spreads were significantly larger than the corresponding CDS spreads. Various studies attribute this negative basis to selling pressure by financial institutions that were pushed to sell off their bond holdings (Augustin, Subrahmanyam, Tang, and Wang, 2014; Haddad, Moreira, and Muir, 2021). Thus, the analysis of the CDS-bond basis and its relationship to E&S scores can inform us about the role of selling pressure on the outperformance of high E&S bonds during our period of study.

We find that E&S scores are significantly related to the CDS-bond basis during the Covid-19 crisis, suggesting that bonds of issuers with low E&S ratings were exposed to greater selling pressure. This finding is consistent with E&S scores acting as a selective factor in the decision of institutional investors on which assets to sell for liquidity. Thus, the outperformance of portfolios with high E&S is not only driven by moderated increases in default risk but also by moderated selling pressure. We also evaluate the role of selling pressure more directly and study mutual fund trading behavior (Falato, Goldstein, and Hortaçsu, 2021; Haddad, Moreira, and Muir, 2021; Ma, Xiao, and Zeng, 2022). We collect mutual funds' monthly bond holdings to build two different bond-level measures of selling pressure. We then analyze selling pressure during March of 2020 for high and low E&S bonds. Consistent with the CDS-bond basis results, we show that low E&S predicts selling pressure as lower E&S bonds face larger selloffs. We then explore the trigger for these selloffs. On one hand, ultimate investors may be selective over which funds to sell and prefer to redeem from less sustainable funds which have a greater proportion of low E&S bond holdings. As such, we could expect low E&S bonds to face greater selling pressure and expansion of credit spreads. Alternatively, to cater to client preferences, mutual fund managers could selectively sell, to a larger extent, those bond holdings with lower E&S scores. We provide some evidence that funds with greater exposure to sustainability risks (higher scores) experienced larger redemptions (or lower net flows). This finding is consistent with ultimate investors selecting to redeem from less sustainable mutual funds. In contrast, we do not find evidence that fund managers were more likely to sell low E&S bonds as compared to high E&S bonds to meet investors' redemptions. In sum, we show that bonds of high E&S firms experience lower selling pressure due to lower investor outflows from sustainability-focused funds rather than as a consequence of fund managers discriminating as to which bonds to sell. Additional tests show that these results are not due to the presence of a specific type of investor in the mutual fund investors' base. Finally, placebo tests confirm that the differential performance of high ES bonds was a unique response to the Covid-19 shock.

This paper contributes to the growing literature that examines firm resilience to the 2020 Covid-19 pandemic and, more precisely, how it correlates with firm E&S scores. While existing studies (Albuquerque, Koskinen, and Santioni, 2023; Albuquerque, Koskinen, Yang, and Zhang, 2020; Demers, Hendrikse, Joos, and Lev, 2021) focus on stock market responses to the pandemic, our work is the first to evaluate whether bond market responses do indeed correlate with firm E&S status, thereby shielding investors from greater losses.[6,7] We show that the moderating role of E&S scores during the Covid-19 crisis in bond markets is related not only to moderated increases in default risk but also to the trading activity of institutional investors. If trading activity is also significantly correlated to E&S scores in stock markets (Albuquerque, Koskinen, and Santioni, 2023), then there is an omitted factor in the studies of Albuquerque, Koskinen, Yang, and Zhang (2020) and Lins, Servaes, and Tamayo (2017), who look at stock market resilience during the 2008 GFC.

Second, we contribute to studies that examine whether E&S matters in bond markets.[8] Our paper is closely related to Amiraslani, Lins, Servaes, and Tamayo (2023) who show that E&S status does not matter for credit spreads during normal times, yet it does during the 2008 crisis when firms with high E&S scores benefited from lower spreads. They attribute this finding to the firm's social capital and the role it plays during a crisis of trust mitigating default risk but overlook the possible impact of trading activity on bond spreads. We complement their

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[6] Other studies (Ramelli and Wagner, 2020; Gormsen and Koijen, 2020; Ohana, Ohana, Benhamou, Saltiel, and Guez, 2022 among others) examine more broadly stock market responses to the pandemic.

[7] Studies on stock markets attribute superior returns of sustainable firms during crises to stronger relations with stakeholders (customers, investors) and stronger fundamentals. For example, Albuquerque, Koskinen, Yang, and Zhang (2020) suggest that socially responsible companies have greater customer (advertising expenditures) loyalty while Demers, Hendrikse, Joos and Lev (2021) explain that stronger firm fundamentals were responsible for high ESG firm outperformance. In addition, Albuquerque, Koskinen, and Santioni (2023) suggest that mutual fund price pressure also played a role. For the GFC of 2008, Lins, Servaes, and Tamayo (2017) show that CSR helped to build trust between companies and a wide range of stakeholders.

[8] Menz (2010) and Stellner, Klein, and Zwergel (2015) examine whether ESG matters in bond markets. Other studies look at the cost of debt and firm social & environmental status: Chava (2014), Goss and Roberts (2011), Jiraporn, Jiraporn, Boeprasert, and Chang (2014).

work and show that the bond resilience of sustainable firms during the Covid-19 crisis was driven not only by differential exposure to default risk, but also importantly by investor trading activities.

Finally, we contribute more generally to the literature that studies the relationship between long-term portfolio outperformance and E&S status. This literature focuses almost exclusively on the stock market. To a large extent, many papers (Geczy, Stambaugh, and Levin, 2021; Pastor, Stambaugh, and Taylor, 2021; Pedersen, Fitzgibbons, and Pomorski, 2021) show that high ESG portfolio outperformance is mainly driven by better firm outcomes. An exception is Gibson, Krueger, and Mitali (2021) who find, over the long-term, that high E&S portfolio outperformance is explained by price pressure in stock markets resulting from growing investor demand. Our study provides further support for this finding and highlights that price pressure is also a key factor to consider in bond markets in the face of the sustained and growing demand for sustainable assets. It suggests that the outperformance of high E&S bonds due to better firm outcomes may have been overestimated.

The rest of the paper is organized as follows. Section 2 presents the data used in the study and summary statistics. Section 3 describes the methodology and evaluates the relation arising between E&S and credit spreads. Section 4 analyzes the association between E&S and the CDS-bond basis to evaluate the role of selling pressure. Section 5 measures selling pressure directly by looking at the trading activity of mutual funds and relates it to bond E&S scores. Section 6 assesses potential triggers of differential selling pressure observed in bonds issued by firms with varying E&S scores. Finally, section 7 briefly concludes.

2. Data

2.1. Bond-related information

In this study, we focus on fixed-rate USD bonds issued by US public firms and obtain data using different sources. The bond transaction data come from the Enhanced Historic Trade Reporting and Compliance Engine (TRACE) database. TRACE reports all bond transactions conducted by Financial Industry Regulatory Authority (FINRA) member companies starting from July 2002, which makes it the most comprehensive database of fixed income trading activity.

We start with an initial sample of 59’761 bonds which are all active bonds with transactions reported to TRACE. To clean up the data of errors and potential outliers, we follow the filtering process in Dick-Nielsen (2014). As per Dick-Nielsen, Feldhütter, and Lando (2012), we retain bonds traded in public markets and drop private placements (Rule 144A).

Following Campbell and Taksler (2003), we drop bonds with a maturity of less than one year and bonds with special features such as convertible, sinking fund, asset-backed and floating rate characteristics, as well as zero coupon bonds. We further drop bonds issued after December 1, 2019, as well as non-USD bonds.[9] For each bond, we select the daily high, low and trading-volume-weighted price for the period January 1 to August 31, 2020. High and low prices are the maximum and minimum intraday bond prices, respectively. We follow Bessembinder, Kahle, Maxwell, and Xu (2009) and use the trading-volume-weighted intraday bond price as it is less noisy than the end-day price. We download from Datastream a set of bond characteristics such as the coupon, duration, the offering market (domestic vs global), the type of security and the year-to-maturity, etc. All bond-related variables are described in Appendix A (Group 2).

Next, we add firm-level accounting variables as of 2019 from Worldscope and several firm-level, market-level and macroeconomic indicators from Datastream. To filter out outliers, we exclude companies (and the respective bonds) with a total debt-to-assets ratio higher than 1 and an EBITDA-to-sales ratio higher than 1 and lower than -1. To measure risk-free interest rates, we use the US Treasury yield curve estimates of the Federal Reserve Board (FED) at a daily frequency.[10] This data includes the Treasury rates' yields for every whole-year maturity, sequentially covering each year from 1 to 30 without any gaps. The detailed list of variables is presented in Appendix A (Group 1 and Group 3).

We then merge bond data with issuer E&S scores from Refinitiv ESG (formerly ASSET4) database.[11] We focus only on parent companies that are domiciled in the US. Appendix B provides a detailed description of this dataset and of the data we collect. We retain the pre-pandemic E and S scores for each firm. We choose E and S scores of 2019 as pre-pandemic scores for sustainable activities in firms (or 2018 if 2019 scores are not available) and compute the E&S score as the average of the individual scores.[12]

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[9] We keep callable and putable bonds in our final sample as in Bai and Dufresne (2018) as they represent about half of all fixed-rate bonds in the data. Filtering out callable and putable bonds from the sample does not alter our results (see Table OA.1 in the Online Appendix).

[10] The US Treasury yield curve is measured following Gürkaynak, Sack, and Wright (2007) and it is downloaded from https://www.federalreserve.gov/econres/feds/the-us-treasury-yield-curve-1961-to-the-present.htm.

[11] Berg, Kölbel, and Rigobon (2022) show that ESG scores from different providers can disagree substantially. In Table OA.2 in the Online Appendix, we alternatively use firm E&S scores from the S&P database (previously, Trucost) as of 2019. Out of 573 firms with Thomson Reuters E&S scores, we are able to get S&P E&S scores for 546 firms. For our sample firms, there is a correlation of 0.72 between E&S scores of the two providers. Using S&P scores in our tests does not have a bearing on our conclusions.

[12] ASSET4 ESG methodology changes as of April 6, 2020. This change leads to the retroactive rewriting of ESG scores. According to Berg, Fabisik, and Sautner (2021), it can have an impact on the robustness of the results showing a positive link between ESG scores and firms' stock market performance. To examine the possible impact of this change on our results, we use a small sample of firms with E&S scores of 2017&2018 that were downloaded in January 2020 (before the methodology change) and compare them with our E&S scores downloaded in June 2020. We find a correlation of 0.72 between rewritten and initial E&S scores. Using data from January 2020 in our tests though significantly reduces our sample and limits the analysis we can perform.

Finally, we require our sample of bonds to have available data on E and S scores and credit ratings. At this stage, our sample includes 5’079 bonds issued by 587 firms.

2.2. Credit spreads, CDS and the CDS-bond basis

Credit spreads. For each bond, we compute the daily yield-to-maturity using trading-volume-weighted prices. We do not use yields reported in Datastream since many bonds are missing. To compute credit spreads, we use the US Treasury yield curve at daily frequency expressed in terms of par yields. We compute daily credit spreads as the difference between the corporate and Treasury rates. For each day, we choose the Treasury rate that is closest (in maturity) to the duration of the bond.[13] If a corporate bond is equally close to two Treasury rate maturities, then we choose the rate with the lower maturity. To filter out outliers, we eliminated credit spreads in the top-bottom 1% as in Campbell and Taksler (2003). This yields a final sample consisting of 4’959 bonds issued by 573 firms or 461’635 bond-days observations.

Table 1 Panel A provides a step-by-step description of the sample selection process. Table 1 Panel B reports the sample industry composition using the Fama-French industry classification. We observe that 29% of bonds (25% of firms) in our sample belong to firms in the finance industry, followed by manufacturing.

Credit default swaps. In our analysis, we use credit default swap (CDS) spreads; first, to compute the CDS-bond basis as described below and, also, as a direct measure of the market perception of a firm credit risk. We download single-name CDS data from Refinitiv EOD. The database provides CDS composite spreads based on information from over 30 contributors around the world. We obtain daily mid-market CDS quotes in US dollars. Prices are expressed in basis points and refer to a notional of USD 10 mio. We select contracts with a “no restructuring” clause as the US market adopts this restructuring rule after 2009 (ISDA 2014 protocol).[14] The dataset provides a CDS term structure for various maturities. We retain and download 5, 7 and 10-year CDS quotes because five-year contracts correspond to the most liquid segment of the market followed by the 7 and 10-year contracts (see Arakelyan and

[13] We pair a bond with the nearest whole-year maturity of a Treasury rate. For instance, a bond that has a duration of 8.60 years is matched with a 9-year maturity Treasury rate, and a bond with a duration of 8.30 years is matched with an 8-year maturity Treasury rate. In Table OA.3 in the Online Appendix, we use linear interpolation to estimate the benchmark Treasury rate from the term structure. We estimate benchmark Treasury rates for maturities at more specific intervals, such as 8.01, 8.02 years, and so on. This allows us to align a bond's duration with a Treasury rate that has virtually identical maturity. For example, under this method, a bond with a duration of 8.60 years would be matched with a Treasury rate that has a maturity of 8.60 years, rather than rounding it up to 9 years. Using linear interpolation, the results remain unchanged.

[14] The market convention for U.S. CDS restructuring rules has shifted from “modified restructuring” to “no restructuring” clauses as of 2009. Similar to recent studies, we choose CDS with “no restructuring” clauses. This contrasts to earlier studies that select CDS with “modified restructuring” clauses.

Serrano, 2016). To estimate the CDS-bond basis, we focus on 5, 7 and 10-year CDS contracts. This allows us to keep a sizeable sample in our analysis. For the analysis of CDS and credit risk, to minimise the impact of liquidity effects on our tests, we focus on 5yr CDS contracts. 5yr CDS contracts provide us with a point estimate of firm-level default probability for 243 underlying firms at a 5-year horizon.

CDS-bond basis. Our main tests study the relationship arising between the CDS-bond basis and E&S scores. The CDS-bond basis refers to the difference between CDS and bond spreads. To compute the CDS-bond basis, we follow Haddad, Moreira, and Muir (2021) and subtract the credit spread from the closest maturity CDS spread provided that, for a given day, both are non-missing. For that, we use 5, 7 and 10-year CDS contracts and bonds with a duration from 3 to 12 years. For example, the credit spread of a bond with a duration of 8 years is matched with a 7yr CDS rate. When the bond maturity has the same distance as two CDS contracts we match it to the contract with the lowest maturity. The matching is possible for 1'488 bonds, issued by 209 firms or 129'667 bond-days observations.[15]

Table 2 reports the number of observations we use in each test in more detail.

2.3. Summary statistics

Table 3 reports summary statistics for the main and control variables used in our analysis. Appendix A provides a detailed description of each variable and how it is computed. Table 3, Panel A introduces descriptive statistics for corporate bond characteristics that are time-invariant, namely the coupon, global dummy, security ordinal variable, year-to-maturity and credit rating. Most of the bonds in the sample are of a type "senior subordinated unsecured" and are offered globally. They are medium and long-term bonds and have investment-grade credit ratings. The average bond is a 12-year-maturity bond.

Panel B presents statistics for daily credit spreads, CDS spreads, CDS-bond basis, daily Treasury bonds yields (Treasury rate) and bond characteristics that change on a daily (Liquidity, Duration) or monthly (Amount) basis. Each bond/day(month) is considered as one observation. The CDS-bond basis refers to the difference between non-missing CDS and credit spreads. As CDS and credit spreads measure very similar credit risks, in theory, we should see them trade at similar levels. However, we see them trade at different levels for the same issuer and maturity giving rise to an average CDS-bond basis of about 97 basis points over our sample

[15] We also construct a restricted CDS-bond basis sample consisting only of 5yr CDS contracts and bonds with durations between 3 to 7.5 years. Robustness analysis shows that restricting only to 5yr CDS to compute the CDS-bond basis does not have a bearing on our conclusions (see Table OA.4 in the Online Appendix).

period.[16] There is considerable variation in credit and CDS spreads, as well as in the CDS-bond basis.

Panel C shows summary statistics for firm-level variables: accounting measures, E and S scores, excess stock returns, and idiosyncratic volatility. For volatility, each firm/day is considered as one observation. On average issuing firms are profitable with operating income to sales of about 26%. For E and S, we use Refinitiv ESG scores that range from 0 (poor ESG performance) to 100 (excellent ESG performance). Companies in our sample have an average S and E score of about 50 and 59, respectively.

Finally, Panel D contains descriptive statistics for macroeconomic variables such as S&P returns and term spreads. These variables change on a daily basis.

3. Credit spreads and E&S scores

3.1. Research design

We start analyzing the link between credit spreads and E&S scores during the crisis and subject the outperformance of high E&S bonds documented in professional circles to rigorous analysis (Amiraslani, Lins, Servaes, and Tamayo, 2023; Stellner, Klein, and Zwergel, 2015; Ge and Liu, 2015). We estimate difference-in-differences regressions with continuous treatment using the Covid outbreak as an exogenous shock to default risk and market dynamics. For identification, we use pre-crisis levels of E&S scores and add a series of controls that are known to be standard determinants of credit spreads. Given the unexpected nature of the shock, firms could not choose E&S policies in anticipation of the crisis, which thereby limits any concerns on reverse causality. Our analysis is similar to that of Amiraslani, Lins, Servaes, and Tamayo (2023) who used monthly credit spreads around the 2008 financial crisis.[17]

Specifically, using daily credit spreads we estimate the following baseline model:

$$\mathrm{CS}_{i,j,t} = \beta_0 + \beta_1 \mathrm{Score}_j + \beta_2\left(\mathrm{Score}_j \times \mathrm{Outbreak}_t\right) +$$
$$\beta_3\left(\mathrm{Score}_j \times \mathrm{Peak}_t\right) + \beta_4\left(\mathrm{Score}_j \times \mathrm{Post}_t\right) + \delta' \mathrm{X} + \mathrm{Industry} * \mathrm{Time\ FE}_{j,t} + \varepsilon_{i,j,t}$$

where $\mathrm{CS}_{i,j,t}$ is the credit spread of bond i of firm j on day t between the period running from January 2 to August 31, 2020. Score_j is the most recent E&S score of firm j in the pre-crisis

[16] Price discrepancies between credit spreads and CDS are well documented. They are particularly relevant during financial crisis, giving rise to the so called CDS-bond basis. Several papers aim to understand these price discrepancies (see for example Fontana, 2012; Bai and Collin-Dufresne, 2018; Longstaff, Mithal, and Neis, 2005; Choi and Shachar, 2014).

[17] A difference-in-difference approach is also used in Lins, Servaes, and Tamayo (2017) and Albuquerque, Koskinen, Yang, and Zhang (2020) to explore the evolution of stock returns for high and low E&S firms around the 2008 and Covid crisis respectively.

period. When scores are not available at the end of 2019, we take those of 2018. We define time dummies and investigate the evolution of credit spread over three periods. Outbreak defines the first phase of the crisis and equals one from February 24, 2020, to March 10, 2020. This period starts just after the announcement of a lockdown in several Italian provinces and runs until the day before Covid-19 was officially declared a pandemic by the World Health Organization (WHO). Peak determines the peak stage of the crisis from March 11, 2020, to March 22, 2020. According to previous studies (see Haddad, Moreira, and Muir, 2021; Falato, Goldstein, and Hortaçsu, 2021), this phase also corresponds to the period when corporate bond markets were under stress and includes days when stock markets experienced extreme losses and volatility. Finally, Post spans the period from March 23, 2020, to August 31, 2020. We consider March 23, 2020, as the beginning of the post-coronavirus period because on this day the Federal Reserve Board (FED) announced a major purchase of up to $300 billion of investment-grade corporate bonds for the first time in history. As Falato, Goldstein, and Hortaçsu (2021) show, this event had a significant rebound effect on the corporate bond markets helping credit spreads to reverse.

X is a vector of bond-, firm- and macro-level control variables. The set of controls is known to be standard determinants of credit spreads and proxy for the expected evolution of credit spreads over the crisis as we describe in detail in section 3.2. When control variables are time-invariant, their value corresponds to that of 2019. When they are time-varying, they are contemporaneous to credit spreads. In our baseline model, we add industry-by-time fixed effects using the two-digit Standard Industrial Classification (SIC) level to control for unobserved, time-varying differences across industries given that industry affiliation was a key indicator of how firms were impacted by the crisis. In alternative specifications, we also consider firm and day-fixed effects to control for other unobservables and to rule out that our results are driven, for example, by more attractive firms or by firms with more capable managers investing more in E&S that are, therefore, doing better during the pandemic. Standard errors are double clustered at the firm and day levels. Clustering at the day level mitigates concerns about the correlation between bonds traded on the secondary market at the same time and issued by the same company. Clustering at the firm-level accounts for the dependence between a bond's yield at day t and the yield of the same bond at day $t-1$.

3.2. Construction of control variables

Next, we explain the nature and role of the control variables that we use in our regression analysis. To start with, we add a set of controls that inform us about the financial strength of the firm, and therefore, its resilience at the onset of the crisis. These are firm-level variables that proxy for default risk status and expected developments over time as a function of starting conditions. We follow Collin-Dufresne and Goldstein (2001) and Campbell and Taksler (2003) and use the following variables: total debt ratio, leverage, pre-tax interest coverage, operating income to sales ratio and market capitalization. The debt ratio is scaled by the book value of equity, while the leverage ratio uses the market value. Interest coverage is the sum of operating income before taxes (EBT) divided by interest expense. Similar to Blume, Lim, and Mackinlay (1998), we create four dummy variables with pre-tax interest coverage of less than 5, between 5 and 10, between 10 and 20, and greater than 20 suggesting that a very high-interest coverage may not affect credit spreads. Following Baghai, Servaes, and Tamayo (2014), Acharya, Davydenko, and Strebulaev (2012) and Fahlenbrach, Rageth, and Stulz (2021) we also include capital expenditures, tangibility, cash holdings and short-term debt. We provide a detailed definition of firm-level variables in Appendix A (Group 1). All these firm-level measures are static and correspond to those outstanding at the end of 2019.

Static firm-level controls are not sufficient to model the evolution of default risk. Firms' resilience does not only depend on starting conditions but also on how hard firms are hit by the crisis. For example, two firms with strong balance sheets will evolve differently if they belong to the hospitality or the technology sector. Some firms experienced significant reductions in sales, while others kept operating normally while others saw larger-than-expected demand. This differential evolution is, to a large extent, correlated with industry affiliation. The use of industry-by-time fixed effects allows us to control for the severity of the impact as the crisis develops. We further control for the cross-sectional heterogeneity in firm responses to the shock using time-varying firm-specific variables such as the excess stock market return and the idiosyncratic volatility as in Campbell and Taksler (2003). Previous studies have often used stock returns and volatility to proxy for the evolution of the firm's financial health and probability of default.

We also add a set of bond level controls and a measure of bond liquidity as credit spreads can also capture a liquidity premium. We follow Campbell and Taksler (2003), Elton, Gruber, Agrawal, and Mann (2001), Amiraslani, Lins, Servaes, and Tamayo (2023) and use coupon, amount outstanding, year-to-maturity, liquidity and credit rating. We measure bond liquidity as the ratio of daily high to daily low prices as in Corwin and Schultz (2012). According to Schestag, Schuster, and Uhrig-Homburg (2016), this is one of the best liquidity measures in related literature. For credit ratings, that also proxy for default risk, we take ratings measured at the end of 2019 and use numerical equivalents from 1 (for credit rating "AAA") to 22 (for credit rating "D"). If an issue is rated by multiple credit rating agencies, then we take the worst credit rating. We also add offering market and security type dummy variables. We describe the construction of these variables in Appendix A (Group 2).

Finally, following Collin-Dufresne and Goldstein (2001), we use macroeconomic variables such as the daily return of the S&P 500 index and the term structure to proxy for the state of the economy and control for common factors affecting credit spreads. We describe the construction of these variables in more detail in Appendix A (Group 3).

3.3. Results

In this section, we evaluate whether firms with higher E&S scores prior to the pandemic had a lower expansion of credit spreads during the Covid crisis compared to firms with lower scores. We estimate the baseline model and report the results in Table 4, Panel A. Columns (1) – (5) show different specifications of the baseline model. Column (1) includes only the E&S score of firms, time dummy variables, and the corresponding interaction terms. In Column (1), the coefficients on E&S interacted with time dummies are negative and statistically significant at the 1% level. This is consistent with high E&S bonds outperforming low E&S bonds during the Covid-19 crisis. Next, we examine the robustness of this finding using the full model. In Column (2), we add firm and bond characteristics, macroeconomic variables and further control for industry-by-time dummy fixed effects, where time refers to the time dummies (Outbreak, Peak, Post). Column (3) uses instead industry-by-day-fixed effects and as such adds additional flexibility to the effect of industry affiliation over time. Across both specifications, all coefficients on E&S scores interacted with time dummies are negative indicating a larger increase in credit spreads for low E&S firms. The differential increase in credit spreads is already significant at the outbreak of the crisis, yet is economically small. It is larger and more significant during the peak and post periods. According to Column (3), a one standard deviation increase in E&S scores leads to a 10 [22.4 * -0.45] basis points lower increase in credit spreads during the outbreak period. However, during the peak and post-period, one standard deviation increase in E&S scores is consistent with a lower increase of credit spreads of 28 and 22 basis points, respectively.[18] In other words, while the level of corporate bond spreads increased notably after the Covid-19 outbreak, this change was lower on average for companies with

[18] We also run an alternative specification based on column 3 (see Table OA.5 in the Online Appendix). Instead of industry-day fixed effects, we use industry fixed effects and add macroeconomic control variables. This robustness analysis shows similar results.

higher E&S scores. Higher E&S scores mitigated the rise of credit spreads during the pandemic.

A concern in previous specifications is the use of time-variant control variables that are likely correlated with the Covid-19 shock, such as the excess stock return or idiosyncratic volatility, and that can lead to biases in the estimated coefficients (Angrist and Pischke, 2009; Gormley and Matsa, 2014). Column (4) replicates the estimation in Column (3) excluding time-varying control variables likely correlated with the crisis. The results are largely consistent with previous estimations. Finally, Column (5) uses industry-by-time dummy and firm-fixed effects while excluding time-invariant firm characteristics. Firm-fixed effects control for time-invariant unobservables and rules out the possibility that our results are driven, for example, by more attractive firms or by firms with more capable managers investing more in E&S that were, therefore, doing better during the pandemic. Across specifications, what stands out is the relative stability of the estimated loadings on time dummies interacted with E&S scores. A one standard deviation higher E&S score leads to a 9-11 basis points lower increase in credit spreads during the outbreak and a 21-36 basis points lower increase during the peak and the post periods.[19] We also note that, before the crisis, firms with high E&S scores had slightly higher credit spreads but statistical significance is only at a 10% level. This pattern mirrors that reported by Amiraslani, Lins, Servaes, and Tamayo (2023, Figure 1) for the Global Financial Crisis of 2008.

Table 4, Panel B, performs a similar analysis but uses a dichotomous variable for E&S rather than a continuous one. We rank E&S and retain only the top and the bottom tercile. We define High E&S that equals one for firms with E&S scores in the top tercile. Across specifications, for each time dummy interaction, again, we obtain similar results. Because we are comparing credit spreads for firms with the highest and lowest E&S performance, the economic value of our estimates is now larger. Using specifications (2) to (5), firms with high E&S scores experience lower increases in credit spread of about 21-24 basis points during the outbreak, 72-89 during the peak and, 53-78 during the post-period than firms with low E&S scores. Further, these differences in credit spreads are both statistically and economically

[19] We also re-estimate Table 4 using only bonds that trade more frequently (see Table OA.6 in the Online Appendix). We run these tests to reduce concerns about the role of infrequent trading in our results. For each bond we compute the monthly average number of days with available prices and drop bonds in the bottom decile. We therefore retain bonds that trade on average more than 8 days per month. The results using this restricted sample do not have a bearing on our conclusions.

significant and consistent with the outperformance of bonds with high E&S scores over the same period.[20]

Figure 1, Panel A, explores the evolution of credit spreads for high and low E&S firms in more detail. To construct the plot, we define two dummy variables based on E&S scores. Low E&S equals one when bonds are issued by firms with E&S scores in the lower tercile. High E&S equals one when bonds are issued by firms in the upper tercile. Using only the upper and lower tercile, we estimate a panel regression of credit spreads on all control variables and daily time dummies interacted with the low and high E&S groups. Figure 1, Panel A, reports the coefficients on these daily time dummies that represent daily average credit spreads for each group. For each high and low E&S group, we plot the cumulative sum of the difference between means of daily credit spreads. We highlight the period from March 11 to March 22 as a shaded area. In the pre-crisis period, we do not distinguish a difference between characteristic-adjusted credit spreads of firms with low and high E&S scores. However, a difference is observable at the outbreak of the crisis, it expands as the pandemic is confirmed but narrows again towards the end of the sample period. During the Covid-19 crisis, credit spreads of low E&S firms become higher than those of high E&S firms. In Figure 1 (B&C), which replicates the plot, yet considers S and E scores separately, we observe a similar pattern.

In Table 1, we show there is heterogeneity in the industry composition of our sample. For example, a large number of bonds are issued by financial firms and only a few by firms in the consumer durable sector. To further investigate whether the results are driven by the composition of our sample we perform additional analysis. In unreported tests, we replicate our analysis considering first bonds issued by non-financial firms and then, those issued by financial firms. Both financial and non-financial firms with high E&S scores show lower increases in credit spreads than firms with low scores. However, the moderating role of E&S scores during the crisis is more prevalent for non-financial firms. Figure 2 displays within industry analysis based on specification (5) in Table 4, Panel A, for the peak period. We use Fama-French industry classification to create industry dummy variables and generate triple interactions of industry dummies by E&S score and by time dummies. Instead of industry-by-time and firm-fixed effects, we use firm and day-fixed effects. The Figure reports that, for all

[20] In Tables OA.7 and OA.8 in the Online Appendix, we replicate Table 4, Panel A, for each of the components - S, for social, and E, for environmental - of the E&S score. We find that both high S and E scores moderate the increase of credit spreads during the crisis.

but three industries, firms with high E&S scores enjoy more muted increases in credit spreads during the peak period.

Our results show that the evolution of credit spreads over the Covid-19 crisis was related to the E&S profile of the issuer, thereby suggesting a role for E&S over and beyond that played by the traditional determinants that control both for starting conditions and the severity of the impact as the crisis develops. Our results mirror those of Amiraslani, Lins, Servaes, and Tamayo (2023) for the financial crisis of 2008 and are consistent with professional reports that highlight the outperformance of high E&S bonds during the Covid-19 crisis. Amiraslani, Lins, Servaes, and Tamayo (2023) examine one potential mechanism underlying these results. They argue that high E&S scores mitigate increases in fundamental default risk.[21] They attribute their findings to the value that bondholders give to a firm's social capital during a period of crises. In contrast, next, we delve into an alternative channel explaining why firms with high E&S scores experienced a lower expansion of credit spreads during the Covid-19 crisis as compared to firms with lower E&S scores.

4. The CDS-bond basis and E&S scores

In this section, we study whether the resilience of bonds issued by high E&S firms can be attributed to factors other than shifts in firm fundamentals. The crisis represents a shock to default risk, leading to an increase in credit spreads, but it also represents a shock to investors' asset holdings as it triggers a demand for liquidity and the need to rebalance portfolios (Haddad, Moreira, and Muir, 2021; Falato, Goldstein, and Hortaçsu, 2021). While credit spreads are largely driven by default risk factors, other non-default components, such as liquidity, have also been related to credit spreads (see Longstaff, Mithal, and Neis, 2005). Pure investor preferences and trading behaviours could also explain the positive relationship arising between high E&S scores and moderated increases in credit spreads. Pure investor preferences for bonds issued by high E&S firms could trigger a discriminated sale of bonds issued by low E&S firms as investors become more discriminating in terms of which assets to sell. This behaviour would put large downward pressure on the prices of bonds issued by low E&S firms, driving up credit spreads. Thus, non-fundamental factors can also affect credit spreads through E&S scores and, therefore, bond performance.

[21] In Table OA.9 in the Online Appendix, we also investigate the role of default risk in the outperformance of bonds issued by high E&S firms during the Covid-19 crisis. We use 5-year CDS spreads as a proxy for the default risk. Consistent with Amiraslani, Lins, Servaes, and Tamayo (2023), we find that firm E&S status moderates increases in default risk during the Covid-19 crisis.

To distinguish whether the differential evolution of credit spreads according to E&S status is driven by investor preferences and trading behaviour rather than shifts in firm fundamentals, we focus on the default-free component of credit spreads. The CDS-bond basis, computed as the difference between the CDS spread and the credit spread, proxies for the non-default component in credit spreads (Longstaff, Mithal, and Neis, 2005). Various studies analyze the determinants of the CDS-bond basis.[22] In particular, Haddad, Moreira, and Muir (2021) document a large and negative CDS-bond basis during the Covid-19 crisis which coincides with our sample period.[23] They attribute negative values to selling pressure at a time when arbitrage activity was not sufficiently strong to eliminate CDS and credit spread discrepancies. Their analysis suggests that selling pressure resulted from the urgent need from specific investors to sell bonds for liquidity, thereby causing disruptions in bond markets.[24] By providing liquidity, the Federal Reserve corporate bond purchase programs helped ease tensions in corporate bond markets and caused prices to recover reducing bond spreads.[25]

Building on Haddad, Moreira, and Muir (2021), the analysis of the CDS-bond basis and its relation to E&S status can inform us about the role of selling pressure on the outperformance of bonds issued by firms with high E&S scores. As investors sell their bond holdings for liquidity, they may be selective in the bonds they sell, for example, selling low E&S bonds to a greater extent to comply with the objective of switching towards more sustainable portfolios. Thus, demand and supply imbalances could be behind our base results.

To analyse the role of selling pressure, we estimate the baseline model using the CDS-bond basis as the dependent variable. We regress the CDS-bond basis on E&S scores and the set of bond-, firm- and macro-level control variables. Our control variables proxy for other possible determinants of the CDS-bond basis such as collateral quality and the liquidity of the

[22] Studies such as Longstaff, Mithal, and Neis (2005), among others, attribute the CDS-bond basis mainly to the illiquidity of the underlying bond. Elton, Gruber, Agrawal, and Mann (2001) argue that differential taxation between corporate bonds and Treasuries could explain the CDS-bond basis, though Longstaff, Mithal, and Neis (2005) did not find support for this hypothesis. Bai and Collin-Dufresne (2018) documented other determinants of the CDS-bond basis, such as the liquidity of the bond, counterparty risk, collateral quality and funding constrains faced by investors to exploit arbitrage. However, Haddad, Moreira, and Muir (2021) highlight that the major factors during the Covid-19 crisis were liquidity issues or selling pressures.

[23] During the Global Financial Crisis of 2008 bond spreads were also significantly higher than CDS and bonds were trading at significant discounts (Bai and Collin-Dufresne, 2018; Choi, Hoseinzade, Shin, and Tehranian, 2020; Fontana, 2012). Similar dynamics have emerged during the Covid crisis (Haddad, Moreira, and Muir, 2021). Note that in frictionless and complete markets, CDS spreads should equal credit spreads. In normal times CDS spreads equate with credit spreads with small deviations (Blanco, Brennan, and Marsh, 2005; Longstaff, Mithal, and Neis, 2005; Hull, Predescu, and White, 2004). However, during periods of crisis, there are limits to arbitrage and a gap opens between the spread and the CDS.

[24] Augustin, Subrahmanyam, Tang, and Wang (2014) also attribute negative values of the CDS-bond basis to the deleveraging activity of investors that are pushed to sell off their bond holdings causing selling pressure.

[25] The FED announced on March 23 a purchase program of investment-grade corporate bonds and, on April 9, announced the expansion of the program and the extension to some high-yield bonds. These interventions eased tensions in corporate bond markets and caused prices to recover. Spreads of bonds that were almost three times larger by March 23 compared to pre-pandemic levels, reversed after the Fed announcements. It was not until the second announcement that the situation further normalized.

underlying bond or taxes. To be precise, Credit rating serves as a control for collateral quality. Liquidity, Amount and Year-to-maturity serve as proxies for the liquidity of the underlying bond. Finally, Coupon is a proxy for the possible role of taxes on the CDS-bond basis, as highlighted in Elton, Gruber, Agrawal, and Mann (2001), due to the asymmetric taxes inherent between corporates and Treasuries.[26]

4.1. Results

Table 5, Panel A presents the results. Column (1) adds the E&S score, time dummies and their interactions. The coefficients on E&S interacted with time dummies are positive and statistically significant. This result is robust to the inclusion of control variables and various fixed effects. In Column (2), we use bond-, firm-level and macroeconomic control variables and industry-by-time dummy fixed effects. We consider industry-by-day-fixed effects in Column (3). Column (4) mirrors Column (3), excluding time-varying control variables. Finally, we add industry-by-time dummies and firm-fixed effects in Column (5). Across all specifications, we find positive and significant coefficients on the E&S scores interacting with time dummies, indicating a larger (and negative) CDS-bond basis for bonds issued by firms with low E&S scores. According to specification (3), a one standard deviation higher E&S score is associated with a 24 basis point lower CDS-bond basis at the peak of the crisis: the period when the CDS-bond basis diverges most across bonds of firms with different E&S scores. A plausible interpretation of these findings is that investors needing to sell bonds put pressure on prices, thereby driving up credit spreads to a far greater extent than would have been predicted by increases in default risk. The price pressure is larger for those bonds issued by firms with low E&S scores, causing credit spreads to increase significantly more than for bonds issued by high E&S firms. This evidence indicates that investors were likely selective in the decision on which bonds to sell for liquidity.

Following specification (3), in the post-period, a one standard deviation higher E&S score is associated with 12 basis points lower CDS-bond basis.[27] Across specifications, the economic significance is about half of that during the peak period, consistent with the FED's announcement of March 23rd that eased tensions in corporate bond markets enabling prices to start recovering (Falato, Goldstein, and Hortaçsu, 2021; Haddad, Moreira, and Muir, 2021) and

[26] Longstaff, Mithal, and Neis (2005) and Bai and Collin-Dufresne (2018) motivate the use of these proxies and provide a detailed discussion of the factors affecting the CDS-bond basis.
[27] We re-estimated the results of Table 5, Panel A, using time dummies interacted with Governance (G) scores, instead of E&S scores (see Table OA.10 in the Online Appendix). Notably, the corresponding coefficients are statistically insignificant, indicating that G scores did not significantly influence the CDS-bond basis during the Covid crisis.

closing the gap in the CDS-bond basis of those bonds issued by firms with high or low E&S scores. Finally, we also note that, before the crisis, E&S scores are unrelated to the CDS-bond basis.

Table 5, Panel B, performs a similar analysis but we employ only those bonds that ranked in the top and the bottom tercile on the issuer E&S score. In this panel, E&S equals one for bonds issued by firms with E&S scores in the top tercile. Across specifications, for each time dummy interaction, we obtain similar results. Because we are comparing the CDS-bond basis corresponding to firms with the highest and lowest E&S scores, the economic value of our estimates is slightly different. Using specifications (2) to (5), those firms with high E&S scores experience lower increases in the CDS-bond basis (less negative) of about 10-16 basis points during the outbreak and 57-66 basis points during the peak period. In all cases, these estimates are statistically and economically significant.[28] During the post-period, the difference in CDS-bond basis between bonds issued by high and low E&S firms narrows and is no longer statistically significant. This is consistent with the expected effect of the FED's first intervention. This result contrasts with that in the previous section where, in the post-period, the differential CDS spread between bonds issued by high and low E&S firms was not reduced.

Our tests do not control for counterparty risk; that is, the risk that the CDS seller cannot honor his or her commitment or, for funding constraints faced by arbitrageurs. While counterparty risk was of primary concern during the Global Financial Crisis, it seems less relevant during our sample period. Furthermore, it is unlikely to be correlated with the firm's E&S scores. Similarly, it is unlikely that funding constraints faced by arbitrageurs correlate with firm E&S status. If arbitrageurs were facing funding constraints, they would do so regardless of which bond-CDS pair they aim to arbitrage. We argue that the differential impact that we find between high and low E&S scores is unlikely to be due to funding constraints or counterparty risk.

Put together, our results highlight how E&S scores predict differential selling pressure at time of a liquidity shock that impacts the performance of bonds during a crisis. From investors point of view, high E&S scores resulted in outperformance but a share of this outperformance was due to investor trading behavior and, as such, one can expect this outperformance not to be long-lasting.

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[28] We implement additional tests to verify that our findings are not influenced by changes in firm fundamentals or default risk. In Table OA.11 in the Online Appendix, in all specifications, we incorporate an additional control variable. In line with He and Xiong (2012), we introduce the interaction between default risk (measured by CDS spreads) and our proxy for liquidity following Corwin and Schultz (2012). Our conclusions remain unchanged.

4.2. Robustness

4.2.1. Selling pressure and investment grade bonds

Haddad, Moreira, and Muir (2021) shows that selling pressure particularly affected certain segments of the market. Investment grade corporate bonds faced higher levels of sell-offs than junk bonds as market participants favoured selling most liquid bonds in the asset liquidation process. If E&S scores are negatively related to credit ratings, our results could simply reflect fund managers overselling bonds with higher credit quality to get liquidity. Even though, we control for credit ratings and bond liquidity in our tests, this may not be sufficient. We address this concern in two steps. First, we estimate a correlation of 0.24 between E&S scores with credit, indicating that high E&S firms tend to have higher credit ratings. Second, we re-estimated Table 5 using a subsample consisting only of investment-grade bonds and report the results in Table 6, Panel A. Again, bonds issued by low E&S firms faced more negative CDS-bond basis, consistent with greater selling pressure and expansion of credit spreads. Thus, our results are not driven by the over presence of bonds issued by low E&S firms in certain segments of the market subject to greater selloffs but rather by the firm E&S status.

4.2.2. The CDS-bond basis and default risk

Bai and Collin-Dufresne (2018) show that collateral quality is a possible determinant of the CDS-bond basis. The idea is that selling pressure could be the results of investors selling bonds as the credit quality of the issuer is expected to deteriorate. Although we control for collateral quality or the issuer default risk via credit ratings and industry-time fixed effects, this approach may not comprehensively address all aspects of default risk. Thus, the differential impact of high and low E&S scores on CDS-bond basis could still be due to factors that we fail to capture with our controls. In Table 6, Panel B, we extend our analysis and re-estimate Table 5 including the CDS spread as an additional control variable for default risk. The results remain largely unchanged, indicating that the differential impact of high and low E&S scores on CDS-bond basis is likely attributable to selling pressure rather than default risk.

5. Direct measures of selling pressure

In this section, to reinforce our interpretation, we study selling pressure from a different angle and perform additional analysis on how the E&S status of the bond issuer relates to bond selloffs. During our sample period, bond markets faced unprecedented selloffs which, to a large extent, were driven by investors' demands for liquidity (Haddad, Moreira, and Muir, 2021;

Falato, Goldstein, and Hortaçsu, 2021). Mutual funds played a key role in this disruption as they were subject to massive redemptions and were thus forced to sell some of their holdings (Ma, Xiao, and Zeng, 2022).[29] Thus, certain corporate bonds held by mutual funds were possibly subject to forced sales. We focus on these bonds and we measure selling pressure more directly.

5.1. Mutual funds data

To evaluate selling pressure more directly, we look at the evolution of mutual fund corporate bond holdings. Individual bond holdings by mutual funds as well as fund level data comes from the CRSP Survivor-Bias-Free US Mutual Fund database. We restrict our analysis to fixed-income, active, open-end mutual funds existing before December 2019 that hold corporate bonds in our sample (those retained in section 2.1) with available E&S scores and key firm and bond-level characteristics. We exclude index funds as well as funds reporting only short positions. We then retain only funds that report holdings with monthly frequency. The main sample includes 280 fixed-income funds that collectively manage $0.7 trillion and covers the period December 2019 till August 2020. Among their bond holdings, these funds hold 1’721 corporate bonds with E&S scores.

For these funds, we compute fund flows in dollars and in percentage as follows:

$$\mathrm{Flow}_{\mathrm{f,t}} = \mathrm{TNA}_{\mathrm{f,t}} - \mathrm{TNA}_{\mathrm{f,t-1}}\left(1 + \mathrm{R}_{\mathrm{f,t}}\right),$$
$$\mathrm{flow}_{\mathrm{f,t}} = \mathrm{Flow}_{\mathrm{f,t}}/\mathrm{TNA}_{\mathrm{f,t-1}} * 100\%$$

where $\mathrm{TNA}_{\mathrm{f,t}}$ and $\mathrm{R}_{\mathrm{f,t}}$ are total net assets expressed in millions and returns of fund *f* in month *t*, respectively. For funds with multiple share classes, we aggregate the data per fund-month. Fund total net assets is the sum of total net assets across share classes. Returns are weighted averages of share class returns.

Figure 3 shows the evolution of aggregate fund net flows in million USD from January to August 2020. Dots represent the average net flows across all funds each month while vertical lines depict net flows in the top-bottom decile. We observe that March 2020 concentrates massive mutual fund redemptions and, consequently, corporate bond selloffs. About 81% of

[29] According to Koijen and Yogo (2023), mutual funds are the second largest player in the US corporate bond market after insurance companies.

funds in our sample experienced outflows in March 2020, with an average net outflow of about USD 120 million. This signals the fund's need to sell a significant amount of bond holdings.[30]

5.2. Direct measures of selling pressure and E&S scores

Selling pressure occurs when various players sell contemporaneously – with some urgency –and there are more sellers than buyers. In March 2020, mutual funds experienced large redemptions and had to sell bonds urgently leading to bond selloffs. We aim to examine whether selling pressure was particularly concentrated in bonds issued by low E&S firms. We develop two different bond level measures of selling pressure.

First, we follow Haddad, Moreira, and Muir (2021) and compute selling pressure as:

$$\mathrm{SP\_1}_{\mathrm{i,j,March}} = \frac{\sum_{\mathrm{f}} \max\left(-\mathrm{flow}_{\mathrm{f,March}}, 0\right) * \mathrm{Holdings}_{\mathrm{i,Feb}}}{\mathrm{Amount\ outstanding}_{\mathrm{i,February}}}$$

where SP_1 is selling pressure for bond i issued by company j in March. flow is the [net] flow of fund f in March, expressed as a %. Holdings is the par value amount of bond i held by fund f and Amount outstanding is the dollar amount of bonds outstanding in millions of dollars, both measured at the end of February. We retain only flows with a negative sign, i.e. outflows. We then normalize the outflow by the fund's total assets under management and multiply by the holdings a mutual fund has of a particular bond the previous month. The outcome is the estimated bond level outflow for a given fund, assuming that the fund sells asset holdings proportionally to outflows (keeping the same asset allocation). Finally, we sum the outcome across all funds and normalize by the Amount outstanding of the bond. SP_1 is only non-zero for those bonds held at least by a mutual fund that experiences outflows and equals zero for those bonds held only by mutual funds with inflows. Descriptive statistics in Table 6 indicate that most mutual funds had outflows during the month of March.

Figure 4 displays the monthly evolution of SP_1 for bonds issued by low E&S firms vs. those of high E&S firms over our sample period. To construct this plot, we classify bonds into high and low E&S groups. The high (low) E&S group includes bonds issued by firms with E&S scores in the top (bottom) tercile. For each month and each group, we plot the average selling pressure. Bonds issued by low E&S firms are subject to greater selling pressure that intensifies in March 2020. Because SP_1 assumes that mutual funds subject to outflows sell

[30] If we consider the universe of fixed-income, active, open-end mutual funds with monthly reporting of holdings (680 funds), about 90% of these funds experienced outflows in March 2020. Unreported analysis shows a similar pattern to that in Figure 3.

portfolio bonds proportionally to outflows, we can infer that less sustainable mutual funds suffered larger outflows. We test this conjecture later in section 6.2.

Our second measure of selling pressure follows Choi, Hoseinzade, Shin, and Tehranian (2020):

$$\mathrm{SP\_2}_{\mathrm{i,j,March}} = \frac{\sum_{\mathrm{f}} \max\left(-\Delta \mathrm{Holdings}_{\mathrm{i,March}}, 0\right)}{\mathrm{Amount\ outstanding}_{\mathrm{i,February}}}$$

where f are funds with flows < percentile (15th). This measure considers reductions in bond holdings by a mutual fund that experiences extreme flows. It directly computes the actual bond level outflow per fund and then aggregates across funds.[31] A value of zero means that mutual funds holding the bond were either not distressed or, if distressed, they did not reduce their bond positions. According to SP_2 in Table 7, 17% of corporate bonds were subject to sales by mutual funds experiencing extreme outflows. Further, mutual funds with extreme outflows sold positions of 44% of their corporate bond holdings.

To evaluate whether bonds issued by low E&S firms are more subject to selling pressure during March 2020, we run the following cross-sectional regression:

$$\mathrm{SP}_{\mathrm{i,j}} = \beta_0 + \beta_1 \mathrm{Score}_{\mathrm{j}} + \delta' \mathrm{X} + \mathrm{Industry\ FE}_{\mathrm{j}} + \varepsilon_{\mathrm{i,j}}$$

where $\mathrm{SP}_{\mathrm{i,j}}$ refers to one of the measures of selling pressure in March 2020 for bond i issued by firm j. As measure SP_2 equals zero for a large number of bonds, we use a probit model. We transform this measure and attribute a value equal to 1 if it is non-zero, and zero otherwise. $\mathrm{Score}_{\mathrm{j}}$ is the most recent E&S score for firm j in the pre-crisis period. X is a vector of firm- and bond level control variables. To control for the possibility that selling pressure is the outcome of worsening firm fundamentals, we include the set of firm-level variables (see appendix). Precisely, we include the list of static firm-level variables described in Appendix A (Group 1) as well as variables that inform us about how strongly a firm is hit during the crisis. We consider the change in idiosyncratic volatility and stock prices as measured from the outbreak of the crisis to the end of the peak period (from Feb 24th to Mar 20th). We also consider industry affiliation and control for industry-fixed effects using the two-digit SIC code. We also include bond level credit rating and bond liquidity. Bond liquidity is the average daily liquidity in February and controls for liquidity preferences of fund managers in the liquidation process to

[31] In Table OA.12 in the Online Appendix, we scale the selling pressure measures by monthly bond trading volume instead of the amount outstanding. For bond trading volume, we consider either the total trading volume from January 2020 or the mean of the total trading volume from December 2019 and January 2020. Results in Table 8 remain qualitatively consistent regardless of the scaling method employed.

meet investor redemptions (Ma, Xiao, and Zeng, 2022). Standard errors are clustered at the firm-level.

Table 8 reports regression results. Specifications (1), (3) and (5) include changes in idiosyncratic volatility and stock prices to control for the evolution of the firm financial conditions during the crisis. Specifications (2), (4) and (6), alternatively, include industry-fixed effects. Columns (3) to (6) report marginal effects from probit estimations. Columns (1) to (4) show that, regardless of how we measure selling pressure, the coefficients on E&S scores are consistently negative and significant. These results indicate that bonds issued by high E&S firms face, or are more likely to experience, lower selling pressure. A one standard deviation increase in E&S is related to a 15.12% or 10.55% [22.4*0.675 & 22.4*0.471] lower probability of facing selling pressure, respectively. Additionally, columns (5) and (6) present the results using a restricted sample of 172 funds which hold at least 50% of corporate bonds in their portfolio.[32] The coefficient on E&S scores is negative and significant in Column (5) but weakens in Column (6), upon the inclusion of industry-fixed effects. A one standard deviation increase in E&S is related to a 14.60% [22.4*0.652 &] lower probability of facing selling pressure, respectively. Confirming our earlier findings, these results suggest that high E&S scores act as a stabilizing mechanism during bond market turmoil. Finally, we re-estimate Table 8 using only the subsample of investment grade bonds and results are unaffected or even stronger (see Table OA.13 in the Online Appendix).

6. Why do bonds issued by low E&S firms face greater selling pressure?

In previous sections, we show that low E&S scores predict greater selling pressure using different measures. Next, we explore possible trigger(s) of these greater selloffs.

6.1. Funds sustainability and investor redemptions

According to Morningstar, during the Covid-19 crisis, investor net flows into mutual funds were related to the fund sustainability focus. While many mutual funds had large outflows, sustainable funds showed resilience and enjoyed inflows indicating that ultimate investors were likely selective in which mutual funds to sell.[33] If ultimate investors selectively choose which mutual funds to sell, prioritizing divestment from less sustainability-focused

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[32] To identify corporate bonds, we used an asset type variable from Thomson Reuters which classifies the entity issuing the fixed-income security. The restricted sample includes 172 funds holding 1604 bonds with E&S scores.

[33] According to Morningstar, "the global sustainable fund universe pulled in USD 45.6 billion in the first quarter of 2020 … which compares with an outflow of USD 384.7 billion for the overall fund universe" (Morningstar, "Global Sustainable Fund Flows", May 2020).

funds holding a greater proportion of bonds issued by low E&S firms, we could expect these bonds to face greater selling pressure and expansion of credit spreads.

In this section, we examine the link between fund net flows and mutual fund sustainability during March 2020 to evaluate whether mutual funds with greater exposure to sustainability risks – and thus holding a larger share of bonds from low E&S firms – experienced larger redemptions. We focus on fixed-income, active, open-end mutual funds existing before December 2019. We exclude index funds as well as funds reporting only short positions. This sample represents funds that report holdings with monthly or quarterly frequency. We further require that funds have sustainability scores available in Morningstar. We measure mutual fund sustainability using two different scores. First, we use the Portfolio Corporate Sustainability Score. This score is assigned only to funds that have a sufficient number of corporate bonds in portfolio. The Score is the asset-weighted average of Sustainalytics' company-level ESG Rating and ranges from 0 to 50. A higher score measures higher ESG-related corporate risk exposure. Second, we use the Globe Rating. This score considers both corporate and sovereign bonds, making it a better representation of the mutual fund portfolio's sustainability. The score ranges from 1 to 5 globes, with a higher number of globes indicating lower ESG risk. We multiply the score by -1 to invert the scale and therefore, make it consistent with the Portfolio Corporate Sustainability Score. Morningstar computes these sustainability scores only when a fund satisfies two conditions. One, a fund is required to hold a minimum of 67% of its assets in long portfolio positions, excluding cash, currency, and derivatives. Two, 67% of all corporate (67% of all sovereign bonds) in a fund's portfolio need to have company (country) ESG Risk Ratings. Our final sample consists of 48 funds with fund-level sustainability scores. We provide descriptive statistics in Table 9.

To investigate whether net flows into mutual funds relate to fund's sustainability, we use fund data at the share class level. We treat different investor-type (retail vs institutional) share classes as separate funds. We aggregate share class level data at the investor-type level following Hartzmark and Sussman (2019). Total net assets are summed across investor-type share classes. Returns are weighted average of the respective share classes returns. Flows are computed at the investor-type level using information on total assets and returns. For each share class we collect control variables from the CRSP database. These variables include the date when the share class was first offered, the net expense ratio, a dummy variable distinguishing between institutional and retail share classes, turnover ratio, the net cash position (as a percentage of TNA) and fund objective code. The expense ratio is calculated as the mean of the ratios from investor-type share classes. Age is based on the oldest share class, using the logarithm of the number of days from its inception to February 29, 2020. Finally, we incorporate additional controls from Morningstar, such as the portfolio market beta, and the star and medal ratings. Star and medal ratings are based on the largest investor-type share classes while the beta is computed as a mean. We summarize all variables used in this test in Appendix A (Group 4).

To explore the link between fund sustainability and fund flows, we estimate the following cross-sectional regression:

$$\mathrm{flow}_{f_c,\mathrm{Mar\,2020}} = \beta_0 + \beta_1 \mathrm{Score}_{f,\mathrm{Feb\,2020}} + \delta' Z + \mathrm{Fund\ objective\ FE}_f + \varepsilon_{f,\mathrm{Mar\,2020}}$$

where $\mathrm{flow}_{f_c,\mathrm{Mar\,2020}}$ is the net flow at the investor-type share class level f_c as of March. $\mathrm{Score}_{f,\mathrm{Feb\,2020}}$ is the fund f sustainability score as of February; and Z is a vector of control variables that are traditional determinants of fund flows in existing studies. To control for fund performance, we use the 1-month and 3-month past return, as well as its star rating and the medal rating. Morningstar star ratings are a retrospective measure of a fund's past performance. The rating is assigned each month and ranges from 1 to 5 with a higher score indicating a better performance. Medal rating is a forward-looking measure showing how likely a fund will outperform its peers over a full market cycle. The rating ranges from Gold to Negative with a Gold score meaning that a fund will likely outperform its peers. We then include total net assets and the net expense ratio to proxy for fund size as larger funds tend to grow (lower flows) at a slower pace than smaller funds. We also control for the turnover ratio, the net cash position, age, portfolio market beta, and an indicator for institutional vs. retail share classes. Finally, we also include the fund objective fixed effects to rule out the possibility that fund flows are driven by fund-type specific differences. We use standard errors clustered at the fund level in the tests.

Table 10 reports the results. In Panel A, we use the Portfolio Corporate Sustainability Score. Across all specifications, the coefficient of the Score is negative and statistically significant. Depending on the specification, a fund having a 5-point higher score experienced between 7.73% and 19.5% lower net flows (greater outflows) during March 2020. In Panel B, we use the Morningstar Sustainability Rating. Again, the coefficient of interest remains negative and statistically significant at the 1% level across all specifications. According to Column (2), a one-globe increase in a fund's sustainability rating corresponds to a 5.79% lower net flows. That is, funds with higher exposure to sustainability risks faced larger outflows. In Table OA.14 in the Online Appendix, we conduct placebo tests and confirm that the differential performance of high ES bonds was a unique response to the Covid-19 shock. In Tabel OA.15 in the Online Appendix, we also examine whether mutual funds with greater exposure to sustainability risks experience higher redemptions due to the presence of a specific type of investor. Our results indicate that fund flows from institutional investors in funds with higher exposure to sustainability risks are similar to those from retail investors. This suggests that institutional investors have liquidation needs or preferences similar to those of retail investors.

In sum, we provide some evidence that funds with greater exposure to sustainability risks (higher scores), holding a larger share of bonds from low E&S firms, experienced larger redemptions (or lower net flows). This evidence is consistent with ultimate investors selecting to redeem from less sustainable mutual funds, which could explain why bonds issued by low E&S firms faced greater selling pressure.

6.2. Fund managers' decisions on which assets to sell

Next, we explore an alternative trigger of greater selling pressure on bonds issued by low E&S firms. There is evidence that mutual fund managers followed a pecking order in the liquidation of assets to meet redemptions. Fund managers first sold most liquid bonds followed by corporate high-credit quality bonds (Ma, Xiao, and Zeng, 2022). It is also possible that, to cater to client preferences, fund managers could select to sell, to a larger extent, bonds issued by low E&S firms, thereby increasing portfolio sustainability. To evaluate this possibility, we follow Ma, Xiao, and Zeng (2022) and examine the sensitivity of bond liquidation to fund outflows. We use the same sample of funds as described in Section 5.1. For each fund, we construct a bond fund level Liquidation measure as of March 2020,

$$\mathrm{Liquidation}_{i,f,March} = \left(\mathrm{Holdings}_{i,f,March} - \mathrm{Holdings}_{i,f,February}\right)/\mathrm{Holdings}_{i,f,February}$$

where Holdings is the par value amount of bond i held by fund f at the end of a month. Liquidation is the percentage change in the amount of a particular bond during March 2020 winsorized at the 1% level. Liquidation is negative (positive) when a fund reduces (increases) the holdings of a particular bond during March. Table 9, Panel B, provides summary statistics of Liquidation for bonds issued by firms with E&S scores in the top-bottom tercile; the sample that we use in the tests below. Only a share of corporate bonds changed positions and, most bonds (80.7%) were not traded by fund managers. To be specific, 3.9% of bonds faced an increase in mutual fund holdings, while 15.4% faced a reduction.

Next, we relate bond liquidation to the outflows of the fund holding the bond as follows:

$$\mathrm{Liquidation}_{i,f,March} = \beta_0 + \beta_1 \mathrm{Outflows}_{f,March} + \delta' N + \text{Objective code FE}_f + \varepsilon_{i,f}$$

Outflows are negative fund-level net flows. We focus only on those funds which experienced outflows in March of 2020 and we estimate the regression separately for two groups.[34] Group one (two) includes low (high) E&S bonds. Low (High) E&S bonds are bonds issued by the bottom (top) tercile of firms with the lowest (highest) E&S score. If fund managers, subject to redemptions, sold massively low E&S bonds, then we should see a higher liquidation-to-outflows sensitivity for the group of low E&S bonds as compared to high E&S bonds. N is a vector of bond-, firm- and fund-level control variables. To control for the possibility that fund managers decision to liquidate particular bonds is the outcome of worsening firm fundamentals we include the set of firm-level variables (see appendix). Precisely, we include the list of static firm-level variables described in Appendix A (Group 1) as well as variables that inform about how strongly a firm is hit during the crisis. We consider the change in idiosyncratic volatility and stock prices measured from the outbreak of the crisis to the end of the peak period (from Feb 24th to Mar 20th). We also consider industry affiliation and control for industry-fixed effects using the two-digit SIC code. Bond level variables include year-to-maturity, credit rating and bond liquidity. Credit rating is lagged by one month. Bond liquidity is the average daily liquidity in February and controls for liquidity preferences of fund managers in the liquidation process to meet investor redemptions. Fund-level variables include one-month lagged returns and total net assets to proxy for fund size and past fund performance. Finally, we add fund objective fixed effects. Standard errors are double clustered at the firm and fund levels.

Table 11 reports the regression results. Specifications (1) and (2) include bond and firm-level control variables, fund returns, total net assets and fund objective code fixed effects. Specifications (3) and (4) include, in addition, industry-fixed effects. Columns (1) and (3) refer to the set of bonds issued by low E&S firms, whereas (2) and (4) conform to the set of bonds issued by high E&S firms. Regardless of the specification used, the liquidation-to-outflows sensitivity is statistically significant but economically lower for the subsample of bonds issued by low E&S firms. The negative sign across regressions indicates that funds with greater outflows were, in general and as expected, selling more bonds. However, the magnitude of the liquidation to outflow sensitivity is lower for bonds issued by low E&S firms. This lower coefficient indicates that fund managers had a lower propensity to sell bonds issued by low E&S firms as compared to bonds issued by high E&S firms following fund outflows. A 1% greater outflow translates into the sale of 1.29% holdings of bonds from high E&S firms and

[34] Results are similar if we estimate the model including both high and low E&S bonds interacted with Outflows in a single regression. Results are reported in Table OA.16 in the Online Appendix.

0.93% of bonds from low E&S firms. Thus, we do not find evidence that fund managers contributed to the selling pressure on low E&S bonds.

Summing up, we find that bonds issued by high E&S firms may experience lower selling pressure due to lower investor outflows from sustainability-focused funds rather than fund managers deliberating as to which bonds to sell.

7. Conclusion

We study whether, and why, E&S firm status worked as a hedge factor during the corporate bond market crashes that followed the Covid-19 outbreak. We investigate the impact of firm E&S scores on corporate bond spreads during the period from January to August 2020. We document that high E&S firms experienced lower increases in credit spreads. E&S resilience has traditionally been attributed to firm fundamental factors and the capacity of firms with higher E&S to better weather shocks. We further evaluate whether the differential evolution of corporate bond spreads, depending on E&S status, is influenced by factors other than shifts in firm fundamentals, such as selling pressure. To this end, we decompose the credit spread into the CDS spread and the CDS-bond basis. We document that high E&S firms experienced lower CDS-bond basis and lower selling pressure compared to low E&S firms. Our findings suggest that the outperformance of high E&S bonds during the crisis was not only due to differential increases in default risk and but also to moderated price pressure. This is consistent with E&S scores acting as a selective factor during the crisis in the decision of investors as to which assets to sell for liquidity. Consistent with this view, we provide evidence that ultimate investors redeemed from those mutual funds holding a greater proportion of low E&S bonds. Overall, we show a role for non-fundamental factors shaping corporate bond spreads suggesting that the capacity of high E&S firms to weather shocks may have been overestimated.

Appendix A: Variables definitions

The table gives definitions and information on construction of all variables used in current study.

Variable	Source	Description
Group 1. Firm characteristics		
S	Refinitv	Social score of a company.
E	Refinitiv	Environmental score of a company.
Log size	Datastream	Natural logarithm of the market value of equity.
Leverage	Worldscope/Datastream (MV equity)	Book value of debt, divided by the sum of the market value of equity and the book value of debt.
Debt	Worldscope	The sum of short- and long-term debt divided by the sum of short- and long-term debt and book value of shareholders' equity.
ST debt	Worldscope	Short-term debt scaled by total assets.
Cov.1 - Cov.4	Worldscope	Interest coverage ratio defined as sum of operating income after depreciation and interest expense divided by interest expense. Following Blume, Lim, and Mackinlay (1998), four indicator variables are identified based on the ratio's boundaries at 5, 10, and 20.
EBITDA/sales	Worldscope	Operating income before depreciation divided by net sales.
Cash	Worldscope	Cash and short-term investments scaled by total assets.
Tangibility	Worldscope	Property, plant and equipment total, net scaled by total assets.
Capex	Worldscope	Capital expenditures scaled by total assets.
Stock ret.	Datastream/CRSP (value-weighted index return)	Daily returns in excess of CRSP value-weighted index return.
Stock price	Datastream	Daily stock price.
Idiosyncratic volatility	Datastream/CRSP (value-weighted index return)	Standard deviation of daily returns in excess of CRSP value-weighted index return over 180 days before the transaction date of a bond.
Group 2. Bond related variables		
Credit spread	Datastream/FED	Difference between yields of corporate and Treasury bonds matched by duration.
CDS spread	Datastream	Spreads of credit default swap contracts available in Datastream.
CDS-bond basis	Datastream/FED	Difference between CDS and credit spreads matched by duration.
Coupon	Datastream	Bond's coupon rate.
Duration	Datastream	Bond’s modified duration.
Global	Datastream	Indicator variable, equal to 1 if the bond issue is offered globally and 0 if the offering is made to the domestic market only.
Security	Datastream	Rank variable that takes the value of 0 to 4 for unsecured, subordinated unsecured, senior unsecured, senior subordinated unsecured and senior secured bonds, respectively.
Amount	Datastream	Bond’s amount outstanding.
Credit rating	Datastream	Numerical equivalent of a credit rating of a bond (e.g., AAA=1,..., D=22) as of the end of 2019. If an issue is rated by multiple credit rating agencies, the representative rating is the worst one.
Liquidity	Datastream	The bid-ask spread estimator constructed from daily high and low prices, using the method of Corwin and Schultz (2012).

Variable	Source	Description
Year-to-maturity	Datastream	The remaining number of years until maturity of a bond.
Treasury rate	FRED	A yield of the closest by maturity to each corporate bond Treasury bond.
Group 3. Macroeconomic-level variables		
S&P returns	Datastream	The daily return of the S&P 500 index.
Term spread	FRED	The difference between ten- and two-year Treasury rates.
Group 4. Fund-level variables		
Flow	CRSP	Net flow of a fund computed as $\text{Flow}_{f,t} = \text{TNA}_{f,t} - \text{TNA}_{f,t-1}(1 + R_{f,t})$.
flow	CRSP	Net flow of a fund expressed in percentage of TNA.
Holdings	CRSP	The par value amount of bond *i* held by fund *f*.
TNA	CRSP	Total net assets of a fund expressed in millions.
R	CRSP	Monthly fund return.
Portfolio Corporate Sustainability Score	Morningstar	Fund sustainability rating measured as an asset-weighted average of Sustainalytics' company-level ESG Risk Rating. Higher score measures higher ESG-related risk exposure.
Globe Rating	Morningstar	Fund sustainability rating ranging from 1 to 5 globes and multiplied by -1. Higher number means more ESG-related risks.
Turnover ratio	CRSP	Turnover ratio of a fund.
Net expense ratio	CRSP	Net expense ratio of a fund.
Net cash position	CRSP	Net cash position of a fund as a percentage of fund TNA.
Institutional	CRSP	An indicator for institutional fund (as opposed to retail or neither).
Age	CRSP	The logarithm of the number of days between the date when the fund was first offered and February 29, 2020.
Beta	Morningstar	Market beta estimated from September 2019 to February 2020.
Star rating	Morningstar	Star rating of a fund which is a backward-looking measure of a funds' past performance.
Medal rating	Morningstar	Medal rating of a fund which is a forward-looking measure showing how likely a fund will outperform its peers over a full market cycle.
Liquidation	CRSP	A percentage change in amount of a particular bond that a fund held in particular month.

Appendix B: Refinitiv ESG database description

Refinitiv ESG database is one of the most comprehensive databases providing ESG scores of companies. Overall, the database covers nearly 1000 firms (headquartered mainly in US and Europe) for which ESG scores are calculated starting from 2002. Refinitiv collects information on firms' socially responsible activities through various sources such as company reports and websites, NGO websites and news. This information is then used to compute over 500 company-level ESG measures. After that, they are grouped into 10 categories and then aggregated into the three pillar scores (social, environmental, and governmental) and the final ESG score. Three pillar scores, as well as overall ESG score, can take a value from 0 to 100. The higher the value, the better relative ESG performance a company has.

For this study, we download social (S) and environmental pillar scores (E) for US corporations. Social pillar score takes into account such topics as workforce, human rights, community, and product responsibility. Environmental pillar score covers resource use, emissions, and innovation topics. We download the data as of June 2020, that is after Refinitiv applied methodology changes to ESG scores (Berg, Fabisik, and Sautner, 2021).

In most of our tests we use E&S score of firms, which is the average of E and S scores. This approach was applied in many studies before (Dyck, Lins, Roth, and Wagner, 2019; Albuquerque, Koskinen, Yang, and Zhang, 2020; Amiraslani, Lins, Servaes, and Tamayo, 2023; etc.)

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Figure 1: Characteristic-adjusted credit spreads for high and low E&S, S and E firms

In Panel A the sample of firms was divided into high and low E&S groups, where low E&S subsample is defined as 33.3% of firms with the lowest E&S score and high E&S subsample – as 33.3% of companies with the highest E&S score. We estimate a panel regression of credit spreads on all control variables and two interaction terms between daily time dummy and high/low E&S dummies. We plot cumulative sums of differences between credit spreads means for each day for each group (high/low E&S). Red and blue lines are the first and second Federal Reserve's debt market intervention on March 23 and April 9. In Panels B and C, we redo the plot for high/low S and E groups, respectively.

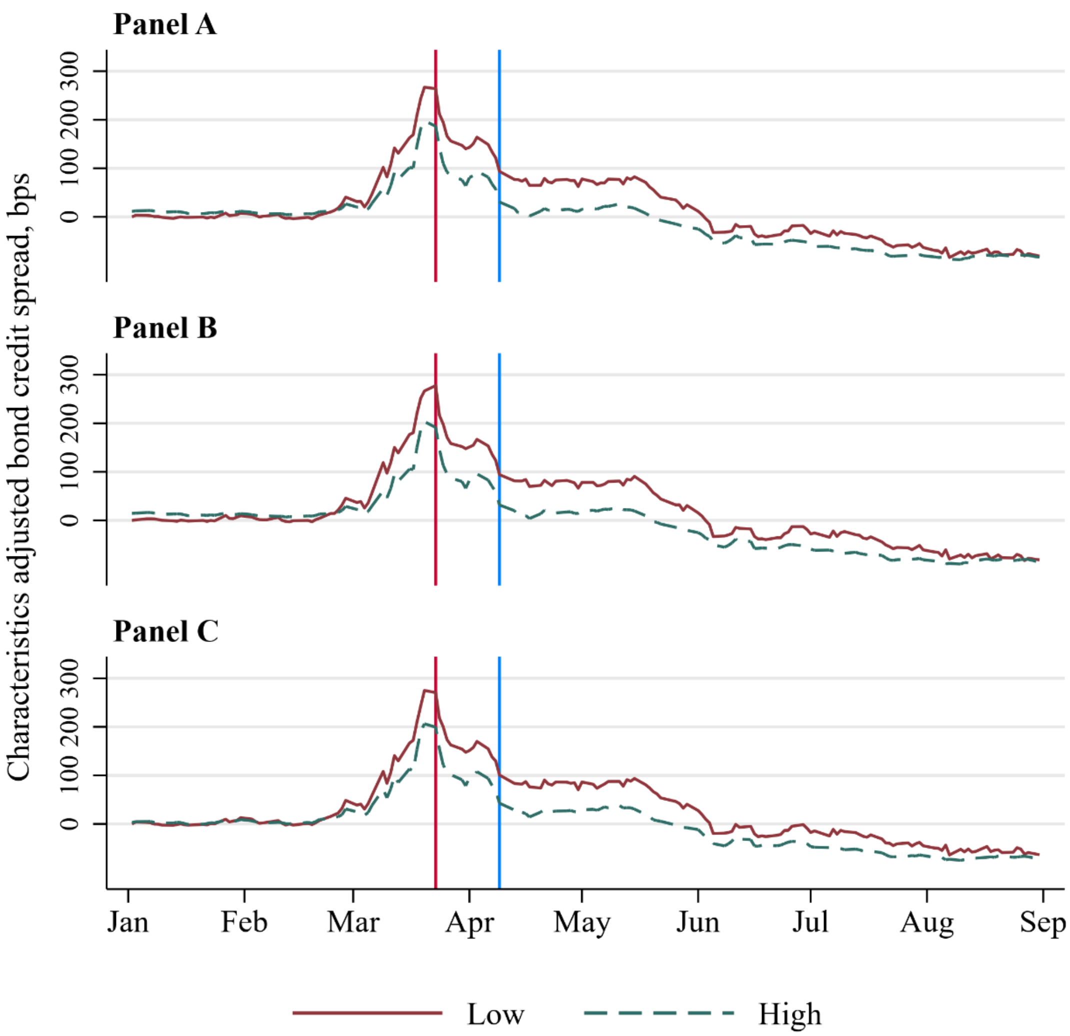

Figure 2: E&S coefficients by industry

Specification (5) in table 3 is adjusted to allow for triple interactions of Peak with E&S dummy and a dummy for each of the Fama and French 12 industries. E&S dummy is defined by the top-bottom tercile. Instead of industry-by-time and firm fixed effects, we use firm and day fixed effects. The figure shows coefficients for the triple interaction terms and 95% confidence intervals based on the firm and day level double clustered standard errors.

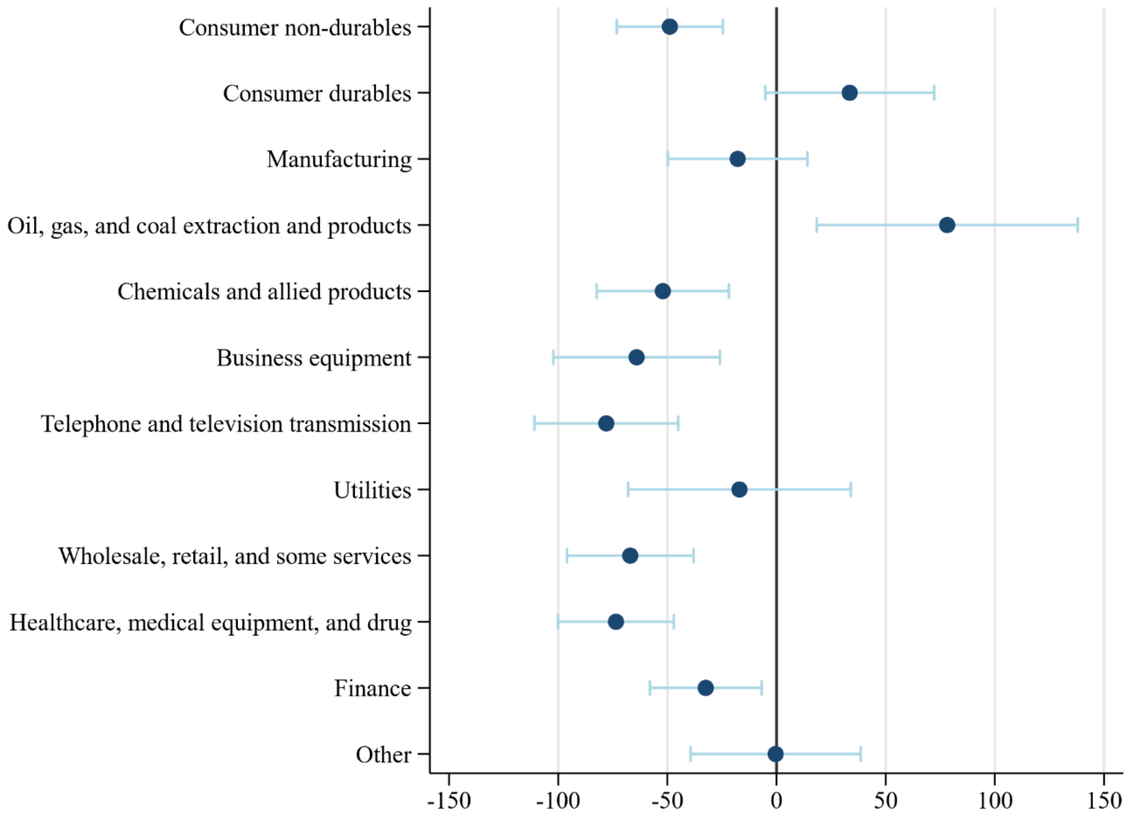

Figure 3: Fund net flows by month

This figure shows the evolution of monthly fund net flows from January to August 2020. Fund net flows expressed in million USD are computed as follows: $Flow_{f,t} = TNA_{f,t} - TNA_{f,t-1}(1 + R_{f,t})$
Dots indicate the average net flows across all funds each month. Vertical lines depict net flows in the top-bottom decile.

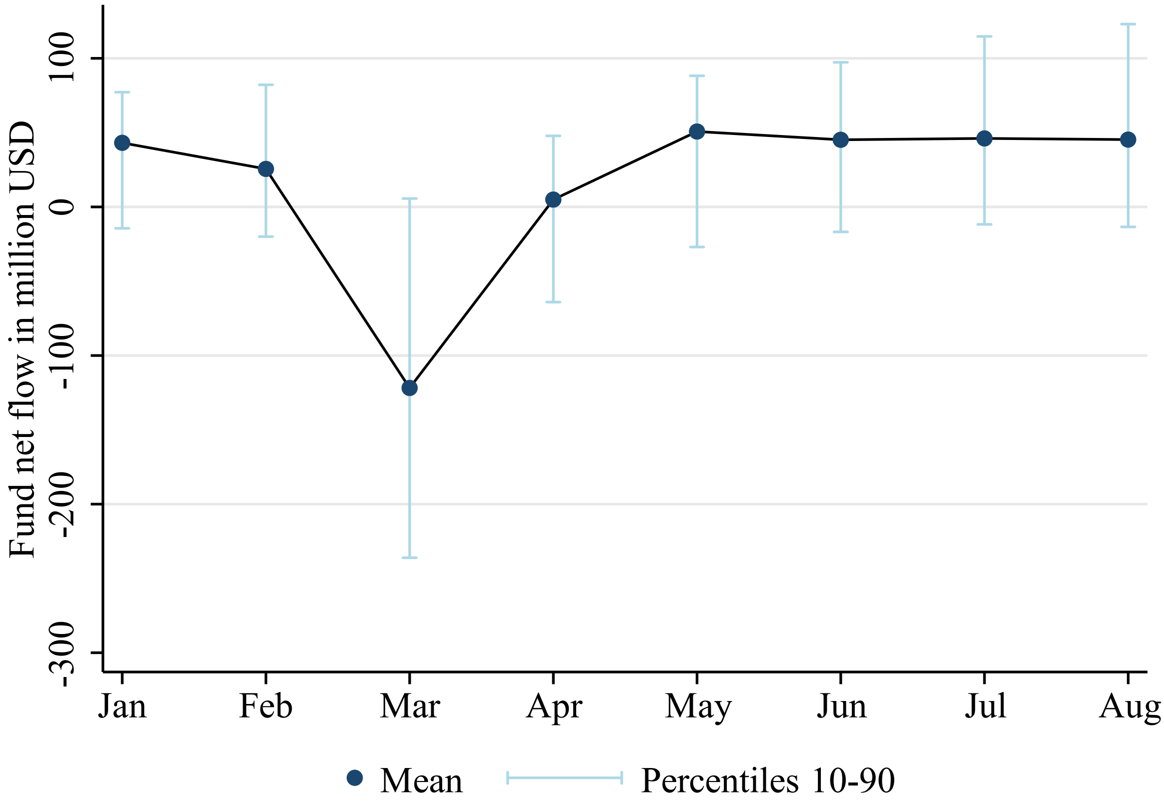

Figure 4: Selling pressure

The sample of firms was divided into high and low E&S groups, where low E&S subsample is defined as the first tercile (33.3%) of firms with the lowest score while high E&S group is the top tercile of companies with the highest score. We plot the average selling pressure (based on Haddad, Moreira, and Muir, 2021) for each month from January to August 2020 for each group (high/low E&S).

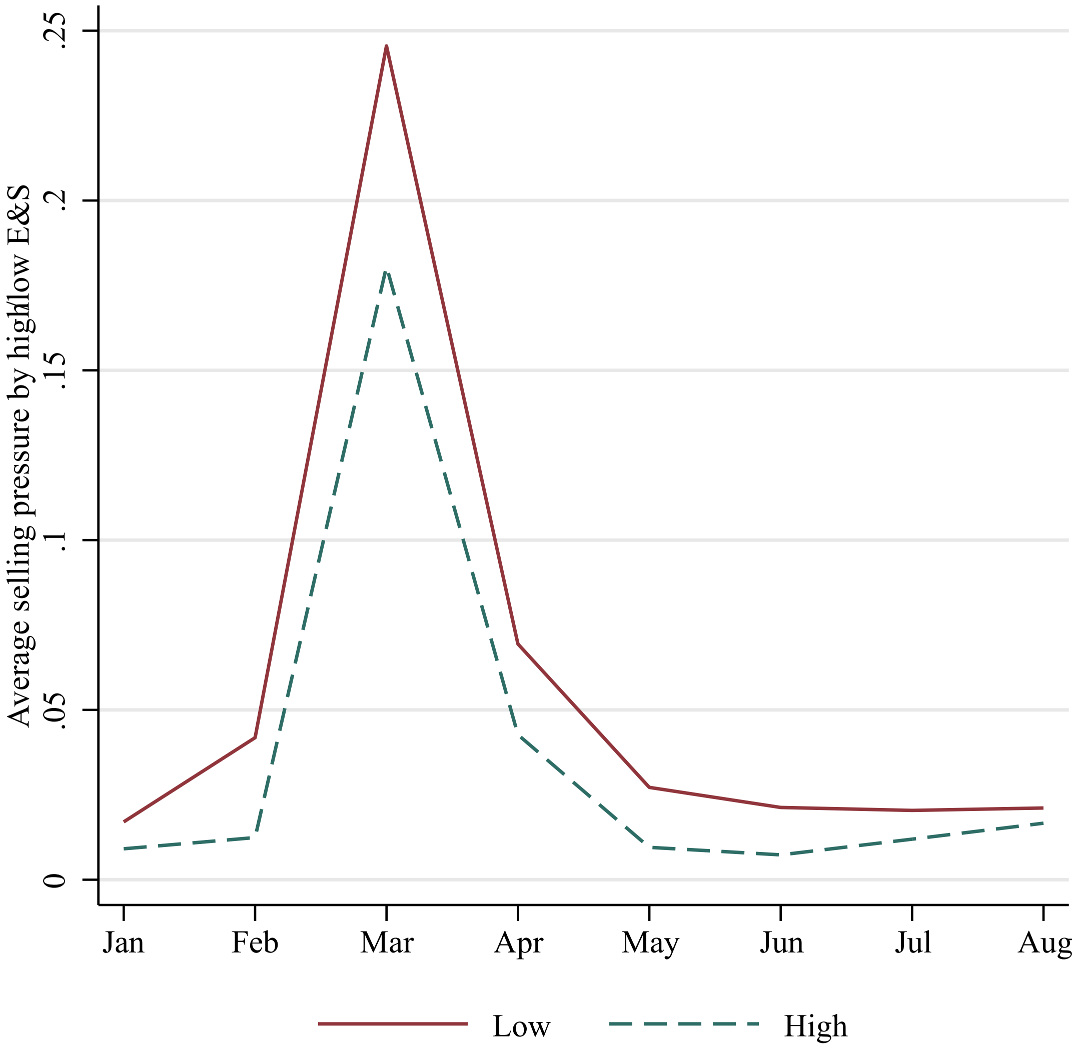

Table 1: Sample construction

Panel A represents a step-by-step sample selection process in this work with a final sample of 4959 bonds and 573 issuers. Panel B shows bonds distribution across Fama-French industries. The whole sample covers the period from January 2 to August 31.

Panel A: Sample selection

	Bonds	Issuers
Active TRACE-eligible bonds	59761	3520
Apply Dick-Nielsen (2014) filters and remove private placements (Rule 144A)	45336	3457
Remove bonds with floating coupon	16434	2617
Remove: bonds with other non-standard features zero-coupon bonds bonds issued after 1 December 2019 bonds not denominated in US dollars bonds with less than 1 year remaining to maturity	12110	2035
Remove: bonds whose issuers are domiciled outside US bonds whose issuers do not have E&S score available	5082	587
Remove bonds with missing credit ratings and E&S scores	5079	587
Eliminate bond spreads in the top-bottom 1%	4959	573

Panel B: Industry composition

Industry	Mean E&S	St.dev. E&S	Bonds	Issuers
Consumer non-durables	75.92	16.81	203	29
Consumer durables	79.04	14.62	150	17
Manufacturing	70.60	12.34	360	51
Oil, gas, and coal extraction and products	62.41	18.33	241	34
Chemicals and allied products	70.59	13.28	117	23
Business equipment	67.77	21.54	231	57
Telephone and television transmission	64.53	19.53	415	19
Utilities	60.91	17.93	807	43
Wholesale, retail, and some services	71.81	18.94	273	45
Healthcare, medical equipment, and drug	75.65	14.30	291	29
Finance	60.44	25.02	1459	146
Other	56.56	20.75	412	80
			4959	573

Table 2: Number of observations

The table presents number of bonds/CDS and bond/CDS-day observations in credit spreads, CDS and CDS-bond basis tests. Panel A shows number of observations for a full sample while Panels B and C for high and low E&S groups of firms, respectively. High E&S group is defined by the top tercile of firms with the highest score and low E&S group - by the bottom tercile of firms with the lowest score.

	Credit spreads	CDS	Basis
Panel A: Full sample			
N issuers	573	243	209
N bonds/CDS	4959	279	1488
Bond/CDS-day observations	461’635	43’363	129’667
Panel B: High E&S group of firms			
N issuers	191	122	108
N bonds/CDS	2796	140	972
Bond/CDS-day observations	266’809	21’912	90’042
Panel C: Low E&S group of firms			
N issuers	191	45	36
N bonds/CDS	1002	49	246
Bond/CDS-day observations	88’521	7’781	14’051

Table 3: Summary statistics

The table presents overall summary statistics. Panel A introduces corporate bonds characteristics that do not change over time. Panel B represents statistics for daily credit spreads, CDS spreads, CDS-bond basis, treasury bonds yields and bond characteristics that change on a daily or monthly (Amount) basis. Each bond/day(month) is considered as one observation. Panel C shows statistics for annual firm characteristics, daily stock excess returns and daily idiosyncratic volatility. For stock returns and volatility, each firm/day is considered as one observation. Panel D contains macro-level variables. Sample covers the period from January 2 to August 31.

	Measure	N	Mean	St.dev.	p25	p50	p75
Panel A: Corporate bonds related variables (unchanged over time)							
Coupon	%	4959	4.380	1.335	3.450	4.125	5.000
Global	0-1	4959	0.803	0.398	1.000	1.000	1.000
Security	0-4	4959	3.000	0.432	3.000	3.000	3.000
Year-to-maturity	years	4959	11.780	9.656	5.000	8.000	19.000
Credit rating	1-22	4959	8.099	2.487	6.000	8.000	10.000
Panel B: Corporate bonds/Treasury bonds related variables (daily or monthly)							
Credit spread	bps	461635	234.574	185.713	108.341	181.569	299.200
CDS spread	bps	43363	152.077	243.639	40.570	73.400	166.080
CDS-bond basis	bps	129667	-97.335	110.191	-146.109	-74.087	-31.085
Liquidity	%	461635	0.259	0.528	0.004	0.065	0.268
Treasury rate	bps	461635	83.588	52.826	37.280	74.280	121.800
Amount	$ bn	36249	643.175	679.201	277.275	500.000	750.000
Duration	days/365	461635	8.034	5.004	4.062	6.257	12.063
Panel C: Firm characteristics (annual or daily)							
E&S	1-100	573	54.031	22.371	36.142	56.546	72.207
S	1-100	573	49.298	27.313	26.768	52.316	72.624
E	1-100	573	58.764	20.769	43.520	60.105	75.829
Log size	$ bn	573	16.324	1.465	15.273	16.271	17.367
Leverage	%	573	32.871	19.342	18.032	29.993	44.000
Debt	%	573	34.850	17.797	22.012	34.719	45.720
ST debt	%	573	2.704	3.511	0.156	1.334	4.041
EBITDA/sales	%	573	26.181	20.808	12.035	21.679	38.495
Cov. 1	0-5	573	7.643	9.848	1.378	4.315	9.487
Cov. 2	0-5	573	33.161	30.742	6.716	20.425	58.124
Cov. 3	0-10	573	4.283	5.263	1.116	2.836	5.692
Cov. 4	0-100	573	3.895	1.502	3.140	5.000	5.000
Cash	%	573	1.759	2.137	0.000	0.146	4.643
Tangibility	%	573	4.062	4.636	0.000	0.262	10.000
Capex	%	573	1.381	7.987	0.000	0.000	0.000
Stock ret.	%	76867	-0.092	3.286	-1.458	-0.133	1.149
Idiosyncratic vol.	%	76867	3.246	1.529	2.150	3.079	4.050
Panel D: Macro variables (daily)							
S&P returns	%	168	0.087	2.530	-0.668	0.305	1.018
Term spread	bps	168	41.848	14.369	28.025	47.180	52.180

Table 4: E&S and credit spreads

The table presents estimation results of difference-in-difference regression described in "Research design" section. The dependent variable across all models is daily credit spreads, expressed in basis points. Independent variable E&S is an average of social and environmental scores of companies taking value from 0 to 100 in panel A. In panel B, E&S is a dummy variable equal to one for 33.3% of companies having the highest score and zero for the bottom tercile of firms. Time dummy variables include Outbreak, Peak and Post. Outbreak is a dummy variable equal to one from February 24 to March 10, 2020. Peak is a dummy variable equal to one for the peak of pandemic period from March 11 to March 22, 2020 and zero otherwise. Post is a dummy variable equal to one from March 23 to August 31 and zero otherwise. The whole sample covers the period from January 2 to August 31 and includes 461'635 observations. Standard errors are double clustered at the firm and day level and presented in parentheses. ***, **, and * indicate that the parameter estimate is significantly different from zero at the 1%, 5%, and 10% level, respectively.

	(1)	(2)	(3)	(4)	(5)
Panel A: E&S analysis					
E&S	-1.562***	0.419**	0.318*	0.500**	
	(0.393)	(0.190)	(0.189)	(0.233)	
E&S * Outbreak	-0.492***	-0.453***	-0.458***	-0.413***	-0.423***
	(0.121)	(0.081)	(0.093)	(0.081)	(0.085)
E&S * Peak	-0.953**	-1.336***	-1.235***	-1.146***	-1.611***
	(0.399)	(0.317)	(0.311)	(0.353)	(0.376)
E&S * Post	-1.109***	-1.137***	-0.973***	-1.288***	-1.523***
	(0.406)	(0.260)	(0.245)	(0.321)	(0.341)
Observations	461635	461633	461171	461171	461629
R-squared	0.158	0.715	0.792	0.750	0.794
Adj R^2	0.158	0.715	0.788	0.745	0.794
Time dummy variables	Included	Excluded	Excluded	Excluded	Excluded
Control variables	Excluded	Included	Included	Included	Included (excluded only firm-level time invariant)
Time-varying control variables	Excluded	Included	Included	Excluded	Included
Industry-time FE	NO	YES	NO	NO	YES
Industry-day FE	NO	NO	YES	YES	NO
Firm FE	NO	NO	NO	NO	YES
Panel B: E&S top-bottom tercile analysis					
E&S	-74.390***	19.589**	13.811	23.270**	
	(20.157)	(8.968)	(9.009)	(11.168)	
E&S * Outbreak	-27.051***	-23.847***	-23.756***	-21.629***	-22.373***
	(7.392)	(5.218)	(5.581)	(5.124)	(5.342)
E&S * Peak	-55.548**	-78.454***	-74.257***	-72.531***	-89.930***
	(22.702)	(16.346)	(16.163)	(18.900)	(20.049)
E&S * Post	-59.989***	-61.935***	-53.739***	-69.503***	-77.983***
	(20.831)	(13.394)	(12.246)	(16.425)	(17.911)
Observations	355330	355328	354514	354514	355326
R-squared	0.171	0.720	0.802	0.765	0.790
Adj R^2	0.171	0.720	0.798	0.760	0.789
Time dummy variables	Included	Excluded	Excluded	Excluded	Excluded
Control variables	Excluded	Included	Included	Included	Included (excluded only firm-level time invariant)
Time-varying control variables	Excluded	Included	Included	Excluded	Included
Industry-time FE	NO	YES	NO	NO	YES
Industry-day FE	NO	NO	YES	YES	NO
Firm FE	NO	NO	NO	NO	YES

Table 5: CDS-bond basis

The table presents estimation results for the baseline model with CDS-bond basis as the dependent variable. Independent variable E&S is an average of social and environmental scores of companies taking value from 0 to 100 in panel A. In panel B, E&S is a dummy variable equal to one for 33.3% of companies having the highest score and zero for the bottom tercile of firms. Time dummy variables include Outbreak, Peak and Post. Outbreak is a dummy variable equal to one from February 24 to March 10, 2020. Peak is a dummy variable equal to one for the peak of pandemic period from March 11 to March 22, 2020 and zero otherwise. Post is a dummy variable equal to one from March 23 to 31 August and zero otherwise. The whole sample covers the period from January 2 to August 31 and includes 129'667 observations. Standard errors are double clustered at the firm and day level and presented in parentheses. ***, **, and * indicate that the parameter estimate is significantly different from zero at the 1%, 5%, and 10% level, respectively.

	(1)	(2)	(3)	(4)	(5)
Panel A: E&S analysis					
E&S	0.461	-0.151	-0.116	-0.114	
	(0.335)	(0.277)	(0.281)	(0.286)	
E&S * Outbreak	0.193***	0.317***	0.245***	0.235***	0.385***
	(0.068)	(0.058)	(0.055)	(0.054)	(0.078)
E&S * Peak	0.648*	1.041***	1.075***	1.058***	1.170***
	(0.357)	(0.349)	(0.370)	(0.371)	(0.358)
E&S * Post	0.902***	0.588**	0.546*	0.538*	0.699**
	(0.315)	(0.290)	(0.282)	(0.281)	(0.331)
Observations	129667	129667	128971	128971	129666
R-squared	0.119	0.502	0.596	0.592	0.681
Adj R^2	0.119	0.501	0.573	0.570	0.681
Time dummy variables	Included	Excluded	Excluded	Excluded	Excluded
Control variables	Excluded	Included	Included	Included	Included (excluded only firm-level time invariant)
Time-varying control variables	Excluded	Included	Included	Excluded	Included
Industry-time FE	NO	YES	NO	NO	YES
Industry-day FE	NO	NO	YES	YES	NO
Firm FE	NO	NO	NO	NO	YES
Panel B: E&S top-bottom tercile analysis					
E&S	16.726	-16.715	-14.605	-14.270	
	(21.321)	(17.427)	(17.434)	(17.623)	
E&S * Outbreak	10.464***	15.172***	10.563***	10.309***	16.357***
	(3.582)	(3.301)	(3.358)	(3.219)	(1.919)
E&S * Peak	35.841*	57.717***	59.617***	59.546***	65.867***
	(18.691)	(13.705)	(14.737)	(14.219)	(11.939)
E&S * Post	38.222*	12.781	12.773	11.490	24.736
	(19.880)	(16.465)	(15.315)	(14.725)	(18.584)
Observations	104093	104093	103803	103803	104092
R-squared	0.113	0.573	0.683	0.680	0.660
Adj R^2	0.113	0.572	0.664	0.661	0.660
Time dummy variables	Included	Excluded	Excluded	Excluded	Excluded
Control variables	Excluded	Included	Included	Included	Included (excluded only firm-level time invariant)
Time-varying control variables	Excluded	Included	Included	Excluded	Included
Industry-time FE	NO	YES	NO	NO	YES
Industry-day FE	NO	NO	YES	YES	NO
Firm FE	NO	NO	NO	NO	YES

Table 6: E&S and basis: robustness analysis

The table presents estimation results of difference-in-difference regression described in "Research design" section. The dependent variable is daily basis, expressed in basis points. The CDS-bond basis refers to the difference between the CDS spreads of 5, 7, and 10-year terms, and the credit spreads with durations ranging from 3 to 12 years. Independent variable E&S is an average of social and environmental scores of companies taking value from 0 to 100. In Panel A, the analysis is based on a sample of bonds that have an investment-grade credit rating (that is, from AAA to BBB-). In panel B, the analysis is conducted on a full sample of bonds and CDS spreads are included as an additional control. Time dummy variables include Outbreak, Peak and Post. Outbreak is a dummy variable equal to one from February 24 to March 10, 2020. Peak is a dummy variable equal to one for the peak of pandemic period from March 11 to March 22, 2020 and zero otherwise. Post is a dummy variable equal to one from March 23 to August 31 and zero otherwise. Standard errors are clustered at the firm-day level and presented in parentheses. ***, **, and * indicate that the parameter estimate is significantly different from zero at the 1%, 5%, and 10% level, respectively.

	(1)	(2)	(3)	(4)	(5)
Panel A: Only investment-grade bonds					
E&S * Outbreak	0.130*	0.335***	0.195***	0.173***	0.379***
	(0.071)	(0.070)	(0.039)	(0.041)	(0.098)
E&S * Peak	1.060***	1.235***	1.229***	1.159***	1.184***
	(0.323)	(0.357)	(0.406)	(0.410)	(0.348)
E&S * Post	0.824***	0.469	0.500*	0.458	0.402
	(0.237)	(0.306)	(0.285)	(0.299)	(0.366)
Observations	111368	111367	110852	110852	111366
Adj R^2	0.111	0.510	0.604	0.599	0.695
Time dummy variables	Included	Excluded	Excluded	Excluded	Excluded
Control variables	Excluded	Included	Included	Included	Included (excluded only firm-level time invariant)
Time-varying control variables	Excluded	Included	Included	Excluded	Included
Industry-time FE	NO	YES	NO	NO	YES
Industry-day FE	NO	NO	YES	YES	NO
Firm FE	NO	NO	NO	NO	YES
Panel B: CDS spread as a control variable					
E&S * Outbreak	0.191***	0.270***	0.170*	0.144*	0.348***
	(0.067)	(0.080)	(0.089)	(0.083)	(0.071)
E&S * Peak	0.656*	0.916***	0.877**	0.789**	1.059***
	(0.343)	(0.313)	(0.359)	(0.344)	(0.322)
E&S * Post	0.923***	0.693*	0.629	0.636	0.828**
	(0.322)	(0.369)	(0.385)	(0.384)	(0.395)
CDS spread	0.031	0.354***	0.445***	0.405***	0.265***
	(0.058)	(0.066)	(0.072)	(0.067)	(0.043)
Observations	129667	129667	128971	128971	129666
Adj R^2	0.121	0.574	0.670	0.657	0.702
Time dummy variables	Included	Excluded	Excluded	Excluded	Excluded
Control variables	Excluded	Included	Included	Included	Included (excluded only firm-level time invariant)
Time-varying control variables	Excluded	Included	Included	Excluded	Included
Industry-time FE	NO	YES	NO	NO	YES
Industry-day FE	NO	NO	YES	YES	NO
Firm FE	NO	NO	NO	NO	YES

Table 7: Summary statistics for selling pressure measures

This table presents summary statistics for selling pressure measures. SP_1 and SP_2 refer to Haddad, Moreira, and Muir (2021) and Choi, Hoseinzade, Shin, and Tehranian (2020) measures defined in section 5.2. SP_2 (CBonds>50%) refers to a restricted sample of 172 funds which hold at least 50% of corporate bonds in their portfolio. The data cover the period of March 2020.

	N	Mean	St.dev.	p25	p50	p75	p90
SP_1	1721	0.106	0.146	0.017	0.053	0.140	0.265
SP_2	1721	0.012	0.054	0	0	0	0.019
SP_2 (CBonds>50%)	1604	0.009	0.048	0	0	0	0.011

Table 8: E&S and selling pressure

This table presents regressions of selling pressure measures on bond E&S scores. The dependent variable is a measure of selling pressure in March 2020. Columns (1) – (2) show the results for OLS model where selling pressure is measured using SP_1. Columns (3) – (6) present results of probit regressions in which the dependent variable equals one for positive values of selling pressure measure SP_2. We show the marginal effects (elasticities) at the means of the independent variables. Columns (5) and (6) use a restricted sample of 172 funds which hold at least 50% of corporate bonds in their portfolio. E&S is an average of social and environmental scores of companies taking value from 0 to 100. Credit rating is a credit rating of a bond as of February 2020. Average liquidity is an average value of bond liquidity for the month of February 2020. Δ Stock price and Δ Idios. vol. are the change in values of stock prices and idiosyncratic volatility between March 20 and February 24, 2020 (that is, between the end of the peak period and the beginning of the outbreak period). Other firm-level control variables include firm log size, leverage, debt, short-term debt, EDITDA/sales, cash, tangibility, capex, interest coverage ratio. We provide detailed definitions of all control variables in Appendix A (Groups 1 and 2). Standard errors are clustered at the firm level and presented in parentheses. ***, **, and * indicate that the parameter estimate is significantly different from zero at the 1%, 5%, and 10% level, respectively.

	(1) SP_1 OLS	(2) SP_1 OLS	(3) SP_2 Probit	(4) SP_2 Probit	(5) SP_2 Probit CBonds>50%	(6) SP_2 Probit CBonds>50%
E&S	-0.001***	-0.001**	-0.675**	-0.471*	-0.652**	-0.468
	(0.001)	(0.001)	(0.266)	(0.280)	(0.275)	(0.295)
Credit rating	0.018***	0.017***	1.423***	1.120***	1.277***	0.937**
	(0.003)	(0.003)	(0.366)	(0.361)	(0.375)	(0.395)
Average liquidity	0.007	0.008	0.247***	0.288***	0.232***	0.295***
	(0.007)	(0.007)	(0.070)	(0.081)	(0.072)	(0.085)
Δ Stock price*(10^{-3})	-0.001**		-0.030***		-0.022***	
	(0.001)		(0.008)		(0.008)	
Δ Idios. vol.	0.020**		-0.121		-0.091	
	(0.010)		(0.159)		(0.163)	
Constant	-0.016	0.183				
	(0.096)	(0.124)				
Observations	1721	1715	1721	1654	1604	1540
Adj R^2 [Pseudo R2]	0.195	0.239	[0.068]	[0.098]	[0.070]	[0.099]
Industry FE	NO	YES	NO	YES	NO	YES
Firm-level control variables	Included	Included	Included	Included	Included	Included

Table 9: Fund-level variables summary statistics

The table presents summary statistics for the dependent and independent fund-level variables we use. In Panel A, Portfolio Corporate Sustainability Score is a Morningstar fund level score measured as an asset-weighted average of Sustainalytics' company-level ESG Risk Rating. A higher score measures higher ESG-related risk exposure. Globe Rating is a Morningstar fund sustainability score that considers both corporate and sovereign bonds. It ranges from 1 to 5 "globes". We multiply this score by -1, so that a higher number means more ESG-related risks. Net flows are at the fund share class level. Panel B includes funds from the liquidation-to-outflows test, where Liquidation is the percentage change in the amount of a particular bond during March 2020 winsorized at the 1% level. Outflows are at the fund level.

	N	Mean	St.dev.	p1	p10	p25	p50	p75	p90	p99
Panel A: Morningstar score tests										
Portfolio Corporate Sustainability Score	48	27.17	5.08	9.72	21.43	24.30	26.62	29.18	35.22	37.24
Globe Rating	48	-2.77	1.19	-5	-5	-3.5	-2.5	-2	-1	-1
Net flow	78	-3.91	10.35	-43.35	-14.80	-8.29	-3.57	-0.73	5.07	33.05
Panel B: Liquidation-to-outflows tests										
Liquidation	8367	-5.76	27.10	-100	-10.85	0	0	0	0	91.61
Outflow	221	5.68	5.12	0.12	0.91	2.04	4.40	7.71	12.18	24.24

Table 10: Fund sustainability and investor redemptions

The table presents results from pooling retail and institutional share classes and running regressions of net flows on fund sustainability scores. Fund sustainability is measured by Morningstar Sustainability scores. In Panel A, Portfolio Corporate Sustainability Score is an asset-weighted average of Sustainalytics' company-level ESG Risk Rating. A higher score measures higher ESG-related risk exposure. In Panel B, we use Globe Rating ranging from 1 to 5 "globes". We multiply this score by -1, so that a higher number means more ESG-related risks. We control for fund 1-month and 3-month past return (in %) and total net assets (in billion USD). Other control variables include Morningstar star and medal rating, the turnover ratio, the net expense ratio, the net cash position, age, portfolio beta and an indicator for institutional vs retail share classes. We provide detailed definitions of all control variables in Appendix A (Group 4). Standard errors are clustered at the fund-level and presented in parentheses. ***, **, and * indicate that the parameter estimate is significantly different from zero at the 1%, 5%, and 10% level, respectively.

	(1) Net flow	(2) Net flow	(3) Net flow	(4) Net flow
Panel A: Portfolio Corporate Sustainability Score				
Portfolio Corporate Sustainability Score	-1.660**	-1.545*	-1.609**	-3.899***
	(0.787)	(0.784)	(0.771)	(1.021)
Fund ret. (past 1 month)		1.133***		
		(0.379)		
Fund ret. (past 3 months)			1.318	
			(1.701)	
TNA (in billion USD)		-1.922**	-1.631**	-2.263**
		(0.767)	(0.777)	(0.816)
Constant	41.841*	40.366*	41.025*	60.007
	(22.389)	(22.489)	(21.773)	(35.127)
Observations	76	76	74	59
Adjusted R^2	0.191	0.223	0.149	0.233
Fund obj. FE	YES	YES	YES	YES
Other fund level controls	NO	NO	NO	YES
Panel B: Globe Rating				
Globe Rating	-5.611***	-5.787***	-5.766***	-6.999***
	(1.800)	(1.824)	(1.698)	(2.479)
Fund ret. (past 1 month)		-0.041		
		(0.460)		
Fund ret. (past 3 months)			0.075	
			(1.315)	
TNA (in billion USD)		-2.162**	-2.195**	-2.488**
		(0.870)	(0.875)	(1.084)
Constant	-18.692***	-17.876***	-17.184***	-66.357**
	(4.428)	(4.607)	(4.168)	(24.223)
Observations	76	76	74	59
Adjusted R^2	0.288	0.329	0.302	0.159
Fund obj. FE	YES	YES	YES	YES
Other fund level controls	NO	NO	NO	YES

Table 11: Liquidation-to-outflow sensitivity for high/low E&S bonds

The table shows results from cross-sectional regressions of bond-fund liquidation measure on fund flows with a negative sign (that is, outflows). Liquidation is the percentage change in the amount of a particular bond during March 2020 winsorized at the 1% level. Columns (1) and (3) present results for low E&S bonds. Columns (2) and (4) show results for high E&S bonds. Low and High E&S groups are defined by the top-bottom tercile. We control for one month lagged fund returns and total net assets (in billion USD). Credit rating is a credit rating of a bond as of February 2020. Average liquidity is an average value of bond liquidity for the month of February 2020. Year-to-maturity is the remaining number of years until maturity of a bond. Time-varying firm control variables include Δ Stock price and Δ Idios. vol. They are computed as a change in values of stock prices and idiosyncratic volatility between March 20 and February 24, 2020 (that is, between the end of the peak period and the beginning of the outbreak period). Other firm characteristics include firm log size, leverage, debt, short-term debt, EDITDA/sales, cash, tangibility, capex, interest coverage ratio. We provide detailed definitions of all control variables in Appendix A (Groups 1, 2 and 4). Standard errors are double clustered at the firm and fund level and presented in parentheses. ***, **, and * indicate that the parameter estimate is significantly different from zero at the 1%, 5%, and 10% level, respectively.

	(1) Low E&S	(2) High E&S	(3) Low E&S	(4) High E&S
Outflow	-0.940***	-1.264***	-0.932***	-1.288***
	(0.161)	(0.185)	(0.159)	(0.183)
Credit rating	0.182	0.676*	0.354	1.049**
	(0.333)	(0.376)	(0.476)	(0.482)
Year-to-maturity	0.026	0.020	0.042	0.048
	(0.071)	(0.080)	(0.082)	(0.079)
Average liquidity	-0.386	-0.766	-0.797	-0.949
	(0.624)	(1.175)	(0.568)	(0.961)
Fund return	-114.502	13.063	-99.660	52.652
	(101.980)	(219.774)	(102.323)	(212.179)
TNA (in billion USD)	0.195***	0.093	0.189***	0.092
	(0.040)	(0.059)	(0.040)	(0.061)
Constant	15.237	-21.619	8.469	-56.726**
	(11.791)	(13.735)	(18.510)	(23.633)
Observations	3184	5180	3183	5179
Adj R2	0.054	0.055	0.056	0.071
Fund objective FE	YES	YES	YES	YES
Industry FE	NO	NO	YES	YES
Firm-level controls	YES	YES	YES	YES