Université de Neuchâtel
Faculté des sciences économiques

THE IMPACT OF SUSTAINABILITY FACTORS ON BOND PERFORMANCE, M&A ACTIVITY AND INVESTOR DEMAND

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IMPRIMATUR POUR LA THÈSE

The Impact of Sustainability Factors
on Bond performance, M&A activity and Investor Demand

Polina EFREMENKO

UNIVERSITÉ DE NEUCHÂTEL
FACULTÉ DES SCIENCES ÉCONOMIQUES

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On this final note, I dedicate this thesis to my father, who passed away after courageously fighting a long and difficult battle with illness.

“Дорогу осилит идущий”

- Russian proverb

Abstract

This dissertation consists of three distinct chapters. The first chapter is co-written with Prof. Carolina Salva and Prof. Sudheer Chava. 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 behaviour and net flows into mutual funds.

The second chapter examines whether the employee-related practices and policies of the target company have an impact on the M&A premiums in international deals between 2003 and 2022. Although the surveys indicate that generally dealmakers consider the target labour practices during the M&A due diligence and include them in the acquisition premiums, results indicate no overall relation between bid premiums and the target workforce practices as measured by Refinitiv workforce scores. The sector-level analysis, focusing on the technology sector where human capital productivity is specifically crucial, further supports the inference of no causal relationship between workforce ratings and the M&A premia. These findings develop our insight into the role workforce policies and practices play in M&A valuation.

The third chapter investigates the Green Economy Mark (GEM), a designation recognizing LSE-listed companies that derive more than 50% of their revenues from environmentally positive products and services. Such green equity labels are expected to reduce the information gap regarding companies' environmental performance and, thereby, attract more sustainability-oriented investors. I explore whether these expected benefits indeed materialize. My analysis shows that the market initially experienced a stock price increase following the announcement of the GEM. However, this reaction quickly reversed, leading to no abnormal returns being realized overall. I find that the GEM designation does not provide any incremental information. I further show that it does not lead to higher demand from both existing and new investors suggesting that the GEM is also unlikely to offer any information processing benefits. The initial reaction may be a short-lived anomaly of sentiment that faded away as the market reassessed the true impact of the GEM. This highlights the importance for exchanges to reconsider green labelling criteria for stocks.

Keywords: bond markets, COVID, ESG, selling pressure, fund flow, M&A premium, labour practices, green label, abnormal return, information asymmetry, investor demand.

Résumé

Cette dissertation se compose de trois chapitres distincts. Le premier chapitre est co-écrit avec le Professeur Carolina Salva et le Professeur Sudheer Chava. Nous documentons une baisse de la base CDS-obligations et une moindre pression de vente durant la crise du COVID pour les obligations émises par des entreprises ayant des scores environnementaux et sociaux (E&S) élevés, par rapport à celles émises par des entreprises à faibles scores E&S. Les obligations des entreprises à hauts scores E&S subissent une pression de vente réduite en raison de sorties d'investisseurs plus faibles des fonds axés sur la durabilité, et non pas parce que les gestionnaires de fonds sélectionnent activement les obligations à vendre. Nos résultats mettent en évidence que la performance des obligations pendant une crise est influencée non seulement par des évolutions des fondamentaux des entreprises, mais également par le comportement de trading des investisseurs et par les flux nets dans les fonds communs de placement.

Le deuxième chapitre examine l'impact potentiel des pratiques et politiques liées aux employés de l'entreprise cible sur les primes de fusions-acquisitions dans les transactions internationales entre 2003 et 2022. Bien que les enquêtes montrent que, généralement, les négociateurs prennent en compte les pratiques en matière de main-d'œuvre de la cible lors de la due diligence et les intègrent dans les primes d'acquisition, les résultats ne révèlent aucune corrélation globale entre ces primes et les pratiques de la main-d'œuvre telles que mesurées par les scores de Refinitiv. L'analyse sectorielle, axée sur le secteur technologique où la productivité du capital humain est particulièrement cruciale, renforce l'hypothèse d'une absence de relation causale entre les évaluations de la main-d'œuvre et les primes de fusions-acquisitions. Ces conclusions approfondissent notre compréhension du rôle que jouent les politiques et pratiques en matière de main-d'œuvre dans l'évaluation des fusions-acquisitions.

Le troisième chapitre étudie le Green Economy Mark (GEM), une désignation qui reconnaît les entreprises cotées à la Bourse de Londres (LSE) tirant plus de 50 % de leurs revenus de produits et services bénéfiques pour l'environnement. Ces labels de capitalisation verte sont censés réduire le fossé informationnel concernant la performance environnementale des entreprises et, par conséquent, attirer davantage d'investisseurs orientés vers la durabilité. J'examine si ces avantages attendus se matérialisent effectivement. Mon analyse montre que le marché a initialement connu une hausse du cours des actions à la suite de l'annonce du GEM. Cependant, cette réaction s'est rapidement inversée, ce qui a abouti à l'absence de rendements anormaux dans l'ensemble. Je constate que la désignation GEM n'apporte aucune information supplémentaire. J'observe en outre qu'elle ne conduit pas à une demande accrue tant de la part des investisseurs existants que des nouveaux, ce qui suggère que le GEM est également peu susceptible d'offrir des avantages en matière de traitement de l'information. La réaction initiale pourrait ainsi être une anomalie de sentiment passagère qui s'est estompée lorsque le marché a réévalué le véritable impact du GEM. Cela souligne l'importance pour les bourses de reconsidérer les critères d'étiquetage vert pour les actions.

Mots-clés: marchés obligataires, COVID, ESG, pression de vente, flux de fonds, prime de fusions-acquisitions, pratiques de travail, label vert, rendement anormal, asymétrie de l'information, demande des investisseurs.

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Introduction

Over the past years, environmental, social, and governance (ESG) factors have attained marked importance in the investment landscape. According to a 2022 report by PwC[1], asset managers globally are expected to increase their ESG-related assets under management to US$33.9 trillion by 2026 from US$18.4 trillion in 2021. This means a projected compound annual growth rate of 12.9%, which is indicative that ESG assets are developing at a high rate. By 2026, 21.5% of the world's total assets under management can be ESG-related. This significant growth underlines how investors are giving increasingly more importance to ESG considerations when making any kind of investment. Such increased interest boosted ESG-focused research with financial analysts and academics examining how ESG impacts portfolio performance, corporate value, and long-term growth potential (e.g., Eccles et al., 2014; Lins et al., 2017; Pedersen et al., 2021). Yet, despite this progress, questions remain about the actual impact of ESG practices across different contexts and asset classes.

This dissertation consists of three different chapters on the following issues related to ESG in financial markets: the resilience of ESG-rated bonds during market crises, the influence of labour practices on acquisition premiums in M&A transactions, and the effectiveness of green designations in enhancing clarity regarding environmental performance of firms and investor engagement. Taken together, these studies give a more nuanced picture of the emerging role of ESG and point to various ways in which ESG factors may affect financial performance and investor decision making.

The first chapter, co-authored with Prof. Carolina Salva and Prof. Sudheer Chava (Georgia Institute of Technology), explores whether the E&S performance of companies served as a hedge factor during the corporate bond market crashes at the time of the COVID crisis. In March 2020, liquidity in corporate bond markets dried up as financial institutions, and investors scrambled to sell their holdings to free up cash. As a result, corporate bond prices fell sharply, causing yields to rise and leading to wider spreads (Haddad et al., 2021; Falato et al., 2021). Several factors limiting arbitrage activity allowed spreads to widen further than they might have otherwise. However, we find that bonds of companies with higher E&S scores experienced lower credit spreads compared to bonds of firms with lower E&S ratings. We show that these pricing discrepancies were driven by a selective

[1] "Asset and wealth management revolution: Exponential expectations for ESG" (2022). *PwC*.

sale of bonds issued by low E&S firms triggered by a demand for liquidity. For that, we analyse the differences in CDS-bonds basis, computed as the difference between the CDS spread and the credit spread, for high and low E&S bonds. Past literature suggests that that the CDS-bond basis took negative values during the Covid-19 outbreak and financial crisis of 2008 (Fontana, 2012; Bai and Collin-Dufresne, 2018) which studies attribute to selling pressure by financial institutions (Augustin et al., 2014; Haddad et al., 2021). We find that high E&S bonds experienced a less negative basis suggesting that these bonds were less exposed to selling compared to low E&S bonds. We further confirm this by using more direct measures of selling pressure from the previous studies (e.g., Choi et al., 2020). Finally, we examine who exactly - investors or fund managers - triggered the selling pressure on low E&S bonds. We do not find that fund managers selectively sold low E&S bonds to meet investors redemptions. Instead, we show that investors chose to redeem to a greater extent from less sustainable funds which forced fund managers of these funds to sell assets to meet the redemptions. Since by definition these funds have more low E&S bonds in their portfolios, it resulted in more selling of these bonds leading to differences in credit spreads of high and low E&S bonds. This study makes significant contribution to the literature by demonstrating how differences in corporate bond spreads between high/low E&S bonds might be explained not only by firm fundamentals but also by investors trading behaviour.

In the second chapter, I examine whether the labour practices and policies of a target company are taken into account in the acquisition premium for the target during M&A deals. The results of various surveys and industry reports motivate me to investigate this question. For instance, a survey by KPMG[2] shows that labour policies related to health, safety, and diversity are considered during M&A due diligence and can potentially influence the M&A premium paid for a target company. Despite this anecdotal evidence, I do not find any relation between bid premiums and target workforce practices as measured by Refinitiv workforce scores. I further conduct a sector-level analysis to see if the link between Refinitiv workforce ratings of target firms and M&A premiums exists in some sectors. In particular, one might expect to observe such a relation when a target firm operates in the technology sector. Greater efforts towards employee well-being as reflected by labour practices and policies lead to more employee engagement which, in turn, improves employee productivity[3]. In the

[2] "ESG Due Diligence in M&A. Clarity on Mergers and Acquisitions" (2023). *KPMG*.

[3] "State of the Global Workplace. The Voice of the World's employees" (2024). *Gallup*.

tech sector, employee productivity is especially critical for gross profits (Bapna et al., 2013). If an acquirer buys a tech target company with low workforce score, it might try to exploit synergistic opportunities by correcting target workforce practices post-merger and thus boosting productivity and profitability for the combined firm. While the initial analysis uncovers a negative correlation between tech target workforce scores and bid premiums, I find that this relation is driven by endogeneity issues as suggested by instrumental variable analysis. Overall, this study is the first to demonstrate that target labour practices and policies are not generally taken into consideration in acquisition premiums, regardless of the sector in which a target firm operates. These findings add depth to our understanding of how workforce policies and practices affect M&A valuations.

In the third chapter, I investigate whether new green equity designations from stock exchanges help bridge the information gap around companies' environmental performance and, thereby, attract sustainability-conscious investors as suggested by the World Federation of Exchanges. To examine whether such green designations yield these expected benefits, I consider the Green Economy Mark (GEM) - the world's first certification scheme for green equity issuers. The GEM recognizes those London Stock Exchange (LSE)-listed companies deriving more than 50% of their revenues from products and services contributing to environmental objectives. To reduce the information asymmetry, the GEM should either provide some new insights to investors or improve their understanding of existing information, thus providing information processing benefits. However, given that GEM is based on publicly available information, I argue that it has limited ability to give any incremental information. Also, since it relies on the existing FTSE Green Revenues database, which reveals the percentage of companies' green revenues, I suggest that GEM represents a simple reclassification of what is already known to investors and, therefore, should not provide any information processing benefits. Consistent with that, I find a short-run market reaction to the GEM announcement in which the stock prices increased at first but very quickly reversed back, leading to no abnormal return overall. This serves as indirect evidence that GEM does not reduce information asymmetry. Further, I show directly that GEM label does not seem to carry any incremental information. I also demonstrate that GEM does not create more demand from existing or new investors. This result provides further confirmation of GEM's inability to give new information but also suggests that it is not able to deliver information processing benefits. The immediate stock market response likely reflects a temporary sentiment shock that disappeared as the market reassessed the GEM's implications. These findings suggest that the current approach being taken by the London

Stock Exchange to green labelling is not as effective as hoped. This study, being the first to examine green equity designations, provides important implications. Stock exchanges have adopted an initiative that is crucial to society. By creating green equity designations, they could potentially attract large investors interested in green investment opportunities, making a significant contribution to climate change mitigation and adaptation efforts. However, as my findings show, the initial attempts to create green equity labels have not led to the desired results. This calls for stock exchanges to refine their criteria for defining "green" equities.

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Chapter 1: ESG and Bond Market Resilience: Evidence from The Covid Crisis

1.1. 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 et al., 2020; Ding et al., 2021; Mahmoud and Meyer, 2020). There has also been a tremendous increase in net flows into sustainable equity funds[4] 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.[5] 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 et al., 2020; Bae et al., 2021; Cheema-Fox et al., 2021). However, the relative performance of bonds is understudied.[6]

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

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[4] 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*.

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

[6] An exception is Amiraslani et al. (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.

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 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.[7] 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 et al. (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 et al. (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

[7] 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.

portfolios (Haddad et al., 2021; Falato et al., 2021).[8] 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 behaviour, in turn, would put significant downward pressure on prices of low E&S 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 et al., 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 et al., 2014; Haddad et al., 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 behaviour (Falato et al., 2021; Haddad et al., 2021; Ma et al., 2022). We collect mutual funds' monthly bond holdings to build two different bond-level measures of selling pressure. We then analyse selling

[8] Halling et al. (2021) explain that ESG scores can also provide information about extra demand from investors with socially responsible preferences well beyond a context of crisis.

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 most of existing studies (Albuquerque et al., 2023; Albuquerque et al., 2020; Demers et al., 2021) focus on stock market responses to the pandemic, our work is among the first to evaluate whether bond market responses do indeed correlate with firm E&S status, thereby shielding investors from greater losses.9,10 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.

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

[10] 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 et al. (2020) suggest that socially responsible companies have greater customer (advertising expenditures) loyalty while Demers et al. (2021) explain that stronger firm fundamentals were responsible for high ESG firm outperformance. In addition, Albuquerque et al. (2023) suggest that mutual fund price pressure also played a role. For the GFC of 2008, Lins et al. (2017) show that CSR helped to build trust between companies and a wide range of stakeholders.

If trading activity is also significantly correlated to E&S scores in stock markets (Albuquerque et al., 2023), then there is an omitted factor in the studies of Albuquerque et al. (2020) and Lins et al. (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.[11] Our paper is related to Amiraslani et al. (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 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. Our paper also aligns with the findings of Fatica and Panzica (2024), who show that green bonds experienced lower sales than conventional bonds during the Covid outbreak. We add to this study by showing that selling pressure was the mechanism explaining pricing discrepancies of bonds issued by firms with high and low E&S scores during the Covid crisis. We also demonstrate that this selling pressure was the result of investors' redemptions from unsustainable funds rather than fund managers' decisions to selectively sell bonds issued by low E&S companies.

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 et al., 2021; Pastor et al., 2021; Pedersen et al., 2021) show that high ESG portfolio outperformance is mainly driven by better firm outcomes. An exception is Gibson et al. (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 1.2 presents the data used in the study and summary statistics. Section 1.3 describes the methodology and evaluates the relation arising between

[11] Menz (2010) and Stellner et al. (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 et al. (2014).

E&S and credit spreads. Section 1.4 analyses the association between E&S and the CDS-bond basis to evaluate the role of selling pressure. Section 1.5 measures selling pressure directly by looking at the trading activity of mutual funds and relates it to bond E&S scores. Section 1.6 assesses potential triggers of differential selling pressure observed in bonds issued by firms with varying E&S scores. Finally, section 1.7 briefly concludes.

1.2. Data

1.2.1. 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 et al. (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.[12] 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 et al. (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 1.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

[12] We keep callable and puttable 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 puttable bonds from the sample does not alter our results (see Table OA. 1 in the Online Appendix).

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.[13] 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 1.A (Group 1 and Group 3).

We then merge bond data with issuer E&S scores from Refinitiv ESG (formerly ASSET4) database.[14] We focus only on parent companies that are domiciled in the US. Appendix 1.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.[15]

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.

1.2.2. 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

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

[14] Berg et al. (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 587 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.

[15] ASSET4 ESG methodology changes as of April 6, 2020. This change leads to the retroactive rewriting of ESG scores. According to Berg et al. (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.

bond.[16] 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.

[Insert Table 1.1 about here.]

Table 1.1, Panel A provides a step-by-step description of the sample selection process. Table 1.1, 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 million. We select contracts with a "no restructuring" clause as the US market adopts this restructuring rule after 2009 (ISDA 2014 protocol).[17] 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 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

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[16] 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.

[17] 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.

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 et al. (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.[18]

[Insert Table 1.2 about here.]

Table 1.2 reports the number of observations we use in each test in more detail.

1.2.3. Summary statistics

[Insert Table 1.3 about here.]

Table 1.3 reports summary statistics for the main and control variables used in our analysis. Appendix 1.A provides a detailed description of each variable and how it is computed. Table 1.3, 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.

Table 1.3, 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.

[18] 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).

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 period.[19] There is considerable variation in credit and CDS spreads, as well as in the CDS-bond basis.

Table 1.3, 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.

1.3. Credit spreads and E&S scores

1.3.1. Research design

We start analysing 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 et al., 2023; Stellner et al., 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 et al. (2023) who used monthly credit spreads around the 2008 financial crisis.[20]

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

$$\mathrm{CS}_{i,j,t} = \beta_0 + \beta_1 \mathrm{Score}_j + \beta_2 \left(\mathrm{Score}_j \times \mathrm{Outbreak}_t\right) +$$

[19] 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 et al., 2005; Choi and Shachar, 2014).

[20] A difference-in-difference approach is also used in Lins et al. (2017) and Albuquerque et al. (2020) to explore the evolution of stock returns for high and low E&S firms around the 2008 and Covid crisis respectively.

$$\beta_3(\text{Score}_j \times \text{Peak}_t) + \beta_4(\text{Score}_j \times \text{Post}_t) + \delta'X + \text{Industry} * \text{Time FE}_{j,t} + \varepsilon_{i,j,t} \quad (1.1)$$

where $CS_{i,j,t}$ 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 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 et al., 2021; Falato et al., 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 et al. (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 1.3.2. 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 $t-1$.

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 et al. (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 et al. (2014), Acharya et al. (2012) and Fahlenbrach et al. (2021) we also include capital expenditures, tangibility, cash holdings and short-term debt. We provide a detailed definition of firm-level variables in Appendix 1.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 et al. (2001), Amiraslani et al. (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 et al. (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 1.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 1.A (Group 3).

1.3.3. Results

[Insert Table 1.4 about here.]

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 1.4, 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.[21] 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 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.[22] 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 et al. (2023, Figure 1) for the Global Financial Crisis of 2008.

Table 1.4, 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

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[21] 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.

[22] We also re-estimate Table 1.4 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.

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 significant and consistent with the outperformance of bonds with high E&S scores over the same period.[23]

[Insert Figure 1.1 about here.]

Figure 1.1, 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 1.1, 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 1.1 (B&C), which replicates the plot, yet considers S and E scores separately, we observe a similar pattern.

[Insert Figure 1.2 about here.]

In Table 1.1, Panel B 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

[23] In Table OA. 7 and Table OA. 8 in the Online Appendix, we replicate Table 1.4, 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.

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 1.2 displays within industry analysis based on specification (5) in Table 1.4, 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 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 et al. (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 et al. (2023) examine one potential mechanism underlying these results. They argue that high E&S scores mitigate increases in fundamental default risk.[24] 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.

1.4. 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 et al., 2021; Falato et al., 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 et al., 2005). Pure investor preferences and trading behaviours could also explain the positive relationship arising between high

[24] 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 et al. (2023), we find that firm E&S status moderates increases in default risk during the Covid-19 crisis.

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.

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 et al., 2005). Various studies analyse the determinants of the CDS-bond basis.[25] In particular, Haddad et al. (2021) document a large and negative CDS-bond basis during the Covid-19 crisis which coincides with our sample period.26 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.[27] 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.[28]

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[25] Studies such as Longstaff et al. (2005), among others, attribute the CDS-bond basis mainly to the illiquidity of the underlying bond. Elton et al. (2001) argue that differential taxation between corporate bonds and Treasuries could explain the CDS-bond basis, though Longstaff et al. (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 et al. (2021) highlight that the major factors during the Covid-19 crisis were liquidity issues or selling pressures.

[26] 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 et al., 2020; Fontana, 2012). Similar dynamics have emerged during the Covid crisis (Haddad et al., 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 et al., 2005; Longstaff et al., 2005; Hull et al., 2004). However, during periods of crisis, there are limits to arbitrage and a gap opens between the spread and the CDS.

[27] Augustin et al. (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.

[28] 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

Building on Haddad et al. (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 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 et al. (2001), due to the asymmetric taxes inherent between corporates and Treasuries.[29]

1.4.1. Results

[Insert Table 1.5 about here.]

Table 1.5, 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

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.

[29] Longstaff et al. (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.

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.[30] 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 et al., 2021; Haddad et al., 2021) and 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 1.5, 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.[31] 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

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[30] We re-estimated the results of Table 1.5, 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.

[31] 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.

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 honour 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 behaviour and, as such, one can expect this outperformance not to be long-lasting.

1.4.2. Robustness

1.4.2.1. Selling pressure and investment grade bonds

Haddad et al. (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.

[Insert Table 1.6 about here.]

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 1.5 using a subsample consisting only of investment-grade bonds and report the results in Table 1.6, 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.

1.4.2.2. 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 1.6, Panel B we extend our analysis and re-estimate Table 1.5 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.

1.5. 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 et al., 2021; Falato et al., 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 et al., 2022).[32] 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.

1.5.1. 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 1.2.1) with available E&S scores and key firm and bond-level characteristics. We

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

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:

$$\mathrm{Flow}_{\mathrm{f,t}} = \mathrm{TNA}_{\mathrm{f,t}} - \mathrm{TNA}_{\mathrm{f,t-1}}\left(1 + \mathrm{R}_{\mathrm{f,t}}\right) \tag{1.2}$$

$$\mathrm{flow}_{\mathrm{f,t}} = \mathrm{Flow}_{\mathrm{f,t}}/\mathrm{TNA}_{\mathrm{f,t-1}} * 100\% \tag{1.3}$$

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.

[Insert Figure 1.3 about here.]

Figure 1.3 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 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.[33]

1.5.2. 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.

[Insert Table 1.7 about here.]

[33] 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 1.3.

First, we follow Haddad et al. (2021) and compute selling pressure as:

$$\text{SP\_1}_{\text{i,j,March}} = \frac{\sum_{\text{f}} \max\left(-\text{flow}_{\text{f,March}}, 0\right) * \text{Holdings}_{\text{i,Feb}}}{\text{Amount outstanding}_{\text{i,February}}} \tag{1.4}$$

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 1.7 indicate that most mutual funds had outflows during the month of March.

[Insert Figure 1.4 about here.]

Figure 1.4 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 portfolio bonds proportionally to outflows, we can infer that less sustainable mutual funds suffered larger outflows. We test this conjecture later in section 1.6.

Our second measure of selling pressure follows Choi et al. (2020):

$$\text{SP\_2}_{\text{i,j,March}} = \frac{\sum_{\text{f}} \max\left(-\Delta\text{Holdings}_{\text{i,March}}, 0\right)}{\text{Amount outstanding}_{\text{i,February}}} \tag{1.5}$$

where f are funds with flows < percentile (15^{th}). 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.[34] 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 1.7, 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:

$$\mathrm{SP}_{i,j} = \beta_0 + \beta_1 \mathrm{Score}_j + \delta' X + \text{Industry FE}_j + \varepsilon_{i,j} \tag{1.6}$$

where $\mathrm{SP}_{i,j}$ 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. Score_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. Precisely, we include the list of static firm-level variables described in Appendix 1.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 meet investor redemptions (Ma et al., 2022). Standard errors are clustered at the firm-level.

[Insert Table 1.8 about here.]

Table 1.8 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

[34] 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 1.8 remain qualitatively consistent regardless of the scaling method employed.

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.[35] 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 1.8 using only the subsample of investment grade bonds and results are unaffected or even stronger (see Table OA. 13 in the Online Appendix).

1.6. 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.

1.6.1. 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[36]. Pastor and Vorsatz (2020) report similar results for equity mutual funds. This evidence indicates that ultimate investors were likely selective in which mutual funds to sell. If ultimate investors selectively choose which mutual funds to sell, prioritizing divestment from less sustainability-focused 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.

[35] 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.

[36] 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).

[Insert Table 1.9 about here.]

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 1.9.

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 1.A (Group 4).

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

$$\mathrm{flow}_{\mathrm{f_c,Mar\ 2020}} = \beta_0 + \beta_1 \mathrm{Score}_{\mathrm{f,Feb\ 2020}} + \delta' \mathrm{Z} + \mathrm{Fund\ objective\ FE_f} + \varepsilon_{\mathrm{f,Mar\ 2020}} \tag{1.7}$$

where $\mathrm{flow}_{\mathrm{f_c,Mar\ 2020}}$ is the net flow at the investor-type share class level $\mathrm{f_c}$ as of March. $\mathrm{Score}_{\mathrm{f,Feb\ 2020}}$ 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.

[Insert Table 1.10 about here.]

Table 1.10 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 Table 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.

1.6.2. 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 et al., 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 et al. (2022) and examine the sensitivity of bond liquidation to fund outflows. We use the same sample of funds as described in section 1.5.1. For each fund, we construct a bond fund level Liquidation measure as of March 2020,

$$\mathrm{Liquidation}_{\mathrm{i,f,March}} = \left(\mathrm{Holdings}_{\mathrm{i,f,March}} - \mathrm{Holdings}_{\mathrm{i,f,February}}\right) / \mathrm{Holdings}_{\mathrm{i,f,February}} \tag{1.8}$$

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 1.9, 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:

$$\mathrm{Liquidation}_{i,f,March} = \beta_0 + \beta_1 \mathrm{Outflows}_{f,March} + \delta' N + \mathrm{Objective\ code\ FE}_f + \varepsilon_{i,f} \quad (1.9)$$

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.[37] 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. Precisely, we include the list of static firm-level variables described in Appendix 1.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.

[Insert Table 1.11 about here.]

Table 1.11 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

[37] 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.

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 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.

1.7. 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.

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Figures

Figure 1.1: 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.

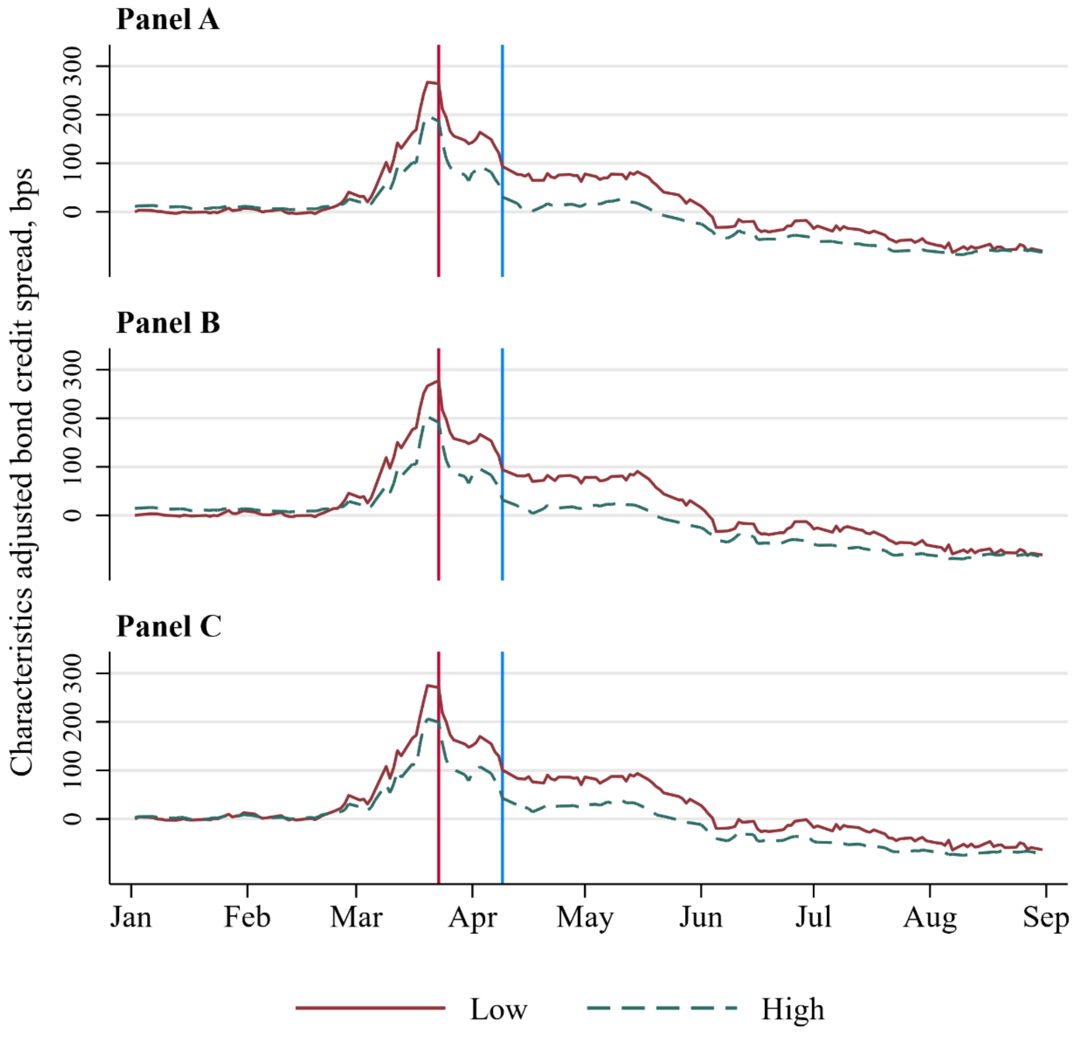


Figure 1.2: E&S coefficients by industry

Specification (5) in Table 1.4 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.

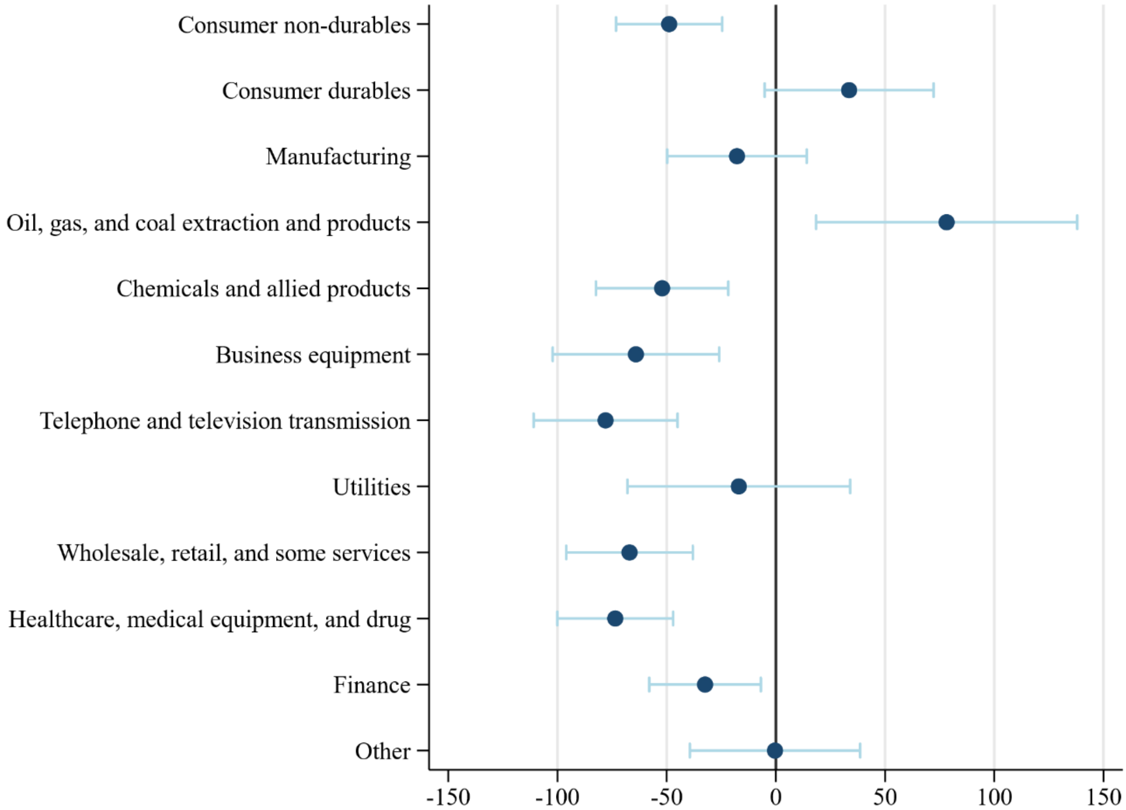


Figure 1.3: Fund net flows by month

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: $\mathbf{Flow_{f,t} = TNA_{f,t} - TNA_{f,t-1}(1 + R_{f,t})}$. Dots indicate the average net flows across all funds each month. Vertical lines depict net flows in the top-bottom decile.

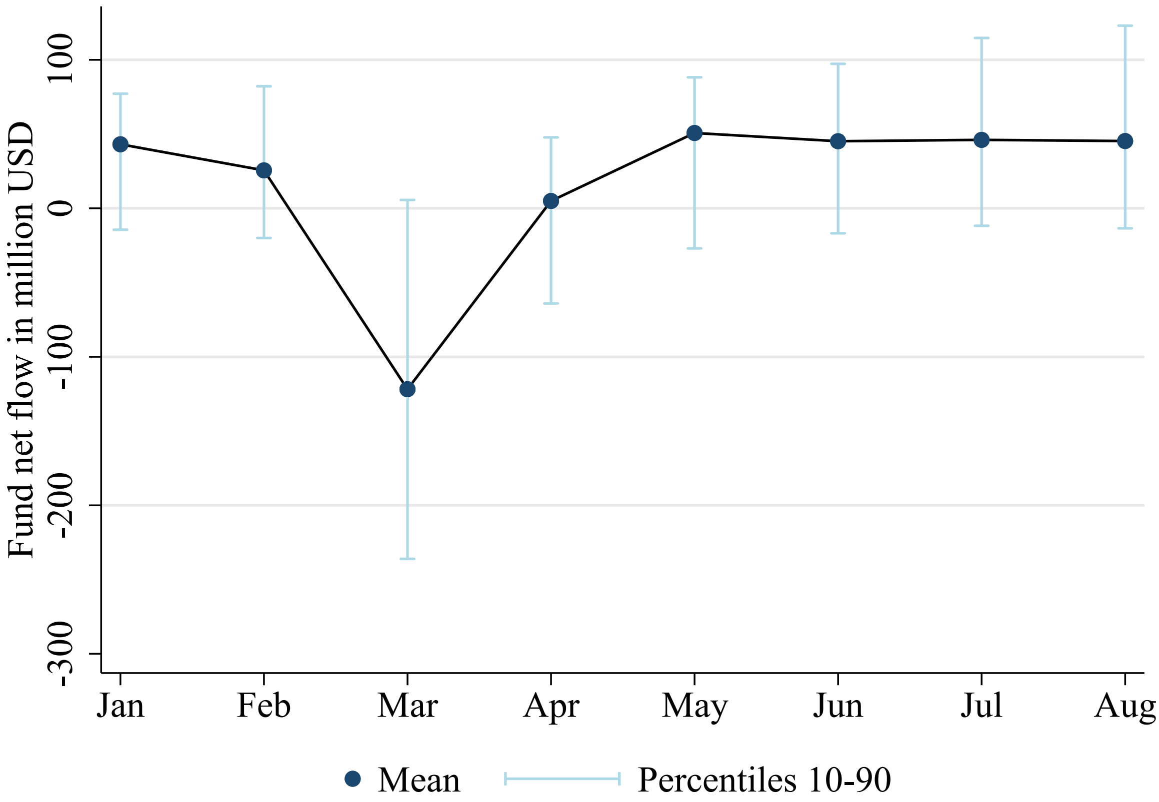
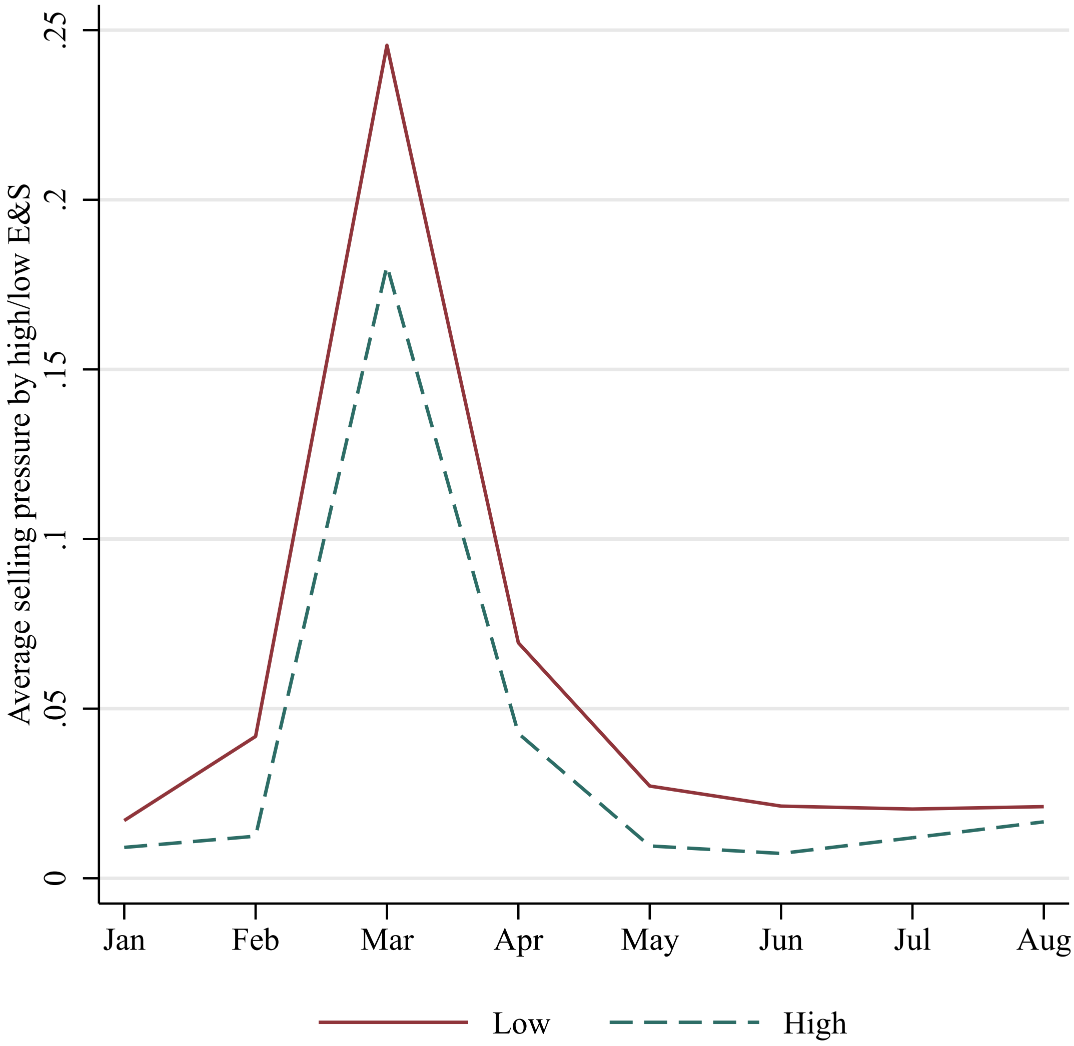


Figure 1.4: Selling pressure

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 et al., 2021) for each month from January to August 2020 for each group (high/low E&S).



Tables

Table 1.1: 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 1.2: 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 1.3: 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	4.38	1.34	3.45	4.13	5.00
Global	0-1	4959	0.80	0.40	1.00	1.00	1.00
Security	0-4	4959	3.00	0.43	3.00	3.00	3.00
Year-to-maturity	years	4959	11.78	9.66	5.00	8.00	19.00
Credit rating	1-22	4959	8.10	2.49	6.00	8.00	10.00
Panel B: Corporate bonds/Treasury bonds related variables (daily or monthly)							
Credit spread	bps	461635	234.57	185.71	108.34	181.57	299.20
CDS spread	bps	43363	152.08	243.64	40.57	73.40	166.08
CDS-bond basis	bps	129667	-97.34	110.19	-146.11	-74.09	-31.09
Liquidity	%	461635	0.26	0.53	0.01	0.07	0.27
Treasury rate	bps	461635	83.59	52.83	37.28	74.28	121.80
Amount	$ bn	36249	643.18	679.20	277.28	500.00	750.00
Duration	days/365	461635	8.03	5.00	4.06	6.26	12.06
Panel C: Firm characteristics (annual or daily)							
E&S	1-100	573	54.03	22.37	36.14	56.55	72.21
S	1-100	573	49.30	27.31	26.77	52.32	72.62
E	1-100	573	58.76	20.77	43.52	60.11	75.83
Log size	$ bn	573	16.32	1.47	15.27	16.27	17.37
Leverage	%	573	32.87	19.34	18.03	29.99	44.00
Debt	%	573	34.85	17.80	22.01	34.72	45.72
ST debt	%	573	2.70	3.51	0.16	1.33	4.04
EBITDA/sales	%	573	26.18	20.81	12.04	21.68	38.50
Cov. 1	0-5	573	7.64	9.85	1.38	4.32	9.49
Cov. 2	0-5	573	33.16	30.74	6.72	20.43	58.12
Cov. 3	0-10	573	4.28	5.26	1.12	2.84	5.69
Cov. 4	0-100	573	3.90	1.50	3.14	5.00	5.00
Cash	%	573	1.76	2.14	0.00	0.15	4.64
Tangibility	%	573	4.06	4.64	0.00	0.26	10.00
Capex	%	573	1.38	7.99	0.00	0.00	0.00
Stock ret.	%	76867	-0.09	3.29	-1.46	-0.13	1.15
Idiosyncratic vol.	%	76867	3.25	1.53	2.15	3.08	4.05
Panel D: Macro variables (daily)							
S&P returns	%	168	0.09	2.53	-0.67	0.31	1.02
Term spread	bps	168	41.85	14.37	28.03	47.18	52.18

Table 1.4: 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	-1.56***	0.42**	0.32*	0.50**	
	(0.39)	(0.19)	(0.19)	(0.23)	
E&S * Outbreak	-0.49***	-0.45***	-0.46***	-0.41***	-0.42***
	(0.12)	(0.08)	(0.09)	(0.08)	(0.09)
E&S * Peak	-0.95**	-1.34***	-1.24***	-1.15***	-1.61***
	(0.40)	(0.32)	(0.31)	(0.35)	(0.38)
E&S * Post	-1.11***	-1.14***	-0.97***	-1.29***	-1.52***
	(0.41)	(0.26)	(0.25)	(0.32)	(0.34)
Observations	461635	461633	461171	461171	461629
R-squared	0.16	0.72	0.79	0.75	0.79
Adj R^2	0.16	0.72	0.79	0.75	0.79
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	-74.39***	19.59**	13.81	23.27**	
	(20.16)	(8.97)	(9.01)	(11.17)	
E&S * Outbreak	-27.05***	-23.85***	-23.76***	-21.63***	-22.37***
	(7.39)	(5.22)	(5.58)	(5.12)	(5.34)
E&S * Peak	-55.55**	-78.45***	-74.26***	-72.53***	-89.93***
	(22.70)	(16.35)	(16.16)	(18.90)	(20.05)
E&S * Post	-59.99***	-61.94***	-53.74***	-69.50***	-77.98***
	(20.83)	(13.39)	(12.25)	(16.43)	(17.91)
Observations	355330	355328	354514	354514	355326
R-squared	0.17	0.72	0.80	0.77	0.79
Adj R^2	0.17	0.72	0.80	0.76	0.79
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 1.5: 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	0.46	-0.15	-0.17	-0.11	
	(0.34)	(0.28)	(0.28)	(0.29)	
E&S * Outbreak	0.19***	0.32***	0.25***	0.24***	0.39***
	(0.07)	(0.06)	(0.06)	(0.05)	(0.08)
E&S * Peak	0.65*	1.04***	1.08***	1.06***	1.17***
	(0.36)	(0.35)	(0.37)	(0.37)	(0.36)
E&S * Post	0.90***	0.59**	0.55*	0.54*	0.70**
	(0.32)	(0.29)	(0.28)	(0.28)	(0.33)
Observations	129667	129667	128971	128971	129666
R-squared	0.12	0.50	0.60	0.59	0.68
Adj R^2	0.12	0.50	0.57	0.57	0.68
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	16.73	-16.72	-14.61	-14.27	
	(21.32)	(17.43)	(17.43)	(17.62)	
E&S * Outbreak	10.46***	15.17***	10.56***	10.31***	16.36***
	(3.58)	(3.30)	(3.36)	(3.22)	(1.92)
E&S * Peak	35.84*	57.72***	59.62***	59.55***	65.87***
	(18.69)	(13.71)	(14.74)	(14.22)	(11.94)
E&S * Post	38.22*	12.78	12.77	11.49	24.74
	(19.88)	(16.47)	(15.32)	(14.73)	(18.58)
Observations	104093	104093	103803	103803	104092
R-squared	0.11	0.57	0.68	0.68	0.66
Adj R^2	0.11	0.57	0.66	0.66	0.66
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 1.6: 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	0.13*	0.34***	0.20***	0.17***	0.38***
	(0.07)	(0.07)	(0.04)	(0.04)	(0.10)
E&S * Peak	1.06***	1.24***	1.23***	1.16***	1.18***
	(0.32)	(0.36)	(0.41)	(0.41)	(0.35)
E&S * Post	0.82***	0.47	0.50*	0.46	0.40
	(0.24)	(0.31)	(0.29)	(0.30)	(0.37)
Observations	111368	111367	110852	110852	111366
Adj R^2	0.11	0.51	0.60	0.60	0.70
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	0.19***	0.27***	0.17*	0.14*	0.35***
	(0.07)	(0.08)	(0.09)	(0.08)	(0.07)
E&S * Peak	0.66*	0.92***	0.88**	0.79**	1.06***
	(0.34)	(0.31)	(0.36)	(0.34)	(0.32)
E&S * Post	0.92***	0.69*	0.63	0.64	0.83**
	(0.32)	(0.37)	(0.39)	(0.38)	(0.40)
CDS spread	0.03	0.35***	0.45***	0.41***	0.27***
	(0.06)	(0.07)	(0.07)	(0.07)	(0.04)
Observations	129667	129667	128971	128971	129666
Adj R^2	0.12	0.57	0.67	0.66	0.70
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 1.7: Summary statistics for selling pressure measures

This table presents summary statistics for selling pressure measures. SP_1 and SP_2 refer to Haddad et al. (2021) and Choi et al. (2020) measures defined in section 1.5.2. 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	0.11	0.15	0.02	0.05	0.14	0.27
SP_2	1721	0.01	0.05	0	0	0	0.02
SP_2 (CBonds>50%)	1604	0.01	0.05	0	0	0	0.01

Table 1.8: 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 1.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**	-0.68**	-0.47*	-0.65**	-0.47
	(0.001)	(0.001)	(0.27)	(0.28)	(0.28)	(0.30)
Credit rating	0.02***	0.02***	1.42***	1.12***	1.28***	0.94**
	(0.003)	(0.003)	(0.37)	(0.36)	(0.38)	(0.40)
Average liquidity	0.01	0.01	0.25***	0.29***	0.23***	0.30***
	(0.01)	(0.01)	(0.07)	(0.08)	(0.07)	(0.09)
Δ Stock price*(10^{-3})	-0.001**		-0.03***		-0.02***	
	(0.001)		(0.01)		(0.01)	
Δ Idios. vol.	0.02**		-0.12		-0.09	
	(0.01)		(0.16)		(0.16)	
Constant	-0.02	0.18				
	(0.10)	(0.12)				
Observations	1721	1715	1721	1654	1604	1540
Adj R^2 [Pseudo R2]	0.20	0.24	[0.07]	[0.10]	[0.10]	[0.10]
Industry FE	NO	YES	NO	YES	NO	YES
Firm-level control variables	Included	Included	Included	Included	Included	Included

Table 1.9: 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 1.10: 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 1.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	-1.66**	-1.55*	-1.61**	-3.90***
	(0.787)	(0.78)	(0.77)	(1.02)
Fund ret. (past 1 month)		1.13***		
		(0.38)		
Fund ret. (past 3 months)			1.32	
			(1.70)	
TNA (in billion USD)		-1.92**	-1.63**	-2.26**
		(0.77)	(0.78)	(0.82)
Constant	41.84*	40.37*	41.03*	60.01
	(22.39)	(22.49)	(21.77)	(35.13)
Observations	76	76	74	59
Adjusted R^2	0.19	0.22	0.15	0.23
Fund obj. FE	YES	YES	YES	YES
Other fund level controls	NO	NO	NO	YES
Panel B: Globe Rating				
Globe Rating	-5.61***	-5.79***	-5.77***	-7.00***
	(1.80)	(1.82)	(1.70)	(2.48)
Fund ret. (past 1 month)		-0.04		
		(0.46)		
Fund ret. (past 3 months)			0.08	
			(1.32)	
TNA (in billion USD)		-2.16**	-2.20**	-2.49**
		(0.87)	(0.88)	(1.08)
Constant	-18.69***	-17.88***	-17.18***	-66.36**
	(4.43)	(4.61)	(4.17)	(24.22)
Observations	76	76	74	59
Adjusted R^2	0.29	0.33	0.30	0.16
Fund obj. FE	YES	YES	YES	YES
Other fund level controls	NO	NO	NO	YES

Table 1.11: 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 1.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	-0.94***	-1.26***	-0.93***	-1.29***
	(0.16)	(0.19)	(0.16)	(0.18)
Credit rating	0.18	0.68*	0.35	1.05**
	(0.33)	(0.38)	(0.48)	(0.48)
Year-to-maturity	0.03	0.02	0.04	0.05
	(0.07)	(0.08)	(0.08)	(0.08)
Average liquidity	-0.39	-0.77	-0.80	-0.95
	(0.62)	(1.18)	(0.57)	(0.96)
Fund return	-114.50	13.06	-99.66	52.65
	(101.98)	(219.77)	(102.32)	(212.18)
TNA (in billion USD)	0.20***	0.09	0.19***	0.09
	(0.04)	(0.06)	(0.04)	(0.06)
Constant	15.24	-21.62	8.47	-56.73**
	(11.79)	(13.74)	(18.51)	(23.63)
Observations	3184	5180	3183	5179
Adj R2	0.05	0.06	0.06	0.07
Fund objective FE	YES	YES	YES	YES
Industry FE	NO	NO	YES	YES
Firm-level controls	YES	YES	YES	YES

Appendix

Appendix 1.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 et al. (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 $\mathrm{Flow}_{f,t} = \mathrm{TNA}_{f,t} - \mathrm{TNA}_{f,t-1}(1 + \mathrm{R}_{f,t})$.
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 1.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 et al., 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 et al., 2019; Albuquerque et al., 2020; Amiraslani et al., 2023; etc.)

Online Appendix

Table OA. 1: E&S and credit spread filtering out puttable and callable bonds

The table presents estimation results of difference-in-difference regression described in "Research design" section. The analysis is based on a sample of non-callable and non-puttable bonds. The dependent variable 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. 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)
E&S * Outbreak	-0.44***	-0.32***	-0.34***	-0.32***	-0.31***
	(0.17)	(0.10)	(0.13)	(0.11)	(0.10)
E&S * Peak	-1.88***	-1.94***	-1.98***	-1.81***	-2.05***
	(0.56)	(0.47)	(0.46)	(0.48)	(0.52)
E&S * Post	-1.61***	-1.57***	-1.50***	-1.59***	-1.96***
	(0.57)	(0.41)	(0.40)	(0.45)	(0.54)
Observations	134362	134359	133235	133235	134356
Adj R^2	0.18	0.76	0.82	0.79	0.83
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 OA. 2: E&S and credit spread/basis using S&P ESG database

The table presents estimation results of difference-in-difference regression described in "Research design" section. The dependent variable in Panel A is daily credit spreads, expressed in basis points. To compute credit spreads, we match a bond's duration with a Treasury rate that has a virtually identical maturity. Treasury yields are estimated using linear interpolation. The dependent variable in Panel B 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 ratings of companies taking value from 0 to 100 as provided by the S&P (previously, Trucost) database. 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: Credit Spread					
E&S * Outbreak	-0.36***	-0.29***	-0.28***	-0.25***	-0.30***
	(0.08)	(0.06)	(0.06)	(0.06)	(0.06)
E&S * Peak	-0.90***	-0.991***	-0.92***	-0.88***	-1.17***
	(0.27)	(0.21)	(0.21)	(0.23)	(0.25)
E&S * Post	-1.11***	-0.81***	-0.68***	-0.92***	-1.05***
	(0.23)	(0.15)	(0.14)	(0.19)	(0.21)
Observations	451369	451366	450980	450980	451362
Adj R^2	0.16	0.71	0.79	0.74	0.79
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-Bond Basis					
E&S * Outbreak	0.13**	0.11**	0.09**	0.08**	0.15***
	(0.05)	(0.04)	(0.04)	(0.04)	(0.04)
E&S * Peak	0.14	0.44**	0.41*	0.40*	0.47**
	(0.25)	(0.21)	(0.23)	(0.23)	(0.21)
E&S * Post	0.51**	0.25	0.20	0.19	0.28
	(0.22)	(0.18)	(0.18)	(0.18)	(0.20)
Observations	129033	129033	128337	128337	129032
Adj R^2	0.09	0.50	0.57	0.57	0.68
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 OA. 3: E&S and credit spread/basis using linear interpolation

The table presents estimation results of difference-in-difference regression described in "Research design" section. The dependent variable in Panel A is daily credit spreads, expressed in basis points. To compute credit spreads, we match a bond's duration with a Treasury rate that has a virtually identical maturity. Treasury yields are estimated using linear interpolation. The dependent variable in Panel B 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 ratings of companies taking value from 0 to 100. 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: Credit Spread					
E&S * Outbreak	-0.51***	-0.45***	-0.46***	-0.41***	-0.41***
	(0.12)	(0.08)	(0.09)	(0.08)	(0.08)
E&S * Peak	-0.97**	-1.34***	-1.24***	-1.15***	-1.60***
	(0.40)	(0.32)	(0.31)	(0.35)	(0.38)
E&S * Post	-1.12***	-1.14***	-0.98***	-1.29***	-1.51***
	(0.41)	(0.26)	(0.25)	(0.32)	(0.34)
Observations	461169	461167	460708	460708	461163
Adj R^2	0.16	0.72	0.79	0.75	0.79
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-Bond Basis					
E&S * Outbreak	0.19***	0.32***	0.25***	0.24***	0.39***
	(0.07)	(0.06)	(0.06)	(0.05)	(0.08)
E&S * Peak	0.65*	1.04***	1.08***	1.06***	1.17***
	(0.36)	(0.35)	(0.37)	(0.37)	(0.36)
E&S * Post	0.90***	0.60**	0.55*	0.54*	0.71**
	(0.31)	(0.29)	(0.28)	(0.28)	(0.33)
Observations	129623	129623	128928	128928	129622
Adj R^2	0.12	0.50	0.57	0.57	0.68
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 OA. 4: E&S and basis using restricted sample

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-year term, and the credit spreads with durations ranging from 3 to 7.5 years. Independent variable E&S is an average of social and environmental ratings of companies taking value from 0 to 100. 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)
E&S * Outbreak	0.26***	0.40***	0.35***	0.34***	0.47***
	(0.07)	(0.08)	(0.08)	(0.07)	(0.09)
E&S * Peak	0.66	1.24***	1.30***	1.26***	1.41***
	(0.41)	(0.38)	(0.40)	(0.40)	(0.36)
E&S * Post	1.10***	0.78**	0.82**	0.75**	0.97***
	(0.33)	(0.33)	(0.32)	(0.31)	(0.35)
Observations	94364	94364	93750	93750	94363
Adj R^2	0.14	0.54	0.62	0.61	0.70
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 OA. 5: E&S and credit spread using specification with macro-level control variables

The table presents estimation results of difference-in-difference regression described in "Research design" section. The dependent variable is daily credit spreads, expressed in basis points. Independent variable E&S is an average of social and environmental ratings of companies taking value from 0 to 100. 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. Control variables include bond-, firm- and macro-level variables. 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.

	Credit Spreads
E&S * Outbreak	-0.40***
	(0.11)
E&S * Peak	-1.31***
	(0.35)
E&S * Post	-1.02***
	(0.33)
S&P 500	1.24
	(2.10)
Term spread	-0.50
	(0.66)
Observations	461635
Adj R^2	0.70
Time dummy variables	Excluded
Control variables	Included
Time-varying control variables	Included
Industry FE	YES
Firm FE	NO

Table OA. 6: E&S and credit spread using most frequently traded bonds

The table presents estimation results of difference-in-difference regression described in "Research design" section. The analysis is based on a sample of bonds that trade on average more than 8 days per month. The dependent variable is daily credit spreads, expressed in basis points. Independent variable E&S is an average of social and environmental ratings of companies taking value from 0 to 100. 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)
E&S * Outbreak	-0.21*	-0.39***	-0.39***	-0.33***	-0.44***
	(0.11)	(0.07)	(0.08)	(0.07)	(0.07)
E&S * Peak	-0.99**	-1.46***	-1.37***	-1.26***	-1.74***
	(0.43)	(0.33)	(0.32)	(0.37)	(0.39)
E&S * Post	-1.09***	-1.19***	-1.02***	-1.35***	-1.58***
	(0.39)	(0.25)	(0.24)	(0.32)	(0.34)
Observations	421561	421561	421035	421035	421561
Adj R^2	0.16	0.72	0.79	0.75	0.80
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 OA. 7: S score and credit spread/basis

The table presents estimation results of difference-in-difference regression described in "Research design" section. The dependent variable in Panel A is daily credit spreads, expressed in basis points. The dependent variable in Panel B 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 S is a social rating of companies taking value from 0 to 100. 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: Credit Spread					
S * Outbreak	-0.59***	-0.51***	-0.52***	-0.48***	-0.45***
	(0.14)	(0.09)	(0.11)	(0.09)	(0.10)
S * Peak	-1.10**	-1.35***	-1.28***	-1.19***	-1.64***
	(0.46)	(0.36)	(0.34)	(0.39)	(0.42)
S * Post	-1.08**	-1.11***	-0.99***	-1.19***	-1.41***
	(0.43)	(0.28)	(0.27)	(0.35)	(0.37)
Observations	461635	461633	461171	461171	461629
Adj R^2	0.15	0.72	0.79	0.74	0.79
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

	(1)	(2)	(3)	(4)	(5)
Panel B: CDS-Bond Basis					
S * Outbreak	0.22***	0.29***	0.24***	0.23***	0.33***
	(0.07)	(0.08)	(0.07)	(0.07)	(0.07)
S * Peak	0.53	0.61	0.68	0.67	0.82**
	(0.41)	(0.40)	(0.42)	(0.42)	(0.40)
S * Post	0.93***	0.41	0.39	0.38	0.45
	(0.33)	(0.30)	(0.29)	(0.29)	(0.34)
Observations	129667	129667	128971	128971	129666
Adj R^2	0.13	0.50	0.57	0.57	0.68
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 OA. 8: E score and credit spread/basis

The table presents estimation results of difference-in-difference regression described in "Research design" section. The dependent variable in Panel A is daily credit spreads, expressed in basis points. The dependent variable in Panel B 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 is an environmental rating of companies taking value from 0 to 100. 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: Credit Spread					
E * Outbreak	-0.32***	-0.30***	-0.30***	-0.27***	-0.29***
	(0.10)	(0.06)	(0.07)	(0.06)	(0.06)
E * Peak	-0.62**	-0.99***	-0.89***	-0.83***	-1.18***
	(0.29)	(0.24)	(0.23)	(0.26)	(0.28)
E * Post	-0.87***	-0.86***	-0.71***	-1.02***	-1.20***
	(0.31)	(0.20)	(0.19)	(0.25)	(0.26)
Observations	461635	461633	461171	461171	461629
Adj R^2	0.14	0.72	0.79	0.75	0.79
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-Bond Basis					
E * Outbreak	0.13**	0.23***	0.17***	0.16***	0.29***
	(0.06)	(0.04)	(0.04)	(0.04)	(0.06)
E * Peak	0.56**	0.96***	0.96***	0.95***	1.00***
	(0.27)	(0.24)	(0.26)	(0.26)	(0.25)
E * Post	0.69***	0.52**	0.47**	0.46**	0.63**
	(0.27)	(0.23)	(0.22)	(0.22)	(0.26)
Observations	129667	129667	128971	128971	129666
Adj R^2	0.11	0.50	0.57	0.57	0.68
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 OA. 9: E&S and CDS spreads

The table presents estimation results for the baseline model with 5-year CDS spreads as the dependent variable, expressed in basis points. Independent variable E&S is an average of social and environmental ratings 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 43'363 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)
Panel A: E&S analysis				
E&S	-1.50***	0.34	0.28	0.44
	(0.33)	(0.42)	(0.41)	(0.44)
E&S * Outbreak	-0.16	-0.25***	-0.21**	-0.21**
	(0.10)	(0.09)	(0.08)	(0.09)
E&S * Peak	-1.25**	-1.15**	-1.13**	-1.17**
	(0.56)	(0.54)	(0.54)	(0.57)
E&S * Post	-1.08**	-1.50***	-1.37***	-1.67***
	(0.52)	(0.51)	(0.50)	(0.56)
Observations	43363	43363	41832	41832
R-squared	0.06	0.58	0.63	0.61
Adj R^2	0.06	0.58	0.56	0.54
Time dummy variables	Included	Excluded	Excluded	Excluded
Control variables	Excluded	Included	Included	Included (excluded only firm-level time invariant)
Time-varying control variables	Excluded	Included	Included	Excluded
Industry-time FE	NO	YES	NO	NO
Industry-day FE	NO	NO	YES	YES
Firm FE	NO	NO	NO	NO
Panel B: E&S top-bottom tercile analysis				
E&S	-75.10***	2.76	1.85	3.99
	(23.68)	(21.12)	(20.46)	(23.16)
E&S * Outbreak	-8.18*	-11.55**	-10.23**	-11.02*
	(4.36)	(4.73)	(4.87)	(5.77)
E&S * Peak	-70.78**	-47.92*	-48.76*	-50.42*
	(30.47)	(28.29)	(27.85)	(29.92)
E&S * Post	-59.61**	-47.48**	-43.70**	-54.15**
	(27.15)	(22.99)	(21.80)	(25.35)
Observations	29693	29693	27914	27914
R-squared	0.10	0.71	0.75	0.73
Adj R^2	0.10	0.71	0.70	0.67
Time dummy variables	Included	Excluded	Excluded	Excluded
Control variables	Excluded	Included	Included	Included (excluded only firm-level time invariant)
Time-varying control variables	Excluded	Included	Included	Excluded
Industry-time FE	NO	YES	NO	NO
Industry-day FE	NO	NO	YES	YES
Firm FE	NO	NO	NO	NO

Table OA. 10: G score and credit spread/basis

The table presents estimation results of difference-in-difference regression described in "Research design" section. The dependent variable in Panel A is daily credit spreads, expressed in basis points. The dependent variable in Panel B 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 G is a governance rating of companies taking value from 0 to 100. 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: Credit Spread					
G * Outbreak	-0.31***	-0.38***	-0.38***	-0.38***	-0.40***
	(0.11)	(0.08)	(0.09)	(0.09)	(0.09)
G * Peak	-0.71*	-1.08***	-1.12***	-1.13***	-1.35***
	(0.43)	(0.31)	(0.31)	(0.35)	(0.35)
G * Post	-0.78**	-1.02***	-0.97***	-1.16***	-1.25***
	(0.33)	(0.26)	(0.24)	(0.29)	(0.31)
Observations	460221	460219	459755	459755	460215
Adj R^2	0.10	0.72	0.79	0.75	0.79
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-Bond Basis					
G * Outbreak	-0.28***	0.01	-0.01	-0.01	-0.01
	(0.02)	(0.05)	(0.05)	(0.04)	(0.04)
G * Peak	-1.63***	-0.35	-0.27	-0.26	-0.28
	(0.10)	(0.28)	(0.27)	(0.27)	(0.29)
G * Post	-0.94***	-0.33*	-0.36*	-0.36*	-0.21
	(0.07)	(0.20)	(0.19)	(0.19)	(0.20)
Observations	129113	129113	128417	128417	129112
Adj R^2	0.08	0.50	0.58	0.57	0.68
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 OA. 11: E&S and basis controlling for the interaction of credit and liquidity risks

The table presents estimation results of difference-in-difference regression described in "Research design" section. The dependent variable in 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 ratings of companies taking value from 0 to 100. 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. Control variables include bond- and firm-level variables, as well as the interaction of CDS spread and bond liquidity proxying for credit and liquidity risks. 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)
E&S * Outbreak	0.28***	0.17*	0.36***
	(0.08)	(0.09)	(0.07)
E&S * Peak	0.98***	0.89**	1.14***
	(0.32)	(0.36)	(0.33)
E&S * Post	0.66*	0.62	0.79**
	(0.37)	(0.39)	(0.39)
CDS * Liquidity	0.05**	0.01	0.06***
	(0.02)	(0.02)	(0.01)
Observations	129667	128971	129666
Adj R^2	0.58	0.67	0.71
Time dummy variables	Excluded	Excluded	Excluded
Control variables	Included	Included	Included (excluded only firm-level time invariant)
Time-varying control variables	Included	Included	Included
Industry-time FE	YES	NO	YES
Industry-day FE	NO	YES	NO
Firm FE	NO	NO	YES

Table OA. 12: E&S and selling pressure scaled by trading volume

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. In Panel A, selling pressure measures are scaled by bond trading volume as of January 2020. In Panel B, selling pressure measures are scaled by average bond trading volume as of December 2019 and January 2020. E&S is an average of social and environmental ratings of companies taking value from 0 to 100. 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%
Panel A: Trading volume as of January 2020						
E&S	-0.02***	-0.02**	-0.41*	-0.22	-0.66**	-0.50*
	(0.01)	(0.01)	(0.25)	(0.26)	(0.28)	(0.30)
Credit rating	0.01	0.05	1.47***	1.25***	1.20***	0.86**
	(0.05)	(0.06)	(0.35)	(0.36)	(0.38)	(0.39)
Average liquidity	-0.49***	-0.38**	0.27***	0.32***	0.24***	0.30***
	(0.15)	(0.16)	(0.07)	(0.08)	(0.07)	(0.08)
Δ Stock price*(10^{-3})	0.01**		-0.02***		-0.02***	
	(0.01)		(0.01)		(0.01)	
Δ Idios. vol.	0.21		-0.21		-0.12	
	(0.23)		(0.14)		(0.17)	
Observations	1687	1681	1687	1622	1589	1520
Adj R^2 [Pseudo R2]	0.08	0.11	[0.08]	[0.10]	[0.07]	[0.10]
Industry FE	NO	YES	NO	YES	NO	YES
Firm-level control variables	Included	Included	Included	Included	Included	Included
Panel B: Average trading volume as of January 2020 and December 2019						
E&S	-0.02**	-0.01	-0.41*	-0.22	-0.66**	-0.50*
	(0.01)	(0.01)	(0.25)	(0.26)	(0.28)	(0.30)
Credit rating	0.07	0.11*	1.47***	1.25***	1.20***	0.86**
	(0.06)	(0.06)	(0.35)	(0.36)	(0.38)	(0.39)
Average liquidity	-0.38***	-0.30**	0.27***	0.32***	0.24***	0.30***
	(0.14)	(0.15)	(0.07)	(0.08)	(0.07)	(0.08)
Δ Stock price*(10^{-3})	0.02**		-0.02***		-0.02**	
	(0.01)		(0.01)		(0.01)	
Δ Idios. vol.	0.21		-0.21		-0.12	
	(0.24)		(0.14)		(0.17)	
Observations	1687	1681	1687	1622	1589	1520
Adj R^2 [Pseudo R2]	0.08	0.12	[0.08]	[0.10]	[0.07]	[0.10]
Industry FE	NO	YES	NO	YES	NO	YES
Firm-level control variables	Included	Included	Included	Included	Included	Included

Table OA. 13: E&S and selling pressure for investment-grade bonds

This table presents regressions of selling pressure measures on bond E&S scores. The analysis is based on a sample of bonds that have an investment-grade credit rating (that is, from AAA to BBB-). 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 ratings of companies taking value from 0 to 100. 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	-1.10***	-0.97**	-1.16***	-1.02**
	(0.001)	(0.001)	(0.37)	(0.38)	(0.40)	(0.42)
Credit rating	0.02***	0.02***	0.58	0.51	0.64	0.38
	(0.003)	(0.003)	(0.43)	(0.42)	(0.48)	(0.48)
Average liquidity	0.01	0.01	0.39***	0.46***	0.37***	0.47***
	(0.01)	(0.01)	(0.08)	(0.09)	(0.08)	(0.09)
Δ Stock price*(10^{-3})	0.001**		-0.05***		-0.04***	
	(0.001)		(0.01)		(0.01)	
Δ Idios. vol.	0.01		-0.50**		-0.46**	
	(0.01)		(0.20)		(0.22)	
Constant	-0.06	-0.03				
	(0.10)	(0.12)				
Observations	1507	1504	1507	1444	1391	1330
Adj R^2 [Pseudo R2]	0.13	0.19	[0.07]	[0.10]	[0.08]	[0.11]
Industry FE	NO	YES	NO	YES	NO	YES
Firm-level control variables	Included	Included	Included	Included	Included	Included

Table OA. 14: Placebo tests: Fund sustainability and investor redemptions

The table shows results from cross-sectional placebo tests of fund net flows on fund sustainability score for June 2019. Fund sustainability is measured by Morningstar Sustainability scores as of May 2019. 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, fund age, fund beta and an indicator for institutional vs retail fund. If the fund offers both retail and institutional share classes, we separately aggregate this information as one retail fund and one institutional fund. Standard errors are robust 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				
Morningstar score	-0.32	-0.17	-0.14	1.57
	(0.56)	(0.60)	(0.60)	(2.22)
Fund ret. (past 1 month)		2.48		
		(2.10)		
Fund ret. (past 3 months)			3.07	
			(2.70)	
TNA (in billion USD)		-0.34	-0.21	-0.10
		(0.27)	(0.24)	(0.65)
Constant	17.39	9.13	4.76	-105.28
	(24.71)	(26.72)	(27.47)	(131.25)
Observations	84	84	84	68
Adjusted R^2	-0.06	-0.08	-0.08	-0.04
Fund obj. FE	YES	YES	YES	YES
Other fund level controls	NO	NO	NO	YES
Panel B: Globe Rating				
Globe Rating	-0.13	-0.05	-0.07	1.84
	(1.19)	(1.24)	(1.25)	(2.91)
Fund ret. (past 1 month)		121.71		
		(138.71)		
Fund ret. (past 3 months)			133.23	
			(160.95)	
TNA (in billion USD)		-0.02	0.01	-0.04
		(0.05)	(0.05)	(0.13)
Constant	2.57	1.46	0.32	-13.58
	(2.85)	(3.50)	(4.26)	(24.56)
Observations	127	126	124	106
Adjusted R^2	-0.04	-0.06	-0.06	-0.10
Fund obj. FE	YES	YES	YES	YES
Other fund level controls	NO	NO	NO	YES

Table OA. 15: Fund sustainability and institutional vs retail investor redemptions

The table shows results from cross-sectional regressions of fund net flows on fund sustainability scores interacted with institutional vs retail fund dummy. 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, fund age and fund beta. If the fund offers both retail and institutional share classes, we separately aggregate this information as one retail fund and one institutional fund. 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				
Score*Institutional fund *(a)*	-1.66**	-1.52*	-1.61**	-3.83***
	(0.79)	(0.79)	(0.78)	(1.06)
Score*Retail fund *(b)*	-1.66**	-1.57*	-1.61**	-3.91***
	(0.80)	(0.79)	(0.78)	(1.02)
Fund ret. (past 1 month)		1.15**		
		(0.39)		
Fund ret. (past 3 months)			1.32	
			(1.73)	
TNA (in billion USD)		-2.11**	-1.65*	-2.19**
		(0.93)	(0.93)	(0.80)
Observations	76	76	74	59
Adjusted R^2	0.18	0.22	0.14	0.22
Fund obj. FE	YES	YES	YES	YES
Other fund level controls	NO	NO	NO	YES
F-test (p-value): (a)=(b)	0.98	0.56	0.94	0.56
Panel B: Globe Rating				
Globe Rating*Institutional fund *(a)*	-5.69***	-6.09***	-5.91***	-7.72**
	(1.84)	(1.92)	(1.77)	(2.84)
Globe Rating*Retail fund *(b)*	-5.47***	-5.28**	-5.54***	-6.22***
	(1.89)	(1.96)	(1.74)	(2.21)
Fund ret. (past 1 month)		-0.02		
		(0.49)		
Fund ret. (past 3 months)			0.11	
			(1.30)	
TNA (in billion USD)		-2.46**	-2.32**	-2.59**
		(1.06)	(1.04)	(1.18)
Observations	76	76	74	59
Adjusted R^2	0.28	0.33	0.29	0.17
Fund obj. FE	YES	YES	YES	YES
Other fund level controls	NO	NO	NO	YES
F-test (p-value): (a)=(b)	0.78	0.36	0.63	0.33

Table OA. 16: 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. 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. 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)	(2)
Outflow * Low E&S	-0.90***	-0.92***
	(0.16)	(0.16)
Outflow * High E&S	-1.27***	-1.28***
	(0.17)	(0.17)
Credit rating	0.46	0.57*
	(0.28)	(0.32)
Year-to-maturity	0.01	0.04
	(0.07)	(0.07)
Average liquidity	-0.65	-0.82
	(0.92)	(0.70)
Fund return	-40.83	-19.99
	(159.39)	(158.87)
TNA (in billion USD)	0.13***	0.12**
	(0.05)	(0.05)
Constant	-9.47	-20.71
	(8.98)	(11.39)
Observations	8364	8363
Adj R2	0.05	0.06
Fund objective FE	YES	YES
Industry FE	NO	YES
Firm-level controls	YES	YES

Chapter 2: Target labour practices and M&A premium

2.1. Introduction

Researchers have extensively studied the role of labour and human capital in finance, particularly in corporate decision-making (e.g., Berk et al., 2010; Chemmanur et al., 2013). Anecdotal evidence suggests that human capital can also be very important in mergers and acquisitions (M&A). In particular, the workforce of the target firm might possess relationships that are essential for realizing the strategic objectives of the acquisition. For example, KPMG's survey[38] indicates that buyers in EMEA region assess target company workforce metrics like health and safety, and diversity policies during M&A due diligence, recognizing that target workforce practices can impact acquisition premiums. At the same time, largest international consulting and law firms like Deloitte[39] and Baker McKenzie[40] recommend that labour practices such as global talent development and workforce diversity should be taken into account in M&A due diligence and premium valuations. Nevertheless, there is a lack of empirical work analysing the impact of target employee-related policies and practices on target gains in M&A deals.

In this paper, I therefore study whether target's workforce-related policies and practices influence M&A premium for target. I use the Refinitiv workforce rating as a measure of target's human capital policies and practices and focus on international M&A transactions completed between 2003 and 2022. I run a cross-sectional regression using the one-week premium measure from the SDC Platinum database as the dependent variable, including a battery of control variables that can determine the size of a bid premium. In this setting, I find that generally there is no statistically significant relation between target labour practices and M&A premium.

I further conduct a sector-level analysis to check if there is a connection of acquisition premiums to workforce ratings of target companies in particular sectors. I specifically focus on targets that operate in technology sector. Past research indicates that in the tech sector human capital productivity plays

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[38] "ESG Due Diligence in M&A. Clarity on Mergers and Acquisitions" (2023). *KPMG*.

[39] "Four ways ESG is reshaping M&A: How ESG is influencing M&A valuation, risk, and more" (2023). *Deloitte*.

[40] "Mitigating ESG Risks in M&A Transactions" (2020). *Baker McKenzie*.

a substantial role in driving gross profits (Bapna et al., 2013). Workforce ratings reflect elements (like fair compensation and job security, opportunities for professional growth, etc.) that foster employee engagement and, in turn, enhance productivity. As an illustration, the 2024 Gallup State of the Global Workplace report[41] reveals that productivity is 18% higher among engaged employees than among those who are less engaged. If workforce productivity is especially pivotal to the profitability of tech firms, this could explain why a link between workforce ratings and M&A premiums is notably evident in this sector. For instance, an acquirer looking at a tech firm with a low workforce score may consider this as an opportunity to create productivity gains by implementing better employee-related policies post-merger. In such a case, a low workforce score is indicative of an opportunity to improve. With effort in increasing employee engagement and better support for the employees, an acquirer can realize productivity benefits leading to increased profitability for the merged firm. Hence, acquirers may want to pay the premium to utilize such synergistic possibilities.

Initial analysis suggests that there is a negative and statistically significant correlation between target workforce score and bid premium when target company is from technology sector. However, the instrumental variable analysis shows that this result is driven by some omitted factor that simultaneously affect both the target workforce score and M&A premiums.

Overall, this study shows that, in general, target employee-related policies and practices are not incorporated in M&A premiums, regardless of the sector in which a target company operates. However, these findings do not exclude the possibility that a target firm's workforce policies might be taken into account in the premium in particular M&A deals.

This paper contributes to the growing literature on the role of human capital in corporate finance. Maksimovic and Titman (1991) show that employees are an important consideration in firm capital structure decisions. Berk et al. (2010) demonstrate that bankruptcy costs associated with human capital risk are often large enough to offset the tax benefits of leverage. Bae et al. (2011) find that firms with high employee-friendly ratings maintain lower debt ratios. I add to this body of work by investigating how employee-related practices and policies can play a role in takeovers and specifically impact the acquisition premium for the target.

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[41] “State of the Global Workplace. The Voice of the World’s employees” (2024). *Gallup*.

Secondly, I contribute to studies examining how ESG-related factors impact the premium paid in M&A deals. From the bidders' perspective, Hussaini et al. (2021) demonstrate that a better ESG rating for the acquirer translates into a higher M&A premium, aligning with the shareholder expense view. From the targets' perspective, the relationship between ESG and bid premiums is mixed. Gomes and Marsat (2018) find that targets' ESG activities are positively associated with bid premiums. However, Jost et al. (2022) observe that targets' ESG performance does not significantly impact M&A premiums. Some studies focus on specific dimensions of ESG. Closely related study by Macias and Pirinsky (2015) find, among other things, that bidders are less likely to acquire and pay a lower premium for targets that have a high KLD employee-friendliness index. Since KLD's index represents company's obligations to provide certain benefits to employees which are legally binding, acquiring a target firm with high KLD's index creates financial and operational burdens for the bidder which explains a lower premium in this context. I differentiate from this study in three ways. Firstly, I examine the relation between acquisition premiums and target workforce ratings from Refinitiv. In contrast to KLD, Refinitiv workforce score is based on voluntary practices that create an environment supporting employee well-being and development rather than legally mandated or binding agreements. In other words, Refinitiv's workforce score provides a broader angle on workforce-related practices of a company. It showcases practices that companies choose to adopt above their legal obligations and underlines a company's proactive actions towards creating a positive and supportive work environment. Secondly, my research focuses only on the analysis of bid premiums and provides more complete research, by incorporating not only the general link between premiums and workforce scores but also the relationship at the sector level, focusing on the tech sector. Lastly, this study examines international deals from 2003 to 2022 while the paper of Macias and Pirinsky (2015) focuses only on US M&A transactions from 1995 to 2009.

The rest of the paper is organized as follows. Section 2.2 presents the data used in the study along with summary statistics. Section 2.3 describes the methodology and evaluates the relationship between the target's workforce score and the acquisition premium. Section 2.4 provides a sector-level analysis with a focus on technology sector. Section 2.5 introduces instrumental variable analysis. Finally, Section 2.6 offers a brief conclusion.

2.2. Data

2.2.1. Dataset construction

This study focuses on worldwide M&A transactions. The main source of data is the SDC Platinum, because it maintains the most extensive historical information on M&A deals, as well as other financial transactions. My initial sample includes 769,716 deals announced between 2003 and 2022 and having a 'Completed' status. I have selected only those deals where both the bidder and target companies are public. Following the approach of previous studies (Gokkaya et al., 2023; Antón et al., 2022; Deng et al., 2013, etc.), I restrict my sample to deals in which the bidder initially owns less than 50% but acquires more than 50% of the target firm.

Next, I merge M&A transaction data with workforce scores from the Refinitiv ESG database. According to Refinitiv, this rating reflects a company's effectiveness in maintaining a healthy and safe workplace, fostering diversity and equal opportunities, offering development opportunities for its workforce, etc. I utilize this rating as a measure of firm employee-related policies and practices. I extract the workforce score for each target and bidder firm as of one year before the respective deal's original announcement date. Additionally, I require that either the bidder or the target be based in the United States.

I further add the economic sector code of targets and acquirers according to the Thomson Reuters Business Classification (TRBC). Following the literature on the topic (Offenberg and Pirinsky, 2015; Cornaggia and Li, 2019, etc.), I exclude deals involving targets and acquirers operating in the financial sector, which is denoted by the TRBC code of 55[42].

To ensure data accuracy, I manually verify the identifiers (PermID) of target and acquirer firms as reported in Refinitiv. I exclude M&A deals where these identifiers do not match the companies listed in SDC Platinum. For the acquisition premium, I use a measure from the SDC Platinum database. This premium is defined as the ratio of the share price paid by the acquirer for the target shares to the target's closing price one week before the original announcement date, minus one. Following previous studies (Officer, 2003; Malmendier et al., 2016; Salva and Zhang, 2022), I only include transactions with premiums that are both positive and below 200%.

[42] In the unreported results, I retain firms belonging to the financial sector. This does not impact my findings.

Accounting and market measures also come from the SDC Platinum database. Accounting measures are taken as of one year, and market variables as of four weeks, before the original announcement date of the respective deal. Sales growth is measured for the three years preceding the deal's announcement. As the final step, I exclude deals for which these data are missing.

[Insert Table 2.1 about here.]

[Insert Table 2.2 about here.]

[Insert Table 2.3 about here.]

My final sample includes 335 M&A transactions. Table 2.1 summarizes the step-by-step sample selection process as described. Table 2.2 and Table 2.3 report the number of deals by year of announcement and by the target firm's country or sector, respectively. I observe that about half of the M&A transactions in my sample were announced in the last six years (between 2017 and 2022). Most of the deals included a US target (92% of the sample) or a target firm operating in the healthcare sector, followed by the technology sector (both at around 23% of the sample).

2.2.2. Refinitiv workforce score

The Refinitiv workforce score is one dimension of the broader Refinitiv ESG rating. The Refinitiv Workforce Rating is an absolute numeric score between 0 and 100, where higher scores indicate better performance. It reflects a company's practices and policies in effectively managing its workforce, with a focus on key dimensions contributing to employee well-being. To be more specific, the dimensions rated fall into the following categories:

1. Diversity and Inclusion – represents policies that allow an inclusive workplace.

2. Employee Development – represents training programs and opportunities for career advancement.

3. Health and Safety - reflects how well a company enforces its health and safety policy.

4. Workplace Flexibility and Family Support – reflects how a firm accommodates employees in terms of personal needs, and if support is provided to balance work and life.

5. Employee Representation and Labour Rights – reflects the presence of an independent trade union or bargaining agreement, thereby representing labour rights and employee voice.

6. Pay and Fairness – reflects how a business treats its workers in terms of compensation and job security.

Compared to the KLD database, which had a wide use in academic literature so far, the rating provided by Refinitiv gives a wider and deeper review of workforce-related factors. The KLD Workforce rating evaluates companies in respect of their adherence to binding legal obligations concerning labour practices. In contrast, Refinitiv's Workforce rating does not directly aim at compliance with any legal obligations but rather provides a broader outlook in respect to practices and policies related to workforce that a company embraces.

Another major provider of workforce ratings, MSCI, differs from Refinitiv by evaluating employee-related practices and policies through the exposure to risk. In MSCI database, the practices in the workforce are not considered as an independent metric but rather as a factor influencing or mitigating the potential risks for the company. In this approach, the focus is on identifying risk in labour relations, human capital, and workforce dynamics that affects the stability of operation and reputation of the company. On the other hand, Refinitiv adopts a more direct and objective approach by rating companies based on workforce level criteria in absolute terms, offering a sharper picture of specific employee policies and practices without emphasizing risk mitigation.

2.2.3. Summary statistics

[Insert Table 2.4 about here.]

Table 2.4 presents summary statistics for all variables used in this study. Panel A of Table 2.4 shows descriptive statistics for the main and control variables at the target company level, including workforce rating, cumulative abnormal returns, various accounting measures and ratios, market variables, three-year sales growth, and operating cash flows. Additionally, I include other ESG-related ratings of the target firms such as product responsibility, community, human rights, environmental and governance scores[43]. A detailed description of these variables is provided in Appendix 2.A, Group 1. To eliminate outliers, I have winsorized the top and bottom 1% of the target's market-to-book[44], return on equity, and runup ratios. Sales growth and liquidity are also winsorized at the top and bottom 1%. Target firms in my sample generally have low workforce scores, with a median rating of 35 out of 100. Most target firms in the sample exhibit high liquidity, positive sales growth, and low capital and R&D expenditures-to-total assets ratios.

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[43] In unreported results I check correlation between different ESG-related scores. The correlation does not exceed 0.50. Therefore, the inclusion of different ESG components in one regression does not create the problem of multicollinearity.

[44] Target book-to-market ratio is negative for 5% of my sample. Removing negative values does not impact my findings.

Panel B reports statistics for deal-related measures. The deal-related variables are the acquisition premium (Premium), and various dummy variables reflecting different deal characteristics. Detailed definitions of each of these variables are in Appendix 2.A, Group 2. Most deals in my sample involve a nonforeign target; only 33% of the deals are cross-border. In the great majority of transactions (82% of deals), target firms belong to the same sector as the bidders. Nearly half of the transactions in the sample (43% of deals) are cash-only.

Panel C shows statistics for variables at the acquirer level. These are acquirer's market-to-book ratio and size. Market-to-book ratio[45] is winsorized at the top and bottom 1%. Here I also include relative size of the deal. These variables are defined in Appendix 2.A, Group 3. For most of the deals, the target size is just 30% or less of the bidder's size.

2.3. Target company workforce score and acquisition premium

2.3.1. Research design

The primary question of this study is whether employee-related practices and polices impact premiums in M&A deals. As previously mentioned, private sector reports suggest that dealmakers find it important to consider workforce metrics, especially employee health & safety and diversity & inclusion areas, in M&A due diligence and, therefore, might incorporate this information into acquisition premiums. To analyse the relationship between bid premiums and targets' labour practices, I conduct a cross-sectional regression. I use the pre-deal workforce scores of the target companies and include a range of control variables that are identified as determinants of premiums according to empirical and theoretical literature.

Specifically, I estimate the following baseline model:

$$\mathrm{Premium_i} = \beta_0 + \beta_1 \mathrm{Target\ Workforce\ score_i} + \delta' X + \mathrm{Sector\ FE_i} + \mathrm{Country\ FE_i} + \mathrm{Deal\ Year\ FE_i} + \varepsilon_i \tag{2.1}$$

where $\mathrm{Premium_i}$ is the premium that the bidder paid in M&A deal i. $\mathrm{Target\ Workforce\ score_i}$ is the workforce score of the target company one year prior to the announcement of deal i. X is a vector of target- and deal-level controls. A detailed description of this set of control variables is provided in section 2.3.2, highlighting how these characteristics explain differences in premiums. Target-related control variables correspond to the year leading up to the deal announcement, with the exception of

[45] Acquirer book-to-market ratio is negative for 2% of my sample. Removing negative values does not impact my findings.

sales growth, which is calculated over the three years preceding the deal announcement. In my baseline model, I include target country and sector fixed effects to control for unobserved differences across countries and sectors. I also add deal announcement year fixed effects to capture unobserved factors that might influence M&A premiums in a given year of announcement. Standard errors are adjusted for heteroskedasticity.

2.3.2. Construction of control variables

In this section, I describe the control variables used in the baseline model and provide the rationale for their inclusion within this research framework. Firstly, I include a set of deal-level controls. I follow Gomes and Marsat (2018) by including the Different Sector and Cross-border dummies. The Different Sector dummy takes the value 1 when target and acquirer companies operate in the same sector. This variable should positively relate to the takeover premium, reflecting the potential of synergy creation in such deals. The Cross-border dummy is equal to 1 for cross-border deals, which generally carry a higher risk of improper valuation than domestic M&A transactions. Following Ayers et al. (2003), I include Toehold and Competition dummies as control variables. The Toehold dummy defines bidders that hold 0.5% or more of the target stock prior to the announcement and proxies for acquirers' bargaining power. The Competition dummy indicates the presence of more than one potential buyer, which can increase the acquisition premium. Finally, I incorporate dummy control variables defining cash-only deals (Comment and Schwert, 1995), tender offers (Huang and Walkling, 1987), and deals with a termination fee agreement (Officer, 2003), which have been shown to be associated with higher premiums on average[46]. The reasons are as follows. An all-cash offer indicates that the acquirer is very confident in the value and potential of the target firm, and that it has the necessary resources or financing to back the acquisition, which can result in higher premiums. Tender offers are directly made to the target company's shareholders; the management and the board are bypassed most of the time. This form of a direct appeal oftentimes pressures the target firm's management and might lead to a higher premium to eventually persuade the shareholders to tender their shares. A termination fee is paid by the target firm to the acquirer if the deal falls through. This fee compensates the acquirer for the risk and cost associated with the failed acquisition attempt. The

[46] After the selection process, my sample does not include deals marked as hostile takeovers, leveraged buyouts, spinoffs, recapitalizations, self-tenders, exchange offers, repurchases, or privatizations, as well as transactions involving bankrupt targets or lockup options.

presence of a termination fee agreement can justify a higher premium as it reduces the risk for the acquirer.

Next, I include a battery of target firm-level control variables. Following Ayers et al. (2003) and Bargeron et al. (2008), I incorporate operating cash flows scaled by total assets, return on equity (ROE), 3-year sales growth, market-to-book and debt-to-asset ratios, and liquidity. I measure liquidity by the current ratio, defined as the ratio of current assets to current liabilities. The low market-to-book and high operating cash flows ratios could suggest low growth opportunities and agency problems and hence provide some scope for improvement by bidders and justify a higher acquisition premium. The remaining variables capture the financial health of a target firm. Financially strong targets have stronger bargaining positions, enabling them to negotiate higher payments in acquisitions. I further control for capital and R&D expenditures scaled by total assets, as in Gomes and Marsat (2018), since these measures can impact potential takeover synergies. Additionally, following Comment and Schwert (1995), I include market value as a control variable. Larger targets tend to receive lower premiums on average because they entail higher integration costs. Market value is measured using the natural logarithm of market capitalization as of 4 weeks before the deal announcement. All accounting variables in this study are as of 1 year before the respective M&A deal was announced. Finally, I follow Betton et al. (2008) and include a runup ratio. This variable is computed as the logarithm of the target stock price 1 day before the deal announcement divided by the target stock price 4 weeks before the deal announcement. As the literature suggests, the runup reflects takeover rumours and therefore should be positively associated with the premium.

2.3.3. Main results

[Insert Table 2.5 about here.]

I estimate the baseline model and report the results in Table 2.5. In Panel A, I show the results using a target workforce rating that ranges from 0 to 100. Columns (1)–(3) reflect different specifications of the baseline model. Column (1) includes the workforce rating of a target firm, as well as target country and sector fixed effects, and deal announcement year fixed effects. I further add target characteristics in Column (2) and deal-related variables in Column (3). Across all specifications, the coefficient on the workforce rating is statistically insignificant.

In addition, I rerun the tests using a dummy variable for the target workforce score instead. The workforce dummy equals one if the rating is higher than 50 and zero otherwise. I use the same specifications as before and report the results in Table 2.5, Panel B. Consistent with Panel A, the coefficient on the workforce rating is statistically insignificant.

Overall, the results indicate that bidders, on average, do not incorporate target employee-related practices and policies into acquisition premiums.

2.4. Sector-level analysis

While there is generally no correlation between M&A premiums and target labour practices as measured by workforce ratings, such a relationship may exist in specific sectors. In particular, previous papers suggest that in the tech sector the productivity of human capital is a major determinant of gross profits (Bapna et al., 2013). Workforce scores capture factors such as supportive management, professional development, etc., all of which are directly tied to employee engagement and, consequently, productivity. For example, there is some evidence[47] that engaged employees exhibit an 18% increase in productivity compared to their less engaged counterparts. If workforce productivity is particularly critical for the profitability of tech firms, this could explain why a link between target workforce ratings and M&A premiums is observed specifically in the technology sector.

A possible mechanism could be that an acquirer might view a low workforce score for a tech firm as an opportunity to increase productivity through the implementation of better employee-related policies after the merger. A low workforce score, in that sense, highlights unrealized potential; by investing in engagement and support, an acquirer can achieve gains in productivity that contribute to higher profitability for the combined firm. This would give a reason for bidders to pay a higher premium in order to exploit this synergy opportunity.

[Insert Table 2.6 about here.]

To confirm that, I conduct a sector-level analysis. According to the Thomson Reuters Business Classification (TRBC), my sample is represented by 11 sectors. In Table 2.6, I show summary statistics for target workforce rating at the sector level[48]. In my sample, Real Estate sector possesses the smallest score (25) on average. Healthcare sector has the largest rating (45) on average, followed

[47] "State of the Global Workplace. The Voice of the World's employees" (2024). *Gallup*.

[48] I do not report statistics for Institutions, Associations & Organizations and Academic & Educational Services sectors because there is only one firm in my sample representing each of these sectors.

by Technology (40), Industrials (38) and Consumer Cyclicals (37) sectors. Workforce score in Technology sector varies from 0.88 to 88.34 out of 100 and the median score is 41.21.

[Insert Table 2.7 about here.]

I create dummy variables for each sector in my sample and interact them with the workforce rating. I use a univariate regression of the acquisition premium on these interaction terms and include also target sector, target country and deal year fixed effects. The results are presented in Table 2.7. As expected, the interaction term for the tech sector is negative and statistically significant at the 5% level, while the coefficients for other sectors are insignificant. In terms of economic significance, a one standard deviation lower workforce score of a tech target relates to 6.6% higher premia.

I further analyse the link between M&A premia and tech target workforce rating in more detail. Similar to section 2.3.1, I estimate the following model:

$$\mathrm{Premium_i} = \beta_0 + \beta_1 \mathrm{Target\ Workforce\ score} * \mathrm{Tech\ sector\ dummy_i} + \quad (2.2)$$

$$\beta_2 \mathrm{Target\ Workforce\ score_i} + \delta' X + \mathrm{Sector\ FE_i} + \mathrm{Country\ FE_i} + \mathrm{Deal\ Year\ FE_i} + \varepsilon_i$$

where $\mathrm{Premium_i}$ is the premium that the bidder paid in M&A deal i. $\mathrm{Target\ Workforce\ score_i}$ is the workforce score of the target company one year prior to the announcement of deal i, $\mathrm{Tech\ sector\ dummy_i}$ is a dummy variable that equals one for target firms operating in the tech sector, which corresponds to number 57 according to the TRBC classification (representing 23% of the deals in the sample). X is a battery of control variables, $\mathrm{Sector\ FE_i}$, $\mathrm{Country\ FE_i}$, $\mathrm{Deal\ Year\ FE_i}$ are target sector, target country and deal year fixed effects respectively.

[Insert Table 2.8 about here.]

The results are reported in Table 2.8. In Panel A, I use a continuous workforce rating ranging from 0 to 100. In Column (1), I add target-level control variables and in Column (2) I further include deal-level control variables. Across both specifications, the coefficients on the workforce rating interacted with the tech sector dummy remain negative and statistically significant at the 1% level, indicating a higher bid premium for lower workforce score of a target in the technology sector.

Some studies suggest that acquirer-related characteristics can also impact premiums paid in M&A deals. Jarrell and Poulsen (1989) show that premiums drop as the target increases in size relative to the acquirer. Moeller et al. (2004) and Lang et al. (1989) suggest that larger bidders and bidders with high market-to-book ratios make acquisitions that generate lower synergy, resulting in lower bid premiums. Therefore, I additionally control for these characteristics. Specifically, I include the relative size of the deal, which is the ratio of the target's market value to the sum of the target's and acquirer's market values. I also control for the acquirer's market-to-book ratio and acquirer size. I include the relative size of the deal in Column (3) and further incorporate bidder size and market-to-book ratio in Column (4). In both specifications, the coefficient on the workforce score interacted with the technology sector dummy is negative and significant, although the significance drops to the 5% level. According to Column (3), a one standard deviation lower tech target workforce rating is associated with nearly an 8% larger M&A premium. This effect is economically meaningful. A study by the Boston Consulting Group[49] shows that the average acquisition premium in technology mergers and acquisitions is around 32% (based on data from 1990 to 2017). Therefore, an 8% higher premium for a tech target with a lower employee score would represent a 25% deviation from the sector average premium.

In Column (5), I further control for other ESG-related scores in addition to the workforce rating. These are human rights, community, product responsibility, environmental, and governance scores. These ratings are correlated with the workforce score. Therefore, if I do not include them in the regression it might result in omitted variable bias. Nevertheless, the coefficient for the interaction between the tech sector dummy and workforce rating remains negative and statistically significant at the 5% level.

Finally, in Column (6) I use the same specification as in Column (5) but replace the dependent variable with another measure of target gains in M&A deals. Specifically, instead of the bid premium, I use the target's cumulative abnormal return (CAR) computed during an event window. I measure target abnormal returns by market-model adjusted returns around the initial acquisition announcements. I use the CRSP value-weighted return as the market return and estimate the market model parameters over the period from event day -232 to event day -30, where event day 0 is the acquisition announcement date. Finally, I compute 7-day target cumulative abnormal returns (CAR) over the event window (-3, +3). To eliminate outliers, I drop observations that are negative or larger than 200%. I report descriptive statistics in Table 2.4, Panel A. Although the correlation between bid premium and target CAR is quite high (0.73), summary statistics suggest that these two measures are

[49] Kengelbach et al. (2018) “The 2018 M&A Report: Synergies Take Centre Stage”. *BCG.*

slightly different. Therefore, I rerun the regression using CAR instead of premium as the dependent variable and report the results in Column (6). The variable of interest is negative and statistically significant, which reconfirms previous conclusions.

In addition, I rerun the tests using a dummy variable for the target workforce score instead. The workforce dummy equals one if the rating is higher than 50 and zero otherwise. I use the same specifications as before and report the results in Table 2.8, Panel B. Mirroring the results in Panel A, the coefficient on the workforce rating dummy interacted with the technology sector dummy is negative and significant across all specifications except the last column where target cumulative abnormal returns are used as a dependent variable. Based on Column (3), low workforce score in the case of technology targets translates into a 12.9% higher premium. This is consistent with my previous findings.

In sum, the results suggest that a lower target employee score is associated with higher M&A premiums when a target firm operates in the technology sector. However, there is a concern that this outcome might be due to the omitted variable bias. I examine this possibility in the next section.

2.5. Instrumental variable analysis

There is a possibility that the results observed in Table 2.7 and Table 2.8 are not causal but driven by some omitted factor that correlates with both, workforce scores of tech targets and acquisition premiums. As one of the examples, companies that have undergone significant workforce reductions and cut back on employee benefits are more likely to face financial difficulties (Macias and Pirinsky, 2015). Financially distressed target companies, in turn, usually receive higher bid premiums in takeover deals (Ang and Mauck, 2011). To address this endogeneity problem, I conduct a 2SLS regression analysis. In this analysis, I use the country-sector median of workforce scores as an instrumental variable for the target workforce rating. This instrument has been widely used in previous studies, including those by Gomes and Marsat (2018) and Arouri et al. (2019). The country-sector median is derived from workforce ratings collected from the entire Refinitiv ESG database from 2002 to the present. I compute the median of these scores by the country of headquarters and TRBC 2-digit code.

My choice of the instrument is based on Ioannou and Serafeim (2012), who demonstrated that a firm's ESG performance is influenced by a time-invariant factor associated with its pairing with a specific country and sector. Essentially, this means that a firm's ESG performance is shaped by the ESG practices of its peers within the same sector and country. This result indicates that the median workforce score is likely to be positively related to a target firm's employee-related rating, hence satisfying the relevance criteria for an instrumental variable. To the extent that this variable is constructed based on the country and sector in which a firm is domiciled, it is unlikely to have a significant influence on the acquisition premium, hence satisfying the exclusion condition of an instrumental variable.

One scenario where the validity of the instrument might be violated is if the technology sector generally has a low employee rating. If the tech sector had the lowest workforce score among sectors, it could be the reason why such acquisitions create the highest synergies. This, in turn, could explain why the effect of workforce rating on bid premiums persists only for targets in the technology sector. In this case, using the country-sector median as an instrument would not be appropriate. However, summary statistics based on my sample (Table 2.6) do not suggest that the tech sector has the lowest employee-related rating[50].

[Insert Table 2.9 about here.]

In Table 2.9, I present the results from the 2SLS regression. The first-stage regression results are displayed in Column (1) , while the second-stage regression results are reported in Column (2). In Column (1), the dependent variable is the target workforce score, and the independent variables include the instrumental variable discussed earlier, target company characteristics, and fixed effects for the target country, target sector, and year of deal announcement. This specification is similar to the one used in Table 2.8, Column (1). As expected, the country-sector median workforce rating has a positive and significant effect on target workforce scores. The p-value for the Sanderson-Windmeijer F-test is 0.001, rejecting the null hypothesis that the instrument is weak. This result confirms the relevance of my instrumental variable. In Column (2), I regress the acquisition premium on the predicted variable for the target workforce score and its interaction with the tech sector dummy. I also include target characteristics and fixed effects. The coefficient estimate on the interaction of the predicted variable for the target workforce rating and the tech sector dummy is statistically insignificant.

[50] In unreported results I also checked statistics based on the entire Refinitiv database. This statistics confirms that the technology sector is neither characterized by the lowest nor the highest workforce score across sectors.

Thus, my finding that tech targets with lower workforce scores receive higher bid premiums than those with higher workforce ratings does not appear to be robust when controlling for endogeneity concerns. The effect of the Refinitiv workforce rating on acquisition premiums for technology target firms is driven by some unobservable factor that simply correlates with the Refinitiv score. In sum, this study suggests that there is no causal relation between M&A premiums and target employee rating regardless of the sector in which the target company operates.

2.6. Conclusion

I explore the relationship between acquisition premiums for target firms and their employee-related policies and practices, as measured by Refinitiv workforce scores. Although surveys indicate that dealmakers assess workforce practices of target companies during M&A due diligence and incorporate these factors into acquisition premiums, I do not find a relationship between target workforce ratings and M&A premia.

I also carry out a more detailed analysis, studying the relationship between target workforce ratings and bid premiums at the sector level. I focus on the technology sector, where human capital is especially important. Initially, I find a negative relation of premiums to workforce ratings when the target company belongs to the technology sector. However, instrumental variable analysis shows that this correlation is induced by an omitted factor that correlates with both premia and Refinitiv workforce scores.

This study thus reveals that, on the whole, employee-related policies are not factored into acquisition premiums in M&A transactions, regardless of the sector involved. Nevertheless, these results do not rule out the possibility that bidders take into consideration employee treatment at target firms in premium decision-making based on specific circumstances surrounding each acquisition. Generally, this study adds depth to our understanding of how workforce policies and practices affect valuations in M&A.

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Tables

Table 2.1: Sample construction
This table illustrates the step-by-step process used for sample selection in the study.

	Number of deals
Deals announced between 2003 and 2022 with a status "completed"	769716
Both the target and the bidder are public companies	30753
The bidder initially owns less than 50% but acquires more than 50% of the target company	9344
Both the target and the acquirer have ESG scores available	884
Either the acquirer or the target is from the United States	572
Exclude offers where either the target or the acquirer operates in the financial sector	440
Exclude deals: - for which Refinitiv has incorrectly reported the PermID - for which a bid premium is unavailable in the SDC Platinum database - that have either a negative premium or a premium exceeding 200%	380
Exclude deals where the target company's accounting or market value data is missing	335

Table 2.2: Number of deals by year and target country

The final sample in this study comprises 335 M&A deals. The selection process is detailed in Table 2.1. This table displays the number of transactions in the sample, categorized by the target company's country of domicile and the year in which each deal was announced.

	US	Netherl.	Sweden	Norway	Australia	Canada	Singap.	UK	Israel	Finland	Total
2004	1	0	0	0	0	0	0	0	0	0	1
2005	2	0	0	0	0	0	0	0	0	0	2
2006	8	0	0	0	0	0	0	0	0	0	8
2007	8	1	1	0	0	0	0	0	0	0	10
2008	5	0	0	0	0	0	0	0	0	0	5
2009	6	0	0	1	0	0	0	0	0	0	7
2010	16	0	0	0	1	0	0	0	0	0	17
2011	11	0	0	0	0	2	0	0	0	0	13
2012	7	0	0	0	1	0	0	0	0	0	8
2013	2	0	0	0	0	0	0	0	0	0	2
2014	17	0	0	0	0	0	0	0	0	0	17
2015	23	0	0	0	1	0	0	0	0	0	24
2016	30	0	1	0	0	0	1	0	0	0	32
2017	38	0	0	0	1	0	0	1	0	0	40
2018	32	0	0	0	0	2	0	0	2	0	36
2019	39	0	0	0	1	1	0	0	0	0	41
2020	18	0	0	0	0	0	0	0	0	1	19
2021	29	0	0	0	1	0	0	2	1	0	33
2022	17	0	0	0	0	2	0	1	0	0	20
Total	309	1	2	1	6	7	1	4	3	1	335

Table 2.3: Number of deals by year and target sector

The final sample in this study comprises 335 M&A deals. The selection process is detailed in Table 2.1. This table displays the number of transactions in the sample, categorized by the target company's sector and the year in which each deal was announced.

	Energy (50)	Basic mater. (51)	Industrials (52)	Consum. Cycl. (53)	Consum. Non-Cycl. (54)	Healthcare (56)	Technology (57)	Utilities (59)	Other	Total
2004	0	0	0	0	0	1	0	0	0	1
2005	0	0	0	0	0	1	1	0	0	2
2006	0	1	1	1	1	1	3	0	0	8
2007	1	1	3	1	0	0	4	0	0	10
2008	0	1	1	0	0	2	1	0	0	5
2009	1	0	1	1	2	0	1	0	1	7
2010	3	1	1	0	2	4	1	5	0	17
2011	2	2	2	0	0	3	1	3	0	13
2012	1	1	2	0	1	3	0	0	0	8
2013	0	0	0	0	0	2	0	0	0	2
2014	1	2	1	2	2	4	3	2	0	17
2015	2	3	4	2	1	2	5	3	2	24
2016	8	3	3	5	2	4	7	0	0	32
2017	3	2	7	7	5	9	5	0	2	40
2018	1	5	1	4	3	4	15	3	0	36
2019	2	2	9	5	0	10	10	0	3	41
2020	2	2	3	1	0	6	5	0	0	19
2021	2	3	4	1	2	10	10	0	1	33
2022	3	0	3	1	0	10	3	0	0	20
Total	32	29	46	31	21	76	75	16	9	335

Table 2.4: Summary statistics

The table presents overall summary statistics. Panel A provides statistics for target-level variables, including workforce rating, cumulative abnormal returns, and accounting and market control variables. Target market-to-book, ROE, runup ratios, as well as sales growth and liquidity are winsorized at the 1% level. Panel B displays descriptive statistics for the acquisition premium and deal-level controls. Panel C offers statistics related to acquirer variables. Acquirer market-to-book ratio is winsorized at the 1% level.

	Mean	St.dev.	min	p25	p50	p75	max
Panel A: Target related variables							
Target workforce score	38.62	23.15	0.79	20.40	35.71	55.65	97.84
Target log market value	7.89	1.37	3.40	7.03	7.95	8.73	11.15
ROE	0.29	34.40	-152.39	-3.48	6.59	15.87	92.12
Sales growth (in %)	9	26.88	-69.107	-0.84	4.092	14.90	147.75
Debt-to-asset ratio	0.24	0.20	0	0.06	0.20	0.36	0.94
Target market-to-book	3.61	6.20	-20.06	1.48	2.58	4.69	34.60
Capex	0.04	0.05	0	0.01	0.03	0.05	0.38
R&D	0.06	0.10	0	0	0.01	0.09	0.63
Operating cash flows	0.05	0.15	-0.79	0.04	0.08	0.13	0.34
Runup	0.02	0.21	-1.26	-0.03	0.03	0.11	0.40
Liquidity	3.05	3.44	0.46	1.36	2.01	3.12	20.82
Target product responsibility score	35.02	25.15	0	15.43	32.76	50.28	98.39
Target community score	55.89	22.41	2.05	37.50	57.73	73.33	98.53
Target human rights score	18.70	29.23	0	0	0	33.82	97.98
Target governance score	41.60	21.32	0.57	23.90	42.16	58.43	93.42
Target environmental score	19.39	22.56	0	0	10.31	33.28	88.26
Target CAR (in %)	25.33	20.78	0.44	11.18	20.50	34.08	149.19
Panel B: Deal related variables							
Premium (in %)	37.42	27.07	0.52	20.29	30.40	47.73	165.74
Cash dummy	0.43	0.50	0	0	0	1	1
Tender offer dummy	0.17	0.37	0	0	0	0	1
Toehold dummy	0.02	0.15	0	0	0	0	1
Termination fee dummy	0.82	0.39	0	1	1	1	1
Cross-border dummy	0.33	0.47	0	0	0	1	1
Different sector dummy	0.82	0.38	0	1	1	1	1
Competition dummy	0.07	0.26	0	0	0	0	1
Panel C: Acquirer related variables							
Acquirer log market value	9.84	1.63	6.05	8.56	9.88	10.98	19.39
Acquirer market-to-book	5.99	17.53	-13.92	1.92	2.96	4.72	148.48
Relative size	0.20	0.16	0.01	0.06	0.17	0.31	0.73

Table 2.5: Target company workforce score and M&A deal premium

The sample comprises 335 completed international mergers and acquisitions (M&A) between 2003 and 2022, as listed in the SDC database. The dependent variable across all columns is the acquisition premium, calculated as the difference between the acquisition price and the target share price one week before the deal announcement, divided by the target stock price one week prior to the announcement. The independent variable, Workforce Score, is a Refinitiv's workforce rating of the target company one year prior to the deal announcement. It ranges from 0 to 100 in Panel A. In Panel B, Workforce Score is a dummy variable equal to one for values higher than 50 and zero otherwise. Control variables include target- and deal-level controls. The detailed definitions are given in Appendix 2.A. Standard errors, adjusted for heteroskedasticity, are presented in parentheses. Significance levels for the parameter estimates are indicated as follows: *** for 1%, ** for 5%, and * for 10%.

	Premia (1)	Premia (2)	Premia (3)
Panel A: Workforce rating			
Workforce score	-0.05	0.02	-0.01
	(0.06)	(0.06)	(0.06)
Observations	328	328	328
Adj R^2	0.13	0.21	0.26
Target sector FE	YES	YES	YES
Deal year FE	YES	YES	YES
Target country FE	YES	YES	YES
Target-level controls	NO	YES	YES
Deal-level controls	NO	NO	YES
Panel B: Dummy workforce rating			
Workforce score	-4.31	-1.78	-2.66
	(2.82)	(2.81)	(2.67)
Observations	328	328	328
Adj R^2	0.13	0.21	0.27
Target sector FE	YES	YES	YES
Deal year FE	YES	YES	YES
Target country FE	YES	YES	YES
Target-level controls	NO	YES	YES
Deal-level controls	NO	NO	YES

Table 2.6: Target workforce score by sector

The table presents summary statistics for target workforce ratings by economic sector based on the sample of firms used in this study (a total of 335 firms). The Thomson Reuters Business Classification (TRBC) is used to define the sector of the target companies. Sectors numbered 61 and 63 are not disclosed because they are represented by only two firms.

	Mean	St.dev.	min	p25	p50	p75	max
Energy (50)	34.44	20.56	2.55	21.21	35.31	41.75	79.03
Basic materials (51)	31.37	20.73	1.52	14.40	28.84	41.91	73.03
Industrials (52)	38.54	24.14	0.79	19.92	33.80	59.90	90.51
Consumer Cyclicals (53)	37.36	22.20	4.13	16.41	36.82	53.64	94.23
Consumer Non-Cyclicals (54)	32.61	19.39	6.18	16.40	31.18	38.24	78.74
Healthcare (56)	45.38	25.46	2.06	24.67	40.65	65.40	97.84
Technology (57)	40.64	22.60	0.88	22.79	41.21	55.59	88.34
Utilities (59)	33.07	21.39	3.57	17.44	24.93	56.44	68.40
Real estate (60)	25.98	22.93	3.79	8.33	19.42	32.13	72.95

Table 2.7: Target workforce score and premia: sector-level analysis

The dependent variable is the acquisition premium, calculated as the difference between the acquisition price and the target share price one week before the deal announcement, divided by the target stock price one week prior to the announcement. The Workforce Score represents a Refinitiv's workforce rating of the target company one year prior to the deal announcement, ranging from 0 to 100. Sector dummy variables are assigned a value of one for target firms operating in the respective sector according to the TRBC classification. Standard errors, adjusted for heteroskedasticity, are presented in parentheses. Significance levels for the parameter estimates are indicated as follows: *** for 1%, ** for 5%, and * for 10%.

	Premia
Workforce score *	-0.11
Energy sector	(0.21)
Workforce score *	0.01
Basic Materials sector	(0.19)
Workforce score *	0.18
Industrials sector	(0.17)
Workforce score *	0.07
Consum. Cycl. Sector	(0.14)
Workforce score *	0.03
Consum. Non-Cycl. Sector	(0.29)
Workforce score *	0.01
Healthcare sector	(0.14)
Workforce score *	-0.29**
Technology sector	(0.10)
Workforce score *	-0.05
Utilities sector	(0.15)
Workforce score *	-0.12
Other sectors	(0.19)
Observations	328
Adj R^2	0.12
Target sector FE	YES
Deal year FE	YES
Target country FE	YES
Target-level controls	NO
Deal-level controls	NO
Acquirer-level controls	NO

Table 2.8: Tech target company workforce score and M&A deal premium

The sample comprises 335 completed international mergers and acquisitions (M&A) between 2003 and 2022, as listed in the SDC database. The dependent variable in Columns (1)-(5) is the acquisition premium, calculated as the difference between the acquisition price and the target share price one week before the deal announcement, divided by the target stock price one week prior to the announcement. In Column (6), the dependent variable is the 7-day cumulative abnormal return of the target around the announcement date. The independent variable, Workforce Score, is a Refinitiv's workforce rating of the target company one year prior to the deal announcement. It ranges from 0 to 100 in Panel A. In Panel B, Workforce Score is a dummy variable equal to one for values higher than 50 and zero otherwise. The tech sector dummy variable is assigned a value of one for target firms operating in the tech sector, corresponding to number 57 in the TRBC classification. The detailed definitions of control variables are given in Appendix 2.A. Standard errors, adjusted for heteroskedasticity, are presented in parentheses. Significance levels for the parameter estimates are indicated as follows: *** for 1%, ** for 5%, and * for 10%.

	Premia (1)	Premia (2)	Premia (3)	Premia (4)	Premia (5)	Target CAR (6)
Panel A: Workforce rating						
Workforce score *	-0.35***	-0.33***	-0.33**	-0.34**	-0.31**	-0.22*
Tech sector dummy	(0.12)	(0.13)	(0.13)	(0.13)	(0.13)	(0.11)
Workforce score	0.09	0.07	0.08	0.09	0.02	0.07
	(0.07)	(0.06)	(0.07)	(0.06)	(0.08)	(0.06)
Relative size			-22.22**	-25.22	-20.02	-19.36
			(10.86)	(20.12)	(20.36)	(16.12)
Observations	328	328	306	299	299	260
Adj R^2	0.23	0.28	0.31	0.29	0.29	0.45
Target sector FE	YES	YES	YES	YES	YES	YES
Deal year FE	YES	YES	YES	YES	YES	YES
Target country FE	YES	YES	YES	YES	YES	YES
Target-level controls	YES	YES	YES	YES	YES	YES
Deal-level controls	NO	YES	YES	YES	YES	YES
Other acquirer-level controls	NO	NO	NO	YES	YES	YES
ESG-related scores	NO	NO	NO	NO	YES	YES
Panel B: Dummy workforce rating						
Workforce score *	-13.28**	-12.53**	-12.86**	-12.53**	-10.91*	-6.26
Tech sector dummy	(5.34)	(5.50)	(5.75)	(5.78)	(5.96)	(4.99)
Workforce score	1.56	0.51	1.40	1.17	-1.58	1.99
	(3.23)	(3.07)	(3.21)	(3.16)	(3.66)	(2.69)
Relative size			-21.88**	-24.33	-19.49	-18.55
			(10.93)	(19.82)	(20.14)	(15.87)
Observations	328	328	306	299	299	260
Adj R^2	0.22	0.28	0.30	0.28	0.29	0.44
Target sector FE	YES	YES	YES	YES	YES	YES
Deal year FE	YES	YES	YES	YES	YES	YES
Target country FE	YES	YES	YES	YES	YES	YES
Target-level controls	YES	YES	YES	YES	YES	YES
Deal-level controls	NO	YES	YES	YES	YES	YES
Other acquirer-level controls	NO	NO	NO	YES	YES	YES
ESG-related scores	NO	NO	NO	NO	YES	YES

Table 2.9: Instrumental variable analysis

Column (1) presents the results of the first stage of the two-stage least squares (2SLS) regression. The dependent variable in Column (1) is the workforce score of a target firm one year prior to the deal announcement, ranging from 0 to 100. The instrumental variable used is the country-sector median of workforce scores from the entire Refinitiv ESG database. Column (2) presents the results of the second stage of the 2SLS regression, with the bid premium as the dependent variable. This premium is calculated as the difference between the acquisition price and the target share price one week before the deal announcement, divided by the target stock price one week prior to the announcement. The premium is regressed on predicted target workforce score and its interaction with a tech sector dummy. This dummy equals one for target firms operating in the tech sector, corresponding to number 57 in the TRBC classification. Control variables include target-level characteristics, as described in Appendix 2.A. All accounting control variables are based on data from one year before the respective M&A deal announcement. Standard errors, adjusted for heteroskedasticity, are presented in parentheses. The symbols ***, **, and * denote that the parameter estimate is significantly different from zero at the 1%, 5%, and 10% levels, respectively.

	Workforce score (1)	Premia (2)
	1st stage	2nd stage
Average workforce score	2.01***	
	(0.61)	
Workforce score * Tech sector dummy		-0.27
		(0.59)
Workforce score		0.32
		(0.36)
Observations	328	328
Target sector FE	YES	YES
Deal year FE	YES	YES
Target country FE	YES	YES
Target-level controls	YES	YES
Deal-level controls	NO	NO
Acquirer-level controls	NO	NO
Sanderson-Windmeijer weak identification F-test (p-value)	0.001	

Appendix

Appendix 2.A: Variables definitions

The table provides definitions and details on the construction of all variables used in this study.

Variable	Source	Description
	Group 1. Target characteristics	
Workforce score	Refinitiv	Workforce score of the company.
Human rights score	Refinitiv	Human rights score of the company.
Community score	Refinitiv	Community score of the company.
Product responsibility score	Refinitiv	Product responsibility score of the company.
Environmental score	Refinitiv	Environmental score of the company.
Governance score	Refinitiv	Governance score of the company.
Target log market value	SDC Platinum	The natural logarithm of the target firm's market capitalization, measured four weeks before the deal announcement.
ROE	SDC Platinum	Return on equity ratio measured one year before the original announcement date of the respective deal.
Sales growth	SDC Platinum	Sales growth of the target firm, based on the three-year compounded annual growth rate in sales preceding the deal announcement.
Debt-to-asset ratio	SDC Platinum	Book value of debt divided by the sum of the book value of debt and the market value of equity. The market value of equity is measured four weeks before the deal announcement, while the book value of debt is based on data from one year before the original announcement date of the respective deal.
Target market-to-book	SDC Platinum	The target firm's market value of equity divided by its total assets. The market value of equity is measured four weeks before the deal announcement, and the total assets are calculated as of one year before the original announcement date of the respective deal.
Capex	SDC Platinum	Capital expenditures scaled by total assets, calculated as of one year before the original announcement date of the respective deal.
R&D	SDC Platinum	Research and development expenses, scaled by total assets, as measured one year before the original announcement date of the respective deal.
Operating cash flows	SDC Platinum	Sales, minus the costs of goods sold, sales and general administrative expenses, and the change in net working capital, divided by total assets. These figures are calculated as of one year before the original announcement date of the respective deal.
Runup	SDC Platinum	Logarithm of the ratio of the target's share price on the day before the announcement to its share price four weeks prior to the announcement.
Liquidity	SDC Platinum	The ratio of current assets to current liabilities, calculated as of one year before the original announcement date of the respective deal.
Target CAR	CRSP	7-day cumulative abnormal return of the target (expressed in percentage) calculated using the market model. The parameters of the market model are estimated based on the return data from the period (−232, −30).
	Group 2. Deal related variables	

Variable	Source	Description
Premium	SDC Platinum	The difference between the acquisition price and the target's share price one week before the deal announcement, divided by the target's stock price one week prior to the announcement.
Cash dummy	SDC Platinum	Dummy variable set to one if the transaction is fully paid in cash.
Tender offer dummy	SDC Platinum	Dummy variable set to one for tender offer deals.
Toehold dummy	SDC Platinum	Dummy variable set to one when the bidder holds 0.5% or more of the target's stock prior to the announcement.
Termination fee dummy	SDC Platinum	Dummy variable set to one if the deal includes termination fees for either the target or the bidder.
Cross-border dummy	SDC Platinum	Dummy variable set to one for deals where the target and acquirer are from different countries.
Different sector dummy	SDC Platinum	Dummy variable set to one if the target and bidder share the same two-digit TRBC sector code.
Competition dummy	SDC Platinum	Dummy variable set to one in cases with more than one potential buyer for the target company.
Group 3. Acquirer related variables		
Acquirer log market value	SDC Platinum	The natural logarithm of the acquiring firm’s market capitalization, measured four weeks before the deal announcement.
Acquirer market-to-book	SDC Platinum	The acquiring firm’s market value of equity divided by total assets, with the market value of equity calculated four weeks before the deal announcement, and total assets as of one year before the original announcement date of the respective deal.
Relative size	SDC Platinum	The target firm’s market value of equity divided by the combined market value of equity of both the target and acquiring firms.

Chapter 3: Green Equity Classifications: Evidence from the London Stock Exchange's Green Economy Mark

3.1. Introduction

As climate change has increasingly become a priority on the public agenda, there has been a growing call for investors to channel capital towards climate change mitigation and adaptation efforts. Investing capital is a natural role for investors, and they are willing to support these initiatives as long as they offer risk-adjusted returns. For instance, investors are increasingly directing their funds towards green bonds, driven by growing awareness of environmental issues[51].

The landscape of green investment opportunities has broadened now, featuring companies that contribute to sustainable economy by providing renewable energy technologies powered by solar, wind, tidal, wave, or geothermal sources, smart grid systems, energy-efficient buildings, low-emission transportation technologies, and sustainable forestry and land use practices. However, investors frequently encounter a shortage of clear and transparent information needed to assess a company's environmental commitment (e.g., Lyon and Maxwell, 2011). The lack of uniform mandatory reporting standards for sustainability practices makes it difficult to objectively assess and compare the environmental impact of various companies. Even when companies disclose their green activities, they may employ varied methodologies. Additionally, companies might overstate or misrepresent the environmental benefits of their products, services, or investments, potentially misleading investors who aim to back genuinely sustainable initiatives.

Stock exchanges have evolved to address some of these challenges. Recently, the World Federation of Exchanges (WFE) developed a global framework called the Green Equity Principles, which individual exchanges can use to create a "green" offering for listed equities. These voluntary principles establish specific criteria for equities to receive a green designation. By doing so, exchanges aim to ensure that the definition of "green" is clear, consistent and accurate. It should help

[51] In 2023, global green bond issuance reached $492.30 billion, up from $446.18 billion in 2022. *Source:* Yuzo Yamaguchi and Marissa Ramos (2024) "Global green bond sales to get boost in 2024 as interest rates may fall". *S&P Global.*

companies with products and services contributing to the green economy bridge the information gap regarding their commercial activities related to environmental solutions. As a result, the green designation should also make these firms more visible and able to attract large sustainability-focused investors. Ultimately, this is intended to enhance the flow of investment towards more sustainable economies.

The aim of this research is to examine whether stock exchanges can indeed bring the expected benefits listed above by creating green offerings. This question is important because it would shed light on whether stock exchanges should continue allocating resources to such initiatives. To answer this question, I study the Green Economy Mark (GEM), which was launched by the London Stock Exchange in October 2019. GEM is the first green designation for equity issuers. Using FTSE Russell's Green Revenues Data Model as its underlying framework, GEM identifies LSE listed companies that derive at least 50% of their total revenues from green products and services.

I begin my analysis by examining the abnormal returns around the GEM announcement. While the London Stock Exchange, echoing the World Federation of Exchanges, expects that the Green Economy Mark could reduce information asymmetry and thereby attract investor demand, I suggest that these benefits may not materialize. Consequently, one should not expect a positive, or at least a persistently positive, stock market reaction.

To reduce information asymmetry, GEM should either give new information on the environmental performance of companies or make existing information more understandable. GEM is not likely, however, to achieve any of these. Firstly, it should not provide any new information on companies' environmental activity since its only source is public information. Secondly, it is based on an already available database that offers an insight into companies' revenues derived from green activities, which green investors likely use already to monitor green opportunities. This limits GEM ability to assist investors in information processing. As such, GEM resembles mere reclassification and thus not a helpful new tool per se. Therefore, GEM is unlikely to influence investors' decisions, which explains why it may not generate a persistent stock market response. While investors may initially react to the announcement of GEM, this reaction is expected to be short-lived as the market would subsequently readjust for what the label actually means, resulting in a subsequent price correction.

Using a standard event study methodology, I find that on the day of the announcement of GEM, the stock prices increased represented by an average abnormal return of 1.35%. Part of this effect is due to the fact that significant advances in the Brexit-related negotiations happened around the same time as the announcement of the first cohort of GEM firms on October 11, 2019. The impact of the GEM announcement is hence driven mainly by the firms which received the mark between 2020 and 2023. For the period 2020-2023 GEM firms, the announcement-day stock market reaction is positive at 2.20% and statistically significant. However, this initial rise is followed by a sharp reversal. The event study indicates a statistically significant negative reaction the day after the announcement, which becomes increasingly statistically and economically significant by the sixth day. The analysis of the cumulative abnormal returns over different windows around the GEM announcement reveals a drop in abnormal returns, where no significant abnormal return remains on the sixth day following the event. This suggests that the GEM is unlikely to reduce information asymmetry and, consequently, increase investor demand. The initial positive reaction likely reflects a temporary shift in sentiment, which faded as the market reassessed the true implications of the GEM.

While the event study analysis indirectly confirms that the GEM does not deliver the expected benefits, I conduct further tests to provide more direct evidence. To test whether GEM offers new insights that investors do not already possess, I compare the stock market reactions of GEM firms that are either covered or not covered by any UK index, as well as companies that either have or do not have ESG ratings available. Companies not covered by any index or ESG scores are likely to provide less comprehensive information on their overall environmental performance, including aspects related to green revenues. Therefore, GEM is expected to provide more incremental information for companies not already covered by indices and ESG ratings. As a result, the abnormal stock market reaction to the GEM announcement should be stronger for these companies. Using data from the LSEG database (previously Refinitiv), I find that abnormal returns on the GEM announcement day do not depend on a firm’s inclusion in an index or ESG database. Thus, it is unlikely that GEM provides new information.

I further test whether the Green Mark designation attracts large investors with green preferences. I compare the percentage change in the number of investors from two quarters before to two quarters after the GEM announcement for GEM and matched companies. The matching group consists of LSE-listed firms similar to GEM companies in terms of sector, sales, EBITDA margin, and size. I focus on institutional investors and UN PRI signatories as proxies for socially responsible investors, and I also examine the number of large individual investors. The results reveal that the change in the shareholder base for GEM companies is not statistically different from the change in the number of investors for the matched firms around the GEM announcement. While the GEM may not expand the investor base, it is possible that it could generate more demand from existing investors. To test this, I compare the percentage change in average stock turnover from two quarters before to two quarters after the GEM announcement for GEM and matched companies. Again, I do not find a statistically significant difference between the two groups. This further confirms that GEM is unlikely to bring new information and suggests that GEM is also unlikely to offer information-processing benefits to investors.

Taken together, this study indicates that the GEM does not reduce the information gap regarding companies' green activities and, therefore, does not lead to increased demand from sustainability-driven investors. Following the GEM announcement, stock prices experience a brief increase, but this is quickly followed by a rapid reversal, resulting in essentially no abnormal return. Investors may not immediately grasp the significance and impact of the GEM label, but over time, they seem to question its implications.

This study suggests that the current implementation of green labels by the London Stock Exchange may not be as effective as expected. That underlines the need for exchanges to refine the criteria on what constitutes "green" equities. For instance, Nasdaq Green Equity Designation gives the label to firms after a fee-based analysis of their green activities by an approved independent reviewer using a proprietary methodology, while London Stock Exchange draws on an existing database developed by its subsidiary, FTSE Russell. Although the differences herein go beyond the scope of the paper, they do represent an interesting avenue for further exploration in the future.

This study makes several contributions to the literature. First, I contribute to the body of work on green firms, which are companies generating revenue from environmentally sustainable economic activities. Guo and Zhong (2023) find that firms with a higher percentage of green revenues tend to hold less cash. Bassen et al. (2023) show that portfolios of high green revenue companies (based on the FTSE methodology) outperform those consisting of low green revenue companies. Kruse et al. (2020) provide evidence that utility firms receiving green revenues benefit simultaneously from their financial and market performance. Klausmann et al. (2024) document evidence that institutional investors are more likely to invest in firms with higher green revenues. I differentiate from these studies by focusing on the world's first green accreditation for firms, which is the Green Economy Mark. It recognizes companies with at least 50% green revenues under the FTSE methodology. To the best of my knowledge, this is the first paper to study the LSE Green Economy Mark.

Secondly, I contribute to the literature on how green labels impact companies. Most research in this area focuses on green labelled bonds. For example, Flammer (2021) and Tang and Zhang (2020) show that stock prices respond positively to green bond issuances. Additionally, institutional ownership increases after a firm issues a green bond, supporting the idea that green bond issuance reduces information asymmetry by signalling a company's commitment to the environment. I distinguish my study by showing that the Green Economy Mark, as an equity green label, does not reduce the information gap. As a result, it generates no abnormal market reaction overall and limits GEM holders' potential to attract a broader investor base.

The remainder of this paper is organized as follows. Section 3.2 explains what the Green Economy Mark is and outlines the process firms must follow to receive this designation. Section 3.3 presents the testable hypotheses. Section 3.4 discusses sample selection and data sources. Section 3.5 presents the empirical results from the event study. Section 3.6 provides an analysis that tests the expected benefits of GEM more directly. Finally, Section 3.7 concludes.

3.2. Green economy mark

In 2019, the London Stock Exchange launched the Green Economy Mark, a new green accreditation for LSE listed or soon-to-list companies and closed-end funds which contribute to two key environmental objectives: climate resilience and resource efficiency. Whereas ESG ratings express a broad measure of a company's performance on environmental, social, and governance dimensions using various criteria, the Green Economy Mark focuses on just one single dimension. It differentiates firms whose revenue is generated from products and services that contribute to a worldwide green economy. The GEM is completely free to acquire.

There are two ways a firm or closed-end fund can be awarded the Green Economy Mark. Firstly, each year, the London Stock Exchange monitors firms covered by FTSE Russell's Green Revenues data model. If a company generates at least 50% of its annual revenue from green sources according to this model, it automatically qualifies for the GEM. In the case of closed-end funds, the investment strategy and at least 50% of investments, based on net asset value (NAV), must align with FTSE Russell's Green Revenues Classification System. LSE contacts qualifying candidates directly via the Investor Relations team, and the Green Economy Mark is assigned unless the candidate objects.

The second route to qualification is that any firm or fund that is not in coverage under FTSE Russell research but thinks it may qualify for the GEM can apply. In this latter case, candidates must complete a form, which splits out their green revenues and provides evidence of relevant publicly disclosed information. Following this, the LSE arranges an initial consultation call with the candidate and verifies its eligibility for the GEM using the FTSE Green Revenues Classification System 2.0 methodology. The LSE has 28 business days to carefully consider and decide whether to award the mark.

The first cohort of GEM holders was introduced on October 11, 2019, during the LSEG Sustainable Finance and Investment Summit. For subsequent cohorts, the mark is awarded on an ongoing basis. While the exact dates of GEM awards are not disclosed by LSE, a company or fund can make an announcement on its own website or via the Regulatory News Service (RNS). Moreover, each year during the summer, LSE publishes a report listing all firms and funds that were awarded GEM in the preceding year.

Every year, LSE also reevaluates the companies and closed-end funds that qualified in the previous year. In case it still qualifies, it automatically retains its Green Economy Mark. If not, LSE removes it from the list. If a firm was acquired, the LSE requests confirmation that the company's qualification for the Green Economy Mark remains in place. Finally, the mark is lost automatically by companies or funds whose trading has been suspended.

3.3. Hypotheses development

As proposed by the World Federation of Exchanges, the main purpose of the green equity designations like GEM is to provide clarity and consistency to the definition of "green," helping investors accurately evaluate the environmental performance of firms. Indeed, as the academic literature shows, investors often face a lack of clear information necessary to objectively compare the environmental impact across different companies (e.g., Lyon and Maxwell, 2011). The London Stock Exchange also points out that there is a lack of consistent information on how issuers generate revenue and achieve growth through environmental solutions[52]. The London Stock Exchange suggests that the Green Economy Mark might help to reduce this information asymmetry. In particular, LSE states that Green Economy Mark might "address the information gap around what constitutes commercial activity relating to environmental solutions"[52]. By reducing information asymmetry, the Green Economy Mark is also expected to offer another benefit: helping firms attract more investors, particularly those with green mandates. The London Stock Exchange supports this statement: "It

[52] Green Economy Mark Factsheet (8 October 2019). *London Stock Exchange*.

facilitates visibility and investment by addressing the information gap… Environmental solutions are more visible and able to attract green or climate aware investors"[52]. If GEM indeed reduces information asymmetry and consequently enhances the shareholder base, this might result from the provision of incremental information or improvements in information processing. In both cases, one might also expect the stock market to respond positively to the GEM announcement.

If GEM helps to reveal previously unknown details about the environmental activities of its holders, customers, employees, and other stakeholders are likely to perceive this eco-friendly behaviour positively. As it can be beneficial to firms at least in the long run[53], investors might reassess the value of GEM firms upward based on the additional information provided by the Green Mark. This reassessment should lead to positive abnormal returns on the day of the GEM announcement as more investors are willing to buy shares at higher prices. The positive market reaction is likely to be particularly strong for firms about which investors had less pre-existing information regarding their environmental efforts prior to the designation (e.g., not covered by UK indices or ESG ratings).

In case GEM enhances the clarity of existing environmental information making it easier to understand, it provides assurance that green revenue or sustainability metrics are accurate and reliable. Such a reduction in perceived risk could make the company more appealing to investors, especially the ones who might have been hesitant to act based solely on company-disclosed information. The attraction of greater investor attention should also result in increased demand for the firm's shares. The Green Economy Mark may not only expand a firm's shareholder base but also strengthen the commitment of existing investors. This aligns with Merton's (1987) hypothesis, which suggests that investors are more likely to invest in securities they recognize. Such increased demand for GEM-designated firms could drive their stock prices higher, explaining the positive abnormal market reactions.

Although green labels can generally offer such benefits, theory suggests that the design of the Green Economy Mark is unlikely to reduce information asymmetry and therefore attract significant investor

[53] Many studies find a positive relationship between ESG and performance. For example, Eccles et al. (2014) show that sustainable companies perform better in terms of ROE and ROA ratios. Flammer (2015) demonstrates how CSR activities are associated with an increase in labour productivity and sales growth. Some studies also find evidence that green status can help companies survive adverse situations (Lins et al., 2017).

demand. Therefore, one should not expect a positive or at least a persistently positive stock market reaction.

Firstly, there is little evidence to suggest the information GEM provides adds anything particularly new for investors. In respect of companies not covered by the FTSE Green Revenues database, the London Stock Exchange would assess a company's potential inclusion in GEM based on publicly available information. If a company happens to be already covered by the FTSE Green Revenues database, then FTSE also relies on publicly disclosed information in its decision-making. Accordingly, such information that would form the basis of assessing whether or not a company crosses the threshold of 50% green revenue already flows to investors, analysts, and other stakeholders. The GEM label essentially serves as a confirmation of what is already evident from these disclosures, without providing any additional analysis or insights beyond publicly available information.

Secondly, it is unlikely that GEM provides meaningful clarity that significantly improves investors' understanding of a company and its green activities. Some GEM firms are already covered by the FTSE Green Revenues database prior to the GEM announcement. Investors, particularly those tracking sustainability metrics, are likely already relying on this database to identify firms with green revenue contributions. Therefore, the 50% threshold set by GEM largely represents a simple reclassification of firms without providing substantive underlying changes. It merely formalizes what is already known through FTSE data.

One might argue that some GEM firms are not covered by the FTSE Green Revenues database and are instead assessed by the LSE based on publicly available data. In this case, GEM could potentially improve the understanding of the environmental activities of these firms. While I do not have data to determine how many GEM firms were not included in the FTSE database prior to the GEM announcement, I consider this scenario unlikely for the following reason. It is relatively improbable that a publicly listed and mature UK firm with 50% or more green revenues would not be covered by the FTSE Green Revenues database. The database includes data on thousands of public companies globally, particularly those that derive a substantial portion of their revenues from environmentally friendly activities. It is more likely that a relatively new public company might not be immediately covered, as it may not yet have been reviewed in detail. However, as we will see further, such firms represent less than 5% of my sample (4 companies in total, each less than 5 years old).

This argumentation leads me to the following hypotheses:

H1: There is no stock market reaction around the GEM announcement.

H2: Abnormal returns around the GEM announcement do not differ based on a company's inclusion in UK indices or the availability of ESG scores.

H3: The investor base does not increase after the GEM announcement.

H4: Demand from existing investors does not increase after the GEM announcement.

3.4. Data and sample selection

3.4.1. Sample selection

In 2023, there were 148 unique companies and closed-end funds that were awarded green economy mark. I gather a complete list of GEM holders from the LSE reports. All companies and funds that were IPOs are also not included in this study since there is no trading information prior to their introduction in the LSE. I also exclude international firms which cross-listed their shares on LSE and received green mark at the same time. It reduces a sample to 122 GEM holders. In this study, I focus only on companies and exclude closed-end funds. Of these 95 firms left, I am able to identify the announcement dates for 82 firms. For the very first cohort of companies that were awarded green mark in 2019 this is the day of the LSEG Sustainable Finance and Investment Summit (October 11, 2019). For companies that received the GEM mark starting from 2020 the LSE does not reveal the exact dates of GEM awards. However, each summer, the LSE releases a report that lists all the firms that received GEM awards in the previous year. I used Lexis/Nexis and companies websites to identify the dates of GEM awards. In most cases, these dates are significantly earlier than the LSE report date featuring the company. I excluded three firms from the sample where the date was later than the respective LSE report date. This results in a sample of 79 firms.

For each stock, I collect daily closing prices from LSEG (previously, Refinitiv). From the same source, I obtain most of the other variables used in this study, including firm-related variables, as well as daily prices for the FTSE All-Share UK market index. In addition, I download European SMB, HML and Momentum factors from Fama-French website.

[Insert Table 3.1 about here.]

[Insert Table 3.2 about here.]

There are 69 GEM firms with available daily prices. These companies represent my final sample. Table 3.1 summarizes the sample selection process, while Table 3.2 shows the number of firms in the final sample, categorized by country, sector and year of GEM designation. Most of the GEM firms in my sample are incorporated in the United Kingdom and other countries with a Common Law legal system, which is characterized by stronger investor and legal protection. The majority of these companies received GEM in 2019 and operate in the Industrial, Basic Materials, or Technology sectors.

3.4.2. Summary statistics

[Insert Table 3.3 about here.]

Table 3.3 presents summary statistics for all variables used in this study. Panel A shows descriptive statistics for the main variables, including a dummy variable for ESG score availability, a dummy variable indicating whether a firm is covered by any FTSE index (such as the FTSE All Share and FTSE AIM All Share indices), as well as changes in the number of institutional investors, individual investors, PRI signatories, and stock turnover around the GEM announcement. To eliminate outliers, I trimmed the change in stock turnover so that it does not exceed 300%. Change in number of investors measures are trimmed so that they do not exceed 150%. On average, GEM firms experience an increase in the number of institutional investors and stock turnover after the GEM announcement, along with a decrease in the number of individual investors and PRI signatories. According to the t-test, only the change in stock turnover and the change in PRI investors are statistically different from zero. Additionally, 36% of GEM companies have an ESG score available in the Refinitiv database, and 88% of GEM firms are covered by at least one FTSE index.

Panel B reports statistics for the control variables used in this paper, including the inverse of the mean daily stock price and the logarithm of the standard deviation of daily returns over the year preceding the GEM announcement. It also covers the age and size of GEM firms, return on equity, and various financial ratios. Firm size reported in Table 3.3 represents a natural logarithm of market capitalization. The average market cap (not reported) of GEM companies is approximately £30 million, which falls into the small-cap category in the UK market. The majority of GEM companies are mature.

The book-to-market ratio, leverage ratio, and return on equity are winsorized to a maximum value of 150%. Additionally, return on equity is constrained to not fall below -150%. The inverse of the price is capped at a maximum of 150, while tangibility and R&D ratios are capped at a maximum of 100%. Most GEM companies have no R&D expenditures. Nine GEM firms have a relatively high leverage ratio of more than 100%, which represents the ratio of a company's total book value of debt to its market capitalization. The reasons for this varied, ranging from capital investments in infrastructure and new technologies to operational restructuring and responses to market volatility. A detailed description of all variables can be found in Appendix 3.A.

3.5. Event study

To analyse abnormal behaviour, I perform an event study with stock returns around the announcement of a Green Economy Mark. Day 0 is the announcement date. The estimation period is from day -150 to day -8 before the announcement. Abnormal returns are estimated as prediction errors of the Fama-French-Momentum four-factor model estimated over an estimation period, using the UK market index, European SMB, HML, and Momentum as explicative variables. The Fama-French Four-Factor Model is widely used in event studies since it is more reliable than CAPM. It includes other sources of systematic risk that determine stock returns. I take the UK market index as the FTSE All-Share Index. The FTSE All-Share gives diverse exposure to stocks and hence is attractive to investors looking for general market exposure. The stock returns and market index returns are computed by taking the natural logarithm of the ratio of current price to the previous price.

In my sample, stocks are infrequently traded. This issue is common for equities traded in non-U.S. markets and is concerning because it can complicate the estimation of model parameters. To address this, I follow the trade-to-trade method recommended by Maynes and Rumsey (1993). Using this approach, returns are computed as

$$R_{i,n_t} = \ln \frac{P_{i,t}}{P_{i,t-n_t}} \tag{3.1}$$

where n_t represents the length of the non-trading interval ending on date t, $P_{i,t-n_t}$ is the last quoted price before this interval. Abnormal returns are determined by subtracting the expected return from the actual return over the event window, which spans from day -10 to day +10, as follows:

$$\begin{gathered} AR_{i,n_t} = R_{i,n_t} - E\left[R_{i,n_t}\right] = \\ R_{i,n_t} - \left[\widehat{\alpha_\imath} n_t - \widehat{\beta_{\imath,m}} R_{m,n_t} - \widehat{\beta_{\imath,SMB}} SMB_{n_t} - \widehat{\beta_{\imath,HML}} HML_{n_t} - \widehat{\beta_{\imath,MOM}} MOM_{n_t}\right] \end{gathered} \tag{3.2}$$

where R_{m,n_t} represents the market index return over the non-trading period that matches the stock return. The coefficients $\widehat{\alpha_\imath} n_t$, $\widehat{\beta_{\imath,m}}$, $\widehat{\beta_{\imath,SMB}}$, $\widehat{\beta_{\imath,HML}}$ and $\widehat{\beta_{\imath,MOM}}$ are estimated using OLS over the estimation window.

To test the null hypothesis of zero abnormal returns on the event date, I aggregate returns across firms for each event time and apply a parametric t-test, as well as nonparametric rank tests as outlined by

Kolari and Pynnönen (2010) and Corrado and Zivney (1992). These tests are particularly helpful in dealing with cross-sectional correlation and non-normality of returns. Since some of the firms in GEM were announced on the same day, cross-sectional correlation should be taken into account.

[Insert Table 3.4 about here.]

Table 3.4 presents the results of the event study of abnormal returns around the GEM designation announcement dates for firms. Panel A summarizes the aggregate abnormal returns. Column (1) shows a positive abnormal return of 1.35% on the announcement date. This effect is statistically significant at the 1% level according to the Kolari test and at the 10% level according to the Corrado test. Panel B provides some summary statistics of aggregate abnormal returns on the day of the GEM announcement (day 0). According to Column (1), the majority (57%) of GEM firms experienced positive abnormal returns on that day.

One of the concerns stems from the fact that some GEM firms were announced on the same day, October 11, 2019. If another event that could impact stock returns also occurred on this day, the effect I capture might be driven, at least partially, by that event rather than the GEM designation. I therefore examine aggregate abnormal returns separately for a subsample of firms that received the GEM designation between 2020 and 2023 and those that received it in 2019.

I report the results for the 2020-2023 subsample in Panel A, Column (2) and for the 2019 subsample in Panel A, Column (3). According to Column (2), the market exhibited a short-term reaction to the GEM announcement, characterized by an initial surge in stock price, which was quickly followed by a reversion. Specifically, there is a positive abnormal return of 2.20% on the day of the announcement. This effect is statistically significant only according to the t-test, but not to Kolari and Corrado tests. In subsequent days after GEM announcement the abnormal returns switch the sign. There is a negative abnormal return of -0.99% (significant at 1% level) on the next day after GEM announcement followed by a negative abnormal return of -1.68% (significant at 5% level) on the sixth day after announcement.

[Insert Table 3.5 about here.]

To measure the total impact of the GEM on stock returns for the 2020-2023 subsample of firms, I examine cumulative abnormal returns (CAR). Table 3.5, Column (2) presents CAR across different event windows. I begin with CAR using an event window that includes both the event day (day 0) and the day after the event (day 1). I start from day 0 because I do not expect any market reactions before the event. As previously discussed, the LSE itself does not publish specific dates when GEM is awarded. That is why I used news from Lexis/Nexis and companies websites to identify the dates of GEM designations. In most cases, the initial source of GEM announcements is the RNS (Regulatory News Service). This is a trusted source of real-time regulatory and corporate news from companies listed on the London Stock Exchange. The likelihood of GEM-related news appearing before an RNS announcement is extremely low due to legal obligations that require potentially market-sensitive information to be released through RNS first. Therefore, this implies one would not expect a prior reaction of the stock price to the announcement date. CAR(0,1) is positive but statistically insignificant. That means the market did not significantly respond to the GEM within the period from day 0, the event day, and day 1, the day after the event. I also computed CAR for the windows from CAR(0,2) to CAR(0,6). The reaction of the stock market in all the windows continued positive, though statistically insignificant. On day 6, the cumulative abnormal returns had almost reached zero at CAR(0, 6) = 0.10%. This would suggest that the initial market response to the event was weak and decays rapidly to become negligible by day six. The initial response most probably reflects temporary sentiment that did not hold as the market reassessed what the true implications of the GEM were.

I continue with the subsample of companies that received the GEM in 2019. According to Panel A, Column 3, there is a positive and statistically significant market reaction of 1% on the announcement day[54]. As with the 2020-2023 subsample, I examine cumulative abnormal returns, starting from CAR(0,1) through to CAR(0,6). The results are presented in Table 3.5, Column (3). All CARs, regardless of the event window, are statistically significant and positive. The estimated effect becomes economically larger as I add more days after the announcement, although, as discussed before, it can be driven at least to some extent by other events happening on the same time.

More specifically, the Brexit negotiations between the UK and the EU saw significant movement on 11 October 2019, especially over the Irish border. The debate centred around what's being called the "backstop"-a way to keep the border between Northern Ireland, a part of the UK, and the Republic of Ireland, an EU member, open with no hard border. UK Prime Minister Boris Johnson and EU leaders

[54] The reaction is also negative two days before the announcement of GEM, and statistically significant, at -0.39%. This decrease is likely due to increasing uncertainty related to the negotiations for Brexit and the increasingly high risk of no-deal Brexit. Especially on 9 October 2019, it was known that negotiations between the UK and EU were running into big obstacles. The talks also focused on a new Brexit deal, but there were disagreements over the Irish backstop and future customs arrangements for Northern Ireland.

discussed alternative solutions that may result in a possible compromise, therefore lightening the mood.

Some firms reacted especially strongly to this news. In particular, the FTSE 250 index saw the biggest one-day gain since 2010 due to its high exposure to the UK economy, as suggested by numerous news sources[55]. These companies are especially sensitive to Brexit developments since a large portion of their operations, revenues, and supply chains are based in the UK. The potential for a Brexit deal reduced fears about higher costs, regulatory challenges, and economic instability that could have come from unresolved border and trade issues, particularly with Ireland. While FTSE 100 companies are more globally diversified and therefore less affected by UK-specific risks, and FTSE Small Cap companies are more local and less exposed to international markets, FTSE 250 firms occupy a middle ground. The FTSE 250 is more domestically focused than the FTSE 100, but it still has more international exposure than the FTSE Small Cap. This made them particularly vulnerable to Brexit uncertainties. As a result, they benefited to a greater extent from the positive news about the potential Brexit deal, which helped stabilize their UK-focused revenues and business conditions by addressing concerns related to the Irish border and other domestic issues.

[Insert Table 3.6 about here.]

To assess whether the effect observed in Table 3.4 (Panel A, Column 3) is attributable to Brexit news, I run a cross-sectional regression where CAR(0,1) is regressed on the FTSE 250 dummy. FTSE 250 dummy equals 1 if GEM firm is included in the FTSE 250 index and 0 otherwise. Generally, these firms make up 12% of the 2019 subsample. The results are reported in Table 3.6. The coefficient of the FTSE250 dummy is statistically significant at 1%, thus documenting that, on October 11, 2019, the Brexit news caused a differential market reaction for FTSE 250 firms relative to non-FTSE 250 firms. This implies that the observed CAR(0,1) are largely driven by the Brexit event and not by the GEM designation.

[Insert Table 3.7 about here.]

I further investigate the abnormal returns surrounding GEM designation announcements for the 2019 cohort after the exclusion of FTSE 250 firms. As shown in Table 3.7, abnormal return on the day of

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[55] "A Boris Johnson election win could send these Brexit stocks surging, analysts say" (December 12, 2019). *Market Watch*; "FTSE250 Soars 25 On Brexit Deal Optimism" (October 11, 2019). *Forex*.

GEM designation announcement decreases from 1% to 0.19% and becomes statistically insignificant. This reinforces the result that the abnormal returns documented for GEM firms during 2019 (Table 3.4, Panel A, Column 3) are a consequence of the event of Brexit and not due to the GEM designation per se. The insignificance of abnormal returns around the announcement of GEM suggests that market reaction is not strongly linked with the designation of GEM.

Overall, the analysis shows that, on average, the Green Economy Mark did not lead to a significant market reaction. GEM was generally met with a negligible market response. This result supports Hypothesis 1. These findings provide indirect evidence that the expected benefits, such as a reduction in information asymmetry and the associated increased demand from green investors, may not have materialized.

3.6. Expected benefits of GEM

In this section, I conduct additional analyses to provide more direct evidence that the expected benefits of the Green Economy Mark (GEM) did not materialize. First, I perform tests using the entire sample of GEM firms. Given that the stock market reaction on October 11, 2019, was primarily driven by Brexit news, I also separately analyse the 2019 and 2020–2023 subsamples of GEM firms. I begin by demonstrating directly that the GEM did not provide any incremental information. I then show that the GEM did not increase demand from large investors with green preferences, further confirming that the GEM did not provide new information or information-processing benefits.

3.6.1. Incremental information

The London Stock Exchange suggests that the GEM helps bridge the gap in understanding what qualifies as commercial activity related to environmental solutions. As discussed earlier, one of the possibilities of how mark can reduce the information gap is by providing new information regarding environmental performance of companies that investors are not yet aware of.

To test this, I assess whether the stock market reaction was different for GEM firms covered by any UK index or ESG scores providers. Companies not covered by any index may have limited publicly available information, including potential information on environmental performance. Similarly, ESG ratings serve as an even more direct existing source of information about a firm's environmental status. These ratings are assigned based on public information, including sustainability reports. Therefore, firms not covered by ESG scores likely provide a less comprehensive information on their environmental performance, including aspects related to green revenues. Given this, it is reasonable to assume that the GEM would provide more incremental information, if any, about firms not included in indices or without ESG ratings. This suggests that the abnormal stock market reaction to the GEM announcement should be stronger for companies not covered by indices and without ESG ratings.

For all GEM firms in my sample, I retrieve information on index coverage and the availability of ESG ratings from the LSEG database (formerly Refinitiv). LSEG is one of the largest providers of ESG scores. I create a dummy variable that equals 1 for companies with available ESG ratings and 0 otherwise. Similarly, I generate a dummy variable for index coverage, which equals 1 for covered GEM firms. I then run a cross-sectional regression where CAR(0,1) is regressed on these dummy variables. If the GEM provides incremental information, I would expect to observe a negative and significant coefficient for cumulative abnormal returns on the ESG and index dummies.

[Insert Table 3.8 about here.]

The results are reported in Table 3.8. Panel A focuses on the entire sample of GEM firms. In this sample, 36% of companies have an ESG rating, and 88% are included in some FTSE indices, providing good variation. In Column (1), I use a univariate regression with the ESG dummy, while in Column (2), I add firm size as a control variable and include fixed effects for the year in which a firm received the GEM. I control for firm size because a priori, the likelihood of larger firms being assigned an ESG rating is higher than that of smaller firms due to the greater public visibility. In controlling for size, I would like to see in isolation the impact of having an ESG rating on the market reactions, irrespective of the firm-size-related characteristics. Year fixed effects account for factors affecting all firms equally within a particular year. I use heteroskedasticity-adjusted standard errors. The results in both columns suggest that the ESG dummy does not have a statistically significant effect on cumulative abnormal returns around the GEM announcement. In Column (3), I report the results of a univariate regression with the Index dummy. The coefficient of CAR on this dummy is also statistically insignificant. These results are inconsistent with the idea that the GEM provides new environmentally related information.

I further conduct tests using similar specifications for the 2019 and 2020–2023 subsamples of GEM firms, reporting the results in Panel B and Panel C, respectively. In Panel B, 35% of companies have an ESG rating, and 93% are included in FTSE indices. In Column (1), the coefficient for the ESG dummy is positive and statistically significant at the 5% level. However, this significance disappears when control variables are included in Column (2). This suggests that the market does not strongly differentiate between firms with and without existing ESG information when reacting to the GEM announcement. The Index dummy also does not have a statistically significant impact on CARs, as shown in Column (3).

For Panel C, 40% of GEM companies are covered by the LSEG ESG database. However, only two companies are not covered by any UK index. I consider, given the low variation, for this subsample of firms only the effect of the ESG dummy on cumulative abnormal returns. I report in Column (1) that the ESG dummy is negative and significant in influencing abnormal returns. However, this significance disappears with the introduction of firm size in Column 2. It suggests that ESG ratings are not providing information incremental to that already captured by firm size.

Overall, the results lead to the conclusion that the GEM is unlikely to provide incremental insights regarding environmental performance of the companies. This is consistent with Hypothesis 2.

3.6.2. Visibility and investor base

If the Green Economy Mark reduces information asymmetry, either by offering new information or by making existing information more understandable (information processing benefits), one might expect that the GEM would attract more investor demand, particularly from investors with green preferences. To test this expected benefit, I examine changes in the investor base around the GEM announcement. Previous research by Dyck et al. (2019) suggests that institutional investors, in particular, encourage firms to improve their ESG profiles. Supporting this, Krueger et al. (2020) provide survey evidence showing that institutional investors are concerned about climate risk. Therefore, I focus on institutional investors, assuming they have green preferences and may be attracted to companies with the Green Economy Mark. As an alternative measure of "green" investors, I use institutions that have signed the United Nations-sponsored Principles for Responsible Investment (PRI), the world's largest initiative on ESG investing (Gibson Brandon et al., 2022). Finally, I also examine changes in large individual investors.

I downloaded the list of investors for each GEM firm in my sample from the LSEG Ownership database, one of the most comprehensive and widely used databases for tracking institutional ownership and significant individual shareholders in publicly traded companies globally. I then compute the number of investors two quarters before and two quarters after the GEM announcement and calculate the percentage change in the number of investors[56]. To test whether these changes in the investor base are driven by the Green Economy Mark, I create a matched group for comparison. The matching firms are selected from a pool of non-GEM companies listed on the London Stock Exchange (either as primary or secondary issues). I use a one-to-portfolio matching approach, where each GEM firm is matched with a portfolio of comparable firms based on sales, EBITDA margin, and TRBC 2-digit sector codes. Within each portfolio, the firm with the closest size (based on average market capitalization from 2019 to 2023) to the GEM company is selected as the control firm. I create a dummy variable, GEM dummy, which takes a value of one for GEM firms and zero for matched firms. Then, I run cross-sectional regressions where change in number of investors measures are regressed on the GEM dummy. Since data on the number of investors is unavailable for some GEM firms, my sample for this test consists of 132 firms (66 GEM and 66 matched firms).

[Insert Table 3.9 about here.]

I present the results in Table 3.9. Panel A focuses on institutional investors, while Panels B and C show the results for PRI signatories and individual investors, respectively. In all panels, I exclude GEM/matched firms and their pairs where the change in the number of investors exceeds 150% to remove outliers[57]. In Columns (1) and (2), I focus on the full sample of GEM firms; in Columns (3) and (4), on the 2020-2023 subsample; and in Columns (5) and (6), on the 2019 subsample. In Columns (1), (3), and (5), I use a univariate regression where the GEM dummy is the only independent variable. Standard errors are clustered at the GEM-matched firm pair level. GEM firms and their matched counterparts are selected based on observable similarities, and this makes them likely to respond similarly to market-wide or industry-wide factors. This introduces correlation in their error terms. Clustering by the firm pair allows to correct for that. In Columns (2), (4), and (6), I add fixed effects for the year of GEM designation and include control variables representing standard determinants of a firm's investor base.

Following the literature (e.g., Grullon et al., 2004; Chava, 2014; Liu et al., 2014), I control for firm size, age, leverage, book-to-market ratio, R&D, tangibility, return on equity (ROE), inverse of the mean daily stock price (Inverse), and logarithm of the standard deviation of daily returns (Volatility)

[56] In unreported results, I also focus on changes from one quarter before to one quarter after the GEM announcement. This does not impact my conclusions.

[57] The results remain qualitatively the same without applying this filter.

over the year preceding the GEM announcement. Firm size is the natural logarithm of market capitalization, which influences investor base due to greater analyst coverage and a larger number of available shares in bigger firms. I include ROE and firm age as controls since profitable and older firms are generally more appealing to investors. Firm age is calculated as the years since incorporation until the year prior to the GEM announcement. The tangibility ratio and the R&D ratio are defined as the proportions of a company's tangible assets and research and development expenditures against total assets. Tangibility reflects lower risk and thus is appealing to conservative investors. High R&D expenditures attract growth-oriented investors interested in long-term gains from innovation. The inverse of the stock price influences investor composition. Low-priced stocks attract retail investors, while high-priced stocks attract institutional investors. Volatility reflects the risk tolerance of the investors. High volatility attracts speculative investors, while low volatility is preferred by more conservative and long-term investors. Finally, I control for the book-to-market and leverage ratios. A high book-to-market ratio implies undervaluation of the stock, thus becoming attractive to value investors. The low ratio attracts growth investors expecting future earnings. Leverage is the ratio between the total debt and market capitalization that may keep risk-averse investors away but could attract speculative investors in cases when the funds are used for high-return projects. Low leverage can be attractive to conservative investors but leads to a limited participation of growth-oriented investors. I use the last year before the GEM announcement for book values and one quarter before for market values. The detailed definitions of control variables are provided in Appendix 3.A.

Across all panels and columns in Table 3.9, the coefficient of the change in the number of investors on the GEM dummy is statistically insignificant. These findings indicate that the changes in the shareholder base observed in Table 3.3 are driven by factors other than the GEM designation. This suggests that the Green Economy Mark does not attract large green investors, consistent with Hypothesis 3.

While GEM does not expand the shareholder base, it is possible that it reinforces demand from existing investors. If GEM increased demand, one would expect an increase in stock turnover after the GEM announcement. Therefore, I also analyse average stock turnover over the two quarters before and the two quarters after the GEM announcement[58]. Stock turnover is defined as the ratio of

[58] In unreported results, I also focus on changes from one quarter before to one quarter after the GEM announcement. This does not impact my conclusions.

stock trading volume to the total number of outstanding shares. As before, I run cross-sectional regressions where percentage change in turnover is regressed on the GEM dummy. My sample for this test consists of 134 firms (67 GEM and 67 matched firms) due to data unavailability on trading volume for some companies.

[Insert Table 3.10 about here.]

The results are presented in Table 3.10. I remove GEM/matched firms and their pairs where the change in turnover exceeds 300% to avoid outliers[59]. Columns (1) and (2) examine the full GEM sample, while Columns (3) and (4) focus on the 2020-2023 period, and Columns (5) and (6) on the 2019 period. Columns (1), (3) and (5) include only the GEM dummy as the main variable of interest, while Columns (2), (4) and (6) additionally include GEM year fixed effects and control variables. I use the same set of control variables as earlier, as they are strong predictors of both the number of investors and stock turnover. These variables capture fundamental aspects of a company's financial profile, market behaviour, and risk-return characteristics, all of which influence investor interest and trading activity (e.g., Do et al., 2023; Acheampong and Elshandidy, 2024). I cluster standard errors at the GEM-matched firm pair level.

According to Table 3.10, the coefficient for the GEM dummy is statistically insignificant across all columns, indicating no difference in stock turnover between GEM and matched firms. Therefore, the changes in stock turnover observed in Table 3.3 are not due to the GEM award. This finding supports Hypothesis 4.

These results indicate that the GEM did not increase demand from investors. This provides further evidence that the GEM does not offer additional insights into companies' environmental activities and also suggests that it is unlikely to deliver information processing benefits. Overall, this section provides direct evidence that the expected benefits of the Green Economy Mark, such as reducing information asymmetry and the associated boost in demand from green investors, have not materialized.

3.7. Conclusion

The World Federation of Exchanges (WFE) encourages individual stock exchanges to establish green equity designations, enabling investors to identify a universe of investible green economy equities.

[59] The results remain qualitatively the same without applying this filter.

As outlined by the WFE, these green designations are intended to reduce the information gap regarding firms' environmental activities and, therefore, attract large investors focused on sustainability. To assess if such green designations generate expected benefits, I look at the Green Economy Mark, the world's first certification scheme for green equity issuers. The GEM recognizes those LSE-listed companies deriving more than 50% of revenues from products and services contributing to environmental objectives.

I find a short-term market reaction to the GEM announcement, where stock prices spiked initially but soon reversed, resulting in no abnormal return overall. Further, my analysis suggests that the GEM label does not appear to provide any incremental information. Finally, I show that GEM does not create more demand from existing or new investors. This result provides further confirmation of GEM's inability to give new information but also suggests it may not be able to deliver information processing benefits. The initial stock market reaction may reflect a temporary sentiment shock, which disappeared as that market reassessed what the GEM really meant.

These findings imply that the current approach of the London Stock Exchange to green labelling is probably less impactful than expected. This supports the perspective that the GEM, being based on publicly available information and an existing database, represents a simple reclassification. Therefore, it has only a limited potential for new insights or improvements in the understandability of existing information. It underlines the need for the refinement of stock exchange criteria with respect to defining "green" equities. For example, the Nasdaq Green Equity Designation is granted to companies following a fee-based assessment by an independent reviewer, who uses a proprietary methodology to evaluate their green activities. This approach may prove more effective compared to the LSE's third-party-based methodology. This issue presents a promising avenue for further research.

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Tables

Table 3.1: Sample construction

This table illustrates the step-by-step process used for sample selection in the study.

	# of firms
All GEM firms/funds from 2019 to 2023	148
Exclude IPOs	122
Exclude closed-end funds	95
Exclude firms without an announcement date available	82
Exclude firms with an announcement date later than the LSE report date	79
Exclude firms without available daily prices	69

Table 3.2: Number of GEM firms

The table presents the number of GEM firms in the sample, classified by country, sector and year of GEM designation. The whole sample includes 69 firms.

Country		GEM year		Sector	
Australia	3	2019	49	Basic Materials	15
Ireland	4	2020	5	Consumer Cyclicals	5
UAE	1	2021	11	Consumer Non-Cyclicals	2
USA	3	2022	4	Energy	7
UK	58			Healthcare	2
				Industrials	21
				Technology	10
				Utilities	7

Table 3.3: Summary statistics

The table presents the overall summary statistics. Panel A provides statistics for the main variables, including the ESG dummy, Index dummy, changes in institutional, individual, and PRI investors, as well as changes in stock turnover. The change in stock turnover is capped at 300%, and the change in the number of investors is capped at 150%. The t-test column presents the t-statistics for testing whether the mean is equal to zero. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively. Panel B displays descriptive statistics for the control variables. The book-to-market ratio, leverage ratio and return on equity are winsorized to a maximum value of 150%. The inverse of the price is winsorized to a maximum value of 150. Additionally, return on equity is constrained to not fall below -150%. Tangibility and R&D ratios are capped at a maximum value of 100%. Definitions of the variables are provided in Appendix 3.A.

	Mean	St.dev.	p10	p25	p50	p75	p90	t-test
Panel A: Main variables								
Change in number of inst. investors (in %)	0.80	29.38	-28.57	-12.40	-3.40	10.72	25	0.22
Change in number of ind. investors (in %)	-2.13	35.60	-38.89	-14.29	-5.19	9.38	33.33	-0.50
Change in number of PRI signatories (in %)	-17.09	60.34	-100	-60	-14.58	15.38	57.14	-2.30**
Change in stock turnover (in %)	18.06	70.31	-59.06	-39.80	7.42	55.90	116.88	2.04**
Index dummy	0.88	0.32	0	1	1	1	1	
ESG dummy	0.36	0.48	0	0	0	1	1	
Panel B: Control variables								
Inverse	6.76	20.55	0.05	0.23	0.95	3.74	16.70	
Volatility	-3.49	0.53	-4.11	-3.88	-3.54	-3.19	-2.67	
Firm age	25.85	23.97	6.08	13.65	17.12	30.53	56.03	
Book-to-market ratio (in %)	52.71	47.49	9.46	21.77	38.82	71.47	150	
Leverage ratio (in %)	33.19	46.06	0	0.67	12.69	38.22	127.73	
Firm size (log market cap)	18.58	2.05	15.91	16.92	18.53	20.04	21.38	
R&D ratio (in %)	2.91	9.60	0	0	0	0.01	11.47	
Tangibility ratio (in %)	39.66	33.25	0	7.66	37.14	59.14	99.13	
ROE (in %)	-11.24	55.95	-85.68	-31.77	-0.38	14.35	45.32	

Table 3.4: Abnormal returns around the announcement of a Green Economy Mark

Panel A shows the average abnormal returns of GEM firms around the announcement of a Green Economy Mark. Column (1) presents the results for the full sample of GEM firms that received the mark between 2019 and 2023. Columns (2) and (3) display the results for different subsamples of firms. Column (2) focuses on firms that received the mark between 2020 and 2023, while Column (3) demonstrates the results for firms that received the mark on October 11, 2019. Abnormal returns are computed using the Fama-French-Momentum four-factor model. Parameters are estimated from day -150 to -8 relative to the announcement date. The FTSE All-Share Index is used as a proxy for the market portfolio. *, **, and *** indicate the significance of the Kolari test at the 10%, 5%, and 1% levels, respectively. †, ††, and ††† indicate the significance of the Corrado test at the 10%, 5%, and 1% levels, respectively. Bold text indicates the significance of the t-test. Panel B shows the summary statistics of abnormal returns on the day of the announcement (day 0). It reports maximum and minimum returns, as well as the percentage of firms with positive and negative abnormal returns.

	Full sample	2020-2023 firms	2019 firms
	(1)	(2)	(3)
Panel A: Average abnormal returns around the announcement of a Green Economy Mark			
Day	AAR	AAR	AAR
-6	0.51%	0.66%	0.45%
-5	0.40%	0.55%	0.34%
-4	0.05%	-0.93%	0.44%
-3	-0.16%	1.03%	-0.65%
-2	-0.37%	-0.33%	-0.39%**†
-1	0.17%	-0.06%	0.27%
0	**1.35%*****†	**2.20%**	**1.00%****
1	-0.58%*	-0.99%*†	-0.42%
2	0.19%	0.29%	0.14%
3	0.51%	0.59%	0.49%
4	-0.09%	-0.38%	0.03%
5	0.20%	0.07%	0.26%
6	-0.44%	**-1.68%****††	0.07%
Panel B: Statistics of abnormal returns at day 0			
% positive AR	57%	65%	53%
% negative AR	43%	35%	47%
Min AR	-7.36%	-3.47%	-7.36%
Max AR	21.69%	21.69%	12.33%
Number of firms	69	20	49

Table 3.5: Cumulative abnormal returns around the announcement of a GEM

The table reports cumulative average abnormal returns of GEM firms around the announcement of the Green Economy Mark over various windows. Column (1) presents the results for the full sample of GEM firms that received the mark between 2019 and 2023. Columns (2) and (3) display the results for different subsamples: Column (2) focuses on firms that received the mark between 2020 and 2023, while Column (3) shows the results for firms that received the mark on October 11, 2019. *, **, and *** denote the significance of the Kolari test at the 10%, 5%, and 1% levels.

	Full sample (1)	2020-2023 firms (2)	2019 firms (3)
CAAR(0,1)	0.77%**	1.21%	0.59%**
CAAR(0,2)	0.95%**	1.50%	0.73%**
CAAR(0,3)	1.47%**	2.09%	1.21%**
CAAR(0,4)	1.38%**	1.71%	1.24%**
CAAR(0,5)	1.58%**	1.78%	1.50%**
CAAR(0,6)	1.14%**	0.10%	1.57%**

Table 3.6: Cross-sectional regression of abnormal returns on FTSE 250 dummy

The dependent variable is the cumulative abnormal returns from day 0 to day 1 surrounding the Green Economy Mark announcement. Only firms that received the mark on October 11, 2019, are considered. The independent variable, FTSE 250 dummy, equals one for GEM firms included in the FTSE 250 index and zero otherwise. Standard errors, adjusted for heteroskedasticity, are reported in parentheses. ***, **, and * indicate that the parameter estimate is significantly different from zero at the 1%, 5%, and 10% levels, respectively.

	CAR(0,1) [2019 firms]
FTSE250 dummy	4.96***
	(0.90)
Constant	-0.02
	(0.52)
Observations	49
Adj R2	0.188

Table 3.7: Abnormal returns around GEM announcement, excluding FTSE 250 firms

The table shows the average abnormal returns of GEM firms around the announcement of the Green Economy Mark, excluding firms covered by the FTSE 250 index. Only firms that received the mark on October 11, 2019, are considered. Abnormal returns are computed using the Fama-French-Momentum four-factor model. Parameters are estimated from day -150 to -8 relative to the announcement date. The FTSE All-Share Index is used as a proxy for the market portfolio.

	2019 firms
Day	AAR
-6	0.47%
-5	0.38%
-4	0.57%
-3	-0.69%
-2	-0.17%
-1	0.23%
0	0.19%
1	-0.21%
2	-0.10%
3	0.44%
4	-0.02%
5	0.33%
6	-0.03%
Number of firms	43

Table 3.8: Cross-sectional regression of abnormal returns on ESG and Index dummy
The dependent variable is the cumulative abnormal returns from day 0 to day 1 surrounding the Green Economy Mark announcement. Panel A shows the results for the full sample of firms, Panel B for the 2019 subsample, and Panel C for the 2020–2023 subsample. Column (1) presents a univariate regression with the ESG dummy as the independent variable, while Column (2) adds firm size as a control variable. The ESG dummy equals one for GEM firms covered by the LSEG ESG database and zero otherwise. Column (3) presents a univariate regression with the Index dummy as the independent variable. The Index dummy equals one for GEM firms covered by any FTSE index and zero otherwise. Definitions of all variables are provided in Appendix 3.A. Standard errors, adjusted for heteroskedasticity, are reported in parentheses. ***, **, and * indicate that the parameter estimate is significantly different from zero at the 1%, 5%, and 10% levels, respectively.

	CAR(0,1) (1)	CAR(0,1) (2)	CAR(0,1) (3)
Panel A: Full sample			
ESG dummy	0.81	-0.55	
	(1.04)	(1.55)	
Index dummy			-0.61
			(2.66)
Firm size		0.46	
		(0.34)	
Constant	0.47	-7.68	1.31
	(0.73)	(6.09)	(2.62)
GEM Year FE	NO	YES	NO
Observations	69	69	69
Adj R2	-0.007	0.003	-0.013
Panel B: 2019 firms			
ESG dummy	3.27***	2.05	
	(0.98)	(1.55)	
Index dummy			0.02
			(2.28)
Firm size		0.37	
		(0.37)	
Constant	-0.55	-7.12	0.56
	(0.59)	(6.60)	(2.23)
GEM Year FE	NO	NO	NO
Observations	49	49	49
Adj R2	0.170	0.177	-0.021
Panel C: 2020-2023 firms			
ESG dummy	-4.96**	-5.12	
	(2.26)	(3.87)	
Firm size		0.15	
		(1.09)	
Constant	3.19	0.46	
	(2.05)	(18.85)	
GEM Year FE	NO	YES	
Observations	20	20	
Adj R2	0.119	0.023	

Table 3.9: Change in number of investors for GEM and matched firms
The dependent variable is the percentage change in the number of investors surrounding the Green Economy Mark announcement. Panel A reports the number of institutional investors, Panel B shows PRI signatories, and Panel C presents individual investors. The independent variable, GEM dummy, equals one for GEM firms and zero for matched firms. To construct the matched sample, each GEM firm is paired with a portfolio of similar firms based on sector, sales, and EBITDA margin. Within each portfolio, the firm with the closest size is selected as the control firm. I remove GEM/matched firms and their pairs where the change in investor base exceeds 150% to avoid outliers. Columns (1) and (2) show the results for the full sample of firms, Columns (3) and (4) for the 2020–2023 subsample, and Columns (5) and (6) for the 2019 subsample. Columns (1), (3), and (5) present univariate regressions, while Columns (2), (4), and (6) include GEM year fixed effects and control variables, as defined in Appendix 3.A. Standard errors, clustered at the GEM-matched firm pair level, are reported in parentheses. ***, **, and * indicate that the parameter estimate is significantly different from zero at the 1%, 5%, and 10% levels, respectively.

	Change in investors [Full sample] (1)	Change in investors [Full sample] (2)	Change in investors [20-23 firms] (3)	Change in investors [20-23 firms] (4)	Change in investors [2019 firms] (5)	Change in investors [2019 firms] (6)
Panel A: Institutional investors						
GEM dummy	5.83	5.71	6.71	6.32	5.52	4.62
	(4.06)	(3.72)	(8.99)	(8.61)	(4.57)	(4.66)
GEM Year FE	NO	YES	NO	YES	NO	NO
Control variables	NO	YES	NO	YES	NO	YES
Observations	130	130	34	34	96	96
Adj R2	0.003	0.274	-0.020	0.645	0.001	0.114
Panel B: PRI signatories						
GEM dummy	4.43	7.34	9.05	5.93	3.01	8.00
	(8.87)	(8.77)	(23.78)	(29.30)	(9.26)	(8.53)
GEM Year FE	NO	YES	NO	YES	NO	NO
Control variables	NO	YES	NO	YES	NO	YES
Observations	128	128	30	30	98	98
Adj R2	-0.006	0.289	-0.029	-0.092	-0.010	0.353
Panel C: Individual investors						
GEM dummy	-0.90	-4.06	2.05	-11.33	-1.81	-2.36
	(5.35)	(5.18)	(13.72)	(16.99)	(5.72)	(6.00)
GEM Year FE	NO	YES	NO	YES	NO	NO
Control variables	NO	YES	NO	YES	NO	YES
Observations	128	128	30	30	98	98
Adj R2	-0.008	0.226	-0.035	0.144	-0.010	0.169

Table 3.10: Change in stock turnover for GEM and matched firms

The dependent variable is the percentage change in average stock turnover surrounding the Green Economy Mark announcement. The independent variable, GEM dummy, equals one for GEM firms and zero for matched firms. To construct the matched sample, each GEM firm is paired with a portfolio of similar firms based on sector, sales, and EBITDA margin. Within each portfolio, the firm with the closest size is selected as the control firm. I remove GEM/matched firms and their pairs where the change in turnover exceeds 300% to avoid outliers. Columns (1) and (2) show the results for the full sample of firms, Columns (3) and (4) for the 2020–2023 subsample, and Columns (5) and (6) for the 2019 subsample. Columns (1), (3), and (5) present univariate regressions, while Columns (2), (4), and (6) include GEM year fixed effects and control variables, as defined in Appendix 3.A. Standard errors, clustered at the GEM-matched firm pair level, are reported in parentheses. ***, **, and * indicate that the parameter estimate is significantly different from zero at the 1%, 5%, and 10% levels, respectively.

	Change in turnover [Full sample] (1)	Change in turnover [Full sample] (2)	Change in turnover [20-23 firms] (3)	Change in turnover [20-23 firms] (4)	Change in turnover [2019 firms] (5)	Change in turnover [2019 firms] (6)
GEM dummy	1.55	4.53	-12.29	0.15	8.30	17.94
	(15.11)	(16.29)	(22.52)	(30.36)	(19.80)	(19.04)
Book-to-market ratio		0.01		-0.41**		0.39
		(0.20)		(0.18)		(0.24)
Leverage ratio		-0.12		0.30		-0.36***
		(0.17)		(0.25)		(0.12)
Firm size		2.04		2.11		6.38
		(4.25)		(7.11)		(4.61)
Volatility		-0.69		-40.30		6.55
		(15.23)		(24.62)		(17.02)
Inverse		0.17		0.24		0.81**
		(0.35)		(0.40)		(0.40)
R&D ratio		0.31		7.27		0.06
		(0.65)		(4.27)		(0.49)
Tangibility ratio		-0.14		-0.02		0.04
		(0.21)		(0.38)		(0.23)
ROE		-0.03		0.28		-0.05
		(0.19)		(0.33)		(0.23)
Firm age		0.32		0.02		0.30
		(0.22)		(0.55)		(0.25)
Constant	27.35**	-17.79	3.26	-167.94	39.10***	-87.60
	(10.33)	(81.88)	(16.79)	(145.09)	(12.80)	(97.74)
GEM Year FE	NO	YES	NO	YES	NO	NO
Observations	122	122	40	40	82	82
Adj R2	-0.008	-0.009	-0.018	0.174	-0.010	-0.001

Appendix

Appendix 3.A: Variables definitions
The table provides definitions and details on the construction of all variables used in this study.

Variable	**Description**
Change in number of inst. investors	Percentage change in the number of institutional investors from two quarters before to two quarters after the GEM announcement.
Change in number of ind. investors	Percentage change in the number of individual investors from two quarters before to two quarters after the GEM announcement.
Change in number of PRI investors	Percentage change in the number of PRI signatories from two quarters before to two quarters after the GEM announcement.
Change in stock turnover	Percentage change in average stock turnover in the two quarters before compared to the two quarters after the GEM announcement. Stock turnover is defined as the ratio of stock trading volume to the total number of outstanding shares.
ESG dummy	Dummy variable equal to 1 if a firm is covered by the LSEG ESG database (previously Refinitiv).
Index dummy	Dummy variable equal to 1 if a firm is covered by any FTSE index.
Inverse	Inverse of the mean daily stock price during the year preceding the GEM announcement.
Volatility	Logarithm of the standard deviation of daily returns during the year preceding the GEM announcement.
Firm age	Number of years since the firm was incorporated up to the year prior to the GEM announcement.
Book-to-market ratio	The ratio of a firm's book value of equity to its market value. Market value is measured one quarter prior to the GEM announcement, while the book value of equity is measured as of the year prior to the GEM announcement.
Leverage ratio	The ratio of a company's total book value of debt to its market capitalization. Market capitalization is measured one quarter prior to the GEM announcement, while the book value of debt is measured as of the year prior to the GEM announcement.
Firm size	The natural logarithm of a company's market capitalization, measured one quarter prior to the GEM announcement.
R&D ratio	The ratio of a company's R&D expenditures to its total assets, measured as of the year prior to the GEM announcement.
Tangibility ratio	The ratio of a company's tangible assets (Inventories + Total Property, Plant, and Equipment) to its total assets, measured as of the year prior to the GEM announcement.
ROE	A company's return on equity, measured for the year prior to the GEM announcement.