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SUSTAINABLE ALPHA IN SOVEREIGN AND CORPORATE BONDS

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We construct fixed income portfolios for sovereign bonds and corporate bonds with sustainable insights. The climate methodology for sovereign bonds can be applied as an overlay on any benchmark and tilts toward sovereigns more prepared with the climate transition and away from those which are less prepared. The tilts reduce sovereign carbon emissions in line with the Paris Agreement. For corporate bonds, we investigate three sustainable signals that predict excess returns: environmental, social, and governance (ESG) scores of corporations scored across various rating and sector buckets, firm carbon emission intensities, and corporate commitments that signal reduced carbon emissions.

1 Introduction

At $68.4 trillion of market capitalization of the Bloomberg Barclays Global Aggregate Index (Global Agg) as of December 2021 compared to $61.0 trillion of the MSCI World Index, fixed income is a critical channel for entities, especially governments and corporations, to raise capital. Yet, while there is now a large and growing literature on environmental, social, and governance (ESG) considerations in equities, there are relatively few studies studying sustainability and the effects of climate in fixed income returns.[1] In this paper, we show how investors can meet sustainable objectives *and* generate sustainable alpha in sovereign and corporate bonds.

We first show how to take into account environmental considerations in sovereign allocations, especially in adjusting sovereign portfolios to reduce carbon emissions. Our framework can be interpreted as tilts to E (the environmental

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component of ESG) for sovereigns better prepared for the climate transition. The tilts satisfy the requirements to be a Paris Aligned Benchmark (PAB), in line with the recommendations set by the European Union Technical Expert Group on Sustainable Finance (EU TEG, 2019) and the guidelines issued by the Institutional Investors Group on Climate Change (IIGCC, 2021). The sovereign climate tilts can be dialed up or down according to investors' risk preferences and overlaid on any sovereign benchmark.

As an example of the sovereign climate framework, we assume a sovereign benchmark that obtains long-run, diversified sovereign exposure. We compute the alphas implied by the benchmark weights and use those in an optimization imposing constraints that lower carbon emissions and uplift sovereign environmental (E) characteristics. Thus, we obtain a maximal risk–return portfolio with improved sovereign E criteria. The flexibility of incorporating any sovereign benchmark is important, given the large sovereign bond allocations by many investors and the flight-to-safety role of sovereign bonds during stress periods (see recently, for example, Jacobsen and Lee, 2020; Ren *et al.*, 2020). At the same time, the incorporation of E data, especially carbon emissions, into sovereign allocations recognizes the essential role that governments have in reducing global warming by setting frameworks and incentives to reduce carbon emissions.[2]

Second, we investigate how sustainable insights can create alpha in corporate bonds. There is much larger breadth in corporate bonds, with around 1,660 issuers in the US and Europe in the Global Agg as opposed to fewer than 10 sovereign reserve issuers. We take advantage of the large breadth in corporate bonds to identify alpha (see Grinold and Kahn, 2000) and formulate three ESG alpha signals. The first takes advantage of the large number and relatively longer history of ESG ratings on equities compared to fixed income (although commentators like Berg *et al.*, 2019, note they can differ widely across providers). Authors like Nagy *et al.* (2016) note that ESG flows can cause momentum in equities, and similar predictability with ESG ratings might occur for any corporate security exposure to ESG: we show that corporate ESG scores also predict bond returns.

The second signal is firm carbon emission intensities, which have been examined in the equities market by several authors (see, for example, Bolton and Kacperzyk, 2021; Aswani *et al.*, 2021; Kazdin *et al.*, 2021), but is less documented in the corporate bond market. Since there are large common components affecting all corporate bonds, especially macro factors, and default risk (see, for example, Ang and Piazzesi, 2003; Collin-Dufresne *et al.*, 2001; Pauksta *et al.*, 2022), our analysis of ESG alpha in corporate bonds examines the relationship of ESG with credit risk and the additivity of ESG signals to credit risk exposure.

The third ESG corporate bond signal examines forward-looking climate transition metrics: we combine several variables that capture how companies are adjusting to a lower carbon, more environmentally friendly world. Specifically, we create a composite signal of carbon transition scores, whether a firm which has issued green bonds (see below) or has signaled through Science-Based Targets initiative (SBTi) commitments that the firm is pro-actively reducing carbon emissions. We find that firm commitments are related to credit risk exposures in fixed income.[3]

In our analysis, we do *not* investigate green bonds or social bonds. These types of bonds are relatively recent but have grown rapidly in issuance and play an important role in financing projects to attain a lower carbon economy. Specifically, the proceeds of green bonds are allocated to finance

low-carbon or environmentally friendly projects, with $270 billion of green bonds issued in 2020.[4] The issuance of social bonds, which are issued to fund projects with positive social outcomes, especially those in line with the Social Development Goals of the United Nations, is much smaller. By definition, these types of bonds satisfy ESG requirements and, as Flammer (2020, 2021) notes, can play valuable roles: as sources of returns in their own right in portfolios, information that signals companies' intentions on ESG to the market, or in policy development. By focusing on the vast majority of outstanding capital in fixed income markets of regular sovereign and corporate bonds, our research is relevant for all fixed income investors' portfolios.

There is still a relatively small literature investigating ESG and climate influences on sovereign and corporate bonds. Cevik and Jalles (2020) find that climate change has impacted sovereign bond yields: climate change affects the resilience and vulnerability of economies and government budgets, in excess of traditional determinants of sovereign risk.[5] This makes it more urgent to show how to take into account sustainable information into sovereign bond allocations—especially as predictors of excess returns. An older literature has examined how country ratings or political risk is priced in markets, with early papers being Howell and Chaddick (1994) and Erb *et al.* (1996), but these studies concentrate mainly on equity markets. Our results are consistent with Martinelli and Vallee (2021) and Rahman *et al.* (2021) who show that taking into account ESG in sovereign bonds does not detract from returns, but our focus is on meeting the requirements of a Paris Aligned sovereign bond portfolio with climate-related sovereign metrics.

Some earlier work on relating sustainable insights into corporate bonds includes Bauer and Hann (2010) and Menz (2010). Both papers fail to find a significant relation between ESG and corporate bond returns, but Polbennikov *et al.* (2016), Ben Slimane *et al.* (2020), and Mendiratta *et al.* (2020) find a positive relation between them. These three papers focus on general ESG scores, whereas we also look at carbon emission data—both past emissions and forward-looking commitments—and returns, which makes our analysis more similar to Dai and Meyer-Brauns (2020) and Dai *et al.* (2021). Consistent with our findings, Gianfrate (2020) shows that distance-to-default, a widely used market-based measure of corporate default risk, is negatively associated with the amount of a firm's carbon emissions and carbon intensity. More recently Diep *et al.* (2021) investigate MSCI ESG scores and corporate bonds but find only weak predictive relations compared to our significant positive predictability of sustainable signals and excess corporate bond returns.

The rest of this paper is organized as follows. In Section 2, we describe an optimization framework to take into account ESG considerations in sovereign bonds, focusing on constructing climate-aware sovereign bond portfolios. In Section 3, we cover three ESG signals for corporate bonds—ESG corporate bond momentum, carbon risk captured by current and past emissions, and climate transition risk in the future as captured by several climate transition metrics. Section 4 concludes.

2 Sustainable Investing in Sovereign Bonds

Sovereign debt has been an important part of investor portfolios since the development of international sovereign debt markets in the 1820s (see Flandreau and Flores, 2009), but only recently have sovereign sustainable priorities become important considerations for investors. In this section, we focus on integrating climate (i.e., Environmental, or E) aspects of sovereigns in

an investment strategy. Governments have perhaps the most important role in reducing climate externalities (see, for example, Nordhaus, 2021). Providers of sovereign ESG scores also place a significant weight on E characteristics, such as those published by the World Bank (Gratcheva *et al.*, 2020).

While our framework is relevant for any sovereign bond portfolio, in our empirical work we specify a sovereign benchmark of equal-weighted 10-year bond futures in Australia, Canada, Germany, Japan, UK, and the US. These represent some of the most liquid and frequently traded developed market sovereign bonds.

2.1 Approach

Our approach is motivated by the urgency to limit global temperature warming to 1.5°C by the end of the 21st century, which was the aim of the Paris Agreement adopted by 186 countries in 2015. According to the most recent Sixth Assessment of the Intergovernmental Panel on Climate Change (IPCC, 2021), this goal requires significant and ongoing decreases in greenhouse gas (GHG) emissions to approach the same level of carbon emissions as 1850–1900 by 2050, which is the so-called net zero transition.[6] In order to help investors align their portfolios with these climate goals, the European Union has adopted a set of standards developed by the Technical Expert Group on Sustainable Finance (EU TEG, 2019). These were adopted into law by the EU in 2020.[7] In addition, we also follow the guidelines issued by the Institutional Investors Group on Climate Change (IIGCC, 2021), which were also formulated to help investors meet the Paris Agreement goals.

We take as given a well-diversified sovereign benchmark. Relative to that benchmark, we specify a series of tilts which overweight the countries best prepared for the transition and to tilt to those countries with lower carbon emissions. Conversely, we downweight countries with poor alignment to the Paris Agreement and countries with higher carbon emissions. This aligns with the recommendations outlined by the EU TEG and IIGCC, which specify to "tilt portfolios towards higher performing issuers... to the maximum extent possible, exceeding the average benchmark score."[8] The benchmark is defined by both the EU TEG and IIGCC as the Climate Change Performance Index (CCPI), which is published by Germanwatch.[9]

Since we specify tilts relative to an exogenously specified benchmark, our approach corresponds to setting a climate overlay. This has several advantages. First, the benchmark builds in the different motivations for investors to hold sovereign bonds, which include diversification to risky assets like equities (Campbell *et al.*, 2020), liquidity and safety (Brunnermeier, 2009), collateral requirements (Gorton and Laarits, 2018), to seek excess returns in sovereign bonds by harvesting style factor premia (Fama and Bliss, 1987; Campbell and Shiller, 1991; Ilmanen, 2011), the regulatory treatment of sovereign issues for insurance companies, pensions, and other institutions (BIS, 2017), and other reasons. The benchmark captures the primary reasons for holding a given sovereign bond portfolio and the climate overlay then adjusts those weights in line with those countries most aligned with the Paris Agreement. Second, our methodology can be applied on any sovereign portfolio. Finally, we can dial up or down the tilts of the climate overlay to trade off climate versus other investment considerations in the investor's sovereign bond allocation.

2.2 Sovereign environmental data

We use two datasets that measure a country's emission as well as climate profile: carbon dioxide (CO_2), and other GHG emissions as well as

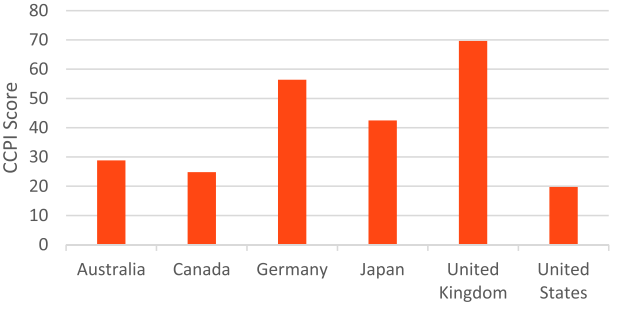
the Germanwatch Climate Change Performance Index (CCPI) for each country. GHG emissions other than CO_2 include methane, nitrous oxide, hydrofluorocarbons, and other fluorinated gases (perfluorocarbons and sulfur hexafluoride).[10] The CO_2 data contains emissions related to fossil fuel use and industrial processes such as cement production. Our data on CO_2 and GHG emissions are obtained from MSCI and are stated in emissions per capita per year in terms of tons per capita. We have CO_2 and GHG emissions at the country level from 2019.

The Germanwatch CCPI incorporates forward-looking metrics and policy assessment relevant for a county's alignment with the Paris Agreement. The dataset covers 57 countries and the EU; these countries account for more than 90% of global GHG emitters and data is available since 2005. The CCPI assesses each country's performance in four categories: GHG Emissions (40% of the overall ranking), Renewable Energy (20%), Energy Use (20%), and Climate Policy (20%).[11] We take CCPI data from 2017 since the underlying methodology of the CCPI has been revised and adapted to the new climate policy landscape of the Paris Agreement since that date.[12]

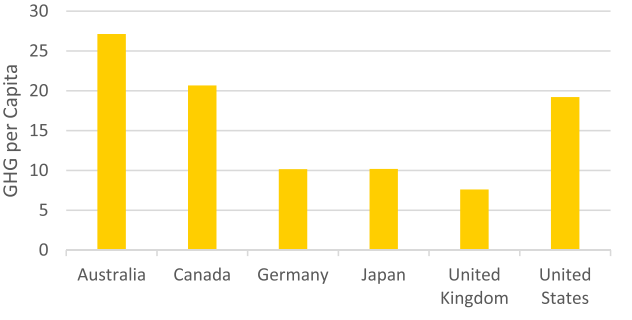
Exhibit 1 shows the latest GHG and CO_2 emissions per capita, as well as CCPI profiles for the countries in our investment universe consisting of Australia, Canada, Germany, Japan, UK, and the US as of last updated in January 2021. The emissions data is reported as April 2019. Since CO_2 is the major component of GHG emissions, both CO_2 and GHG are highly correlated, at around 95% across the developed markets countries in the cross-section. Australia has the highest emission intensity of both CO_2 and GHG, at 17.27 and 27.12 tons per capita, respectively, followed by Canada and the US, while the UK has the lowest within the group, at 5.45 and 7.61 tons per capita, respectively. Looking at the CCPI scores at 2021, the UK is ranked the highest by CCPI (with a score of 69.7) in our universe, followed by Germany and Japan. US is the worst with a score of 19.7.

Exhibit 1 Summary statistics of carbon emissions and CCPI at 2021.

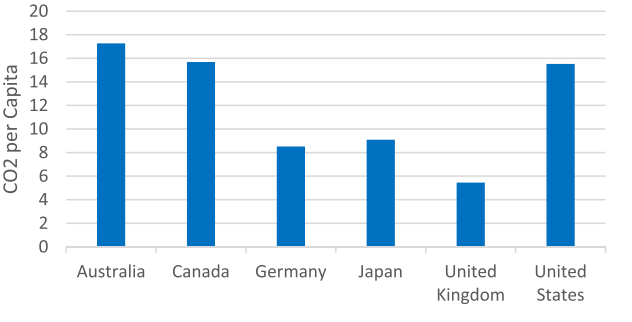
Panel A: Climate change performance index score by country



Panel B: GHG emissions per capita by country



Panel C: CO_2 emissions per capita by country



Data last updated as of January 2021. CCPI metric updates once a year and is sourced from https://ccpi.org/download/the-climate-change-performance-index-2021/. GHG emissions and CO_2 emissions are both represented in tons per capita and measures emissions per capita per year in a country.

2.3 Optimization

We denote the sovereign weights of the benchmark index as h_{bmk}. We first infer implied alphas, $\alpha_{implied}$, from the benchmark weights. We assume a mean–variance representative agent, so we can write, following Black and Litterman (1991) and others:

$$\alpha_{implied} \propto V h_{bmk}, \tag{1}$$

where V is the covariance matrix of the benchmark sovereign returns.

To incorporate our E targets, we specify a new optimization taking the implied alphas from the benchmark and additional constraints to upweight the CCPI rating and reduce carbon emissions:

$$\max_h \alpha_{implied}^\top h - \lambda h^\top V h, \tag{3}$$

such that

$$\begin{aligned} A_{ccpi} h &\geq 1.10 \times A_{ccpi} h_{bmk} \\ A_{GHG} h &\leq 0.86 \times A_{GHG} h_{bmk} \\ A_{CO2} h &\leq 0.86 \times A_{CO2} h_{bmk} \end{aligned} \tag{4}$$

where h are the holdings of the E-optimized portfolio such that $h - h_{bmk}$ reflects the active Environmental tilts relative to the sovereign benchmark.

The climate constraints in Equation (4) can be interpreted as follows. First, we target an increase of 10% or more in the CCPI score. Second, we specify a reduction of 14% or more reduction in GHG and CO_2 emissions intensity relative to the benchmark. These increases in the CCPI score and decreases in GHG and CO_2 emissions can be changed for different investors placing more or less importance in the E considerations. We calibrate the risk aversion coefficient, λ, such that without additional constraints (i.e., using only Equation (3)), $h = h_{bmk}$.

In addition, we further specify other investment constraints:

$$\begin{aligned} \sum h &= \sum h_{bmk} \\ h &\geq 0.05 \times h_{bmk} \\ Duration \cdot h_{bmk} - 0.5 &\leq Duration \cdot h \\ &\leq Duration \cdot h_{bmk} + 0.5 \end{aligned} \tag{5}$$

The first constraint is that the active weights, $h - h_{bmk}$, sum to zero, which reflects the active tilts relative to the benchmark. The second constraint places a lower bound of 5% below benchmark weights. This also ensures that we take no leveraged sovereign weights relative to the benchmark. Finally, we specify the duration exposure to be similar to the current sovereign benchmark at within ±0.5 years of deviation from benchmark duration. The duration of the equal-weighted sovereign benchmark is around 7.5 years.

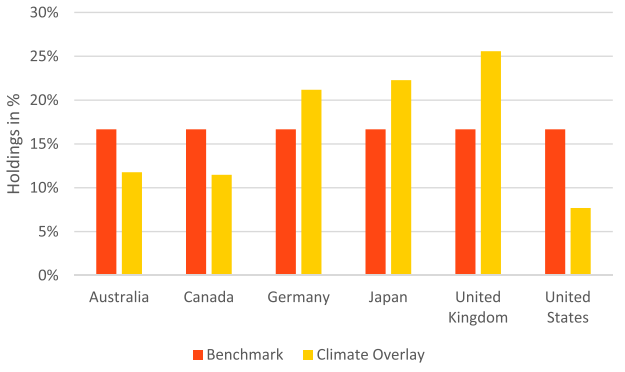
2.4 Empirical climate tilts

We apply the methodology to a sovereign benchmark of equal-weighted 10-year bond futures in Australia, Canada, Germany, Japan, UK, and the US.

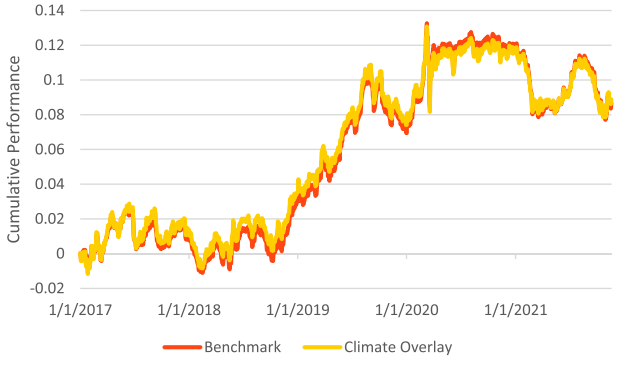
Exhibit 2 presents the results of the optimization in Equations (3)–(5) in this universe. Panel A reports the holdings of the E-optimized portfolio in blue relative to the equal-weighted benchmark in green (each with a weight of 16.7%) as of November 2021. The climate optimization downweights the US, at 7.7%, because the CCPI score of the US is significantly low at 19.7 relative to the CCPI of the portfolio of 40.3 (see Exhibit 1). Conversely, the weight of the UK is 25.6%: the large overweight is due to the high CCPI of the UK at 69.7, and that the GHG and CO_2 emissions of the UK are low relative to the portfolio. Australia and Canada have high carbon emission intensities, at

Exhibit 2 Developed markets original benchmark versus portfolio with climate overlay.

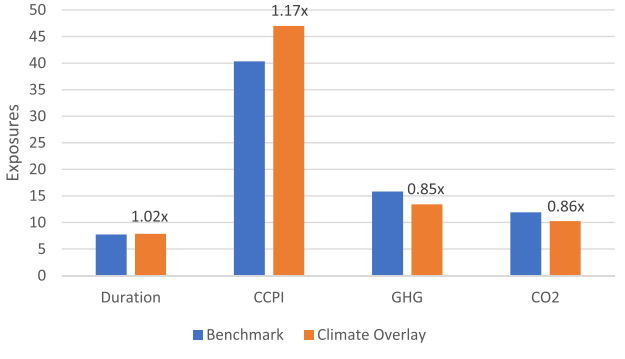
Panel A: Holdings at November 2021



Panel B: Cumulative returns



Panel C: Climate exposures versus benchmark as of November 2021



17.3 for Australia and 15.7 for Canada for GHG per capita, compared to 11.9 for the benchmark portfolio. This explains the underweight positions to Australia and Canada, and the optimizer consequently overweights the UK, Germany, and Japan.

In Panel B of Exhibit 2, we report cumulative returns of the climate overlay. The optimization is run at the daily frequency. The CCPI climate ratings are updated annually in December and we use the same ratings information for the following year. MSCI GHG and CO_2 emissions per capita are available at the monthly frequency, and we forward-fill the data over the next month. We show both the raw cumulative returns of the sovereign portfolio and the optimized portfolio with climate tilts and cumulative active returns, which are the returns of the optimized portfolio minus the sovereign benchmark. The raw returns of the benchmark and climate portfolio are very close. Over the sample from 2017 to 2021, the Sharpe ratio of the portfolio with the climate overlay is 0.56 and the climate overlay itself has an information ratio (IR) of 0.07. At the beginning of the sample, there is some outperformance, whereas from November 2018 to April 2020 the excess returns detract. Nevertheless, there is a close correspondence. We do not expect the climate overlay to itself have alpha—we explore explicit sustainable alpha signals in the next section; rather Panel B shows that the climate portfolio tracks the sovereign benchmark closely.

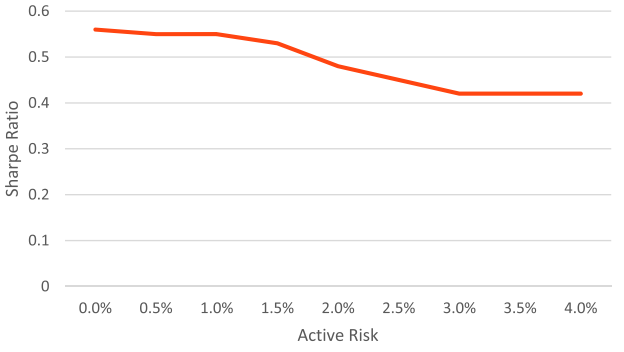
In Exhibit 2, Panel C, we show statistics of the benchmark portfolio versus the climate-optimized portfolio at November 2021. The minimum increase in the CCPI score specified in the optimization is 10% (see Equation (4)), but we are able to raise the CCPI score from 40.3 to 47.0, by 17%. The GHG and CO_2 intensities are decreased by 15% and 14%, respectively. At this date, the duration constraint is not binding; the durations of the sovereign benchmark and the climate portfolio are 7.73 and 7.87 years, respectively.

2.5 *Climate and performance trade-offs*

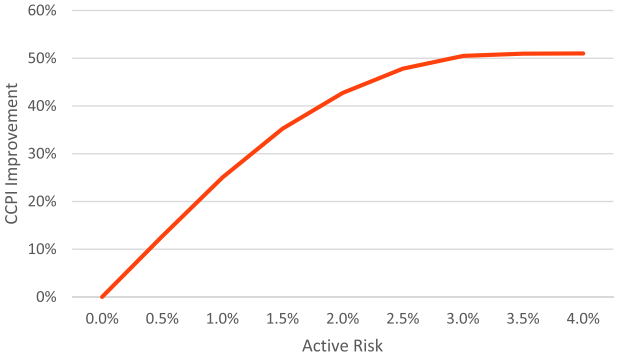
To investigate the relation between active risk and the sovereign portfolio's carbon/climate profile, we perform the following exercise. We investigate an optimization problem where we seek to maximize the portfolio's CCPI score subject to a certain active risk limit. We also impose the constraint that the portfolio has duration of ± 0.5 years relative to the benchmark (see Equation (5)). We do not constrain CO_2 or GHG outcomes, unlike our previous exercise; rather, the purpose is to tabulate these and other climate outcomes as we change active risk. This exercise allows us to plot a trade-off between active risk and climate outcomes.

Exhibit 3 Active risk and climate outcomes.

Panel A: Sharpe ratio versus active risk trade-off



Panel B: CCPI score improvement versus active risk trade-off



Panel C: GHG per capita reduction versus active risk trade-off

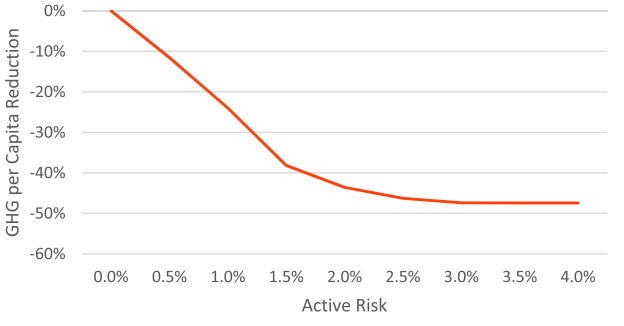


Exhibit 3 (*Continued*)

Panel D: CO_2 per capita reduction versus active risk trade-off

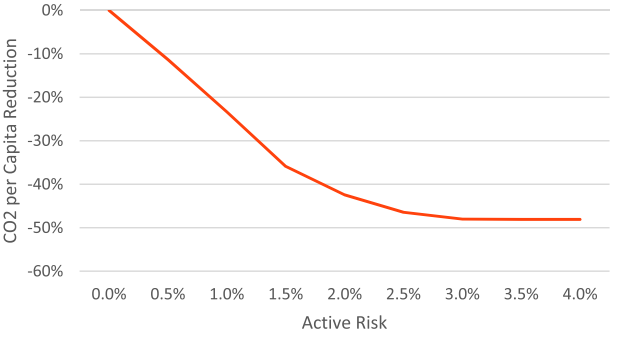


Exhibit 3 shows how taking additional active risk can give improve performance and climate characteristics. As we allow deviations from the benchmark up to 1% active risk, the decrease in the Sharpe ratio is negligible. Upwards of 1% active risk, the IR decreases; at 2% and 3% active risk, the IRs are 0.48 and 0.42, respectively. Also, in Exhibit 3, we graph the changes in GHG and CO_2 intensities as ratios, where the benchmark corresponds to one. There are significant decreases in GHG and CO_2 up to 1% active risk: the GHG intensity is 15.82 tons per capita for the benchmark, which decreases by 24% to 12.02 tons per capita at 1% active risk. After 1% active risk, there are still reductions in GHG and CO_2, but the derivative is smaller. Going from 1% to 2% active risk, for example, the rate of decrease in GHG is 19% compared to 24% from zero to 1% active risk. Thus, for active risk up to 1%, there is negligible reduction in the Sharpe

ratio while we can obtain large improvements in climate outcomes.

3 Sustainable Alpha in Corporate Bonds

We turn our attention to investigating ESG alpha signals in corporate bonds. The corporate bond universe gives much broader coverage than the small number of sovereign issuers, and thus there is greater statistical power for testing alpha signals. In addition, the increased breadth of the corporate universe translates into IRs for portfolios, as proved by Grinold and Kahn (2000). We describe three ESG signals that have predictive power for future corporate bond returns: corporate ESG scores, company carbon emission intensities, and corporate commitments of carbon emissions. These signals have been previously documented in the equities literature, but our focus is on US Investment Grade (IG) and US High Yield (HY) corporate bond portfolios.[13]

3.1 Data and portfolio construction

The US Investment Grade and US High Yield universes are sourced from the Bloomberg Barclays indexes. The ESG score, Low Carbon Transition, and Clean Technology revenue data are from MSCI. The carbon emission data as well as carbon commitments from the Science-Based Target Initiative (SBTi) are obtained from the Carbon Disclosure Project (CDP).

To evaluate the fixed income ESG insights, we focus on spread returns which we define as corporate bond total returns minus the return of duration-matched rates. We evaluate the signals with a long-only portfolio optimization that we benchmark against the Bloomberg Barclays US IG and US HY indexes and rebalance monthly. We standardize all signals across the broad credit rating buckets: 6A (AAA, A, AA) and BBB in IG and BB, B and CCC rating in HY and sector buckets (Financials, Industrials, and Utilities).

We create optimized portfolios with the alphas being the ESG insights, while constraining the portfolio's duration times spread (DTS) to ± 50 DTS and sector DTS by ± 100 DTS relative to the benchmarks.[14] We also constrain the maximum issuer-level active overweights to 20 DTS. We use a multifactor risk model which has sector and rating risk factors, and supplement specific risk estimates from backward-looking data with forward-looking fundamental characteristics.

One major caveat to our exercise is that we do not take into account transactions' costs. Our motivation for doing this is that these are the purest expression of individual insights. However, many studies, like Edwards *et al.* (2007), have shown that corporate bond transactions costs are significantly larger than similarly sized equity market trades—and in fact, Biais and Green (2019) show that although corporate bond trading costs have declined particularly for small investors, they are still higher than they were during the 1940s. Trading costs can be especially high during liquidity crises (O'Hara and Zhou, 2021). Nevertheless, trading costs can be significantly lower for institutions with better market access (see recently, among many others, Dick-Nielsen and Rossi, 2019; Goldstein and Hotchkiss, 2020). This means that, unless an institution has market access or access to trading technology that significantly lowers transactions costs, our sustainable insights are unlikely to be profitable as standalone alpha credit strategies. They may, however, be suitable for inclusion in a portfolio with other alpha signals, especially in a strategy that employs transaction cost intimidation at the overall portfolio level.[15]

We specify the optimization problem as follows:

$$\max_{h} \alpha^{\top} h - \lambda h^{\top} \Sigma h, \tag{6}$$

where h are bond holdings, α are the ESG fixed income alpha signals, λ is the risk aversion

parameter, and Σ is the covariance matrix. We impose the following constraints:

$$\sum_i h_i = 1$$

$$h_i \geq 0 \quad \textit{for all } i$$

$$\sum_i w_i Sector\ DTS_i \text{ in target DTS range}$$

$$\sum_i w_i DTS_i \text{ in target DTS range} \tag{7}$$

In words, we work with a long-only portfolio, and the portfolio and sector DTS are within the prescribed ranges relative to the benchmark.

3.2 ESG ratings and corporate bond returns

Our first sustainable alpha signal is the ESG score of a company. We use the MSCI Industry Adjusted ESG Scores, which are the most widely used ESG scores in the industry. These scores range from 1 to 10. In our bond universe, there is an average coverage of 97.4% and 81.7% over January 2016 to September 2021 for IG and HY, respectively. In the case of missing ESG scores, we do not take any active positions and take benchmark issuer weights. We cross-sectionally standardize the ESG scores across credit rating and sector buckets. These adjusted scores are then treated as the alpha inputs into the optimization problem of Equations (6) and (7).

Allocating to higher ESG names does lead to positive performance, and this is particularly true in the last two years. Panel A of Exhibit 4 graphs the performance of IG and HY with ESG ratings predictors relative to the benchmarks. We clearly see the drawdown in the first quarter of 2020 from COVID, where IG and HY drew down by 12.8% and 14.3%, respectively. The performance of ESG in fixed income is particularly strong from that time. Below, we show that this period coincides with strong flows to ESG names. It is unlikely due to the liquidity provided by the Federal Reserve (see, for example, O'Hara and Zhou, 2021) as it has persisted from that time to now. Interestingly, the outperformance of the ESG score is greater in IG than in HY. As shown in Panel B of Exhibit 4, the ESG ratings strategy has an IR of 1.38 in IG and 0.70 in HY with average annual returns of 71.9 bps and 52.9 bps, respectively. This could be from ESG considerations being less important in HY names. It cannot come from the changes in the ESG scores per se as there is, on average, larger improvement in ESG scores for HY compared to IG. Specifically, the ESG scores improve from 4.9 in the benchmark to 7.6 for HY and from 3.5 in the benchmark to 5.1 for IG.

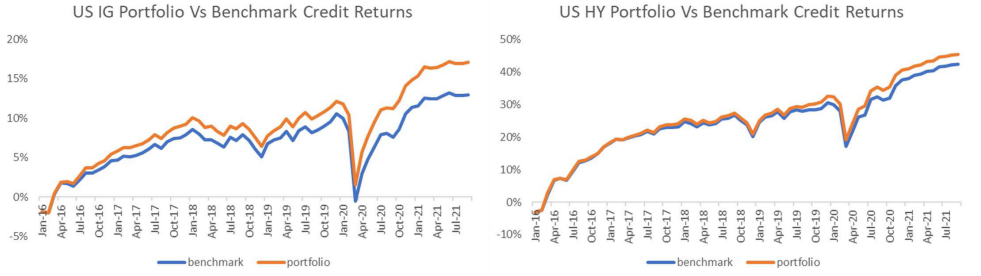
3.2.1 Relation to bond characteristics

Why are ESG scores related to bond performance? The significant positive exposure of equities with high ESG ratings to the quality factor in equities has been documented by several authors, including Melas *et al.* (2016), Kulkarni *et al.* (2017), and Chan *et al.* (2020).[16] In fixed income, ESG scores are also related to measures of fixed income quality. Panel C of Exhibit 4 shows that corporate bond option-adjusted spreads (OAS) and the ESG rating of the issuer are negatively correlated. Across both the US IG and HY universes, the correlation between OAS and ESG scores is −19% and −23% respectively. Additionally, BBB bonds have 10% lower and CCC bonds have 20% lower ESG scores than the rest of the IG and HY universes. The quality factor has been a rewarded style factor in equities for decades (see originally Sloan, 1996), and we observe the same pattern in fixed income.

According to equilibrium models with ESG and non-ESG investors, like Berk and van Binsbergen (2021), Pastor *et al.* (2021), and Pedersen *et al.* (2021), the larger the demand for ESG,

Exhibit 4 US IG and HY ESG score strategies.

Panel A: Cumulated returns of US IG and HY ESG score strategies



Panel B: Performance statistics of US IG and HY ESG score strategies

Long Only Portfolio Performance from Jan 2016–Sept 2021

Universe	Annual Active Ret (Bps)	Annual Active Vol (Bps)	IR	2016 (Bps)	2017 (Bps)	2018 (Bps)	2019 (Bps)	2020 (Bps)	2021 (Bps)	Benchmark ESG Score	Portfolio ESG Score
US IG	71.89	52.24	1.38	80.21	55.89	−6.40	22.66	200.43	60.58	3.49	5.11
US HY	52.90	75.07	0.70	5.63	86.05	−12.40	121.85	89.35	13.68	4.91	7.62

Panel C: Percentage Correlations of ESG score and credit attributes

	US IG			US HY		
	esg_score	oas	Probability of Default	esg_score	oas	Probability of Default
esg_score		−22.62	−10.90		−13.89	−13.61
oas	−27.91		70.60	−15.10		82.50
Probability of Default	−13.38	62.78		−14.49	78.02	

*Correlations (Spearman in bottom/Pearson on top)

the greater the flows to ESG companies and the larger the assets in ESG strategies. This increased demand for ESG corresponds in the long-run to lower expected returns for ESG companies. This suggests that the high returns to corporate bonds whose issuers have high ESG scores may benefit from lower costs of capital and greater safety. The lower OAS and probabilities of default in Panel C of Exhibit 4, are consistent with this economic story.

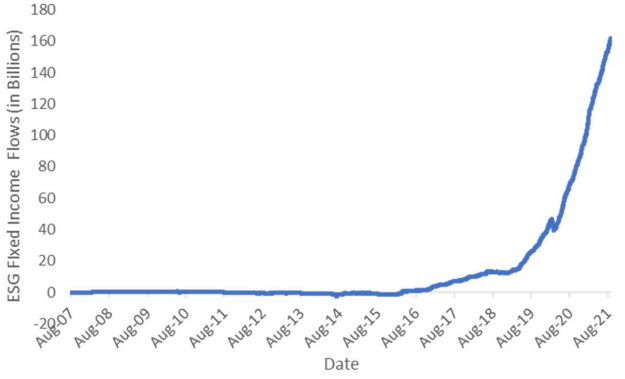
Avramov *et al.* (2021) develop a dynamic pricing model for ESG flows. Whereas in the long run there may be a negative relation between ESG scores and expected returns, Avramov *et al.* (2021) show that in the short run, there may be positive gains to ESG stocks as those ESG stocks migrate to higher prices induced by increased demand. There certainly have been significant recent flows into ESG fixed income ETFs and mutual funds. Panel A of Exhibit 5 plots the global flows into fixed income ETFs and mutual funds computed with the Emerging Portfolio Fund Research (EPFR) dataset over August 2007 to September 2021. There is some early increase in flows in 2018 to 2019, but flows accelerated in 2020 to 2021. We expect flows to continue to accelerate over the next few years

as more regulations come into effect, such as the Sustainable Finance Disclosure Regulation (SFDR) in Europe, and investors also increase demand.

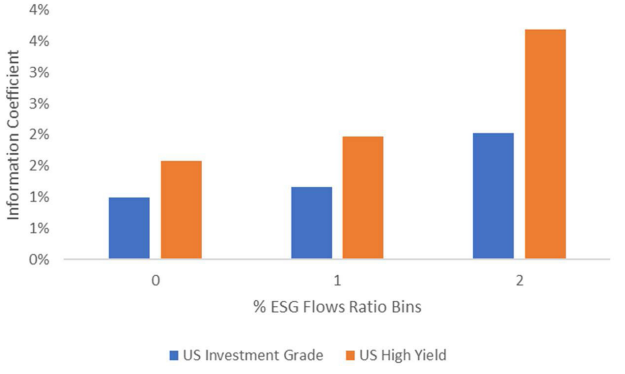
Finally, in Panel B of Exhibit 5, we investigate the information coefficients (ICs) of the ESG issuer signal in different bins sorted by ESG flow ratios. We define the ESG flow as the ratio of ESG fixed income flows to total fixed income flows in a month. Panel B shows that when there is a high proportion of ESG flows, the ESG score has a higher IC. This is true for both US investment grade and high yield asset classes. These patterns are consistent with the outperformance of ESG scores in fixed income being related to flow-related information.

Exhibit 5 ESG flows in fixed income.

Panel A: Global flows in ESG fixed income ETFs and mutual funds (in billions)



Panel B: Signal information coefficients and ESG flow ratios



3.3 *Carbon emission intensity in corporate bonds*

We now turn to looking at carbon emission intensities as a predictor of corporate bond returns. We use Carbon Disclosure Project (CDP) data for Scope 1 and Scope 2 carbon emissions and define carbon emission intensity as Scope 1 plus Scope 2 emissions divided by enterprise value. The denominator follows the recommended practice for defining carbon emission intensity for Paris Aligned strategies (see the EU TEG and IIGCC). Similar to the ESG score signal, we cross-sectionally standardize the signals and create optimized portfolios following Equation (6) with the constraints (7) allowing us to track the risk characteristics of the Bloomberg–Barclays indexes.

3.3.1 *Credit spreads and carbon emission intensities*

To examine how credit spreads of corporate bonds are related to carbon emissions and other bond characteristics, we set up a cross-sectional regression with the bonds' credit spreads as the dependent variable. On the right-hand side of the regression, we place carbon emission intensity and probability of default, which is interpreted as a measure of credit risk in corporate bonds by Kang *et al.* (2018) and Pauksta *et al.* (2022). The probability of default is computed using a Merton (1974) model following Correia *et al.* (2012, 2018).

Panel A of Exhibit 6 reports the results over the period January 2013 to September 2021. Carbon intensity has a positive relationship with credit spreads, as evidenced by the positive coefficients and enormous t-statistics, which are 33.8 and

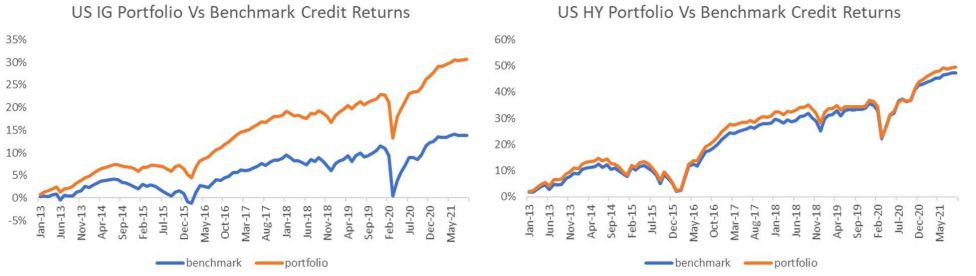
Exhibit 6 Carbon emission intensity.

Panel A: Credit spreads, carbon emission intensity and credit attributes

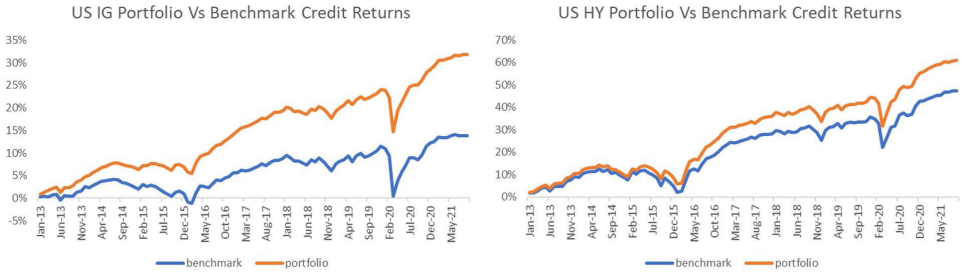
Regression Statistics

	US IG			US HY		
Intercept	6.33	5.17	6.48	7.61	6.67	7.81
Probability of default	0.26		0.26	0.40		0.38
t-stat	159.63		157.35	263.64		236.00
Carbon intensity		0.03	0.01		0.07	0.02
t-stat		33.83	19.68		55.85	28.75
# Of Observations	60,764	60,764	60,764	44,703	44,703	44,703
R Sq	28.80%	5.80%	30.20%	60.90%	7.40%	62.20%

Panel B: Returns of US IG and HY Carbon Intensity Strategies



Panel C: Returns of US IG and HY carbon intensity strategies, taking into account probability of default



Panel D: Performance statistics of US HY and IG carbon intensity strategies

Long Only Portfolio Performance from Jan 2013–Sept 2021

Universe	Factors	Annual Active Ret (Bps)	Annual Active Vol (Bps)	IR	Max Drawdown	Mean Drawdown	Turnover (%)
US IG	prob of def	191.76	90.38	2.12	−58.29	−5.44	338.99
US IG	carbon int.	158.97	99.87	1.59	−188.06	−20.01	217.55
US IG	prof of def + carbon int.	204.98	88.11	2.33	−28.42	−3.21	337.56
US HY	prob of def	154.81	96.18	1.61	−108.07	−22.21	231.7
US HY	carbon int.	23.29	123.09	0.19	−430.99	−120.72	147.63
US HY	prof of def + carbon int.	162.13	92.05	1.76	−83.61	−15.23	221.65

55.9 for the US Investment Grade and US High Yield universes, respectively. The probability of default, being a direct measure of credit risk, is very closely linked with credit spreads and we explore if carbon emission intensity can be additive in explaining credit spreads on top of the Merton-based measure. When carbon intensity is added as an additional regressor to the regression with probability of default, it still maintains the positive relationship and increases the overall *R*-squared across both IG from 28.8% to 30.2% and HY from 60.9% to 62.2%.

3.3.2 Carbon emission intensities and returns

Panel B of Exhibit 6 shows cumulated returns of the optimized portfolios with spread adjusted by carbon emission intensity as a predictor compared to IG and HY benchmarks. The outperformance of the carbon intensity signals is significantly larger compared to the ESG scores (see Exhibit 4). There also has been more consistency in the outperformance, whereas the ESG score outperformance is concentrated in the last two years. Over the sample from January 2013 to September 2021, the cumulative outperformance for the optimized carbon intensity portfolios is 159 bps for IG and 24 bps for HY. However, on its own, carbon intensity is not a replacement for credit risk, as is evidenced in the relatively lower performance in high yield, where credit risk dominates.

In Panels C and D of Exhibit 6, we examine the performance of carbon emission intensity controlling for credit risk. We examine the spreads adjusted for only credit risk and carbon intensity risk separately, and together as joint predictors. Panel C shows the cumulated returns of the combined risk factors. Drilling deeper into sector performance (not reported in Exhibit 6), we find the biggest impact comes from the Energy and Basics sectors. These are sectors that are extremely important in the climate transition because they are essential to society and yet have some of the largest emissions, and there are relatively large spreads between the companies with the largest and smallest lower carbon emission intensities. There is also better performance in distressed years, lower drawdowns, and turnover. For example, during the COVID drawdown in March 2020, the carbon intensity portfolios experienced a drawdown of −9.4% for IG and −10.5% for HY compared to −11.1% for the IG benchmark and −13.4% for the HY benchmark.

Panel D of Exhibit 6 shows the performance statistics corresponding to Panel C of the optimized portfolios which use carbon intensity as well as credit risk. Accounting for credit risk it leads to better risk adjusted returns for carbon intensity, improving the IR to 2.3 in IG and 1.76 in HY. The additional return is around 10 bps for both universes, alongside a reduction in volatility.

3.4 Corporate commitments and bond returns

ESG scores and carbon emission tend to be backward-looking metrics, and we now turn to a forward-looking view of corporate target settings. These help gauge a company's ambition on becoming more aligned to the climate transition by specifically outlining the firm's plans to reduce carbon emissions.

3.4.1 Data

We take a range of corporate commitments from different data providers including the Science-Based Target initiative (SBTi) and MSCI. When evaluating companies that are being proactive in adapting to a lower carbon economy, we look at four metrics: corporate green bond issuance, carbon emission reduction commitment via SBTi, MSCI low carbon transition (LCT) scores, and

the percentage revenue from Clean Technology at the issuer level. We aggregate the four variables by normalizing them and then equally weighting them to calculate the average. We refer to the combined score as "corporate commitments."

We construct the green bond issuance as the proportion of green debt to total debt for each issuer. We note that green issuers are generally higher market cap and higher rated companies. We define companies who have made carbon commitments as those who have signed up to reduce their carbon emissions by 2°C or lower by 2050. We obtain this data from SBTi and assign these companies a score of one and the rest zero. The MSCI LCT score calculates a company's climate transition risk by aggregating Scope 1, 2, and 3 emissions, emissions avoided, and the quality of the company's climate management into a score between 0 (highest risk) and 10 (lowest risk). Finally, the percentage revenue from Clean Technology is defined as percentage revenue derived from products and services related to energy efficiency, pollution prevention, green building, alternative energy, and sustainable water.

Using all four of these variables improves coverage than using only one, minimizes green washing, and adds robustness to the signal construction. Since IG companies are larger and more focused on climate transition, it is not surprising that there is better coverage in IG than HY companies. Approximately 20% of issuers have issued green debt in IG, but only 2% of issuers in the HY space have done so. Clean technology revenue is available for about 15% of both benchmarks. On average, 12% (8%) of IG (HY) companies have signed up for corporate commitments through SBTi. Finally, LCT scores cover 97% of the IG benchmark and 82% of the HY benchmark. Once all four signals are combined, the resulting signal has close to 98% coverage of the IG benchmark and 82% coverage of the HY benchmark. For issuers where there is no coverage, we take no active positions and match the benchmark positioning.

3.4.2 Characterizing corporate commitment data

We first show that corporate commitments predict future carbon emissions. We run a regression setting carbon emissions over the next 12 months as the dependent variable, and on the right-hand side we place the different commitment predictors. We also include controls for the current level of carbon emissions and firm size which is proxied by sales. We acknowledge that emission data is still patchy, and the length of the sample is short (see Busch *et al.*, 2020), so the results of these regressions should be interpreted with care.

Panel A of Exhibit 7 presents the results. After controlling for size of the company and current carbon emissions, all metrics are predictive of reduction in carbon emissions, as evidenced with negative coefficients and significant t-statistics. SBTi commitments and LCT scores have the highest t-statistics at -17.6 and -15.4 respectively. We combine all four metrics equally to create a more robust representation of how prepared a company is for a low carbon economy.

In Exhibit 7, Panel B, we explore the relation between corporate commitments and firm productivity variables: return on equity (ROE), return on assets (ROA), and profitability (Cashflow/Total Assets). We run a regression setting with profitability metrics over the next 12 months as the dependent variable, and corporate commitments on the right-hand side, while including controls for the current profitability levels. For all three profitability variables, corporate commitments have a positive coefficient, along with significant t-statistics. Thus, corporate commitments are

Exhibit 7 Characterizing corporate commitments.

Panel A: Predicting future carbon emissions 12 months ahead (Jan 2015–Sep 2021)

Regression Statistics

	US IG				
Intercept	−3.75	0.71	4.41	2.94	0.62
Carbon emissions	0.92	0.87	1.08	0.83	0.86
t-stat	27.26	179.76	38.77	67.11	176.74
Sales	−0.07	−0.06	−0.33	−0.07	−0.05
t-stat	−7.70	−7.33	−6.98	−3.98	−6.49
pct green debt	−2.79				
t-stat	−2.20				
SBTi		−0.34			
t-stat		−17.58			
pct clean tech			−0.11		
t-stat			−3.36		
Low carbon transition score				−0.28	
t-stat				−15.35	
Corporate commitments					−0.16
t-stat					−20.71
# Of Observations	1,195	30,874	1,420	7,358	30,874
R Sq	53.60%	55.10%	56.80%	64.50%	55.30%

Panel B: Predicting Firm Productivity 12 months Ahead (Jan 2015–Sep 2021)

Regression Statistics

	US IG		
Dependent Variable	roa_12m	roe_12m	Profitibility_12m
Intercept	0.55	1.25	0.49
roa	0.87		
t-stat	474.21		
Roe		0.92	
t-stat		556.84	
Profitibility			0.85
t-stat			481.85
Corporate_commitments	0.13	0.31	0.01
t-stat	12.42	9.72	4.34
# Of Observations	89,023	88,547	84,144
R Sq	71.90%	78.02%	73.50%

contemporaneously positively related with firm measures of productivity.

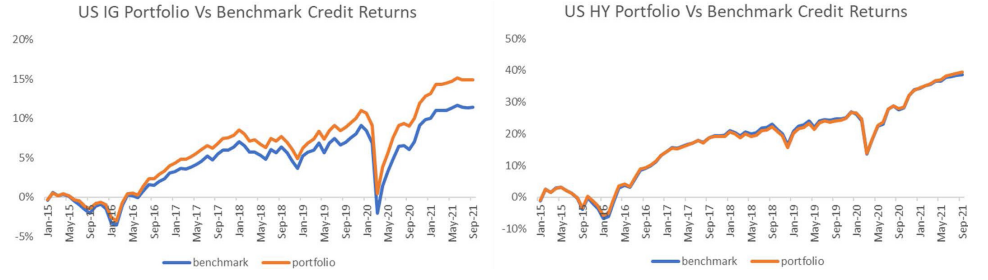
3.4.3 *Corporate commitment and excess bond returns*

Exhibit 8 reports the performance of the corporate commitment strategy over January 2015 to September 2021. Again, we cross-sectionally standardize the combined signal and create optimized portfolios following Equation (6) with the constraints in Equation (7). Panel A graphs the cumulated returns of corporate commitments in IG and HY, and Panel B reports associated performance statistics. There is strong outperformance, corresponding to an IR of 1.04 and average excess returns of 50.7 bps per year, for IG. In contrast, there is little evidence of outperformance in HY: Panel A shows the optimized corporate commitment strategy hugs the benchmark returns very closely and Panel B reports the IR is only 0.16. Perhaps this is not surprising because IG companies have more resources to prepare for climate transition.

Panel C of Exhibit 8 partitions the returns of the corporate commitment strategy into market regimes defined by bands of monthly S&P 500 returns: very negative at −2%, negative between

Exhibit 8 Corporate commitments.

Panel A: Returns of US IG and HY corporate commitment strategies



Panel B: Performance statistics of US IG and HY corporate commitment strategies

Long Only Portfolio Performance from Jan 2015–Sept 2021

Universe	Annual Active Ret (Bps)	Annual Active Vol (Bps)	IR	2015 (Bps)	2016 (Bps)	2017 (Bps)	2018 (Bps)	2019 (Bps)	2020 (Bps)	2021 (Bps)
US IG	50.74	49.00	1.04	52.38	32.21	61.62	−23.90	75.58	102.74	41.86
US HY	9.51	58.61	0.16	31.09	−21.42	5.48	−6.69	−2.28	53.94	6.50

Panel C: Regime performance of US IG and HY corporate commitment strategies

	SPX Regime Performance (2015–2021) Average Active Monthly Return (bps)			
Universe/ Regime	Very negative (< −2%)	Negative (between −2% and 0)	Positive (between 0 and +2%)	Very positive (> 2%)
US IG	72.90	8.30	12.10	9.50
US HY	36.50	31.00	6.80	−11.10

−2% and 0%, positive between 0% and +2%, and very positive with daily returns greater than 2%. In regimes with the most negative returns, the IG and HY corporate commitment portfolio returns are 72.9 bps and 36.5 bps, respectively, above the benchmarks. The IG strategy tends to have outperformance, on average, in all market regimes. The excess returns of the HY strategy decline monotonically from very negative to very positive regimes, and underperforms at −11.1 bps, on average, in the most positive S&P 500 regime. These defensive properties are attractive for diversification for multi-asset investors.

4 Conclusion

We show how to incorporate sustainability considerations in sovereign and corporate bonds. For sovereign bonds, we show how to incorporate positive tilts to countries that are more prepared with the climate transition to a net zero future (the same level of greenhouse gases as pre-industrialization) and negative tilts to countries that are less prepared. These tilts use information from the Climate Change Performance Index along with explicit reductions in carbon dioxide and greenhouse gases, which follow the recommendations laid out by the EU's Technical Expert Group on Sustainable Finance (EU TEG) and the Institutional Investors Group on Climate Change (IIGCC) for Paris Aligned Benchmarks. The methodology of the sovereign climate overlay can be applied on any sovereign benchmark.

In corporate bonds, we take advantage of the much larger breadth to formulate sustainable alpha signals. We show that ESG ratings, carbon emission intensity, and measures of forward-looking corporate commitments on carbon emissions have predictive power for fixed income excess returns. While some of these signals were originally formulated in equities and have previously been documented to predict equity returns, an important contribution is to show that they also have predictability in fixed income returns. Our findings might mean that similar sustainability signals can also generate alpha in other asset classes—an exciting area for future research.

Endnotes

1 Among others, see Kulkarni *et al.* (2017), Pedersen *et al.* (2021), and Alessandro and Jondeau (2021) for designing portfolios with increased ESG profiles along with standard risk and return objectives. There is also a relatively large literature using ESG variables to predict excess returns in equities, including Edmans (2011), Serafeim (2018), Chan *et al.* (2020), and Dimson *et al.* (2020). Madhavan *et al.* (2021) and Bruno *et al.* (2021) study the relationship of ESG with active managers' alpha and style factors, respectively.

2 See The Intergovernmental Panel on Climate Change (IPCC), www.ipcc.ch, which is the body of the United Nations for assessing climate change and helping to coordinate government responses.

3 In equities, firm commitments are related to the quality factor, as shown by Schwaiger *et al.* (2021). Kang *et al.* (2018) and Pauksta *et al.* (2022) argue that a form of the quality in fixed income is related to credit risk. See Ang (2014) for a summary of style factors.

4 The first green bond was issued in 2007 by the European Investment Bank. See Baker *et al.* (2018), Tang and Zhang (2020), and Flammer (2021) for recent studies on green bonds. For social bonds, see the Social Bond Principles issued by the ICMA at https://www.icmagroup.org/sustainable-finance/the-principles-guidelines-and-handbooks/social-bond-principles-sbp/. Peeters *et al.* (2020) advocate the issuance of social bonds to mitigate the effects of the COVID-19 pandemic. Schmittmann and Chua (2021) find that green bond issuers have lower emission intensities relative to other firms, and also lower their emission intensity over time at a faster rate than other firms.

5 While there is relatively little academic work climate and sovereign bonds, practitioners have started to recognize the importance of climate risk for government bond prices, like BlackRock (2019, Getting Physical: Scenario Analysis for Assessing Climate-Related Risks), Swiss Re (2021, The Economics of Climate Change), and the World Bank.

6 See https://www.ipcc.ch/site/assets/uploads/2021/08/IPCC_WGI-AR6-Press-Release_en.pdf. The only one of the climate shared socioeconomic pathways (SSP)

considered by IPCC (2021) that meets the criteria of the Paris Agreement is SSP1-1.9. The recommendations by the EU TEG and IIGCC are specifically intended to help investors create portfolios that seek to attain SSP1-1.9.

[7] See COMMISSION DELEGATED REGULATION (EU) of 17.7.2020 supplementing Regulation (EU) 2016/1011 of the European Parliament and of the Council as regards minimum standards for EU Climate Transition Benchmarks and EU Paris-aligned Benchmarks.

[8] See https://ec.europa.eu/info/sites/default/files/business_economy_euro/banking_and_finance/documents/190930-sustainable-finance-teg-final-report-climate-benchmarks-and-disclosures_en.pdf

[9] https://germanwatch.org/en/CCPI

[10] These non-CO_2 emissions defined under the Kyoto protocol and are converted to CO_2 equivalents. See Annex A of https://unfccc.int/sites/default/files/resource/docs/cop3/l07a01.pdf

[11] The full set of metrics included in the CCPI are described at ccpi.org/methodology

[12] The methodology was revised to include emissions from deforestation by CCPI in 2013. Some other sectors, such as agriculture, were not included until 2017 due to data issues. In 2018 the methodology changed to include all GHG emissions (from only energy-related CO_2) and Germanwatch started to check whether countries set their targets correctly and are fulfilling their promise made in 2015 at the climate conference in Paris.

[13] Kazdin *et al.* (2021) report that carbon emission intensities positively predict returns, but Bolton and Kazperczyk (2021) find the opposite. Taking into account that forward-looking corporate commitments of carbon emissions is required to construct Paris Aligned investment portfolios as determined by the EU TEG and IIGCC.

[14] DTS is a risk sensitivity measure and is the sensitivity of a bond to a relative change in the option-adjusted spread (OAS). It is a measure of debt quality and computed as duration multiplied by OAS (see Ben Dor *et al.*, 2007).

[15] See Ben Dor *et al.* (2012) for examples of quantitative strategies that combine various alpha signals and use control for risk, transaction costs, and other considerations.

[16] This spillover from information in equity markets to fixed income makes this signal similar to more general momentum interactions between equities and bonds (see, for example, Gebhardt *et al.*, 2005).

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References

Alessandrini, F., David, B. and Jondeau, E. (2021). "ESG Screening in the Fixed-Income Universe," Swiss Finance Institute Research Paper No. 21-77, 2021.

Ang, A. (2014). *Asset Management: A Systematic Approach to Factor Based Investing*, New York, NY: Oxford University Press.

Ang, A. and Piazzesi, M. (2003). "A No-Arbitrage Vector Autoregression of Term Structure Dynamics with Macroeconomic and Latent Variables," *Journal of Monetary Economics* **50**, 745–787.

Aswani, J., Raghunandan, A., and Rajgopal, S. (2021). "Are Carbon Emissions Associated with Stock Returns?" SSRN Working Paper.

Avramov, D., Lioui, A., Liu, Y., and Tarelli, A. (2021). "Dynamic ESG Equilibrium," SSRN Working Paper.

Baker, M., Bergstresser, D., Serafeim, G., and Wurgler, J. (2018). "Financing the Response to Climate Change: The Pricing and Ownership of U.S. Green Bonds," NBER Working Paper.

Ben Slimane, M., Guendal, T. L., Roncalli, T., and Sekine, T. (2020). "ESG Investing in Corporate Bonds: Mind the Gap," SSRN Working Paper.

Berk, J. and van Binsbergen, J. H. (2021). "The Impact of Impact Investing," SSRN Working Paper.

Ben Dor, A., Dynkin, L., Hyman, J., Houweling, P., Van Leeuwen, E., and Penninga, O. (2007). "DTS (Duration Times Spread)," *Journal of Portfolio Management* **33**, 77–100.

Ben Dor, A., Dynkin, L., Hyman, J., and Phelps, B. D. (2012). *Quantitative Credit Portfolio Management: Practical Innovations for Measuring and Controlling Liquidity, Spread, and Issuer Concentration Risk*, New York, NY: John Wiley & Sons.

Bauer, R. and Hann, D. (2010). "Corporate Environmental Management and Credit Risk," SSRN Working Paper.

Berg, F., Koelbel, J. F., and Rigobon, R. (2019). "Aggregate Confusion: The Divergence of ESG Ratings," MIT Working Paper.

Biais, B. and Green, R. (2019). "The Microstructure of the Bond Market in the 20th Century," *Review of Economic Dynamics* **33**, 250–271.

BIS. (2017). "The Regulatory Treatment of Sovereign Exposure," Discussion Paper.

Black, F. and Litterman, R. (1991). "Asset Allocation: Combining Investor Views with Market Equilibrium," *Journal of Fixed Income* **1**, 7–18.

Bolton, P. and Kacperzyk, M. (2021). "Do Investors Care About Carbon Risk?" *Journal of Financial Economics* **142**, 517–549.

Brunnermeier, M. K. (2009). "Deciphering the Liquidity and Credit Crunch 2007–2008," *Journal of Economic Perspectives* **23**, 77–100.

Bruno, G., Esakia, M., and Goltz, F. (2021). "Honey, I Shrunk the ESG Alpha: Risk-Adjusting ESG Portfolio Returns," Scientific Beta Working Paper.

Busch, T., Johnson, M., and Pioch, T. (2020). "Corporate Carbon Performance Data: QuoVadis?" *Journal of Industrial Ecology*, jiec.13008.

Campbell, J. Y., Pflueger, C., and Viceira, L. M. (2020). "Macroeconomic Drivers of Bond and Equity Risks," *Journal of Political Economy* **128**, 3148–3185.

Campbell, J. Y. and Shiller, R. J. (1991). "Yield Spreads and Interest Rate Movements: A Bird's Eye View," *Review of Economic Studies* **58**, 495–514.

Cevik, S. and Jalles, J. T. (2020). "This Changes Everything: Climate Shocks and Sovereign Bonds," IMF Working Paper.

Chan, Y., Hogan, K., Schwaiger, K., and Ang, A. (2020). "ESG in Factors," *Journal of Impact and ESG Investing* **1**, 25–45.

Collin-Dufresne, P., Goldstein, R. S., and Martin, J. S. (2001). "The Determinants of Credit Spread Changes," *Journal of Finance* **56**, 2177–2207.

Correia, M., Richardson, S., and Tuna, I. (2012). "Value Investing in Credit Markets," *Review of Accounting Studies* **17**, 572–609.

Correia, M., Kang, J., and Richardson, S. (2018). "Asset Volatility," *Review of Accounting Studies* **23**, 37–94.

Dai, W. and Meyer-Brauns, P. (2020). "Greenhouse Gas Emissions and Expected Returns," SSRN Working Paper.

Dai *et al.* (2021). "Outsourcing Climate Change," European Corporate Governance Institute—Finance Working Paper No. 723/2021.

Dick-Nielsen, J. and Rossi, M. (2019). "The Cost of Immediacy for Corporate Bonds," *Review of Financial Studies* **32**, 1–41.

Diep, P., Pomorski, L. and Richardson, S. A. (2021). "Sustainable Systematic Credit," SSRN Working Paper.

Dimson, E., Marsh, P., and Staunton, M. (2020). "Divergent ESG Ratings," *Journal of Portfolio Management* **47**, 75–87.

Edmans, A. (2011). "Does the Stock Market Fully Value Intangibles? Employee Satisfaction and Equity Prices," *Journal of Financial Economics* **101**, 621–640.

Edwards, A. K., Harris, L. E., and Piwowar, M. S. (2007). "Corporate Bond Market Transaction Costs and Transparency," *Journal of Finance* **62**, 1421–1451.

Erb, C. B., Harvey, C. R., and Viskanta, T. E. (1996). "Political Risk, Economic Risk, and Financial Risk," *Financial Analysts Journal* **52**, 29–46.

EU Technical Expert Group on Sustainable Finance. (2019). "TEG Final Report on Climate Benchmarks and Benchmarks' ESG Disclosures." https://ec.europa.eu/info/sites/info/files/business_economy_euro/banking_and_finance/documents/190930-sustainable-finance-teg-final-report-climate-benchmarks-and-disclosures_en.pdf

Fama, E. F. and Bliss, R. F. (1987). "The Information in Long-Maturity Forward Rates," *American Economic Review* **77**, 680–692.

Flammer, C. (2020). "Green Bonds: Effectiveness and Implications for Public Policy," in Kotchen, M. J., Stock, J. H., and Wolfram, K. D., eds., *Environmental and Energy Policy and the Economy*, NBER and University of Chicago Press Vol. 1, pp. 95–128.

Flammer, C. (2021). "Corporate Green Bonds," *Journal of Financial Economics* **142**, 499–516.

Flandreau, M. and Flores, J. H. (2009). "Bonds and Brands: Foundations of Sovereign Debt Markets: 1820–1830," *Journal of Economic History* **69**, 646–684.

Gebhardt, W. R., Hvidkajer, S., and Swaminathan, B. (2005). "Stock and Bond Market Interaction: Does Momentum Spill Over?" *Journal of Financial Economics* **75**, 651–690.

Gianfrate, G. (2020). "Climate Change and Credit Risk," EDHEC-Risk Institute Working Paper.

Goldstein, M. A. and Hotchkiss, E. S. (2020). "Providing Liquidity in an Illiquid Market: Dealer Behavior in US Corporate Bonds," *Journal of Financial Economics* **135**, 16–40.

Gorton, G. B. and Laarits, T. (2018). "Collateral Damage," NBER Working Paper.

Gratcheva, E. M., Emery, T., and Wang, D. (2020). "Demystifying Sovereign ESG," World Bank Group.

Grinold, R. C. and Kahn, R. N. (2000). *Active Portfolio Management*, New York, NY: McGraw-Hill.

Howell, L. D. and Chaddick, B. (1994). "Models of Political Risk for Foreign Investment and Trade: An Assessment of

Three Approaches," *Columbia Journal of World Business* **29**, 70–91.

Ilmanen, A. (2011). *Expected Returns: An Investor's Guide to Harvesting Market Rewards*, New York, NY: Wiley & Sons.

IIGCC. (2021). "Net Zero Investment Framework: Implementation Guide, " https://www.parisalignedinvestment.org/media/2021/03/PAII-Net-Zero-Investment-Framework_Implementation-Guide.pdf

IPCC. (2021). "Climate Change 2021: The Physical Science Basis," *Contribution of Working Group I to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change*, UK: Cambridge University Press, in press.

Jacobsen, B. and Lee, W. (2020). "Risk Parity Optimality Even with Negative Sharpe Ratio Assets," *Journal of Portfolio Management* **47**, 110–119.

Kang, J., Parker, T., Radell, S., and Smith, R. (2018). "Reach for Safety," *Journal of Fixed Income* **27**, 6–21.

Kazdin, J., Schwaiger, K., Wendt, V.-S., and Ang, A. (2021). "Climate Alpha with Predictors Also Improving Firm Efficiency," *Journal of Impact and ESG Investing* **2**, 35–56.

Kulkarni, P., Alighanbari, M., and Doole, S. (2017). "The MSCI Factor ESG Target Indexes: Single and Multiple-Factor Indexes with ESG Integration," MSCI Working Paper.

Madhavan, A., Sobczyk, A., and Ang, A. (2021). "Toward ESG Alpha: Analyzing ESG Exposures through a Factor Lens," *Financial Analysts Journal* **77**, 69–88.

Martinelli, L. and Vallee, L.-S. (2021). "Measuring and Managing ESG Risks in Sovereign Bond Portfolios and Implications for Sovereign Debt Investing." *Journal of Portfolio Management* **47**, 198–223.

Melas, D., Nagy, Z., and Kulkarni, P. (2016). "Integrating ESG into Factor Portfolios," MSCI Research Insight.

Mendiratta, R., Varsani, H. D., and Giese, G. (2020). "Foundations of ESG Investing in Corporate Bonds: How ESG Affected Corporate Credit Risk and Performance," MSCI Research Insight.

Menz, K. M. (2010). "Corporate Social Responsibility: Is It Rewarded by the Corporate Bond Market? A Critical Note," *Journal of Business Ethics* **96**, 117–134.

Merton, R. C. (1974). "On the Pricing of Corporate Debt: The Risk Structure of Interest Rates," *Journal of Finance* **29**, 449–470.

Nagy, Z., Kassam, A., and Lee, L.-E. (2016). "Can ESG Add Alpha? An Analysis of ESG Tilt and Momentum Strategies," *Journal of Investing* **25**, 113–124.

Nordhaus, W. D. (2021). *The Spirit of Green,* New Jersey: Princeton University Press.

O'Hara, M. and Zhou, X. A. (2021). "Anatomy of a Liquidity Crisis: Corporate Bonds in the COVID-19 Crisis," *Journal of Financial Economics* **142**, 46–68.

Pastor, L., Stambaugh, R. F., and Taylor, L. A. (2021) "Sustainable Investing in Equilibrium," forthcoming *Journal of Financial Economics*.

Pauksta, E., Kaul, K., Parker, T., Radell, S., and Ang, A. (2022). "Investing in US Core Fixed Income with Macro and Style Factors," *Journal of Portfolio Management* **48**, 1–23.

Pedersen, L. J., Fitzgibbons, S., and Pomorski, L. (2021). "Responsible Investing: The ESG-Efficient Frontier," *Journal of Financial Economics* **142**, 572–597.

Peeters, S., Schmitt, M., and Volk, A. (2020). "Social Bonds Can Help Mitigate the Economic and Social Effects of the COVID-19 Crisis," EMCompass Note 89, International Finance Corporation.

Polbennikov, S., Desclee, A., Dynkin, L., and Maitra, A. (2016). "ESG Ratings and Performance of Corporate Bonds," *Journal of Fixed Income* **26**, 21–41.

Rahman, L., Rosten, J., Monroy, P., and Huang, S. (2021). "Does ESG Matter for Sovereign Debt Investing?" *Journal of Fixed Income* **31**, 51–64.

Ren, H., Siwinski, S., Yu, C., and Ang, A. (2020). "Public Pension Portfolios in a World of Low Rates and Low Risk Premiums," *Journal of Investment Consulting*, forthcoming.

Schwaiger, K., Snow, J., Wendt, V.-S., and Ang, A. (2021). "Active Paris Aligned Equity Investing," BlackRock Working Paper.

Schittmann, J. and Chua, H. T. (2021). "How Green Are Green Debt Issuers?" *IMF Working*, Paper No. 2021/194

Serafeim, G. (2018). "Public Sentiment and the Price of Corporate Sustainability," *Financial Analysts Journal* **76**, 25–46.

Sloan, R. G. (1996). "Do Stock Prices Fully Reflect Information in Accruals and Cash Flows about Future Earnings?" *Accounting Review* **71**, 289–315.

Tang, D. Y. and Zhang, Y. (2020). "Do Shareholders Benefit from Green Bonds?" *Journal of Corporate Finance* **61**, 1–18.

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