Credit alpha and CO_2 reduction: A portfolio manager approach

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Abstract

This paper discusses the challenges of carbon-dioxide emission measurement on corporate credit portfolios. We illustrate how it can be difficult to translate traditional CO_2 reductive strategies into incentives for portfolio managers. As an alternative approach to the footprinting techniques commonplace in equities, we introduce the ECO_2BAR model which looks at CO_2 emissions from an ordinal standpoint and takes a risk-based approach to measuring this in credit portfolios. We build out the model to encompass important credit alpha factors such as short positions, leverage and derivatives as well as explicit green investments such as green bonds. We apply the model on two sets of data, where the first is a historical real traded investment-grade credit portfolio and the second is a systematic CDS trading strategy. In the traded portfolio, we find that it has been possible to own a clearly CO_2 efficient portfolio whilst still generating average alpha of 4.5 percentage points per annum. In the CDS-based strategy, alpha loss turns out to be insignificant with reasonable investment constraints on high-CO_2 emitting issuers. We conclude that there is a good potential for low-CO_2 strategies in a variety of operational, mainstream credit trading settings.

JEL Classification: G11

[1] This work has benefited from feedback from Peter Tchir, Orith Azoulay, Christopher Kaminker, Megan Bowman, seminar participants at AP4 and others. The presented model has used the capital structure identifier system (ERIDs) developed together with Graham Rennison. Remaining views and errors are the sole responsible of the author.

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1 Introduction

The prevalence of ESG (Environmental, Social, Governance) investing has increased manifold over the past decade. Originally, ESG investing limited itself to excluding certain types of companies with inherent 'bad products' and has to that regard been fairly successful. In today's debt capital markets, it is harder than it used to be to receive financing if you are perceived to provide perceived unethical products. Simultaneously, there has been a growing societal concern over the existence, and effects of, global warming. There is a clear consensus scientific view that greenhouse gas (GHG)[3] emissions are the cause behind global warming, as represented in for example the IPCCs findings.[4] The COP21 meeting in Paris in 2015 committed the international community to stop global warming at +1.5 degrees Celsius. This implies a large number of policy actions[5] that will affect corporates and financial markets over the decades to come.[6]

The capital markets have caught on to CO_2 reduction strategies not only out of adjustment to policies but also because of a demand from end-clients and fiduciaries, despite varied empirical evidence on outperformance of ESG based portfolios in isolation.[7] Measuring, and reducing, the inherent CO_2 emissions (called the 'footprint') of an equity investment portfolio has been a practicable way to be active in this space. Following this, the Carbon Disclosure Project, which aims to make companies report their different GHG emissions, has investor signatories representing more than $100 trillion in capital. With data at hand, it is quantitatively rather straightforward to mimic an equity benchmark portfolio but with decreased carbon footprint.[8]

The CDP and other similar projects have generally taken the equity investor's perspective and used an assumption that a one unit of equity takes an equal amount of GHG footprint as its share of the equity capital structure. The debt part, such as corporate bonds, has mostly been left in the periphery of the analysis, despite being similar in terms of the amount of financing provided. Some work is being conducted (see e.g. Burns et al. (2016)) on the carbon intensity of nation states and consequently government bonds. This papers looks to fill some of the gap in terms CO_2 measurement of corporate bond portfolios.[9]

[3]This paper focuses on CO_2, carbon-dioxide, emissions as a subset of all GHGs. CO_2 constitutes approximately 75% of global GHG emissions, IPCC (2014). We use the terms GHGs and CO_2 interchangeably.

[4]IPCC (2014).

[5]The Paris agreement explicitly mentions finances in Article 2, 1. (c): "Making finance flows consistent with a pathway towards low greenhouse gas emissions and climate-resilient development.", United Nations (2015).

[6]See Carney (2015), Carney (2016) for a perspective on how climate risks and financial risks are intertwined.

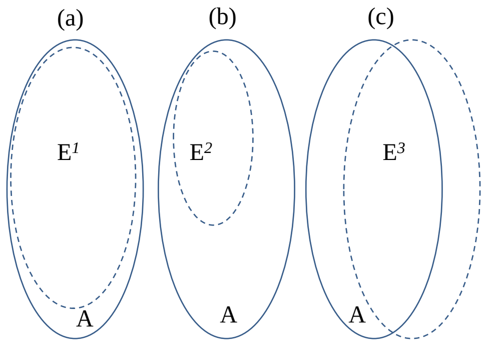
[7]See Friede et al. (2015) for a meta-study of the impact of ESG factors on corporate financial performance. One of the main conclusions of the paper is the divergence of results between portfolio and non-portfolio studies. In non-portfolio studies, ie. where one investigates ESG correlation in company internal financial factors, there is clear positive correlation. In the portfolio studies, looking at how portfolios of financial assets with some ESG strategy inherent in them, the results are neutral.

[8]Under the assumption of some allowance of tracking error between the benchmark portfolio and the carbon reduced portfolio and (which sometimes seem to forgotten) a well defined utility function for the trade-off between tracking error and CO_2 reduction.

[9]Between government bonds and corporate bonds, one also has a large debt market in terms of SSA (Supras, sovereigns and agencies) which complicate things even further. That market is beyond the scope of this paper.

Moreover, most of the present analysis of ESG has focused on beta-type exposures, responding to questions such as how you reduce the carbon footprint of a passive investment, such as a S&P 500 tracking vehicle[10] or a broad corporate bond index.[11] Little is written on in terms of how you combine active alpha-purposed trading while observing a reduced carbon strategy. We are of the view that structural impediments in the market-place, such as illiquidity, investment guidelines around issues like credit rating, lack of technical capacity to use derivatives and some behavioural effects such as herding actually allows for the generation of consistent alpha in credit as an asset class. This paper looks to fuse the traditional quantitative ESG analysis with the nuts and bolts of trading a real credit portfolio.[12]

Figure 1: Three hypotheses around alpha opportunity sets for unconstrained (A) and ESG (E^i) strategies.



In a slightly more structured format, what we want to test is variant of the hypotheses in Figure 1. The graph shows Venn diagrams of the alpha investment opportunity sets (and hence potential excess returns) under an unconstrained invesment mandate (A) and ones constrained on the back of an ESG factor like CO_2 reduction (E^i). In scenario (a), we see that the set (and hence potential return) is almost as big in the constrained as the unconstrained setting, $E^1 \simeq A$. In (b), we have $E^1 \ll A$, so that potential returns of the ESG strategy are much lesser than those of the unconstrained strategy. Lastly, in (c), one claims that ESG in itself can create returns, potentially greater than those of the original opportunity set. This can easily be refuted counterfactually,[13] but the logical argument is simply that in case of A, you should always be able to follow the investment strategy of E^3, otherwise it is not unconstrained.[14]

[10] E.g. Andersson, Bolton and Samama (2016)

[11] E.g. de Jong and Nguyen (2016)

[12] In a (2015) study, EY finds that 25% of investment professionals regularly factor in extra-financial information such as ESG into their portfolio decisions. We believe that this may be due to the impracticalities, further discussed below, of doing it, as well as scepticism that it does not reduce alpha.

[13] For example, it was difficult to generate excess performance in US high-yield (HY) credit in 2016 without having significant exposure to the Energy sector. The US HY Energy sector is predominantly driven by shale-gas and coal companies, neither of which are the ESG proponents favourites. From the trough to peak, the return was a stellar 76%. But the preceding peak to trough was 48%, and with a peak to peak return of -7%.

[14] This is a point that certainly is advocated by trading practitioners.

This paper first develops tools so that we can actually quantify CO_2 criteria and the associated alpha opportunity set, and secondly, relate the size of that set E^i to A. In the end, we want to test whether the hypothesis in 1 (a) can be rejected or not, under the condition that the ESG impact inherent in E^i is big enough.

We approach this by introducing an ordinal scoring methodology called ECO_2BAR. The ordinal rather than cardinal methodology that allows us to circumvent some of the hindrances in measuring absolute CO_2 footprints, but still opens up for strategies to reduce emission intensity of the portfolio. The systems uses a risk-based approach to weight GHG impact so that there is a clear, predictable link between portfolio decisions and the resulting scoring of the portfolio for portfolio managers. It is, once set up, easy to implement in a live trading environment and can, which we believe to be crucial, handle more complex trading positions than just owning straight cash bonds.

To show the model's practical feasibility, we apply it to a real traded credit portfolio that has been run at AP4 since 2011, accounting for factors such as credit derivatives and implied leverage and investments in green bonds. In this exercise, besides showing ECO_2BAR to be an operationally viable system, we also show that it has been possible to reduce the CO_2 intensity of the portfolio while retaining significant positive alpha. We corroborate this result in a separate on a systematic long-short trading strategy, where we find that reasonable investment constraints, such as excluding the worst tiers of issuers according to the model, does have insignificant effect on returns of the strategy.

1.1 Structure of the paper

The first section discusses the impediments to reliable GHG footprinting in credit in general, and corporate bonds in particular. We then introduce the ECO_2BAR scoring model as an alternative way to conduct GHG measurement in section two. In the empirical section, we proceed to evaluate the methodology for a real traded investment portfolio, developing a risk-based measure that allows for more trading complexity than just standard cash bonds and also test for correlation between the score and excess returns. Thereafter, we run a second stability test of the ECO_2BAR score on a market neutral CDS strategy. The last section concludes and suggest further avenues of research.

2 Traditional CO_2 benchmarking - challenges in credit portolios

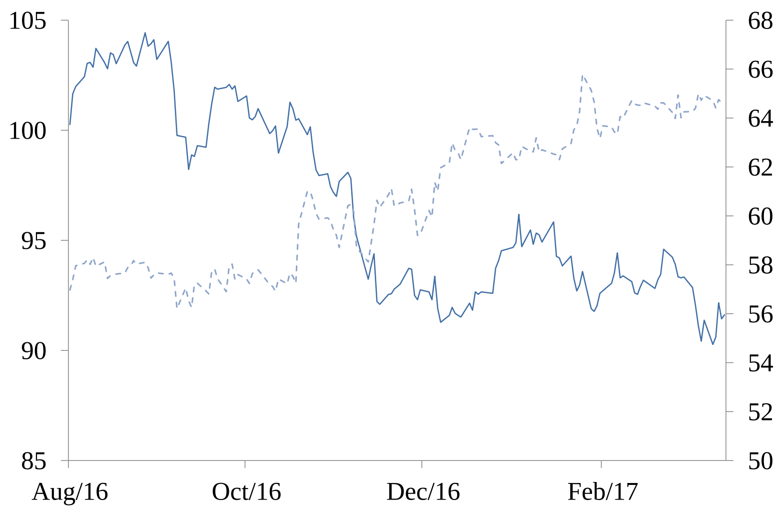
In this section, we look at a number of issues of allocating a company's CO_2 emissions into it's individual bonds. This is a field where theory is evolving and we hope that there might be stronger foundations for the allocation decision in the future, eg. by implementing a Merton (1974) approach. We present these caveats not out of a desire to undermine efforts to do this type of measurement, but from the perspective of receiving of being able to hold relevant discussions around GHG benchmarking with traditional portfolio managers and traders.

2.1 Allocation in the capital structure

Assume a company that has \$1bn in equity and \$1bn in debt in the form of corporate bonds. It emits 200mn tons of CO_2 per year. What is the share of the CO_2 emissions that should be attributed to \$1mn bonds? What is the proper ratio to allocate the emissions between the equity and the debt? In an extreme form, one could argue that equity should assume all of the CO_2 as the equity holders actually hold sway over the company with voting rights at the annual general meeting. A small debt investor would have virtually no way to impact the company. However, the company can potentially replace equity with debt along the lines of Miller and Modigliani (1958) of neutrality between different types of capital in the capital structure, which would be an argument for an equal treatment of debt and equity. Anveden et al. (2017) suggest using Miller-Modigliani theorem in conjunction with weighted average cost of capital to get a key between debt and equity share of CO_2 emissions. Whatever approach is used, it will have a big impact on total portfolio CO_2 measurement, effects that are likely to dwarf the impact individual portfolio managers can have by selecting CO_2 effective assets in their individual portfolios.

As a starter on where things get complicated in real-life situations, consider

Figure 2: Microsoft equity (MSFT US, dashed line, RHS) and newly issued MSFT 3.7 08/2046 bonds (cash price, solid line, LHS.)



measuring the company's capital structure in market capitalization terms in a case where the company starts performing badly. One day, the equity part has a market cap of \$500mn whereas debt has swelled to \$1.5bn. Should this shift the burden of the CO_2 in any direction? On the one side, a bondholder in a highly-leveraged, worse credit quality company holds much more influence in terms of the company's decisions if there are refinancings that are due. A practical example of this can be seen in the amount of covenants introduced in bond documentation as we traverse from investment-grade rated debt down into high-yield. But how quickly does the shift of power translate into what asset class should take responsibility for the footprint? This is unclear at best.

The market capitalization issue is also interesting on its own. The debt part of the capital structure will very much be tied to nominal interest rates whereas equity market capitalization should in some sense be inflation adjusted. An issuer who issued long (20yr+) bonds in 2016H2 saw the market value of that debt fall with more than 15%, whereas equity market cap increased. If your debt and equity exhibit a pattern such as that in Figure 2, should the burden of CO_2 between debt and equity shift accordingly?

Lastly, we return to the endogeneity issue with debt. The company management one day goes out and replaces part of the market traded bond capital with bank loans, or it turns out that in addition to $1bn of bonds, they actually have a revolving loan facility with drawn lines. How do we treat a non-public part of debt versus a public one? How do we treat different parts of seniority of the capital structure: the company might have $750mn of senior unsecured debt and then $250mn of junior debt? Again, without an appropriate key for how emissions should be split between debt and equity, the question of capital structure within the debt side of the balance sheet is hard to untie. For a portfolio manager, uncertainties with regards to potentially binding investment constraints that are outside their control are a great concern.

2.2 Practical aspects

The differences in time-horizons between ESG analysts and portfolio managers is material. For a portfolio manager, decisions regarding risk allocation to issuers can be forced to take place within in a matter of hours or minutes. ESG data on the other hand is reported annually at best, and with long lags between when the data is released and the period it covers. Often, the sustainability reports which formalize how well an investment managers is performing in areas like CO_2 reduction is published several months after closing of the financial year.

The primary market[15] is an illustrative example. By the start of a trading day, quite little is known about who will issue, at what maturity or where in the capital structure. A portfolio manager that is tasked with considering slow-moving, hard-to-calculate, GHG impacts on fast risk decisions will struggle to do this. This is not unimportant. If there is a discussion on management level in a fund to introduce footprinting, portfolio managers are likely to start expecting not only end of year measurement, but also end-of-year targets on the footprint, effectively imposing limits on how to trade their books. Hence, an expectation that footprinting will be burdensome will lead to unnecessary resistance to actually implementing it. From the argument in Figure 1 one can derive that traders are rational in resisting any reduction in their trading opportunity set.

As discussed above the difference in terms of allocating emissions depending on the issuers underlying credit is a thorny one. One of the key aspects in credit trading is the selection of high versus low beta,[16] especially in cash only

[15]The primary market refers to the initial offering of a bond to investors, generally through a public syndication process.

[16]High- and low-beta refers to high- and low credit risk, eg. the allocation between high-yield and investment-grade bonds.

portfolios. Again, a certain way to get challenged on trying to make a carbon defensive credit portfolio is to make the high vs low beta decision be correlated to the GHG footpring. It appears to us that many systems in place today have a certain bias where "good" companies tend to be large, low risk, low (bond-) yielding companies, and "bad" companies are the reverse. If that holds true, the potential return of the "good" portfolios will be lesser than the "bad" ones. When designing a system for a reduction strategy, this low versus high beta bias must be handled well.

Another important decision in credit trading is that of how to allocate your capital across the curve. Should \$1 invested in 2yr bonds carry the same weight as \$1 invested in 30yr bonds? From a risk standpoint, the answer is clearly no,[17] but it is not at all that obvious from the perspective of the ESG analyst. This question often seems to be bypassed, creating a clear divide between practitioners and strategists.

Furthermore, a large proportion of trading is conducted not directly in the issuing entity's capital structure, but in separate financial instruments such as credit default swaps (CDS). This is where measurement of CO_2 emissions really struggle in today's standards. The loop-hole offered in terms of divesting from "dirty" issuers in bonds space, but then applying the risk through derivatives will be all too obvious to experienced market participants. A system that does not account for the complete portfolios footprint in some way will lose credibility as it will be all too easy to arbitrage in terms of its CO_2 exposure.

Finally, green bonds is a rapidly growing market but has had a tendency to cater to separate sustainability portfolios rather than mainstream investment portfolios.[18] If one wants to achieve a 'greening' of credit markets, given the small relative size of the green bond outstanding versus broader corporate bond market,[19] getting broad portfolios involved should be crucial. From a methodological standpoint, one would ideally like to be able to ascribe a negative CO_2 footprint to green bonds in the portfolio, but only very few issuers provide this making the incentives to own green bonds in a mainstream portfolio limited from a quantitative footprinting perspective.

3 An ordinal CO_2 measurement approach

Seeing the obstacles around attribution of emissions to corporate bonds on an absolute, cardinal manner, we instead proceed with and relative, ordinal approach based on scoring of issuers' carbon impact. The basic idea is simple: we assign scores on all the issuers in a given universe based on their CO_2 impact along a reasoning that company A is *worse*, *better*, or *equal* to company B in terms of its emission. This relative approach enables the aggregation of

[17]As an example, for certain large issuers trading desk will even allocate different traders to the short- and long-end of the issuer's bond curve.

[18]It is even common during syndication of green bonds to ask investors whether they are dedicated green money or not, with the implication that dedicated money will get better allocation. This is obviously an obstacle to more mainstream portfolios trying to invest in 'green' assets.

[19]By end of 2017Q1 the total amount of green bonds issued from the inception of the market in 2007, in all currencies and across corporate bonds and SSAs amounted to approximately \$200bn. During the same quarter, more than \$500bn of corporate bonds (not SSAs) were issued in US dollars, according to Bloomberg.

portfolio risk into a top-level score for the whole portfolio in a feasible and operationalizable way.

For our study, we use emissions data from large-cap corporations provided by the Carbon Disclosure Project[20] (CDP). This data is linked to issuing entities in terms of the relevant equity and bonds ISIN, accounting data and credit default swap contracts.[21] In terms of quality, this is a sparse dataset with issues of time-lags, non-completeness and differences in accumulation by geography, sectors et cetera. This is not to say it is futile to construct quantitative strategies, rather it stresses the need of a robust stratification process as the one we propose. Again, our practical experience would make us argue that it is imperative to have a system that can robustly manage all the irregularities of the data and do it on a time-scale that is relevant to trading decisions.

In Table 1, we present some summary statistics for a list of Fortune 500 companies, grouped by GICS sectors. Out of the 500, we have 436 reporting GHG impact in both scope 1 and 2. The scope 1 exposures relate to actual generation of CO_2 within the company itself, whereas scope 2 refers to indirect emissions. Total CO_2 exposure of the list amounts to 3.5 billion tonnes annually, which is approximately 10% of estimated global emissions.[22] The market capitalization in equities amount to \$27tn and nominal debt-load to \$12.6tn. The latter number might appear small in relation to equity market capitalization, but note that these are large cap companies where the average gearing is much lesser than in a sample of mid- or small-caps.

In the following subsections, we stratify our sample along two dimensions, for which we find support in the data as well as qualitative justifications. We also, split the sample between dedicated green bonds and "other bonds".

3.0.1 Issuer sector score: Issuer sector score: C_t^n

There is a very strong clustering of CO_2 footprints in terms of sectors, as shown in Table 1. An Energy sector company, however good efforts are to reduce CO_2, will be hard pressed to be lower in emissions than a company in the Information technology sector just by the nature of the corporate activities. Although Utilities, Materials and Energy sectors can have companies that are almost completely based on renewable energy, these companies are usually still too small to make it into a large-cap list like the Fortune 500.

We classify sectors with an impact score of 1 to 3 based on the sectors total emissions, where a higher score means bigger footprint.[23] Sectors are sorted into

[20] https://data.cdp.net/. The public data-set is on a Fortune 500 set of companies. Note that an ordinal model like ECO_2BAR is less sensitive than a cardinal model to the particulars of any absolute data-set. This also makes it straightforward to pick another data provider and implement that data in the model.

[21] Our database covers 600+ issuing entities, with a focus on large cap bonds issuers in global credit markets.

[22] 10% might appear a small number. This just illustrates some of the difficulties with the data. For example, some of the largest emitters of CO_2 (oil companies, utilities) are state-owned or private companies, sometimes with and sometimes without a traceable debt load. With increasing political pressure on reducing emissions, we also see some large caps divesting CO_2 intensive activities to private companies that tend to be less well tracked in data-sets like this (cf. the European utility sector in 2015-17). We plan to return to this topic (and how to score it) in future work. Note though that an ordinal approach as in this paper is less sensitive on the broader portfolio scale to tricking CO_2 measurement.

[23] The scoring is counterintuitive in the sense that a higher score is *worse*, but this is following

Table 1: Fortune 500 companies with available CO_2 data, by sector in metric tons, in mn. USD. Scoring categories (3,2,1) separated by dashed lines.

	Scope					Market cap.	
	1	2	1+2	Mean	#	Equity	Debt
Utilities	1012	27	1039	48.18	21	627	522
Materials	827	195	1022	24.32	34	2,508	660
Energy	860	68	928	17.20	50	2,994	1,169
Consumer Stap.	58	61	119	1.60	36	2,250	883
Industrials	99	33	132	2.19	45	3,527	1,399
Financials	69	16	86	0.66	106	6,605	3,620
Consumer Disc.	32	53	85	0.73	44	2,614	1,269
Telecom Services	10	50	60	0.36	29	1,570	1,020
Health Care	12	15	27	0.40	30	1,941	960
Information Tech.	10	28	38	0.34	28	1,603	888
Real Estate	0	2	2	0.02	13	811	229
Sum	2989	548	3537	8.73	436	27,055	12,625

each category based on their percentile rank in total emissions. As an example of Table 1, all Utility, Energy and Materials companies have 3 as their sector score. Formally, for the individual company, we put this as:

$$C_t^n \in 1, 2, 3$$

where C_t^n is the sector score for issuer n at time t. In table 1, the split of the sectors between the different scores, going from 3 to 1, is marked by the dashed lines.

3.0.2 Issuer within sector relative score: R_t^n

The second part of the scoring is based on the emissions of a company *relative* to other companies in the same sector. Arguably, the biggest CO_2 reductions in absolute numbers might be achieved by switching from high-emitters to (relative) low-emitters in a sector with high absolute impact. A key question here is whether we should normalize CO_2 by company value or some other metric?[24] In table 2, we show the explanatory power between total emissions as dependent value and enterprise value[25] as independent variable across sectors.

In certain sectors, such as Energy, Financials and Telecoms, there is a very strong correlation between enterprise value and CO_2 emissions. Somewhat surprisingly the Utilities sector does not exhibit any significant correlation. To proceed, we apply a procedure where we do a percentile ranking of issuers so that:

the notion of higher CO_2 emissions being *worse*. We suggest thinking about it as a sCO_2re.

[24]This is a question with no consensus answer on what is best. We take the approach here that although 'better' measurements of carbon intensity of issuers exist, they are often not practicable at the portfolio manager level. Hence, we opt for straight market valued data.

[25]We simply calculate enterprise values the market capitalization and the outstanding debt added together, dated for the same time-period as the CO_2 data.

Table 2: Explanatory power of enterprise value on total CO_2 emissions, by sector.

Sector	R^2
Utilities	1.4%
Materials	1.2%
Energy	58.1%
Consumer Staples	2.6%
Industrials	5.2%
Financials	46.2%
Consumer Disc.	12.4%
Telecom Services	68.2%
Health Care	2.4%
Information Tech.	0.4%
Real-estate	0.5%

(i) when sector $R^2 > 10\%$, rank on CO_2 normalized for EV
(ii) when sector $R^2 \leq 10\%$, rank on CO_2 based on absolute emissions

In other words, we normalize for size of company in the sectors where this is a significant explanatory variable for emissions. We translate the ranking into three separate categories so that

$$R_t^n \in [1, 2, 3]$$

where R_t^n is the relative with-in sector score for issuer n at time t.

3.0.3 Green bond score: G^m

Lastly, we want to allow for positive impact by individual bonds that are dedicated funding for green project, so called green bonds. In terms of scoring, we apply a 0 to ISINs where there is a green bond flag, and 1 otherwise in Bloomberg's bond database.[26] We note that there is an advanced discussion in the market place around how green a green bond really is (from "dark" to "light"-green), and that there may be investors wanting this to be reflected in a scoring approach. Given the model presented below, it is straightforward to tier the Green Bond flag (or even make it continuous) to reflect different quality.[27] Again, we want to highlight that we intend our approach to be practical for portfolio managers, and believe that a parsimonious binary approach has better chance of an uptake than a fairly complex continuous weighting.

3.1 Balancing scores - the ECO_2BAR model

Given the previous rankings, we suggest the following total score, called ECO_2BAR,[28] on a bond ISIN level:

$$S_t^m = G^m \cdot (C_t^n \cdot R_t^n) \tag{1}$$

[26] This is not an exhaustive list in terms of the whole green, or climate change aligned, bond universe, but it does cover large cap issuers such as the ones considered in our sample

[27] For example, see Natixis (2017) for a systematic approach to score inherent green qualities in green bonds.

[28] *E*rlandsson CO_2 *B*alanced *R*anking

Table 3: Fortune 500 companies with available CO_2 data, by sector, in USD, and associated ECO_2BAR scores

Sector	Market caps Equity	Debt	Mean CO_2 score S_t^m	Count
Utilities	440	497	5.82	17
Materials	1,084	300	5.91	34
Energy	2,170	741	5.92	37
Industrials	2,258	525	3.95	43
Consumer Staples	2,770	736	3.95	38
Financials	5,618	6,248	4.00	90
Consumer Disc.	2,202	662	4.00	36
Health Care	2,618	513	1.97	29
Information Tech.	4,041	491	1.96	28
Telecom Services	1,492	589	1.95	22
Energy	145	40	1.80	5
Sum	24,836	11,342	3.75	379

where S_t^m is the final score for bond m at time t, G^m is the Green Bond flag for bond m , C_t^n is the sector score for issuer n and R_t^n is the relative with-in sector score for issuer n.

Given the scoring suggested above:

$$S_t^m \in [0, 1, 2, 3, 4, 6, 9]$$

so that a high CO_2-emitting utility would receive a score of 9, whereas a green bond will receive a 0 score. A well-ranked Energy company ($R_t^n = 1$, $C_t^n = 3$) will rank equal to a poorly performing Health Care sector company($R_t^n = 3$,$C_t^n = 1$) which we find strikes a good balance between enticing companies to perform better than their peers, and for the portfolio to be enticed to reduce exposure to bad sectors. The multiplicative effect $(\cdot)$ means an exponential effect of being a high-emitting company in high-emitting sector. This is a reflection of the high non-linearity between sectors in terms of their total CO_2 emissions shown in Table 1. From a qualitative ESG standpoint this also makes sense, as the impact of making the right decisions in worse performing sectors is much higher than doing it in well-performing sectors.

Table 2 provides summary statistics of the remaining data as we calculate ECO_2BAR scores. The reduction in total market caps is in the range 20-25%, as is the count reduction of number of companies. Average scores conform to expected values as $E(R_t^n) = 2$ and $E(S_t^m)$ given 11 categories is 3.8.

4 Evaluating a traded portfolio using ECO_2BAR

We now turn to implementing the ECO_2BAR scoring to a real traded portfolio for the years 2011-2016. Note that the purpose of this exercise is not to prove that a better score is correlated to a higher excess return in the portfolio. Instead, we want to evaluate ways to measure actual portfolios and performance related measures in terms of the score. It should be noted that the traded portfolio has not had any CO_2 reductive constraints imposed on it, although it has been run under AP4's broader investment hypothesis around climate change.[29] The ECO_2BAR system presented in this article has been developed in 2017. This means that the actual portfolio has been traded *ex ante* to the model presented here.

The portfolio has been traded against a bespoke benchmark[30] provided by Merrill-Lynch on a bond index containing high average rating level (A-AA) benchmark-sized bonds in USD, EUR and GBP. The actual investment portfolio is investment-grade only, with similar size restriction, same currencies but also including SEK. The SEK side is benchmarked to a high-grade benchmark provided by Svenska Handelsbanken. All performance indicators are duration hedged/net of interest rate movements, so that the results are in almost pure excess returns format.[31]

Following the analysis in the previous section, we only use emissions data from the CDP's Fortune 500 list. Unless explicitly stated otherwise, we only run the analysis on the part of the portfolio which is also a part of the Fortune 500. As such, a certain proportion of the portfolio is not covered by the analysis. We adjust for that when linking the cash portfolio to the size of the derivatives portfolio.

As an actively traded portfolio, the total market value of the portfolio has deviated significantly from the internal benchmark allocation, as government bonds from the broader fixed income book have been bought/sold when selling/buying corporate bonds. We call this deviation 'implied leverage' as it mimics repo operation a levered investor would use. The amount of leverage, implied or direct, might be the single most important factor in generating alpha in a macro-traded credit portfolio. Leverage poses a methodological problem in terms of measuring some form of CO_2 footprint. On an absolute basis, one could argue that owning more credit, ceteris paribus, your share of absolute GHG emissions should be bigger and we could agree with that. From a practical standpoint, however, an absolute approach will be strongly contested in terms of its restrictive effect on alpha generation potential.

We think that this can be bridged by realizing that increases in size of the portfolio will generally come from the reduction of the portfolio somewhere else. As mentioned, in the context of the portfolio we discuss here the "leverage" is in the form of selling one asset versus buying another one. In practice, to buy \$1m more in credit, the portfolio needs to sell \$1mn of government bonds. So the added footprint of more credit should have the reduced footprint of the reduced government exposure subtracted from it. Hence, if the governments inherent CO_2 footprint (or scoring) is in excess of that of the purchased credit, one could argue that applying leverage in this form is actually reductive in terms of GHG exposure rather than additive.[32]

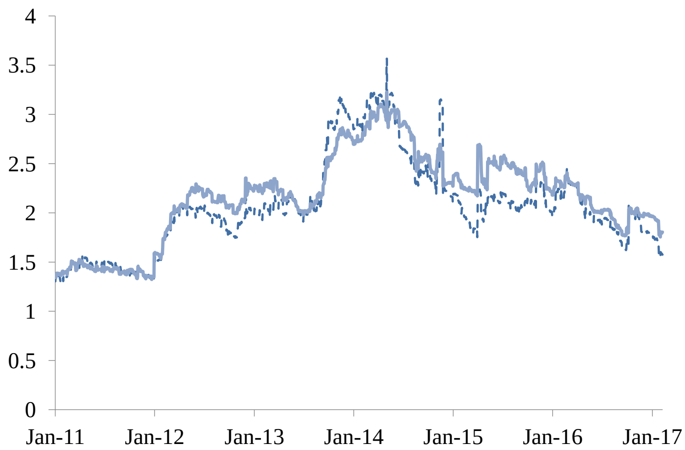
[29] This has been expressed in a number of annual reports available at www.ap4.se.

[30] The exact composition of the both benchmark and actual portfolio rules is proprietary information. Please contact the author for further information.

[31] Some intraday interest rate movements are not explicitly hedged in the performance measurement. These effects are small however.

[32] There is some initial work on trying to footprint government bonds, e.g. Burns et al. (2016)). If one wants to make the example extreme, the US is the largest GHG emitter per capita in the world, and would likely end up with a rather high ECO_2BAR score. Hence, selling US Treasuries to buy a lower GHG emitting credit portfolio should in some way be considered a "good". However, there are some major issues around double-counting here that still need to be resolved.

Figure 3: Turns of implied leverage in risk terms (dotted line) and market-value terms (straight line). An actual portfolio identical to the becnhmark would render a 1.



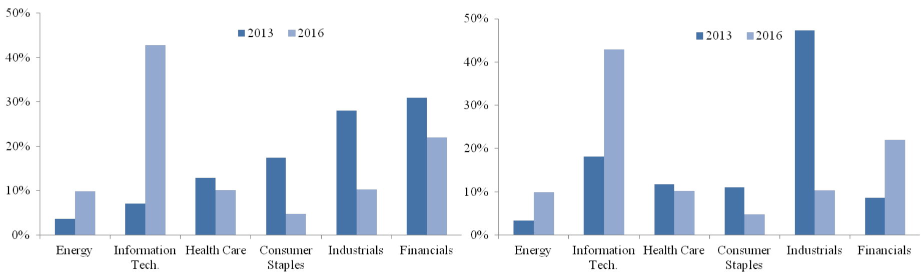
In Figure 3, we plot the implied leverage of the traded portfolio's cash holdings in two different measurements. It is clear that the traded cash portfolio has been run with high exposures compared to the benchmark, running up too 3x as much risk in 2014, and that cash leverage has been changing over time. This cash overweight should be connected with the risks/hedges run in the derivatives book, mainly in credit default swap (CDS) indices, which we delineate below.

4.1 Using duration as a weighting mechanism

There is a vast risk difference between making a $1mn investment in a 1yr bond and making the same investment in a 30yr bond, although the positions have an identical amount of nominal risk exposure. The nominal element in interest rates moreover makes the actual market exposures vary wildly between short- and long-term instruments. Rather than taking an exposure approach, we argue for using a risk-based approach. We utilize "modified duration contribution" (MDC), which is a measure of how much each individual bonds contributes to the total portfolios sensitivity to yield changes.[33] This has the advantage of being a measure that automatically makes a trade-off between between nominal/market value exposure and the actual maturity of that exposure. Furthermore, the duration risk measure is likely to already be incorporated in a modern portfolio system. On the flip-side, because of positive convexity, the risk contribution of a bond as measured by MDC is decreasing in spreads. In other words, as a bond gets riskier, its MDC decreases, which is clearly counter-intuitive. The effects of this within an investment-grade context are small however, and on balance with large data issues to correct for this, we proceed with MDC as

[33] This is simply calculated as the market value of the individual bond over the market value over the whole portfolio multiplied by the bond's modified duration.

Figure 4: Sector split in benchmark, 2013 and 2016.



(a) Based on risk (MDC). (b) Based on market exposure.

a parsimonious way to infer risk but recognizing that further sophistication is possible.[34]

To aggregate ECO$_2$BAR score, we use a straight linear weighting in terms of risk contributions to the portfolio:

$$S_t^{Pf} = \sum_{m=1}^{K} \omega_m$$

where ω_m is the %-age contribution of bond m in terms of modified spread duration to the total applicable portfolio. K denotes the number of bonds in the portfolio.

Figure 5 plots the ECO$_2$BAR scores for the benchmark and actual portfolios for the observed sample, 2011-2016. Looking at the benchmark, we can see how the score has declined from 4.78 to reach as low as 3.19 by the end of the sample. The main thrust of this benchmark decline comes in 2015 and is the result of consecutive rating downgrades of oil majors as oil prices declined. This made several high-scoring issuers fall out of the index and thus reduced the average score. The average for the sample is 3.88 which is almost right on the naïve mean of 3.85. The benchmark only contains two green bonds throughout the sample. Note that the rating revisions are more binary than the market capitalization measures resulting in the discontinuous appearance of the time-series.

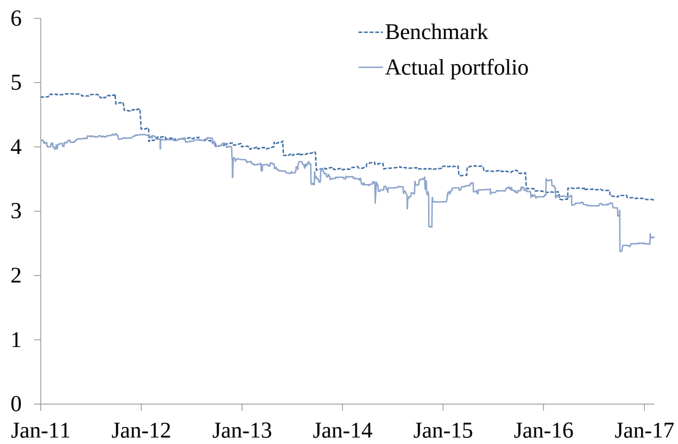
Turning to the actual cash bond portfolio, we see that it has mostly been better scoring than the benchmark. There is a notable drop in the score due to a fairly large investment in a large-cap issuer's green bond in 2016. The exit value of around 2.5 indicates a portfolio that is heavily tilted towards bonds with lesser carbon impact than a random sample. On closer inspection, see Figure 6, when we remove the flagging of green bonds, we see that the portfolio ends up with a slightly higher ECO$_2$BAR than the benchmark (3.42). The green bond component starts having an big impact in 2016 and reduces the score in terms

[34] An alternative measure is DTS, duration times spread, which incorporates the beta factor of spreads and recognizes higher volatility/risk as spreads increase, for a further discussion see Ben Dor et al. (2005). The drawback of DTS is of a practical nature, where spread calculations introduce complexities that bond data is not always well-suited to be subjected to. Note that in our second empirical exercise, we frame the test in a way that is aligned with the DTS measure.

of 0.9 units by the end of the sample.[35] Clearly, the green bond component has helped making the total footprint improve, but note that this is the large-cap, cash only part of the portfolio.

From a statistical standpoint, we note that the data looks less well-behaved than the benchmark. This is a function of more aggressive position movements in the traded portfolio than in the benchmark. For example, a few of the spikes in scores are based on new issues being traded both in and out within a few trading sessions.

Figure 5: ECO_2BAR score of benchmark portfolio and actual traded cash portfolio.



4.2 Scoring of a synthetic overlay

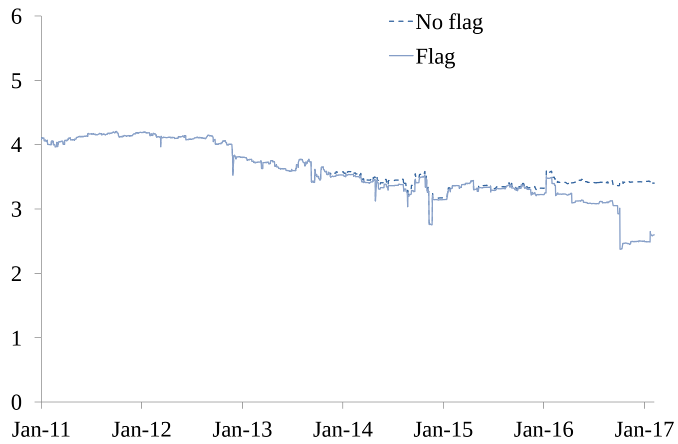
In "Synthetic credit for real money: Why? How?"[36] we argue for the alpha potential in the use credit derivatives in a portfolio like the one described in the previous section. For example, the relationship between cash bonds spreads and matched CDS spreads can vary significantly over time even when they should have equivalent value in default probability pricing terms.[37] Another very common use of CDS is hedging of macro- or market beta risk, where portfolio managers derisk portfolios through buying protection on CDS indices, rather than trying to liquidate the underlying bonds of their portfolio. In a implicitly levered portfolio like the one under study, CDS indices are the products with enough liquidity to hedge general credit risk.

[35] As a historical context, the first green corporate bond was issued in 2013. Despite exponential growth since then, the whole market was less than \$200bn by end of 2016 to be compared to the \$12tn of debt we finds in our Fortune 500 sample.

[36] Presentation to Creditflux CreditDimensions conference in New York, 17 Jan 2017. Available upon request.

[37] For an introduction to basis trades, see Elizalde and Doctor (2009) or see Kim, Li and Zhang (2017) for an econometric perspective on the relationship between bonds and CDS.

Figure 6: ECO₂BAR score of actual traded cash portfolio with and without flagging of green bonds



A long risk position in a CDS has the same properties in terms of portfolio risk as being long a bond. The difference in terms of considering CO_2 factors is that by selling protection (going long risk) on the CDS, the investor does not provide any additional financing for the actual underlying issuer. As such, one could argue that the position in CDS is irrelevant for purposes of thinking around ESG factors. But derivative spreads are often used as guidance for pricing of issuing new debt, so that the spread has second order effects on the cost of debt for the issuer.[38] Hence one could argue that the CDS position is additive in terms of CO_2 exposure. By selling protection on CDS, we lower the cost of financing for the underlying issuer, albeit marginally. This goes both ways, a long-protection (short risk) position in CDS should then be considered a negative for the underlying issuer as it increases the cost of financing, and should thus render a GHG reductive score.

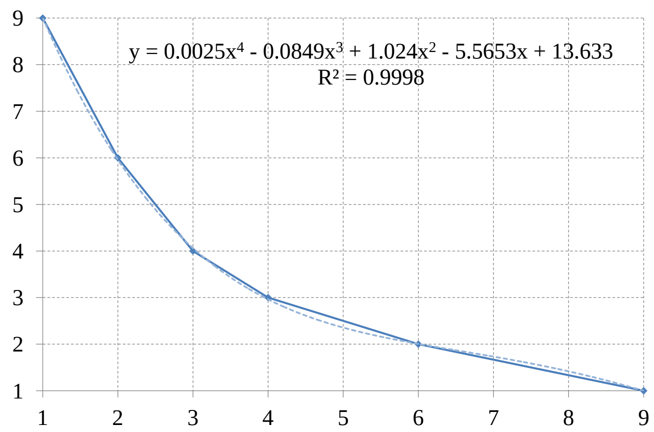
We think the argument here should be what impact either a bond or a CDS has at the margin. A "small" investor will not make or break a new issue for an issuer but their order might have a marginal effect on the cost of financing. Also, trading bonds in the secondary market has no direct financing effects on the issuer, but only in terms of the marginal pricing of the secondary (and hence eventually the primary) curve of the issuer. Hence, with this at-the-margin argument, we proceed by accounting for CDS in a similar way to cash bonds.

A follow on question comes to how we should treat short risk positions, either through repo-ing bonds or buying protection on CDS? The simplest way would

[38]One could even argue an even stronger effect of CDS. The 'bond vigilantes' of the 1990s are today more likely to use CDS than cash bonds. So at the extreme, being short risk through CDS can give a big leverage vis-à-vis the issuer. As a case in point, the (short-risk) sovereign CDS regulation in Europe, whereby it is not permissible to have naked shorts on Euro-sovereign highlights the potential impact of CDS buyers.

be to allow a negative weight be multiplied with the ECO_2BAR score, essentially introducing negative scores for shorts. But from a quantitative standpoint it should be noted that ECO_2BAR is a relative/ordinal system, which means that absolute operations such as switching signs might be inappropriate. Consider an example of holding a bond of an issuer with a 9 score, and being short risk through CDS for exactly the same amount and risk. The resulting score of this position would be 0. In case where the bond trades cheaper than the CDS (a so called negative basis trade), a portfolio manager could leverage up this trade, ie. buy large amounts of the bond and significantly reduce the score of the portfolio, which seems like an unreasonable effect.

Figure 7: Inversion function of ECO_2BAR score for CDS short risk positions.



Rather than do it additively, we use an inversion of the score instead. Simply put, to go short an ECO_2BAR 9 scored issuer results in a 1 score, rather than a (minus) -9 score. In the bond/CDS example, the resulting weighted ECO_2BAR score would be the straight average, 4.5. This inverse relationship is shown in Figure 7.[39] In the graph, we also show the specification of a polynomial that has a very tight fit to the discrete (linearly interpolated) curve in the original model, which allows us to switch from discrete scores in the single issuer case to the continuous score in case of aggregates such as positions in CDS indices.

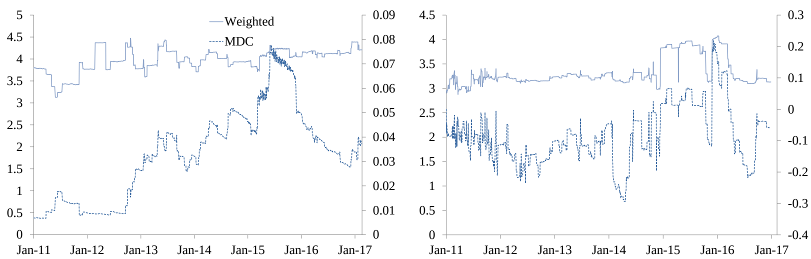
Given the flexibility of the ordinal approach in ECO_2BAR, quantifying the relative greenness of a synthetic portfolio is rather straightforward if the risk-measures are in place:

$$S_t^{CDS} = \sum_{n=1}^{N} \phi_{i,t} \cdot D_t^n$$

[39] An interesting example of the inversion effect comes in the case of relative value trades in CDS. Suppose the portfolio manager goes long risk in a low scoring Utility company, $S_t^m = 3$, and short in a high scoring Utility with $S_t^m = 9 \Rightarrow \left(S_t^M\right)^{-1} = 1$. The resulting score of the position is 2. In other words, the model provides a good incentive to put on synthetic relative value trades that clearly act CO_2 reductive, even if the underlying portfolio is already relatively green ($2 \leq S_t^{pf} \leq 4$).

where ϕ_i is the share of MDC for the total portfolio that belongs to issuer n in CDS, and D_t^n is the sustainability score for issuer n at time t. Note that, along the inversion of negative risk (short) positions ϕ_i is calculated as the absolute value of MDC for the whole single-name book. Again, this is the effect of using an ordinal rather than cardinal system.

Figure 8: Risk-weighted ECO$_2$BAR score (solid line, LHS) and modified duration contribution (dotted line, RHS) for CDS portfolios



(a) Single-names

(b) Indices

Translating this into a portfolio that contains both bonds and CDS, we get:

$$S_t^{Pf} = \sum_{m=1}^{K} \omega_{m,t} \cdot S_t^m + \sum_{n=1}^{N} \phi_{i,t} \cdot D_t^n$$

Note that the risk-share factors $\omega_{m,t}$ and $\phi_{i,t}$ are calculated as share of total spread duration risk for the combined bonds and CDS portfolio.

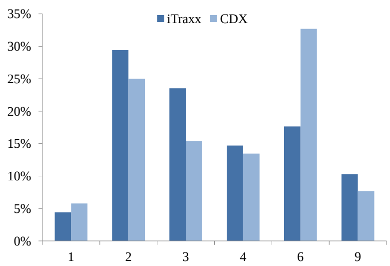
We illustrate a time-series of the traded, scored single-name CDS portfolio in Figure 8a. The score has been in a range between 3.12 and 4.47 over the sample time period, with a mean of 3.96. This means that relative to the non-benchmarked expected mean, 3.85, the single-names have been marginally additive in terms of CO_2 exposure.

Turning to the CDS indices such as iTraxx Main and CDX.IG[40], they are commonly used tools to hedge market exposure in credit portfolios. The indices are equal-weighted over 125 issuers[41] making it relatively easy to aggregate an ECO$_2$BAR score for the whole index. We try two different ways of aggregating scores. First, as shown in the left panel of Figure 9, we simply take the scores of individual issuers, where available, and aggregate across the indices. The resulting number for iTraxx Main is 3.91. Second, we try a broader approach based on sector average scores weight that by sector weights in the index, whereby we cover many more issuers. The resulting score for iTraxx Main is then 4.21. For CDX.IG, the same numbers are 4.21 and 3.8. meaning that the large-caps in

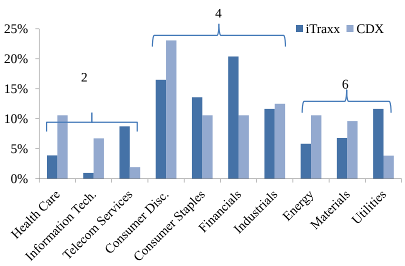
[40]The iTraxx and CDX families of indices are trademarks of Markit.

[41]There is a larger family of CDS indices: CDX.HY and iTraxx Xover cover high-yield issuers across the US and Europe respectively. iTraxx Senior Financials is a sub-index of iTraxx Main covering 30 financials.

Figure 9: CDS indices and aggregation of index ECO$_2$BAR score.



(a) Constituent single-names ECO$_2$BAR score statistics.



(b) Sector based ECO$_2$BAR statistics.

CDX.IG with published data score worse than the large-caps in iTraxx Main. On the other side, the sector composition in CDX.IG is slightly better, with a higher allocation to the best scoring sectors (eg. 19.2% in the 2 bucket for CDX, compared to 13.6% for iTraxx Main).

Figure 8b shows the portfolios MDC contributions of CDS index trades. The average contribution is clearly negative indication that the book has been a buyer of protection on average. This in turn has moved the ECO$_2$BAR score more in general toward the 3 level, as the CDS indices in themselves have a score around 4. This introduces somewhat of an inconsistency in terms of a low scoring portfolio like the cash portfolio described above, whereby going short a CDS index actually adds to the total portfolio score. We prefer to think of this as "collateral damage" being caused by going short. An index that would score around 3 in ECO$_2$BAR would give short positions scoring around 4, but it would in effect also mean that the investor would be shorting many more relatively good companies to bad ones. This is what gets penalized.

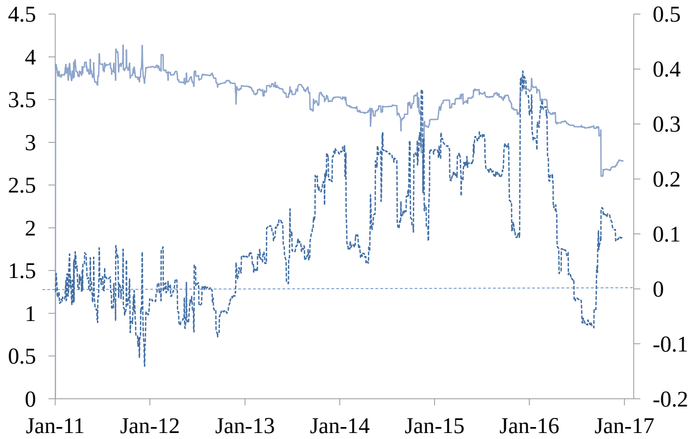
Figure 10 captures the risk position of the complete large-cap book and with the associated ECO$_2$BAR score. The left hand scale is the weighting of the actual portfolios versus the benchmark in terms of MDC. A 0 indicates flat risk versus the benchmark, in terms of MDC. As the graph indicates, there is no obvious correlation between the total risk positioning in the book and the declining score. The one point we note is the relatively large move in 2016H2 where the score drop at the same time as the total risk amount increases. Again, this is due to one fairly significant investment in a green bond.

We look at actual excess returns and their interrelationship with computed ECO$_2$BAR scores. On the left-hand side of Figure 11, we plot cumulative excess return[42] for the traded portfolio[43] versus the aggregate ECO$_2$BAR score over

[42]Excess P&L is based on AP4's performance attribution system. For more information on the performance attribution, please contact the author. In summary terms, the performance system look at individual bonds excess return over their benchmarks. The excess return numbers are calculated including asset allocation based leverage, ie. it is the excess return on the traded portfolio expressed as a percentage over the size of the benchmarked portfolio. They are also calculated as straight returns, ie. no reinvestments.

[43]As a reminder, this includes all positions in cash bonds and single-name CDS in issuers with GHG data in the Fortune 500 list, and CDS index positions weighted to reflect the scored issuers weight versus the non-scored in the total book.

Figure 10: ECO_2BAR score (solid lines, LHS) and total modified duration contribution (dashed line RHS) of full portfolio.



2011-2016. The portfolio has produced annual excess returns of 4.55% while also lowering its score over the sample. There is some degree of volatility clustering in returns, with the 2012 period being volatile due to the European sovereign crisis and early 2016 with the large market sell-off that preceded the European Central Bank's CSPP program.[44]

We run a battery of statistical tests on the relationship between excess returns ($\Delta XsRet_t^{pf}$) and changes in ECO_2BAR score ($\Delta XsRet_t^{pf}$) in 11 following the baseline relationship:

$$\Delta XsRet_t^{pf} = \alpha + \beta \cdot \Delta ECO_2BAR_t^{pf} + \epsilon_t \tag{2}$$

Despite different specification,[45] we find no evidence of statistically significant linkages in terms of the parameter β. The point estimate of β is slightly negative indicating lower $ECO_2BAR \Leftrightarrow$ higher excess return, but not to the degree that it should be accepted versus the null hypothesis of no relationship. On the other hand, μ turns up significant in our tests, indicating that there has been a consistent alpha component in the traded book.

From our perspective, these are firm result. We would be surprised if a fairly simplistic quantitative model without any qualitative overlays could generate alpha on its own. What is important to show, however, is that CO_2 impact reduction appears to not take a toll on profit potential. To express it in terms of the Figure 1, our results support case (a) where $E^1 \simeq A$. In other words, the investment opportunity set has not been signficantly curtailed by the cosntraints inherent in E^1.

[44] In March 2016, the ECB announced a programme of buying corporate bonds following a period of heightened volatility.

[45] We test different sampling frequencies, orthogonal regressions, auto-correlation adjustments among other things.

Figure 11: Cumulative excess return (solid line, RHS) vs ECO_2BAR (dotted line, LHS).

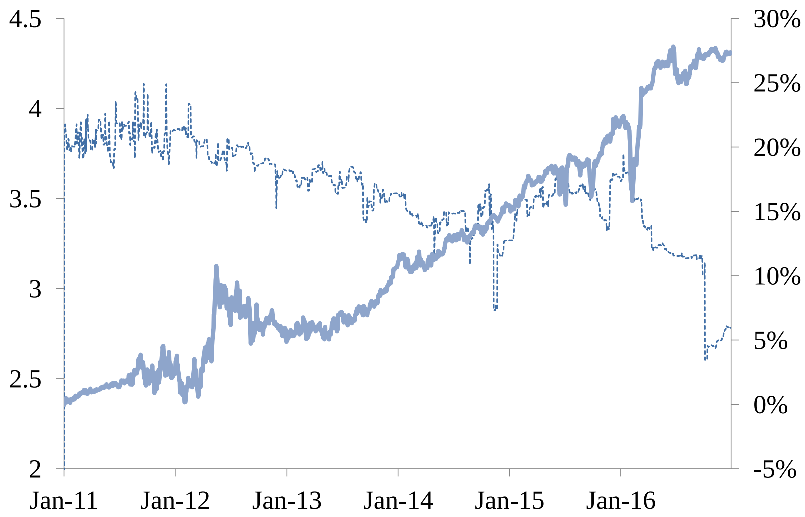


Figure 12: Change in ECO_2BAR (line, RHS) vs annual excess returns (bars, LHS).

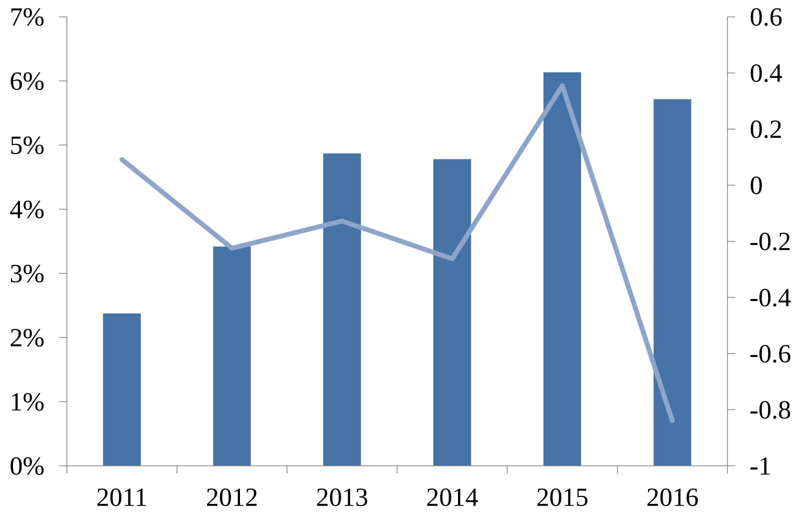
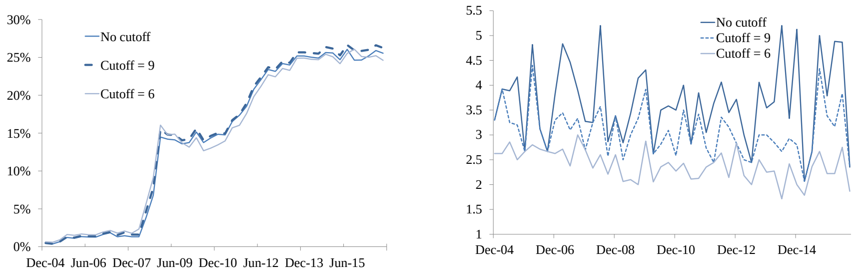


Figure 13: DIEM strategies under ECO$_2$BAR cutoff rules.



(a) Cumulative returns.

(b) Reduction in ECO$_2$BAR score under different cut-offs.

5 Costs of CO_2 constraints in a systematic alpha strategy

In this section, we proceed to a model without much lesser potential for cross-correlation between alpha, ECO$_2$BAR scores and unobserved factors. The Dynamic Indicator of Equity Momentum (DIEM) is a purely statistical model originally introduced in, and virtually unchanged since 2007, see Erlandsson (2008) and Rennison and Erlandsson (2008), providing a long out-of-sample testing period. The original pieces provide more detail: in brief the model generates approximately market-neutral long-short CDS portfolios, where the signals to go either long or short risk a particular name is based on relative equity momentum (normalized for volatility and in comparison with other credits trading at approximately the same spread). At a given point in time, the model goes long as the same amount of notional as it goes short and at similar spread levels in a fashion that renders it expectation-wise market neutral. It is indiscriminate of sector in the sense that it may pair up a long risk position in a Telecom company against a short risk position in a Materials company, as long as they have similar spreads and strong versus weak equity signals.

The experiment we conduct is to apply selection criteria conditional on the ECO$_2$BAR score to see whether the alpha of the strategy changes once constraints are applied. The most obvious test is to see what happens to the performance of the strategy when we disallow it to go long risk (the equivalent of buying bonds) in poorly scoring issuers. Some results of this exercise are presented in Figure 13.[46]

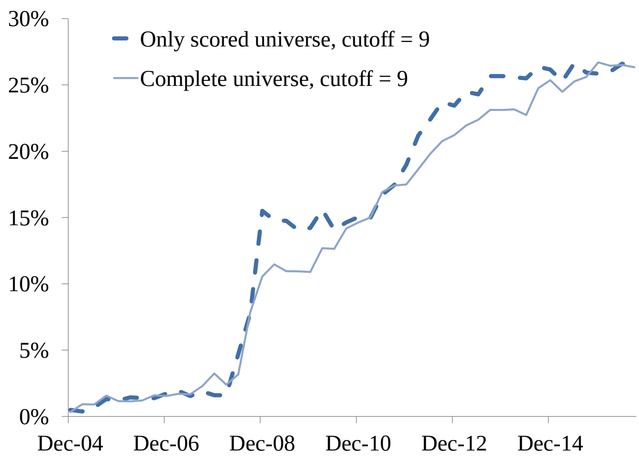
The constraints we apply are quite simple. In the first one, we disallow the strategy to go long risk in any name with 9 as ECO$_2$BAR score (it is prohibited to buy bonds from a high CO_2-emitter to put it in cash terminology). In the second version, we discard longs in credits with a 6 or 9 score. As the figure illustrates, the cumulative excess returns of all three strategies are close to each

[46]We run the strategy with a quarterly roll frequency, aligned with single-name CDS roll dates so as to remove costs to be 'on-the-run'. We do not impose transaction costs on this exercise as it intends to illustrate alpha generation based on the trade ideas, not the actual market technicalities.

other, with the 9 exclusion strategy coming out on top. All strategies produce significant alpha, although lumped into the 2008 to 2013 part of the sample,[47] for a total of 20% excess return unlevered and before transaction costs. This might sound underwhelming but should be considered in the light of being equivalent to 1.8% of excess return per annum, which in isolation would be considered a large number in credit.

Statistical testing gives no significant evidence of out- or underperformance of the three strategies. Along the reasoning above, this a rejection of the hypothesis that the GHG reducing strategy is adding alpha in itself. But the key take-away should rather be that avoiding the worst scoring issuers will not lower the model's alpha potential. What the restrictions achieve though, as illustrated Figure 13b is a (statistically) significant reduction in ECO_2BAR scores. A cutoff of credits with a 9 score lowers the ECO_2BAR for the portfolio with 0.6, a cutoff at 6 means a 1.3 score reduction.[48]

Figure 14: DIEM results with non-scored universe included.



We perform a second test whereby we use a full credit universe, irrespective of whether CO_2 emissions data is available or not, but continue to apply restrictions to those entities with poor ECO_2BAR scores. This is illustrated in Figure 14. We see that the performance of the full universe based model is marginally better by the end of the sample, but is actually worse in certain periods. The lack of a dramatic difference in alpha potential switching from a full universe to a scored only suggests that simply removing non-reporters from the selectable issuer universe should not impose large alpha costs. Note again that this is with

[47] We remind the reader that this study is conducted solely on large-caps, Fortune500, company with available data. For example, in the earlier part of the sample this generates survivorship bias as few of the companies going bankrupt in 2005-2008 were ever available to provide CO_2 data.

[48] An obvious extension to the model to cope with lack of data be to score non-reporters only with regards to their sector. The appropriateness of this should be investigated empircially, and remains outside the scope of this paper.

regards to larger cap issuers, dynamics may be different when it comes to more heterogenous issuers in the small-cap space.

6 Conclusions

This study has discussed obstacles to CO_2 emissions footprinting in corporate credit portfolios from the perspective of a portfolio manager that would actually have to implement any reductive strategy. We have introduced the ECO₂BAR model which addresses some practical concerns and offers alternative ways around difficult yet-to-solve problems, such as how to allocate CO_2 between different parts of the capital structure.

In the empirical sections, we show the system's flexibility to incorporate many of the factors important to active credit managers, such as leverage and derivatives. When evaluating the ECO₂BAR score in a historical, traded credit portfolio as well as in the context of a systematic, quantitative strategy, we find that having lower/better scores and implicitly a lower carbon footprint in the portfolio, does not impede on alpha significantly. It also appears that missing data, in the form of issuers not reporting CO_2 emissions does not pose a significant cost on alpha potential.

Given these positive results, we see a variety of potential usages for the ECO₂BAR model. Traditional cash-only credit portfolios are obvious candidates, but we think the strength in the approach is actually the broad array of credit books it can measure. For example, there is no reason why one could not aggregate scores for a hedge-fund levered credit book or for a bank's trading book. The integration of the benefits of green bonds even for more sophisticated credit trading books is also a potentially powerful feature.

At the current stage, it might be premature to develop explicit quantitative goals based on the model, as it still will benefit from refinements (see below), but it is useful for diagnostic evaluation of actual traded portfolios in isolation and versus benchmarks. It could also be used for studying the carbon intensity of different benchmark indices making strategic selection of benchmark indices potentially CO_2 reductive.

6.1 Suggestions for further work

Again, we want to underline that the above analysis has been conducted on a large-cap subset of a complete portfolio. Expanding the data-set in terms of breadth and depth is 'just' a matter of collecting more data and is a natural extension of the work presented in this article. Preliminary analysis of the AP4 credit book indicates that a significant proportion of green bond holdings are not included in the above analysis as they often have been issued by smaller companies. Larger corporations tend to have bigger frictions in terms of rebuilding finance system to cope with the use-of-proceeds tracking often required for green bonds.

A second quite important point of development on the above methodology comes from the complexity around bank balance sheets. As illustrated in Table 1, Financials appear to have a quite small total CO_2 number, despite being very large in terms of their capital structures. Financials typically account for 50% of all corporate bond issuance. What is missing in this data is the balance sheet exposure of banks to potentially high CO_2 emitting sectors. If a certain bank lends 100% of its book to Energy companies, it seems reasonable it should have a much higher CO_2 penalty in some way. In a complete data-set, this would not be a problem, as we would account for the CO_2 at the emitting entity level. In practice, however, most bank loans go to smaller companies which neither contribute Scope 1 and Scope 2 measures, but most importantly, are not traded in the capital markets. A possible critique of our work would be that with large Financials exposure, we omit these effects. We agree that this might be a valid criticism and hope for improved lending based CO_2 measurements in the future. As a counterargument, however, we note that the Financials sector has an ECO_2BAR score of 2 – "Neutral", and that by proxy, Financials with CO_2 intensive loan books might be less prone to achieve low ECO_2BAR with-in sector scores. This is also the sector where there is most complexity with regards to capital structure; future work should attempt to address this.

Lastly, there are natural extensions of the ECO_2BAR model into the passive CO_2 efficiency space. Optimizing on a corporate bond index' CO_2 intensity given input on tracking-error sensitivities should be straightforward, using similar algorithms to those used in low-carbon equity index tracking. Numerically, green bonds could potentially give arise to corner solutions: for a poorly scoring company (example: utility company), an aggresive optimization could land in 100% of risk being allocated to a green bond in the capital structure and nothing to the rest of outstanding bonds. Such properties are generally not desirable to mainstream investors. In theory, the solution is simple as you just have to adjust the "gain" of improving the score versus the "loss" of introducing a higher tracking error in the optimization process. In practice, fine-tuning gain versus loss functions over a diverse, sparse set of data is a challenge, but definitely not impossible and we intend to address this in future work.

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