ESG Investing in Corporate Bonds: Mind the Gap*

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Abstract

This research is the companion study of three previous research projects conducted at Amundi that address the issue of socially responsible investing (SRI) in the stock market (Berg *et al.*, 2014; Bennani *et al.*, 2018a; Drei *et al.*, 2019). The underlying idea of this new study is to explore the impact of ESG investing on asset pricing in the corporate bond market. For that, we apply the methodologies that have been used by Bennani *et al.* (2018a) for testing ESG screening in active and passive management. In particular, we consider the sorted portfolio approach of Fama and French (1992), and the index optimization method that consists in minimizing the tracking risk with respect to the benchmark while controlling for the ESG excess score. Moreover, we test how ESG has impacted the cost of corporate debt. Three investment universes are analyzed: euro-denominated investment grade bonds, dollar-denominated investment grade bonds, and high-yield bonds. Results differ from one universe to another. In particular, we observe that ESG has had a more positive impact on EUR IG bonds in recent years than on the USD IG and HY investment universes. Nevertheless, we observe a common trend that ESG is increasingly integrated into the pricing of corporate bonds and is a concern when building an investment portfolio. Moreover, we also show that ESG does not only affect the demand side, but is also a significant factor when it comes to understanding the supply side.

Keywords: SRI, ESG investing, environmental, social, governance, asset pricing, active management, bond picking, passive management, credit rating, yield spread, cost of debt.

JEL classification: G10, M14, Q01.

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1 Introduction

The financial system is perpetually evolving and price formation is constantly incorporating new information. Investors are paying increasing attention to sustainability criteria, which impacts asset prices. This phenomenon is likely to go on since demand for responsible financial instruments is increasing faster than supply. For instance, Bennani *et al.* (2018a) and Drei *et al.* (2019) showed that the relationship between **ESG** ranked portfolios and performances in the equity market is characterized by a positive premium on best-in-class stocks with respect to worst-in-class stocks, precisely because of the increasing demand for high **ESG** rated securities. These two studies also showed that, during the recent period, **ESG** tilted portfolios in developed countries outperformed traditional capitalization-weighted benchmarks. These studies also raised the question whether or not ESG should be considered as a risk factor. The answer to this question is multifaceted, time-varying and subject to regional biases but they concluded that the ESG style factor is a new common risk factor in the Eurozone. The goal of this research is to extend these studies to the case of corporate bonds and to better understand how ESG impacts this market.

In the case of the stock market, Bennani *et al.* (2018a) considered the impact of ESG screening on three investment strategies: active management, passive management and factor investing. In what follows, we reproduce their methods for the first two strategies. Concerning active management, we implement the Fama-French approach for testing a style factor and investigate the relationship between **ESG** scoring and the performance of sorted portfolios. For passive management, the underlying idea is to replicate the performance of a bond index by improving the **ESG** excess score of the optimized portfolio while controlling its tracking error. Since factor investing is a new topic in corporate bonds (Houweling and Van Zundert, 2017; Ben Slimane *et al.*, 2019), this management style is less mature than in equity markets. In our opinion, it is too soon to test the assumption that ESG may be a new risk factor in the corporate bond market. Therefore, we replace the third dimension by considering the impact of ESG on the cost of debt. While the first two strategies (active and passive management) mainly concern investors, the third dimension concerns both investors and issuers. Of course, a corporation could use equity financing to support its business development. Nevertheless, capital increases are less frequent than debt issues, and the cost of equity is directly related to the stock price. In the case of debt financing, the cost is generally related to the corporation's credit rating. Therefore, the third research focus tests the relationship between **ESG** ratings and the cost of debt.

Concerning active management, most ESG studies have been focused on equities. Some were particularly dedicated to a specific pillar, for instance Gompers *et al.* (2003) on governance, while others used aggregated ESG information (Galema *et al.*, 2008; Jegourel and Maveyraud, 2010). The meta-analysis[1] of Friede *et al.* (2015) showed that we can mostly expect positive results when analyzing the effects of ESG on corporate financial performance. However, compared to equity, there are very few studies that analyze the impact of ESG screening on bonds. For instance, Menz (2010) investigated the relationship between the valuation of Euro corporate bonds and corporate social responsibility (CSR) and concluded that "*CSR has apparently not yet been incorporated into the pricing of corporate bonds*". In a similar way, a neutral or slightly positive effect of socially responsible investment was demonstrated by Derwall and Koedijk (2009) when they compared the performance of SRI and conventional bond funds. This overall neutrality, sometimes associated with a lack of maturity in incorporating ESG information into the bond market, was also highlighted by Bauer *et al.* (2005), Cortez *et al.* (2009), Berg *et al.* (2014) and Bektić (2017). In the CAPM approach, active management performance is captured by measuring the alpha. However,

[1] Aggregating the results of more than 2 000 empirical studies.

Lin *et al.* (2019) constructed industry- and credit rating-controlled quintile portfolios but found no significant evidence of ESG factor contribution to a positive alpha in the bond market. On the contrary, Oikonomou *et al.* (2014) found that corporate social performance is rewarded on the corporate debt market. Results of Leite and Cortez (2016) are slightly positive, but highly dependent on the country. For instance, they found that "*French SRI bond funds match the performance of their conventional peers, German funds slightly outperform and UK funds significantly underperform conventional funds*". Polbennikov *et al.* (2016) also noted a slight outperformance of high **ESG** rated over low **ESG** rated bonds after controlling for varying risk exposures. Hoepner *et al.* (2017a) went deeper in the analysis and showed that, between 2001 and 2014, the absence of ESG related controversies, but more generally of any significant news, led to significant outperformance. This paper found positive results through alternative channels to direct **ESG** score leveraging. In the same line of thought, Hoepner *et al.* (2017b) demonstrated the materiality of ESG engagement by showing that funds from asset management companies without ESG expertise displayed a significantly worse performance over the 2000–2013 period. The underlying conclusion is that despite the fact that the transmission channels are still unclear, ESG matters in fixed-income. Since most of these studies are based on data before 2014, it is interesting to conduct new tests, in particular when we consider one of the main findings of Bennani *et al.* (2018b) and Drei *et al.* (2019). Indeed, these authors showed that there was a radical break around 2013/2014, with a greater incorporation of ESG criteria in North American and Eurozone stock markets. As such, one question is whether we observe similar patterns in the corporate bond market as we do in the equity market.

In the context of active management presented previously, academic studies generally compared the performance of responsible to traditional active funds. Nevertheless, it is extremely difficult to draw conclusions, because these two types of funds may use different management styles in terms of duration, country exposures, etc. Some professionals have preferred to study the impact of ESG screening when an index is tilted using SRI criteria. For instance, Berg *et al.* (2014) used the Merrill Lynch large cap corporate bond index as the benchmark. They then built optimized portfolios by considering some deviations with respect to this benchmark[2]. As already said, they found any significant added value, neither positive nor negative, in terms of outperformance, and concluded that "*SRI management can therefore be a relatively cost-free way to benefit from this evolution*". The two studies by Barclays are also based on optimization techniques, the goal of which is to track and tilt a benchmark. Polbennikov *et al.* (2016) exhibited a modest outperformance, while Dynkin *et al.* (2018) concluded that "*tilting a portfolio systematically to companies with better ESG ratings has been beneficial to performance*". In our study, we consider a similar approach to the one used by these three previous research projects. Using the same methodology developed by Bennani *et al.* (2018a), we build optimized portfolios by improving the **ESG** score and minimizing the tracking risk. Results of optimized portfolios are very important because the comparison with the benchmark is straightforward. Moreover, they can help to confirm or not the results of sorted portfolios.

The relationship between corporate social responsibility and firms' access to finance has been studied by academic researchers and central banks. However, '*access to finance*' is a rather broad concept and, before going through the review of the academic literature on the matter, we qualitatively reiterate the distinction that must be made between cost of capital, cost of equity and cost of debt. With cost of debt, we have the returns demanded

[2]For instance, the modified duration and the option adjusted spread of each sector of the optimized portfolio must be matched within ± 5 basis points of their benchmark counterparts, the weight of each currency cannot deviate from ± 5 basis points, the currency risk is the same for the optimized portfolio and the benchmark, etc.

by lenders while the cost of equity focuses on the returns demanded by the investors that are part of the ownership structure. In other words, the cost of capital includes the cost of debt and the cost of equity[3]. Therefore, it makes sense for the cost of equity to better reflect a certain sensitivity toward extra-financial values. A first reason could be related to how the liquidity of the equity is making it more responsive to available information. Additionally, owners are directly associated with the firm while lenders, that are not part of the board, fix the cost of the debt based purely on financial statements and covenants. However, this two-world vision is biased since investors, and especially institutions such as insurance companies, pension funds and sovereign wealth funds, consider both stocks and bonds in their allocation. If an investor is sensitive to ESG criteria and is a responsible investor, he must apply his ESG policy on both his equity and fixed-income investment, and not only for stocks. Moreover, it is possible that the increasing integration of extra-financial information will spread into credit rating evaluation. For instance, Devalle *et al.* (2017) showed that "*ESG performance, especially concerning social and governance metrics, meaningfully affects credit ratings*". If **ESG** ratings affect credit ratings, we can expect an effect on the bond valuation and the transmission channels to bond markets must be theoretically defined and empirically assessed. From a bond picking perspective, the consensus is that companies with better corporate social responsibility generally face lower capital constraints (Cheng *et al.*, 2014). The causal relationships between environmental, social and governance pillars and the cost of capital have been assessed independently. It appears that corporate governance criteria such as shareholder rights, board independence or corruption, have an importance in defining firms access to equity capital (Ashbaugh-Skaife *et al.*, 2004; Garmaise and Liu, 2005; Chen *et al.*, 2011). Concerning the cost of debt, Mentz (2010) also noted that "*the debt market exhibits a considerable weight for corporate finance, for which reason creditors should basically play a significant role in the transmission of CSR into the valuation of financial instruments*". However, he found that the risk premium for a socially responsible firm was slightly higher. On the other hand, Klock *et al.* (2005) investigated the relationship between the cost of debt and a governance index and found positive results. Their study, which focused on two dimensions of governance (anti-takeover and shareholder protection), demonstrated that these dimensions lower the cost of debt financing. Bhojraj and Sengupta (2003) also demonstrated that corporate governance mechanisms – reduction of agency risk of self-interest management and information risks from partial disclosure – higher bond rating and lower bond yield. The environmental pillar has also been studied. El Ghoul *et al.* (2018) showed that high corporate environmental responsibility reduces the cost of equity capital. Bauer and Han (2010) studied the importance of environmental management for bond investors and their findings suggest that "*firms with environmental concerns pay a premium on their cost of debt financing and are assigned lower credit ratings. In contrast, firms with proactive environmental engagement benefit from a lower cost of debt financing*". If we consider the social pillar, Oikonomou *et al.* (2014) demonstrated that good corporate social responsibility was rewarded by reducing the cost of debt, whereas corporate social transgressions were penalized by increasing bond yield spreads. Cooper and Uzun (2015) showed similar results with higher significance in the manufacturing and financial industries. All in all, these studies seem to show that poor extra-financial performance, whether or not it is captured by credit ratings, increases the risk and therefore the cost of the debt. These studies are not limited to corporations. Indeed, there are some academic articles that provide evidence that socially responsible indicators for countries also have an impact on sovereign bond risk and government borrowing costs (Drut, 2010; Crifo *et al.*, 2017; Margaretic and

[3]The cost of capital is generally calculated by the weighted average cost of capital (WACC), which combines the cost of debt and the cost of equity respectively weighted by the proportion of debt and equity in the capital structure.

Pouget, 2018; Capelle-Blancard *et al.*, 2019). The framework of Crifo *et al.* (2017) is particularly appealing to understand the specific impact of **ESG** rating beyond the effect of the credit rating. This is why we adopt this approach in order to understand the link between **ESG** rating, credit rating and cost of capital for corporations.

This article is structured as follows. The first three sections are dedicated to the euro-denominated investment grade corporate bond markets. We have focused on EUR IG bonds because the ESG market is mainly driven by European investors. In Section Two, we analyze active bond management with ESG screening. For that, we consider the sorted portfolio approach and deduce the composition of the five quintile portfolios. Therefore, we can assess the performance of long/short Q_1 versus Q_5 portfolios. Section Three is dedicated to passive bond management. We consider the approach of optimized portfolios that control the tracking risk with respect to the benchmark while improving the **ESG** score of the corresponding bond index. Section Four analyzes the relationship between the **ESG** score and the yield spread of bonds. This helps to understand how ESG investing has impacted corporations' cost of capital. In Section Five, we extend the three previous approaches to other investment universes. In particular, we consider dollar-denominated corporate bonds, and we also test high-yield bonds to show if the results differ from investment grade bonds. Finally, Section Six offers some concluding remarks.

2 The performance of ESG investing in active management

Academics generally use the real returns of bond mutual funds to evaluate the performance of active management in the fixed-income universe. A typical example is the research of Huij and Derwall (2008), who investigated persistence in the relative performance of bond mutual funds from 1990 to 2003. Another example is the famous article of Blake *et al.* (1993), who compared the performance of bond funds and bond indexes from 1979 to 1988. The first approach allows us to assess the persistence of the performance whereas the second approach indicates if active managers outperform a passive management strategy. These methods are also used to evaluate the performance of SRI fixed-income funds. In this case, we can compare the average return of a set of SRI bond funds to the average return of a set of traditional bond funds. Or we can also compare the average return of a set of SRI bond funds to the return of a multi-index portfolio. In these approaches, the big issue is to compare '*apples to apples*'. Indeed, it is very important that there is no bias between the two samples in terms of duration, credit spread, sectors, etc. Otherwise, the comparison is biased and may be explained because the two samples ultimately exhibit two different investment styles[4]. For instance, Leite and Cortez (2016) compared the performance of SRI fixed-income funds to the performance of conventional bond funds, whereas Derwall and Koedjik (2009) considered an APT model with several risk factors and estimated the alpha generated by SRI screening. Leite and Cortez (2016) found that the results may be related to the holding of sovereign bonds, which is more conservative in SRI bond funds. Derwall and Koedjik (2009) also indicated that their sample of SRI bond funds is heterogenous, because these funds are differently exposed to environmental, social and governance pillars. In what follows, we consider the approach of Bennani *et al.* (2018a) that allows us to control the composition of the bond portfolio. Another advantage is that the results do not depend on the selected sample and the benchmark, but they depend on the methodology of the

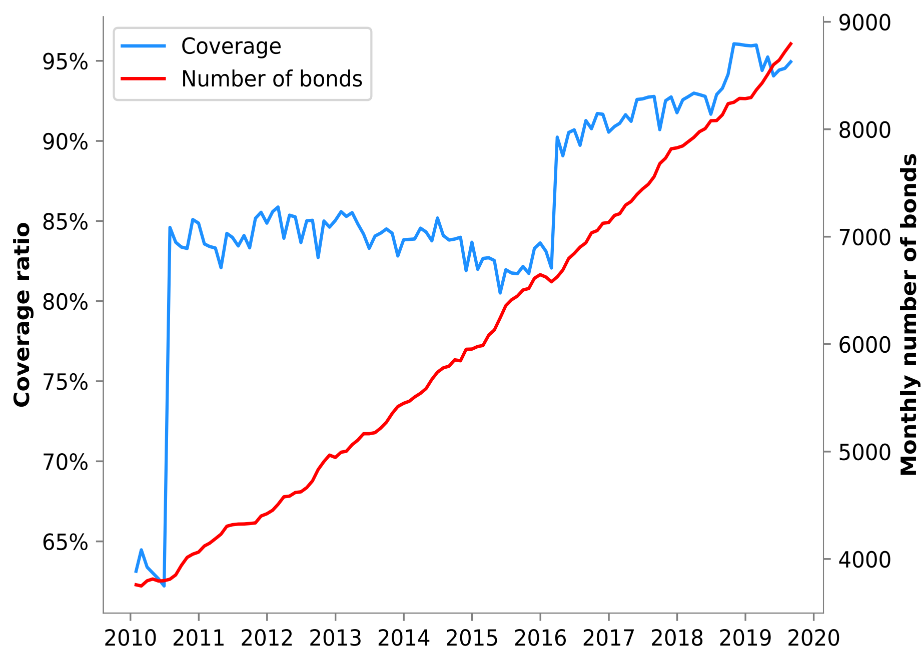
[4]No-one would choose to compare the performance of IG and HY bond funds or the performance of money market and long-term bond funds.

ESG scoring. Nevertheless, the sorted portfolios method gives another interesting point of view about the impact of **ESG** screening on active management.

2.1 Data

The data corresponds to the EUR- and USD-denominated corporate bonds from the Intercontinental Exchange Bank of America Merrill Lynch (ICE BofAML) Large Cap (investment grade) Corporate Bond and Global High Yield Indexes on a monthly basis from January 2010 to August 2019. For each bond, we use the bond return, the modified duration, the credit spread, the yield-to-maturity and the sector classification provided by the index sponsor. We filter the universe by excluding distressed bonds[5] in order to overcome their fanciful credit spreads or returns. To give an idea of the size of the investment universe, the database contains 28 424 separate bonds issued by a total of 5 282 issuers. To each issuer, we associate the **ESG** scores provided by Amundi when it is available. In Figure 1, we report the monthly number of bonds and the coverage ratio of **ESG** rated bonds for the investment grade (EUR + USD) universe. We notice that the number of bonds increases from 2010 to 2020. In 2019, the monthly number of bonds reaches almost 9 000. The coverage ratio also increases during the period, but we observe some jumps because of the coverage improvement of the ESG database. At the beginning of 2010, the coverage ratio was equal to 65%, but it jumps to 85% some months later. Then, we observe another jump in mid-2016. On average, the coverage ratio of **ESG**-rated bonds to the total number of bonds is satisfactory in the IG universe where it exceeds 85% reaching 95% in August 2019.

Figure 1: **ESG**-rated bonds (EUR and USD IG bonds)

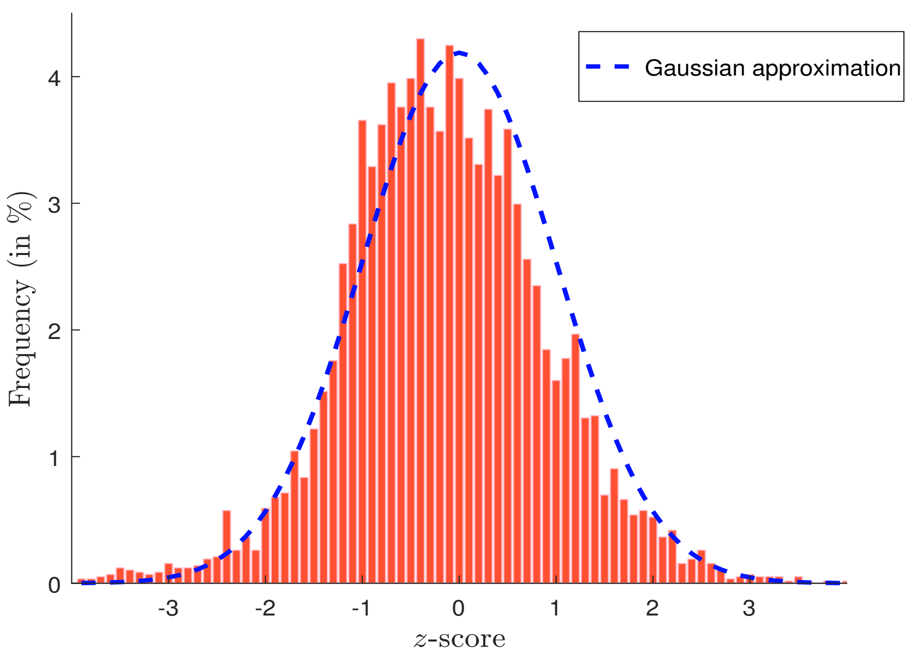


Remark 1 *In what follows, we report the results for the EUR IG universe. The case of USD-denominated and high-yield bonds is discussed in Section 5 on page 24.*

[5] They mainly have a rating below CCC.

For the **ESG** scores, we consider the scoring system provided by the Amundi ESG Research department. For each company and each month, we assess the **ESG** score and its three components: **E** (environmental), **S** (social) and **G** (governance). These scores are based on the data of four external providers and are reviewed and validated by internal ESG analysts. The scores are normalized sector by sector in order to obtain a z-score shape, implying that they generally have a range between -3 and $+3$. This also means that the scores are sector-neutral and they are approximatively distributed as a standard Gaussian probability distribution. An example is given in Figure 2, which shows the empirical distribution of the global **ESG** score at the end of December 2018. The Gaussian approximation is very good even though we observe that the empirical distribution exhibits a low positive skewness. On average, the z-score is then equal to zero if we consider all the corporations together or if we consider a specific sector. The sector-neutrality of z-scores is an important property of many **ESG** scoring systems.

Figure 2: Empirical distribution of the **ESG** score (December 2018)



2.2 The sorted portfolios method

To build the active management strategy, we use the sorted portfolios method of Fama and French (1992). Every month, we rank the bonds with respect to their score, and form five quintile portfolios[6]. Portfolio Q_1 corresponds to the 20% best-ranked bonds, whereas Portfolio Q_5 corresponds to the 20% worst-rated bonds. The selected bonds are then equally-weighted and each portfolio is rebalanced on a monthly basis, implying that the portfolio is invested the first trading day of the month and is held for the entire month. An example with a universe of 10 bonds is provided in Table 1. In the second column, we give the value taken by the **ESG** score. Since there are 10 bonds, each quintile portfolio is composed of two bonds. Q_1 portfolio corresponds to the bonds with the two best scores. This is why Q_1

[6]Given a universe of bonds, each portfolio is composed of 20% bonds.

is composed of the bonds B_8 and B_9. Therefore, we obtain the following sorted portfolios: $Q_1 = (B_8, B_9)$, $Q_2 = (B_4, B_6)$, $Q_3 = (B_1, B_2)$, $Q_4 = (B_3, B_7)$ and $Q_5 = (B_5, B_{10})$. Instead of using the global **ESG** score, we can also use the **ESG** pillars, that is the **E**, **S** and **G** scores.

Table 1: An illustrative example

Bond	**ESG** Score	Rank	Q_i	Weight
B_1	-0.3	6	Q_3	50%
B_2	0.2	5	Q_3	50%
B_3	-1.0	7	Q_4	50%
B_4	1.5	3	Q_2	50%
B_5	-2.9	10	Q_5	50%
B_6	0.8	4	Q_2	50%
B_7	-1.4	8	Q_4	50%
B_8	2.3	2	Q_1	50%
B_9	2.8	1	Q_1	50%
B_{10}	-2.2	9	Q_5	50%

By construction, sorted portfolios are sector-neutral. However, we have performed some clustering because some sectors are small[7]. The aggregations are: banking and insurance into Banking sector, basic industry and technology & electronics into Basic sector, capital goods and transportation into Capital Goods, media and telecommunication into Communication, cyclical sectors (automotive, consumer cyclical, leisure and services) into Consumer Cyclical, non-cyclical sectors (consumer goods, consumer non-cyclical, healthcare and retail) into Consumer Non-Cyclical, and finally utility and energy sectors are gathered together into Utility & Energy sector. Table 2 shows the average weight of the different sectors in the benchmark. The lion's share goes to the Banking sector, followed by the Utility & Energy and Consumer Non-Cyclical sectors. The remaining four sectors each represent less than 10% of the weight. Sorted portfolios are then built using the same structure of weights as the benchmark, while the selected bonds are equally-weighted within a sector.

Table 2: Sector breakdown of the benchmark (EUR IG, 2010–2019)

Sector	Average Weight
Banking	44.76%
Basic	6.49%
Capital Goods	6.92%
Communication	8.88%
Consumer Cyclical	5.43%
Consumer Non-Cyclical	10.24%
Utility & Energy	17.29%

2.3 Results of the long-only sorted portfolios

Results are reported in Tables 3 and 4. For each sorted portfolio, we calculate the annualized credit return and total return. According to ICE (2018), the '*credit return*' indicates the

[7]These aggregations do not impact the results for active and passive management since the z-scores are sector-neutral. However, they are motivated by Section 4, which is dedicated to the cost of capital. Indeed, we use panel data regressions, and using groups with a small number of observations is not relevant.

Table 3: **ESG** sorted portfolios (EUR IG, 2010–2013)

	Benchmark	Q_1	Q_2	Q_3	Q_4	Q_5
Credit return						
Return (%)	2.49	2.52	2.28	2.35	2.55	2.57
Volatility (%)	3.80	3.57	5.07	4.88	4.28	3.80
Sharpe Ratio	0.65	0.71	0.45	0.48	0.60	0.68
Skewness	-0.89	-0.93	-1.01	-0.69	-1.07	-0.92
Kurtosis	1.31	0.95	2.11	1.77	1.74	1.53
Max Drawdown (%)	-6.88	-6.33	-9.63	-9.74	-8.00	-6.90
Hit Ratio (%)			50	56	52	60
Total return						
Return (%)	5.75	5.93	5.64	5.73	5.78	5.64
Volatility (%)	3.76	3.62	4.85	4.68	4.16	3.62
Sharpe Ratio	1.53	1.64	1.16	1.22	1.39	1.55
Skewness	-0.31	-0.24	-0.57	-0.24	-0.48	-0.32
Kurtosis	0.47	-0.67	1.92	1.78	0.80	0.47
Max Drawdown (%)	-2.64	-2.54	-5.11	-4.80	-3.81	-2.86
Hit Ratio (%)			44	54	54	62
Metrics						
DTS	766	738	830	868	842	761
Duration	4.22	4.28	4.26	4.25	4.31	4.01
OAS	183	175	200	208	199	192

Table 4: **ESG** sorted portfolios (EUR IG, 2014–2019)

	Benchmark	Q_1	Q_2	Q_3	Q_4	Q_5
Credit return						
Return (%)	1.54	1.80	1.59	1.52	1.48	1.43
Volatility (%)	2.18	2.27	1.97	2.06	2.12	2.27
Sharpe Ratio	0.71	0.79	0.81	0.74	0.70	0.63
Skewness	-0.18	-0.06	-0.17	-0.12	-0.11	-0.18
Kurtosis	0.33	0.43	0.27	0.59	0.43	0.40
Max Drawdown (%)	-3.05	-3.15	-2.67	-3.06	-3.22	-3.63
Hit Ratio (%)			56	60	54	57
Total return						
Return (%)	3.82	4.20	3.75	3.77	3.71	3.66
Volatility (%)	2.48	2.57	2.33	2.34	2.47	2.58
Sharpe Ratio	1.54	1.63	1.61	1.61	1.50	1.42
Skewness	-0.31	-0.25	-0.39	-0.28	-0.24	-0.43
Kurtosis	0.12	0.28	0.10	0.13	0.18	0.30
Max Drawdown (%)	-3.04	-3.06	-2.77	-2.60	-2.90	-3.98
Hit Ratio (%)			62	63	60	62
Metrics						
DTS	626	628	572	599	618	701
Duration	5.16	5.24	5.07	5.09	5.15	5.18
OAS	113	113	106	110	111	128

Table 5: **E**nvironmental sorted portfolios (EUR IG, 2010–2013)

	Benchmark	Q_1	Q_2	Q_3	Q_4	Q_5
			Credit return			
Return (%)	2.49	2.64	2.58	2.30	1.88	2.33
Volatility (%)	3.80	4.00	5.34	4.32	4.50	3.26
Sharpe Ratio	0.65	0.66	0.48	0.53	0.42	0.71
Skewness	-0.89	-0.99	-1.00	-0.90	-0.82	-1.04
Kurtosis	1.31	1.18	2.92	1.62	1.51	1.13
Max Drawdown (%)	-6.88	-7.05	-10.59	-7.91	-8.35	-5.97
Hit Ratio (%)			48	54	60	60
			Total return			
Return (%)	5.75	5.82	5.89	5.78	5.11	5.56
Volatility (%)	3.76	3.84	5.24	4.24	4.20	3.20
Sharpe Ratio	1.53	1.51	1.12	1.36	1.22	1.74
Skewness	-0.31	-0.31	-0.60	-0.44	-0.26	-0.37
Kurtosis	0.47	-0.35	3.36	0.78	0.76	0.03
Max Drawdown (%)	-2.64	-2.98	-6.11	-3.60	-3.63	-1.98
Hit Ratio (%)			46	50	58	58
			Metrics			
DTS	766	753	873	844	821	724
Duration	4.22	4.19	4.23	4.35	4.24	4.08
OAS	183	186	209	196	196	181

Table 6: **E**nvironmental sorted portfolios (EUR IG, 2014–2019)

	Benchmark	Q_1	Q_2	Q_3	Q_4	Q_5
			Credit return			
Return (%)	1.54	1.70	1.59	1.48	1.39	1.66
Volatility (%)	2.18	2.10	2.05	2.02	2.11	2.21
Sharpe Ratio	0.71	0.81	0.78	0.73	0.66	0.75
Skewness	-0.18	-0.17	-0.05	-0.16	-0.17	-0.07
Kurtosis	0.33	0.16	0.51	0.52	0.48	0.47
Max Drawdown (%)	-3.05	-3.00	-2.67	-2.91	-3.12	-3.35
Hit Ratio (%)			50	57	54	49
			Total return			
Return (%)	3.82	4.19	3.78	3.68	3.73	3.84
Volatility (%)	2.48	2.54	2.35	2.33	2.44	2.52
Sharpe Ratio	1.54	1.65	1.61	1.58	1.53	1.53
Skewness	-0.31	-0.38	-0.30	-0.19	-0.24	-0.31
Kurtosis	0.12	0.32	-0.02	0.13	0.11	0.20
Max Drawdown (%)	-3.04	-3.10	-2.74	-2.49	-2.93	-3.47
Hit Ratio (%)			59	60	54	59
			Metrics			
DTS	626	624	573	586	612	680
Duration	5.16	5.38	5.06	5.04	5.18	5.06
OAS	113	109	106	108	111	128

Table 7: **S**ocial sorted portfolios (EUR IG, 2010–2013)

	Benchmark	Q_1	Q_2	Q_3	Q_4	Q_5
			Credit return			
Return (%)	2.49	2.68	2.01	1.87	2.62	2.79
Volatility (%)	3.80	4.25	4.64	4.52	4.15	3.64
Sharpe Ratio	0.65	0.63	0.43	0.41	0.63	0.77
Skewness	-0.89	-0.90	-0.97	-1.04	-0.81	-0.74
Kurtosis	1.31	0.89	1.56	1.48	2.26	1.31
Max Drawdown (%)	-6.88	-7.92	-9.00	-9.13	-8.00	-5.97
Hit Ratio (%)			48	58	50	48
			Total return			
Return (%)	5.75	6.29	5.39	5.13	5.88	5.69
Volatility (%)	3.76	4.16	4.43	4.24	4.06	3.55
Sharpe Ratio	1.53	1.51	1.22	1.21	1.45	1.60
Skewness	-0.31	-0.32	-0.43	-0.51	-0.26	-0.25
Kurtosis	0.47	-0.47	1.22	0.64	1.08	0.57
Max Drawdown (%)	-2.64	-3.24	-4.30	-4.13	-3.98	-2.46
Hit Ratio (%)			48	62	56	60
			Metrics			
DTS	766	827	830	836	773	729
Duration	4.22	4.42	4.31	4.29	4.07	3.98
OAS	183	189	199	199	191	185

Table 8: **S**ocial sorted portfolios (EUR IG, 2014–2019)

	Benchmark	Q_1	Q_2	Q_3	Q_4	Q_5
			Credit return			
Return (%)	1.54	1.79	1.72	1.46	1.57	1.37
Volatility (%)	2.18	2.50	2.17	1.97	1.92	2.30
Sharpe Ratio	0.71	0.71	0.79	0.74	0.82	0.60
Skewness	-0.18	-0.10	-0.07	-0.24	0.01	-0.16
Kurtosis	0.33	0.40	0.21	0.45	0.51	0.73
Max Drawdown (%)	-3.05	-3.44	-2.98	-3.03	-3.16	-3.52
Hit Ratio (%)			57	59	56	59
			Total return			
Return (%)	3.82	4.24	4.06	3.67	3.67	3.68
Volatility (%)	2.48	2.70	2.53	2.28	2.29	2.62
Sharpe Ratio	1.54	1.57	1.60	1.61	1.60	1.41
Skewness	-0.31	-0.17	-0.45	-0.22	-0.17	-0.39
Kurtosis	0.12	0.25	0.52	0.02	0.01	0.27
Max Drawdown (%)	-3.04	-3.12	-3.06	-2.60	-2.45	-4.04
Hit Ratio (%)			60	59	63	65
			Metrics			
DTS	626	664	619	581	593	704
Duration	5.16	5.30	5.24	5.00	4.99	5.27
OAS	113	117	112	109	110	127

Table 9: **G**overnance sorted portfolios (EUR IG, 2010–2013)

	Benchmark	Q_1	Q_2	Q_3	Q_4	Q_5
			Credit return			
Return (%)	2.49	2.44	2.36	2.65	2.45	2.18
Volatility (%)	3.80	3.18	4.64	4.33	4.75	4.18
Sharpe Ratio	0.65	0.77	0.51	0.61	0.52	0.52
Skewness	-0.89	-0.99	-0.74	-1.02	-1.05	-0.91
Kurtosis	1.31	1.06	2.04	1.63	1.60	1.42
Max Drawdown (%)	-6.88	-5.52	-8.56	-8.20	-9.17	-8.23
Hit Ratio (%)			44	31	33	46
			Total return			
Return (%)	5.75	5.75	5.65	5.85	5.71	5.49
Volatility (%)	3.76	3.42	4.49	4.16	4.43	3.95
Sharpe Ratio	1.53	1.68	1.26	1.41	1.29	1.39
Skewness	-0.31	-0.25	-0.20	-0.59	-0.50	-0.27
Kurtosis	0.47	-0.12	1.82	1.03	0.87	0.09
Max Drawdown (%)	-2.64	-2.08	-4.14	-4.08	-4.55	-3.51
Hit Ratio (%)			42	44	33	46
			Metrics			
DTS	766	684	798	809	858	862
Duration	4.22	4.25	4.20	4.16	4.15	4.24
OAS	183	161	194	204	210	204

Table 10: **G**overnance sorted portfolios (EUR IG, 2014–2019)

	Benchmark	Q_1	Q_2	Q_3	Q_4	Q_5
			Credit return			
Return (%)	1.54	1.49	1.78	1.54	1.62	1.35
Volatility (%)	2.18	2.06	2.11	2.06	2.27	2.21
Sharpe Ratio	0.71	0.72	0.85	0.75	0.71	0.61
Skewness	-0.18	-0.12	0.05	-0.18	-0.14	-0.17
Kurtosis	0.33	0.60	0.73	0.35	0.31	0.26
Max Drawdown (%)	-3.05	-3.24	-2.72	-3.07	-3.02	-3.38
Hit Ratio (%)			41	49	49	50
			Total return			
Return (%)	3.82	3.84	4.05	3.69	4.04	3.46
Volatility (%)	2.48	2.43	2.39	2.39	2.60	2.48
Sharpe Ratio	1.54	1.58	1.69	1.54	1.56	1.39
Skewness	-0.31	-0.25	-0.19	-0.42	-0.32	-0.43
Kurtosis	0.12	0.41	-0.05	0.51	-0.00	0.27
Max Drawdown (%)	-3.04	-2.99	-2.69	-2.79	-3.10	-3.47
Hit Ratio (%)			46	51	40	51
			Metrics			
DTS	626	592	597	612	665	676
Duration	5.16	5.15	5.02	5.12	5.35	5.11
OAS	113	108	112	111	116	124

return in excess of the total return of a risk-matched basket of governments or interest rate swaps, thus neutralizing the interest rate and yield curve risk and isolating the portion of performance attributed solely to credit and optionality risks[8]. The total return corresponds to the mark-to-market return of the portfolio, including bond price and coupon effects. We have split the 2010–2019 period into two sub-periods: before 2014 and since 2014. The reason for this split is the results of Bennani *et al.* (2018a), who found that there is a radical break around 2013/2014. For the two periods, Portfolio Q_1 exhibits the highest total return and Sharpe ratio. It is almost the case for the credit return. For the total return, we generally observe a decreasing function with respect to Portfolios Q_1 to Q_5. Regarding volatility, spread and maximum drawdown measures, we observe an inverted U-shape before 2014 and a U-shape since 2014. On the contrary, the duration is almost the same across the five quintile portfolios. It follows that the average spread and DTS related to Portfolio Q_1 are lower than those of Portfolio Q_5. The hit ratio corresponds to the number of months (expressed in %), where Q_1 outperforms the other sorted portfolios. For instance, the hit ratio Q_1/Q_5 is equal to 62% if we consider total return. This means that Portfolio Q_1 outperforms Portfolio Q_5 62% of the time on average. We notice that these hit ratios are generally larger than 50%, meaning that the best-in-class portfolio generally outperforms the other quintile portfolios, and not only the worst-in-class portfolio.

Remark 2 *Another interesting point is that Portfolio Q_1 systematically outperforms the benchmark. However, we reiterate that this is purely theoretical since we do not include transaction and rebalancing costs, and the investment capacity of sorted portfolios is lower than the benchmark since we use an equally-weighted scheme when we form the quintile portfolios.*

The previous results concern the global **ESG** score. If we consider the individual pillars **E**, **S** and **G**, the results are similar, with some exceptions. We observe again the same shape listed above for the volatility, spread, DTS and maximum drawdown measures. In most cases, the average OAS related to Portfolio Q_1 is lower than the one related to Portfolio Q_5. The exceptions are **E**nvironmental and **S**ocial before 2014. In terms of performance, Portfolio Q_1 stands out from the crowd in all pillars excluding **G**overnance where returns are in the middle of the table[9].

2.4 Results of the long/short $Q_1 - Q_5$ strategy

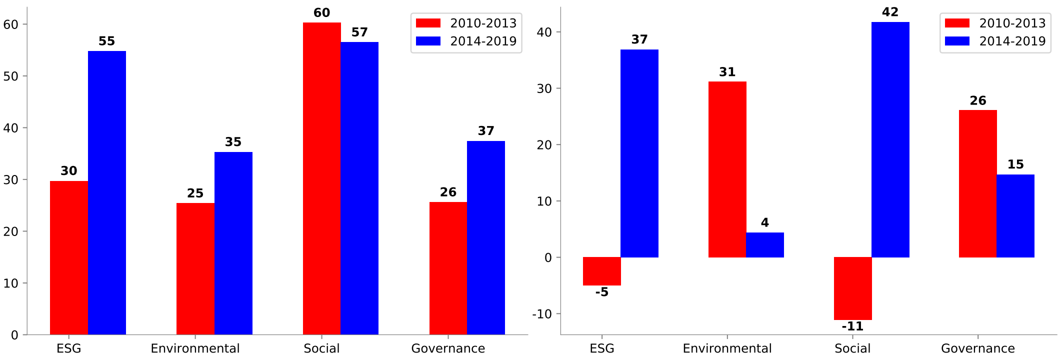
We now consider the strategy that is long in Portfolio Q_1 and short in Portfolio Q_5. In Figure 3, we can see how incorporating ESG and its subdimensions into the EUR IG corporate bond market has changed. In terms of total return, all $Q_1 - Q_5$ portfolios exhibit a positive performance, both in 2010–2013 and 2014–2019. We also see an improvement for the **ESG**, **E**, and **G** scores. If we consider the credit return measure, **ESG** and **S** long/short portfolios exhibited negative performances before 2014, whereas all the components have posted positive performances since 2014. For instance, the annualized credit return of the **ESG** long/short portfolio is equal to 37 bps between 2014 and 2019. These results are remarkable because Portfolio Q_1 has generally a lower carry than portfolio Q_5, when it is measured by the OAS or DTS. This means that market-to-market effects compensate the short carry exposure. Among the three pillars, **S**ocial is the new winning pillar[10].

[8] See the definition of the excess return in ICE (2018) on page 23. We rename it in credit return, in order to avoid confusion of the term excess return which is already used when considering the passive management strategy.

[9] The same conclusion applies to the hit ratio.

[10] During the 2010–2013 period, the winning pillar was **E**nvironmental.

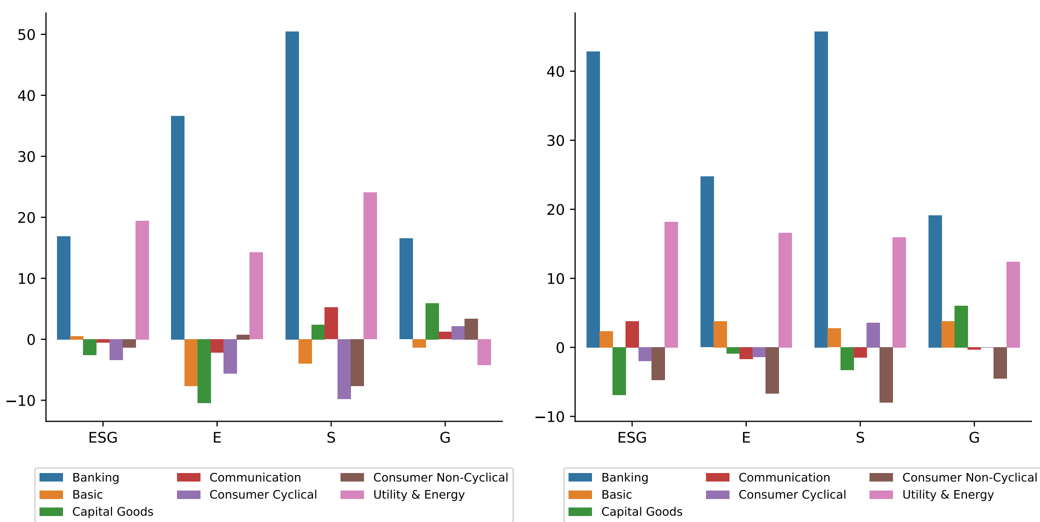
Figure 3: Annualized return in bps of the long/short $Q_1 - Q_5$ strategy (EUR IG, 2010–2019)



(a) Total return (b) Credit return

In Figures 4 and 5, we report the contribution of each sector. We note that the performance of the long/short portfolios is driven as expected by two main sectors: Banking, and Utility & Energy[11]. In particular, we observe an improvement for the Banking sector, which posted a negative contribution to the **ESG** score during the 2010–2013 period. We also observe that the other sectors generally made poor (positive or negative) contributions. If we consider the contributions larger than 5 bps and if we focus on the most recent period, we observe negative contributions from Capital Goods to the **ESG** and **S** portfolios, Communication to the **E** portfolio and Consumer Non-cyclical to the **G** portfolio.

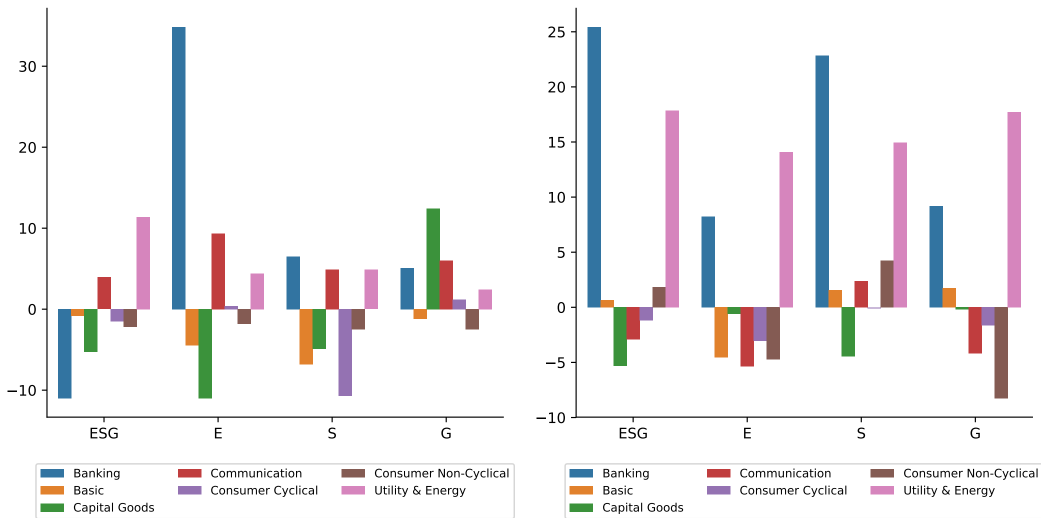
Figure 4: Contribution in bps to total return (EUR IG, 2010–2019)



(a) 2010–2013 (b) 2014–2019

[11]We reiterate that the sorted portfolios are risk-neutral with respect to the benchmark, and these two sectors represent more than 60% of the allocation.

Figure 5: Contribution in bps to credit return (EUR IG, 2010–2019)



(a) 2010–2013

(b) 2014–2019

3 Implementing ESG screening in passive management

The goal of passive fund managers is to replicate the performance of a market index by holding the same securities or a sampling of the securities that comprise the index. Therefore, they track the index portfolio by exhibiting the same risk/return characteristics. In the fixed-income space, modified duration (MD) and duration-times-spread (DTS) are the most widely used risk metrics. Indeed, historical price volatility, which is used to measure the risk of equity portfolios, is not a reliable predictor of bond volatility, since bonds are less frequently traded and mature over time. This is why fund managers use modified duration, which is the sensitivity of the bond return to interest risk, and DTS, which measures the systematic exposure to credit risk by quantifying sensitivity to a shift in the yield spread (Ben Dor *et al.*, 2007).

The goal of ESG investing is to select assets that have a better **ESG** score than the investment universe. In the case of active management, we can implement a best-in-class investment policy (by selecting the assets with the highest scores), a worst-in-class investment policy (by excluding the assets with the lowest scores) or a full integration policy. In the case of passive management, the same policies can be implemented. In what follows, we focus on the integration policy, which consists in improving the **ESG** score of the tilted portfolio compared to the **ESG** score of the index portfolio. Most of the time, passive investors also add an exclusion layer. However, we do not consider this case, because the results depend on the threshold score of the exclusion policy and are then more difficult to interpret.

3.1 The optimization problem

For the purpose of ESG integration in passive management, we adopt the same methodology developed by Bennani *et al.* (2018a) for equities. Let $\mathcal{S}_i$ be the **ESG** score of the asset i. If we consider a portfolio $x = (x_1, \ldots, x_n)$, we calculate the **ESG** score of this portfolio as the weighted average of the individual scores:

$$\mathcal{S}(x) = \sum_{i=1}^{n} x_i \cdot \mathcal{S}_i$$

If we consider a benchmark[12] $b = (b_1, \ldots, b_n)$, we can calculate the **ESG** excess score of Portfolio x with respect to Benchmark b as follows:

$$\begin{aligned}\mathcal{S}(x \mid b) &= \sum_{i=1}^{n} (x_i - b_i) \cdot \mathcal{S}_i \\ &= \mathcal{S}(x) - \mathcal{S}(b)\end{aligned}$$

Let us reiterate here that **ESG** scores are in fact z-scores between -3 and $+3$ with an average that is equal to zero. This is why we generally observe that $\mathcal{S}(b) \approx 0$ because there is no reason that a benchmark such as a capitalization-weighted index has a positive or a negative **ESG** score. It is generally a neutral **ESG** portfolio. On the contrary, an **ESG** portfolio x aims to have a better **ESG** score than the benchmark: $\mathcal{S}(x \mid b) > 0$. When building an optimized **ESG** portfolio, there is of course a trade-off between the **ESG** excess score $\mathcal{S}(x \mid b)$ and the active (or tracking) risk $\mathcal{R}(x \mid b)$ with respect to the benchmark. For instance, if the active risk is equal to zero, the **ESG** excess score will be equal to zero. If we consider a high **ESG** score (e.g. larger than 1.5), we also have to incur a high active risk. Therefore, the optimization problems becomes:

$$x^{\star}(\gamma) = \arg\min \mathcal{R}(x \mid b) - \gamma \cdot \mathcal{S}(x \mid b)$$

If γ is set to zero, the optimized portfolio $x^{\star}(0)$ is the benchmark portfolio b. If γ is set to infinity, the optimized portfolio $x^{\star}(\infty)$ corresponds to the bond with the largest z-score. The parameter γ can then be calibrated in order to target a given excess score $\mathcal{S}^{\star}$: $\mathcal{S}(x \mid b) = \mathcal{S}^{\star}$. In our analysis, the targeted excess score will take its values from 0 to 1.

An issue when building tilted portfolios is the choice of the active/tracking risk. In the case of equities, $\mathcal{R}(x \mid b)$ is defined as the tracking error volatility of Portfolio x with respect to Benchmark b. In the case of bonds, we generally use two measures. First, we can match the modified duration of the several sectors that are in the benchmark. Let $\mathcal{R}_{\mathrm{MD}}(x \mid b)$ be the modified duration risk of Portfolio x with respect to Benchmark b. We have:

$$\begin{aligned}\mathcal{R}_{\mathrm{MD}}(x \mid b) &= \sum_{j=1}^{N_{\mathcal{S}ector}} \left(\mathrm{MD}_j(x) - \mathrm{MD}_j(b)\right)^2 \\ &= \sum_{j=1}^{N_{\mathcal{S}ector}} \left(\left(\sum_{i \in \mathcal{S}ector(j)} x_i \cdot \mathrm{MD}_i\right) - \left(\sum_{i \in \mathcal{S}ector(j)} b_i \cdot \mathrm{MD}_i\right)\right)^2\end{aligned}$$

where $N_{\mathcal{S}ector}$ is the number of sectors, $\mathrm{MD}_j(x)$ and $\mathrm{MD}_j(b)$ are the contributions to the modified duration of Sector j in Portfolios x and b, and MD_i is the modified duration of Bond i. An alternative is to use the DTS risk measure:

$$\begin{aligned}\mathcal{R}_{\mathrm{DTS}}(x \mid b) &= \sum_{j=1}^{N_{\mathcal{S}ector}} \left(\mathrm{DTS}_j(x) - \mathrm{DTS}_j(b)\right)^2 \\ &= \sum_{j=1}^{N_{\mathcal{S}ector}} \left(\left(\sum_{i \in \mathcal{S}ector(j)} x_i \cdot \mathrm{DTS}_i\right) - \left(\sum_{i \in \mathcal{S}ector(j)} b_i \cdot \mathrm{DTS}_i\right)\right)^2\end{aligned}$$

[12] In our case, the benchmark is represented by an index portfolio.

where $\mathrm{DTS}_j(x)$ and $\mathrm{DTS}_j(b)$ are the contributions to the DTS of Sector j in Portfolios x and b, and DTS_i is the DTS of Bond i. We can also define a hybrid approach, where the risk measure is an average of the MD and DTS active risks:

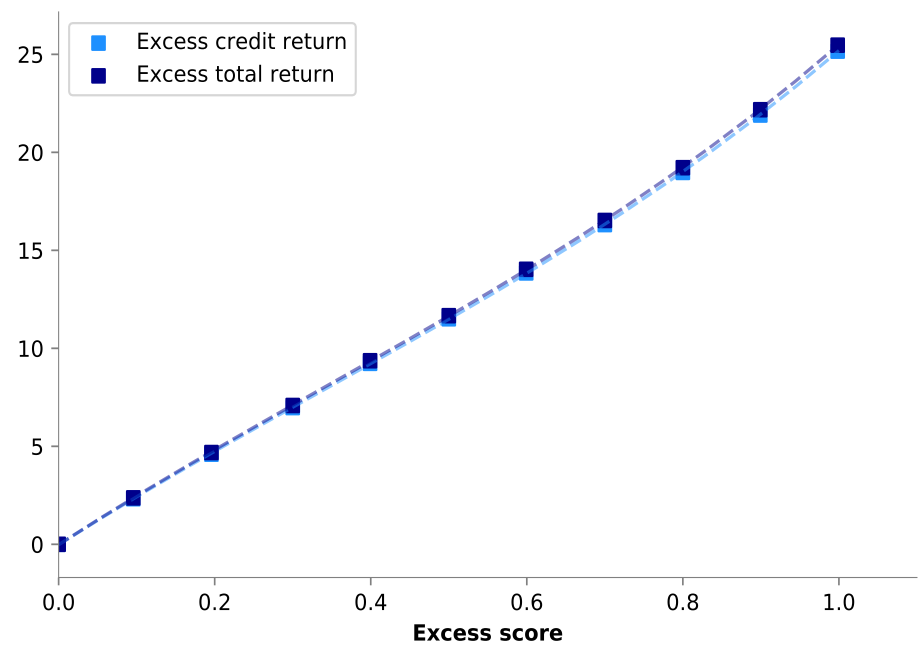
$$\mathcal{R}(x \mid b) = \frac{1}{2}\mathcal{R}_{\mathrm{MD}}(x \mid b) + \frac{1}{2}\mathcal{R}_{\mathrm{DTS}}(x \mid b)$$

In fact, we can interpret $\mathcal{R}_{\mathrm{MD}}(x \mid b)$ as an interest rate risk measure and $\mathcal{R}_{\mathrm{DTS}}(x \mid b)$ as a credit risk measure, while $\mathcal{R}(x \mid b)$ is an integrated interest rate/credit risk measure.

Remark 3 *It is worth highlighting that optimized portfolios are theoretical as no minimum lot sizes*[13]*, lot sizes*[14]*, liquidity costs and transaction costs are considered.*

3.2 Tracking error of ESG tilted portfolios

Figure 6: Tracking error in bps of **ESG** optimized portfolios (EUR IG, 2010-2019)



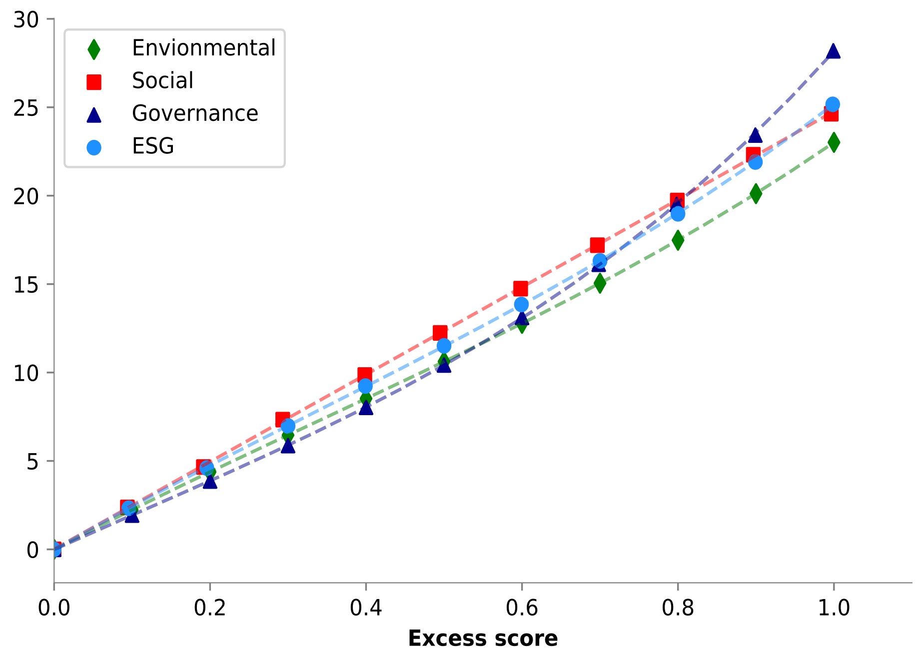
Starting from an **ESG** excess score equal to zero, we progressively increase the **ESG** score of the optimized portfolio until it reaches $\mathcal{S}^\star = 1$, while minimizing the integrated risk $\mathcal{R}(x \mid b)$ with respect to the ICE BofAML EUR IG Bond Index, which is our benchmark[15]. In Figure 6, we report the relationship between the **ESG** excess score $\mathcal{S}(x \mid b)$ and the ex-post tracking error (TE), which is calculated using the two types of returns: total return and credit return. We note that the tracking error is almost the same whether we use the total

[13] The minimum lot size is the minimum nominal amount of a bond we can trade.

[14] This is the incremental nominal amount of bond that can be traded.

[15] In Appendix A.1 on page 31, we report the results based on the interest rate risk $\mathcal{R}_{\mathrm{MD}}(x \mid b)$ or the credit risk $\mathcal{R}_{\mathrm{DTS}}(x \mid b)$ on a standalone basis. We notice that they may differ from the integrated risk measure. However, the difference is mainly explained by the fact that MD or DTS optimized portfolios take some active bets in terms of credit spread and duration (see Figures 36 and 37 on page 43).

Figure 7: Tracking error in bps of optimized portfolios (EUR IG, 2010-2019)



return or the credit return. Moreover, we verify that the increase in the **ESG** excess score leads to an increase of the ex-post tracking error. For instance, targeting $\mathcal{S}^{\star} = 1$ requires accepting a tracking error of 25 bps. We retrieve the results we have found for equity indices (Bennani *et al.*, 2018a; Drei *et al.*, 2019): "*Investors must accept a tracking error risk if they want to implement ESG in a passive management framework, where the benchmarks correspond to market capitalization-weighted indices*". Figure 7 shows the decomposition of the tracking error[16] between **E**, **S** and **G** scores. The different pillars present the same tracking error range until the excess score reaches 0.9. Above this threshold, **G** contribution to the TE increases in relative terms compared to the other pillars. This result differs from the one we obtained for equities, since the **G** contribution is higher whatever the targeted excess score $\mathcal{S}^{\star}$.

3.3 Performance of ESG tilted portfolios

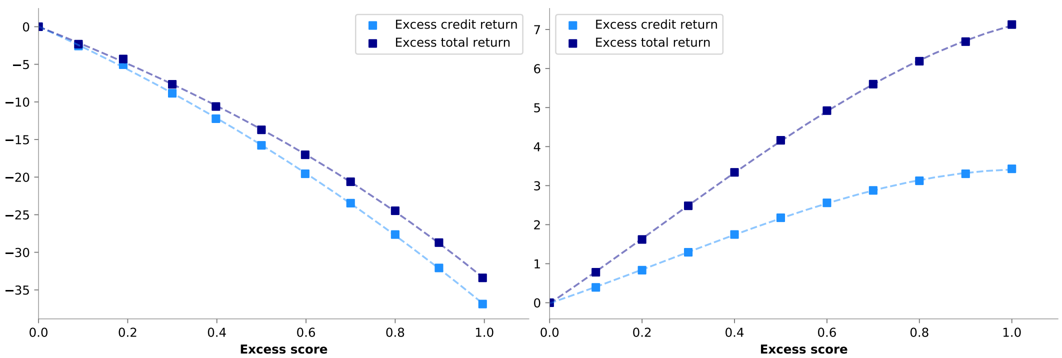
Figure 8 shows the impact of the ESG integration on the excess return of optimized portfolios for the 2010–2013 and 2014–2019 periods. During the first period, the excess return is negative, meaning that ESG passive investors were penalized. This is particularly true when optimized portfolios targeted high excess scores. For instance, an **ESG** excess score of +1 produced an underperformance of −35 bps per year. Since 2014, a small positive outperformance is observed peaking at +7 bps when the **ESG** tilt is set to +1. We also notice an increasing relationship between the **ESG** excess score and the excess return.

Figure 9 displays the contribution of the different sectors to the excess total return[17]. It follows that the underperformance observed in the first period and the relative outperformance of the second period are mainly explained by the performance of the Banking sector

[16] We only report the relationship with the credit return, because the result is the same for the total return.
[17] See Figure 29 on page 41 when the excess total return is replaced by the excess credit return.

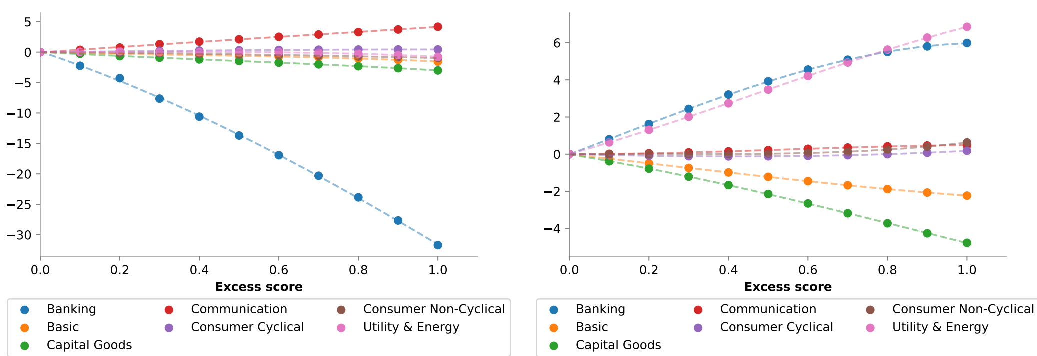
in both periods and, to a lesser extent, the Utility & Energy sector after 2014. We also note the positive performance of the Communication sector in both periods.

Figure 8: Excess return in bps of **ESG** optimized portfolios (EUR IG, 2010–2019)



(a) 2010–2013 (b) 2014–2019

Figure 9: Contribution in bps to excess total return (EUR IG, 2010–2019, **ESG**)



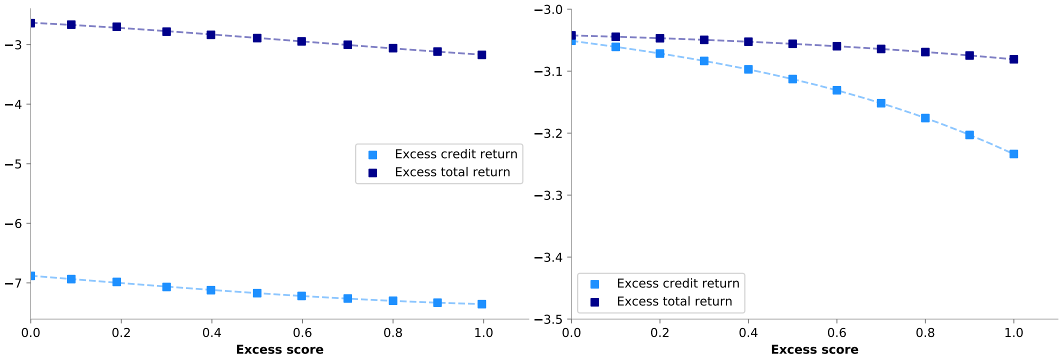
(a) 2010-2013 (b) 2014-2019

The largest peak-to-trough loss, as measured by the maximum drawdown, is a decreasing function of the excess score. Drawdowns are higher as far as excess credit returns are concerned (Figure 10). This result is consistent with the fact that the credit component is more volatile in a standalone basis. In the first period, we also notice that drawdowns are around -3% for the total return and are around -7% for the credit return. After 2014, drawdowns evolve in a narrow range around -3%.

3.4 Results using the individual pillars

We now consider the individual pillars (**E**nvironmental, **S**ocial and **G**overnance) and compare their performance in Figure 11. During the 2010–2013 period, all pillars underperform. Of the three pillars, **E**nvironmental is the best pillar and its excess return declines to -21 bps when the targeted excess score is set to $+1$. **G**overnance is the worst pillar, and its excess return reaches -46 bps for the same tilt. After 2014, excess returns are between 0

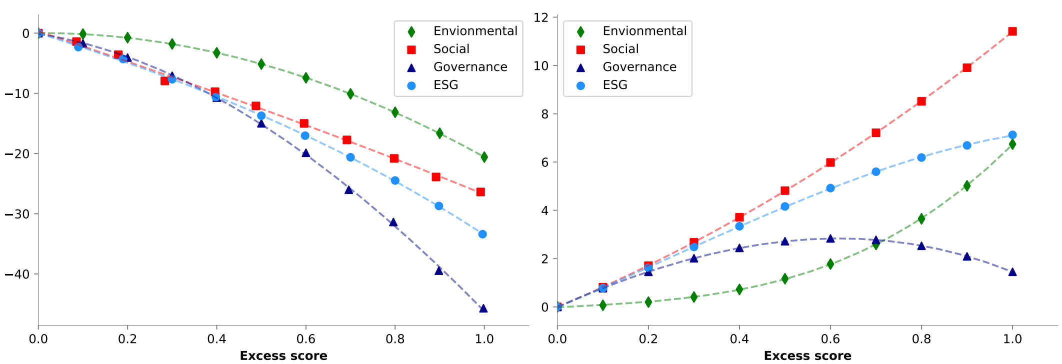
Figure 10: Maximum drawdown in % of optimized portfolios (EUR IG, 2010–2019, **ESG**)



(a) 2010-2013 (b) 2014-2019

and +12 bps. **S**ocial is the winning pillar and outperforms significantly, peaking at +11 bps. Excess returns of **E**nvironmental and **G**overnance seem to be negatively correlated.

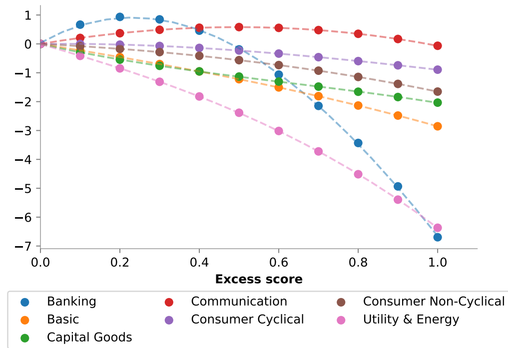
Figure 11: Excess total return in bps of optimized portfolios (EUR IG, 2010–2019)



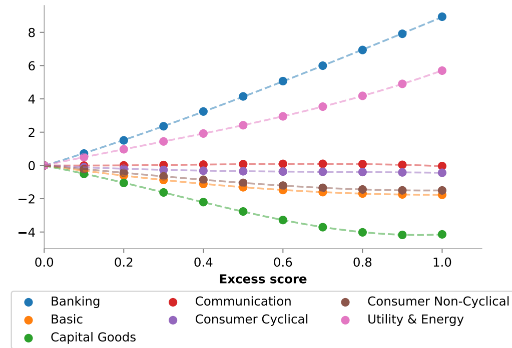
(a) 2010–2013 (b) 2014–2019

Figures 12, 13 and 14 respectively show the contributions to excess return of the **E**, **S** and **G** pillars. The underperformance in the first period is mainly attributed to the Banking sector in the case of the **S**ocial pillar, and to both the Banking and Utility & Energy sectors for the **E**nvironmental and **G**overnance pillars. In the second period, the contribution of the Utility & Energy sector is positive in all pillars and increases with respect to the excess score. The Banking sector contributes positively and to a greater extent in **E** and **S** pillars but presents a symmetric parabola peaking at +2 bps when it comes to **G**. With the exception of Capital Goods, the other sectors have small, generally negative, contributions. Capital Goods contributes negatively in the case of **E** and **S**, almost half the contribution of the Banking sector.

Figure 12: Contribution in bps to excess total return (EUR IG, 2010–2019, **E**nvironmental)

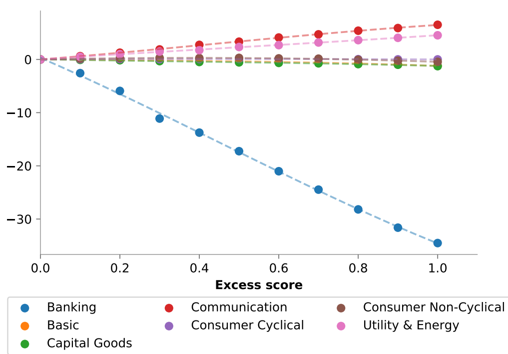


(a) 2010–2013

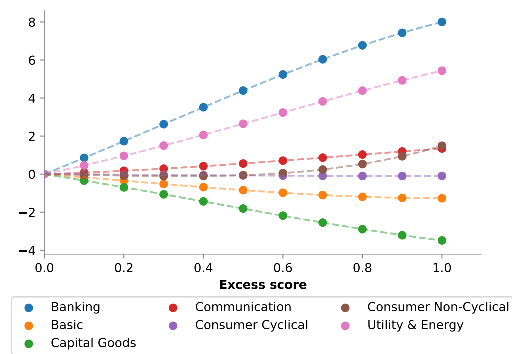


(b) 2014–2019

Figure 13: Contribution in bps to excess total return (EUR IG, 2010–2019, **S**ocial)

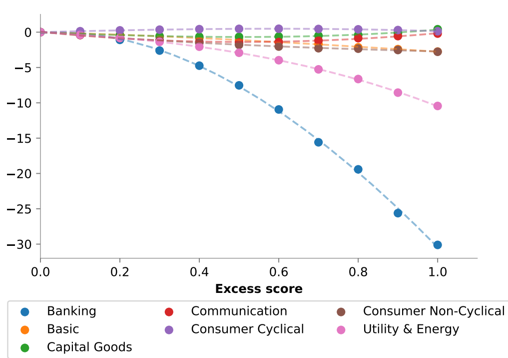


(a) 2010–2013

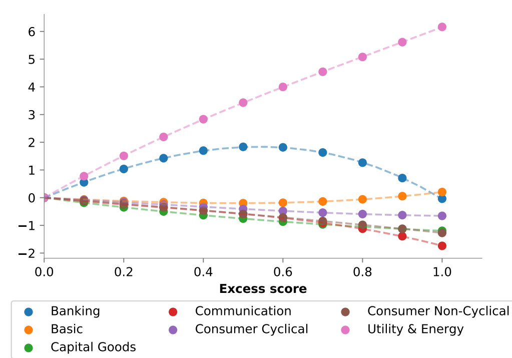


(b) 2014–2019

Figure 14: Contribution in bps to excess total return (EUR IG, 2010–2019, **G**overnance)



(a) 2010–2013



(b) 2014–2019

4 Relationship between ESG scores and yield spreads

As explained in the introduction, there is some evidence that ESG impacts the cost of capital[18]. A bad **ESG** rating can then increase the cost of equity or the cost of debt. However, the relationship between **ESG** rating and the cost of capital is not straightforward since we need to precisely define this latter concept. For example, there are several approaches for calculating the cost of equity (dividend capitalization model, CAPM formula, etc.), and its computation is sensitive to assumptions and parameters. On the contrary, the cost of debt is easier to calculate since it is equal to the risk-free rate plus a credit premium, which can be proxied by the yield spread. However, demonstrating that ESG impacts the cost of borrowing requires us to isolate the marginal effects of ESG with respect to other explanatory variables. For example, it is obvious that credit ratings also influence the cost of debt. The big challenge is then to build an integrated model that considers all the factors that can affect the cost of debt. For that, we use the approach developed by Crifo *et al.* (2017) that measures the marginal effect of **ESG** ratings. These authors have tested their model on sovereign bonds. Using another set of explanatory variables, we apply this approach to corporate bonds.

4.1 The interconnectedness between ESG ratings and credit ratings

In Table 11, we report the statistics of the **ESG** score with respect to the credit rating. By construction, the mean and the standard deviation of the **ESG** score are equal to zero and one when we consider all the corporations, because the **ESG** score is a normalized z-score. We verify that the standard deviation is close to one and does not significantly depend on the credit rating. On the contrary, we notice that the mean **ESG** score depends on the credit rating. For instance, the **ESG** score takes a value of 0.384 on average when we consider AAA- or AA-rated bonds[19], whereas it is equal to -0.381 for CCC-rated bonds. We reiterate that credit ratings have been showed to be correlated to **ESG** signals (Devalle *et al.*, 2017). For instance, Ashbaugh-Skaife *et al.* (2006) demonstrated that firms with strong governance benefits from higher credit rating. Figure 15 shows that this relationship can indeed be extended to **ESG** scores.

Table 11: **ESG** score with respect to the credit rating (2010–2019)

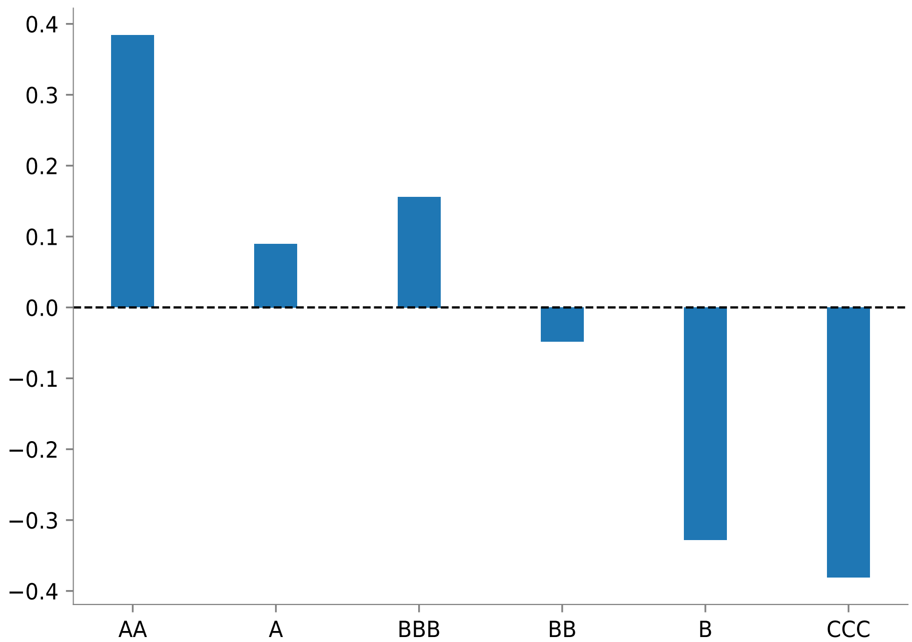
Rating	Mean	Median	Stdev	Skewness	t-statistic
AA	0.384	0.452	1.058	-0.020	3.266
A	0.090	0.088	1.056	0.011	1.676
BBB	0.156	0.101	0.997	0.122	3.945
BB	-0.048	-0.109	1.002	0.131	-0.795
B	-0.328	-0.414	0.957	0.196	-4.534
CCC	-0.381	-0.394	1.095	0.129	-2.525
All ratings	0.046	0.000	1.031	0.092	1.804

Nevertheless, it does not mean that **ESG** ratings and credit ratings give the same information about a corporation. If it was the case, we would observe a perfect correlation, meaning that the range will be between -3 and $+3$, and not between -0.381 and $+0.384$.

[18] See for instance Bhojraj and Sengupta (2003), Klock *et al.* (2005), Cooper and Uzun (2015), and El Ghoul *et al.* (2018).

[19] In the sequel, We note AA the cluster including both AAA- or AA-rated bonds.

Figure 15: Average **ESG** score with respect to the credit rating (2010–2019)



4.2 An integrated credit-ESG model

Barth *et al.* (2019) recently showed that investors may improve credit risk management by considering ESG factors in Europe. To investigate the relationship between ESG and credit spread, we adopt the model introduced by Crifo *et al.* (2017). We run a panel data regression model with fixed time effects using all the **ESG** rated bonds in the 2010–2019 period. Let $\mathrm{OAS}_{i,t}$ be the option adjusted spread of Bond i at time t. We assume that the logarithm of the yield spread depends on the **ESG** score and other control variates:

$$\begin{aligned} \ln \mathrm{OAS}_{i,t} \quad = \quad & \alpha_t + \beta_{esg} \cdot \mathcal{S}_{i,t} + \beta_{md} \cdot \mathrm{MD}_{i,t} + \sum_{j=1}^{N_{\mathcal{S}ector}} \beta_{\mathcal{S}ector}(j) \cdot \mathcal{S}ector_{i,t}(j) + \\ & \beta_{sub} \cdot \mathrm{SUB}_{i,t} + \sum_{k=1}^{N_{\mathcal{R}ating}} \beta_{\mathcal{R}ating}(k) \cdot \mathcal{R}ating_{i,t}(k) + \varepsilon_{i,t} \end{aligned} \tag{1}$$

where $\mathcal{S}_{i,t}$ is the **ESG** z-score of Bond i at time t, $\mathrm{SUB}_{i,t}$ is a dummy variable accounting for subordination of the bond, $\mathrm{MD}_{i,t}$ is the modified duration, $\mathcal{S}ector_{i,t}(j)$ is a dummy variable for the j^{th} sector[20] and $\mathcal{R}ating_{i,t}(k)$ is a dummy variable for the k^{th} rating[21]. As previously, we consider the seven sectors (Banking, Capital Goods, Basic, Communication, Consumer Cyclical, Consumer Non-Cyclical and Utility & Energy), whereas ratings are grouped into the following six clusters: AA[22], A, BBB, BB, B and CCC[23].

[20] We have $\mathcal{S}ector_{i,t}(j) = 1$ if the i^{th} corporation belongs to the j^{th} sector at time t. Otherwise, $\mathcal{S}ector_{i,t}(j)$ is equal to zero.

[21] We have $\mathcal{R}ating_{i,t}(k) = 1$ if the i^{th} corporation has the k^{th} credit rating at time t. Otherwise, $\mathcal{R}ating_{i,t}(k)$ is equal to zero.

[22] We recall that it corresponds to the AAA–AA cluster.

[23] In order to identify and estimate the panel regression model, we omit the Banking sector and AA rating category dummy variables. Indeed the model already includes a constant, meaning that we have to exclude

In Table 12, we report several statistics of the regression model for the EUR IG universe[24]. The coefficient of determination R^2 calculates the explanatory power of the model. R^2 is relatively high at around 60% while the number of observations is equal to 191 579! We also notice that it has increased during the 2014–2019 period by 6% on average. The VIF statistic is the acronym of the variance inflation factor, a measure of multi-collinearity of two exogenous variables. As a rule of thumb (O'Brien, 2007), a VIF lower than 5 indicates a low dependence between the independent variables. We verify that VIF is relatively low in both periods and pillars, even if it has slightly increased in the second period. The excess contribution stands for the difference in R^2 between the regression with the **ESG** score and the regression without the **ESG** score. We observe that this excess contribution becomes significant after 2014. For instance, it is equal to +4.0% for the **ESG** score.

Table 12: Results of the panel data regression model (EUR IG, 2010–2019)

	2010–2013				2014–2019			
	ESG	**E**	**S**	**G**	**ESG**	**E**	**S**	**G**
R^2	60.0%	59.4%	59.5%	60.3%	66.3%	65.0%	65.2%	64.6%
VIF	2.50	2.49	2.49	2.53	3.14	3.15	3.13	3.13
Excess R^2	0.6%	0.0%	0.2%	1.0%	4.0%	2.6%	2.9%	2.3%
$\hat{\beta}_{esg}$	-0.05	-0.01	-0.02	-0.07	-0.09	-0.08	-0.08	-0.08
t-statistic	-32	-7	-16	-39	-124	-98	-104	-92

Testing that the **ESG** score has a significant impact on the yield spread is equivalent to assuming hypothesis $\mathcal{H}_0 : \beta_{esg} < 0$. In Table 12, we report the value taken by $\hat{\beta}_{esg}$ and the corresponding t-statistic for the **ESG** score and its three pillars. All the betas are negative and significant at the 99% confidence level. The negative relationship between the score and the yield spread has also increased during the 2014–2019 period. On average, one unit of the **ESG** score implies a reduction of 9 bps after having neutralized the effects of credit rating, subordination, duration and sector. This means that the yield spread difference between a best-in-class corporation and a worst-in-class corporation is equal[25] to 53 bps. If we consider a more realistic case where the extreme scores are measured by the empirical interval of the z-score for a rating, the **ESG** cost of capital is equal to 31 bps. Whereas **G**overnance was the most discriminant pillar between 2010 and 2013, we do not observe that a pillar discriminates more than another for the recent period.

5 Extension to other investment universes

The previous sections focused on EUR IG corporate bonds. We now extend the study in two directions. First, we consider USD IG corporate bonds. We can expect some differences since ESG concerns are not the same on both sides of the Atlantic. Second, we apply our methodology to high-yield bonds. Again, we may think that ESG is less integrated in this investment universe, because the first goal of distressed corporations is to manage

some dummy variables to avoid the multi-collinearity problem. This means that the beta associated with one specific sector (or credit rating) represents the excess spread with respect to the Banking sector (or AA-rated bonds).

[24] By construction, the dummy variables for the BB, B and CCC ratings are deleted because we consider IG bonds.

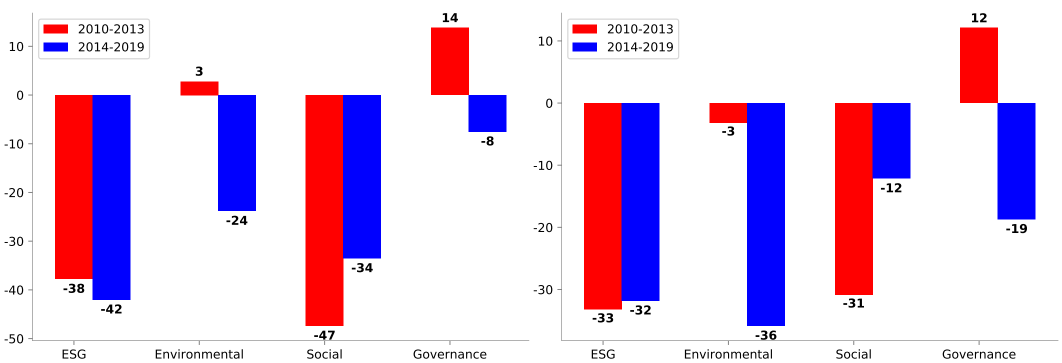
[25] We assume that the best-in-class corporation has a z-score of $+3$ whereas the worst-in-class corporation has a z-score of -3. Computational details are given in Appendix A.5 on page 58.

the return to profitability and reduce the default risk. Finally, we revisit the EUR/USD divide in IG bonds and show that it mainly corresponds to an opposition between Europe and North America. Indeed, this opposition concerns more European and American corporations whatever the currency of the bond issuance.

5.1 The case of USD-denominated IG corporate bonds

Compared to EUR IG corporate bonds, the case of USD-denominated IG bonds is interesting because it is a more diversified investment universe. In Table 21 on page 46, we report the sector breakdown of the benchmark. We notice that the USD investment universe is less concentrated in the Banking sector.

Figure 16: Annualized return in bps of the long/short $Q_1 - Q_5$ strategy (USD IG, 2010–2019)



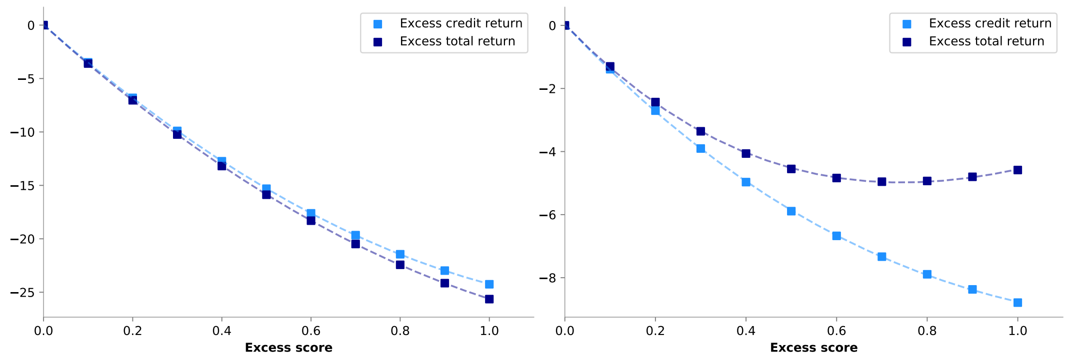
(a) Total return (b) Credit return

If we consider sorted portfolios, we do not observe a clear ranking between the quintile portfolios[26]. For both periods and types of return, Portfolio Q_1 returns are among the lowest returns. One explanation is that Portfolio Q_1 generally may exhibit a lower duration. The Sharpe ratio is comparable across the quintile portfolios except Portfolio Q_4. We also notice that OAS and DTS are two decreasing functions with respect to the **ESG** score. If we look at the **G**overnance pillar, Portfolio Q_1 is generally ranked third most of the time, but it also exhibits the lowest volatility, maximum drawdown, spread and DTS and almost the highest Sharpe ratio. If we consider Figure 16, the return of the long/short $Q_1 - Q_5$ strategy is negative for **ESG** and its pillars except for **E**nvironmental and **G**overnance before 2014. Moreover, we do not see a positive trend that the performance of **ESG** screening has been improved these last years.

We now consider the integration of **ESG** screening in passive management. In Figure 42 on page 53, we notice that the relationship between the **ESG** excess score and the ex-post tracking error volatility is similar to the one observed for the EUR IG universe. For instance, if we target an excess score $\mathcal{S}^{\star} = 1$, we must accept a tracking error of 30 bps[27]. Figure 17 shows the impact of the **ESG** integration on the excess return of optimized portfolios. It is highly negative between 2010 and 2013, but this underperformance has been reduced during the 2014–2019 period. As such, ESG passive investors have been penalized, but we clearly observe a trend that this is decreasingly the case. This trend is confirmed if we consider the individual pillars **E**, **S** and **G**. In Figures 43 and 44 on page 53, we observe a substantial

[26] See Tables 22 to 29 on page 47 in Appendix A.2.
[27] It was equal to 25 bps in the case of EUR IG corporate bonds.

Figure 17: Excess return in bps of **ESG** optimized portfolios (USD IG, 2010–2019)



(a) 2010–2013 (b) 2014–2019

difference between the 2010–2013 and 2014–2019 periods. For instance, optimized portfolios based on the **S**ocial pillar posted a positive excess total return during the recent period. In a similar way, the cost for implementing the **G**overnance pillar was limited to 6 bps. Like Drei *et al.* (2019), we observe that **E**nvironmental is the laggard pillar.

Finally, we have tested the impact of **ESG** on the cost of debt. Results are reported below in Table 13. First, we notice that the excess R^2 is low even for the second period. Second, only the coefficient of the **G**overnance pillar is negative during the first period. This is not the case for the recent period. Indeed, the relationship between the **ESG** score and the yield spread is negative and significant, except for the **S**ocial pillar. However, the relationship for USD IG corporate bonds is weaker than the one observed for EUR IG corporate bonds. For example, the cost of debt between a best-in-class corporation and a worst-in-class corporation is equal to 24 bps, which is 29 bps below than the yield spread difference we have observed for EUR IG corporate bonds. If we consider the empirical distribution of z-score for defining best- and worst-in-class scores by rating, the **ESG** cost of capital is 15 bps, which corresponds to the half of the figure calculated in Euro[28]. Another interesting result is that **G**overnance is the most discriminant pillar when analyzing the cost of borrowing.

Table 13: Results of the panel data regression model (USD IG, 2010–2019)

	2010-2013				2014-2019			
	ESG	**E**	**S**	**G**	**ESG**	**E**	**S**	**G**
R^2	52.7%	52.8%	52.8%	53.4%	60.6%	60.5%	60.3%	60.9%
VIF	2.64	2.67	2.62	2.58	2.97	3.00	2.99	2.94
Excess R^2	0.0%	0.2%	0.2%	0.7%	0.3%	0.2%	0.0%	0.7%
$\hat{\beta}_{esg}$	-0.00	0.03	0.03	-0.07	-0.04	-0.03	-0.00	-0.06
t-statistic	-2	19	21	-43	-48	-40	-0	-73

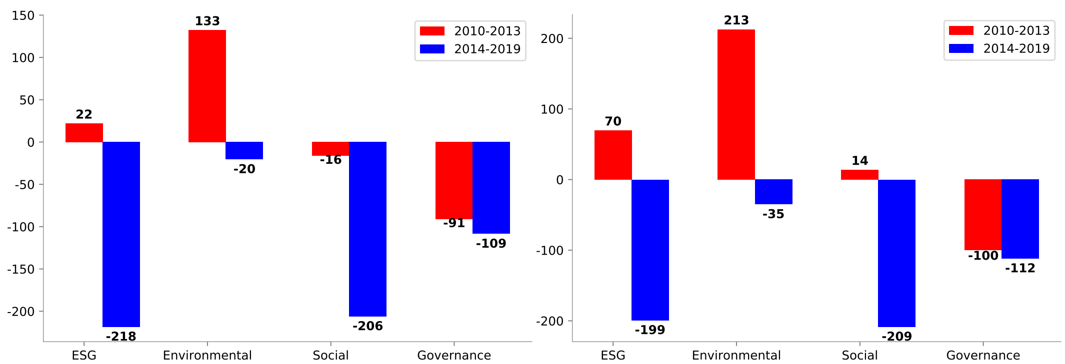
[28]We reiterate that this second approach for computing the cost of capital makes more sense, because a AAA bond has no realistic chance of receiving a -3 **ESG** z-score. Similarly, a CCC bond with a $+3$ **ESG** z-score is unlikely.

5.2 The case of high-yield bonds

We now consider the investment universe of high-yield bonds. However, we must be very careful about the interpretation of the results since the coverage ratio is far from satisfactory. In Figure 46 on page 55, we have reported the time evolution of **ESG**-rated high-yield bonds. Even though the coverage reaches 65% in 2019, it was only equal to 20% in 2010.

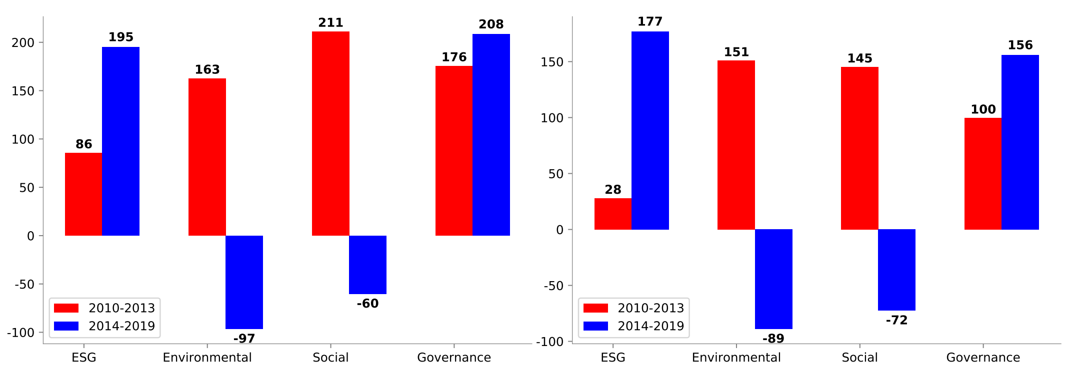
In the case of active management, results of **ESG** sorted portfolios are reported in Figures 18 and 19. These results are difficult to interpret[29]. In the case of EUR HY bonds, we do not observe that best-in-class bonds have outperformed worst-in-class bonds and we don't see an improvement over the 2014–2019 period. We obtain better results for USD HY bonds during the first period. On the more recent period, it seems that **G**overnance is the only pillar that is interesting to implement in the universe of USD HY bonds.

Figure 18: Annualized return in bps of the long/short $Q_1 - Q_5$ strategy (EUR HY, 2010–2019)



(a) Total return (b) Credit return

Figure 19: Annualized return in bps of the long/short $Q_1 - Q_5$ strategy (USD HY, 2010–2019)

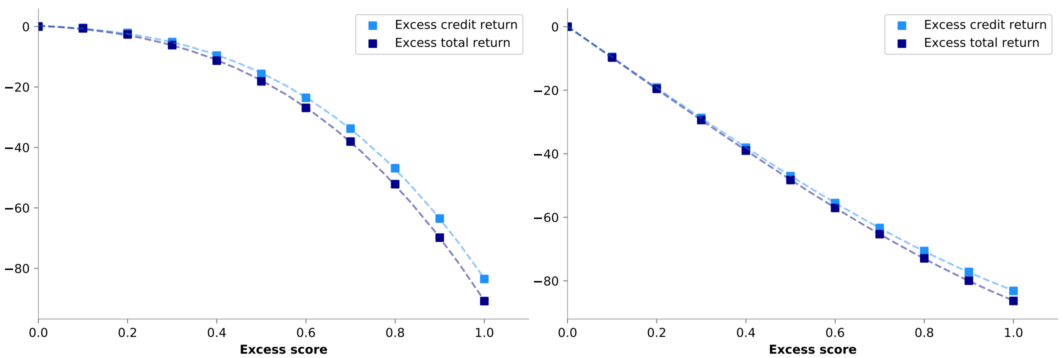


(a) Total return (b) Credit return

[29] Indeed, the sorted portfolio method is implemented with only the **ESG** rated bonds. Therefore, the results are extremely noisy and may be biased.

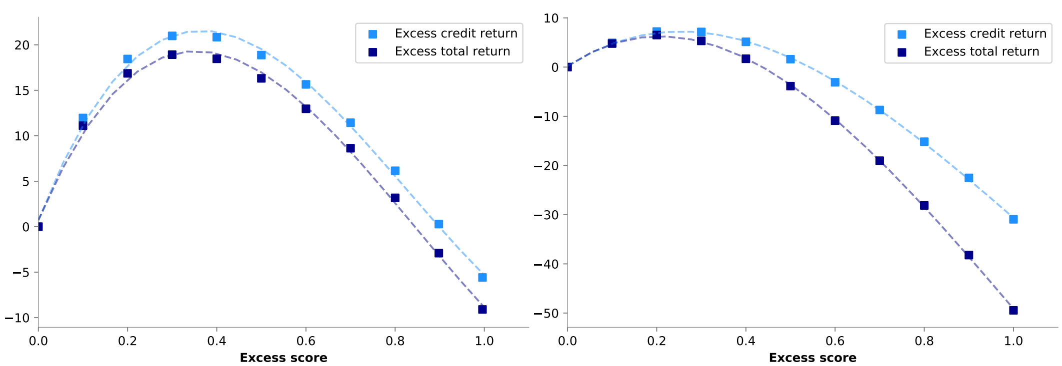
In the case of passive management[30], we first observe that optimizing the benchmark with an **ESG** tilt induces more tracking error risk in the high-yield space than in the IG bond universe. According to Figures 47 and 48 on page 56, targeting an excess score $\mathcal{S}^{\star}$ equal to one requires accepting a tracking error larger than 100 bps whereas it was below 30 bps in the case of investment grade bonds. Concerning the performance of optimized portfolios, excess total and credit returns are negative during the 2014–2019 period.

Figure 20: Excess return in bps of **ESG** optimized portfolios (EUR HY, 2010–2019)



(a) 2010–2013 (b) 2014–2019

Figure 21: Excess return in bps of **ESG** optimized portfolios (USD HY, 2010–2019)



(a) 2010–2013 (b) 2014–2019

Concerning the relationship between ESG and the cost of debt, results are reported in Tables 14 and 15. As expected, the coefficient of determination R^2 is lower for high-yield bonds than for investment grade bonds. Adding the **ESG** score does not help to significantly improve the explanatory power of the panel data regression model. In the case of EUR HY bonds, the 2010–2013 period is characterized by a rejection of the $\mathcal{H}_0$ hypothesis. This is not the case for the recent period. Indeed, being a best-in-class **ESG** corporation helps to reduce the cost of debt. This is particularly true if we consider the **G**overnance pillar. In the case of USD HY bonds, the impact of ESG is not significant and, moreover, the $\mathcal{H}_0$ hypothesis is rejected.

[30] In this case, the **ESG** score of non-rated HY bonds is set to zero when we perform the optimization.

Table 14: Results of the panel data regression model (EUR HY, 2010–2019)

	2010-2013				2014-2019			
	ESG	**E**	**S**	**G**	**ESG**	**E**	**S**	**G**
R^2	56.0%	55.9%	55.8%	56.0%	39.2%	38.9%	39.1%	40.1%
VIF	2.00	1.99	1.98	2.06	2.04	2.01	2.04	2.02
Excess R^2	0.2%	0.2%	0.0%	0.2%	0.5%	0.1%	0.3%	1.4%
$\hat{\beta}_{esg}$	0.04	0.03	0.01	0.05	-0.04	-0.02	-0.03	-0.07
t-statistic	7	6	2	6	-14	-7	-11	-24

Table 15: Results of the panel data regression model (USD HY, 2010–2019)

	2010-2013				2014-2019			
	ESG	**E**	**S**	**G**	**ESG**	**E**	**S**	**G**
R^2	31.4%	31.5%	31.6%	31.4%	42.6%	42.6%	42.7%	42.6%
VIF	1.98	1.98	2.02	1.98	1.59	1.58	1.59	1.59
Excess R^2	0.1%	0.2%	0.3%	0.0%	0.1%	0.0%	0.1%	0.0%
$\hat{\beta}_{esg}$	0.01	0.02	0.03	0.01	0.02	0.01	0.02	0.01
t-statistic	5	9	11	4	9	7	11	8

5.3 The transatlantic divide

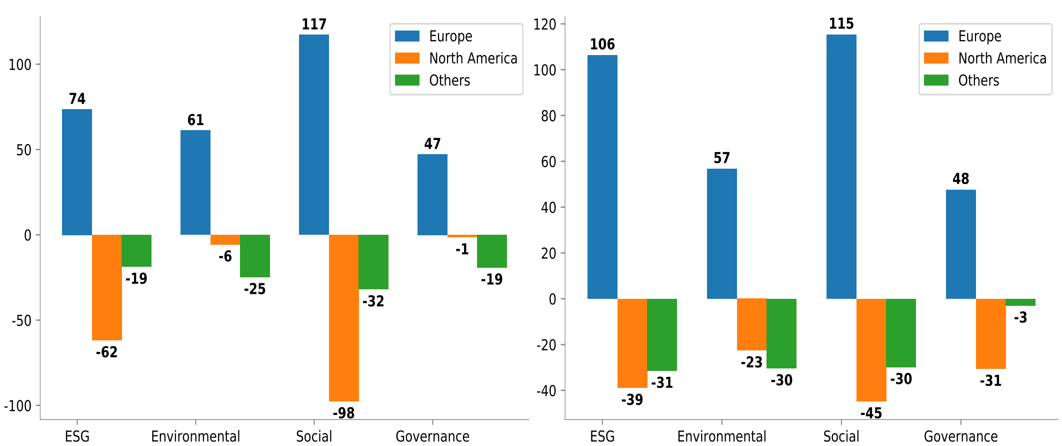
Since it is usual to differentiate bond markets by currency, we have studied EUR and USD IG bond universes separately. In the case of stock markets, the traditional approach is to differentiate the regions (Bennani *et al.*, 2018a). For instance, Drei *et al.* (2019) observed a transatlantic divide since the results for North America and the Eurozone are different for the 2018–2019 period:

> [...] "*we notice a major divergence between America and Europe in ESG equity trends. While these two regions both showed positive advancements in ESG integration in the 2014–2017 period, we now observe a setback in North America but some progress in the Eurozone. The returns of North American long/short portfolios are less than in the previous 2014–2017 period for all dimensions, and even slightly negative on the Environmental pillar. On the other side, the Eurozone gains even more momentum on some pillars and stays positive for all long/short portfolios, hence the idea of a halt in the convergence of these two investment universes, or a transatlantic divide*" (Drei *et al.*, 2019).

In the case of corporate bonds, we observe another divide that concerns the currency in which the bond is denominated. Since a large part of EUR IG bonds is issued by European corporations and a large part of USD IG bonds is issued by American corporations, it is tempting to conclude that the gap is between Europe and North America, but we must also beware of rapid shortcuts.

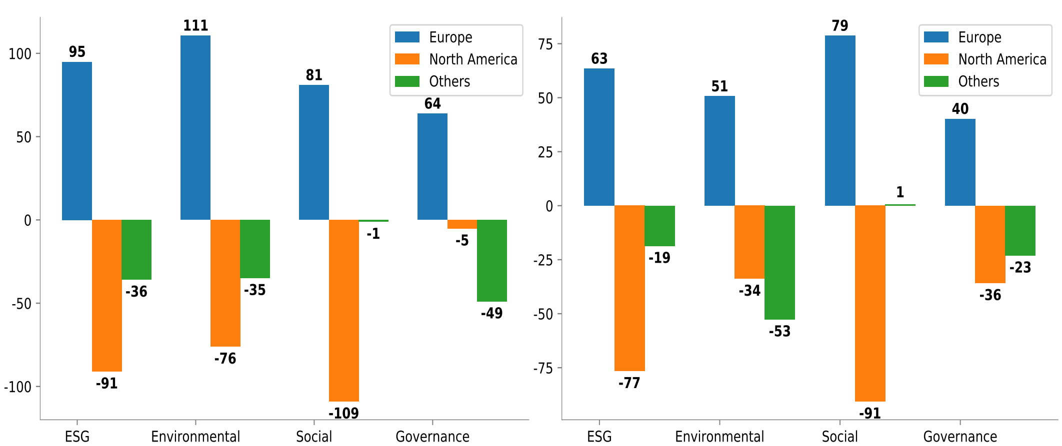
In order to understand if the EUR/USD divide is in fact another transatlantic divide, we have calculated the contribution to credit return of the different regions for the long/short $Q_1 - Q_5$ strategy. For instance, a EUR-denominated bond can be issued by an European corporate, but also by a firm which is located outside Europe. In a similar way, a USD-denominated bond can be issued by an American corporate, but also by a firm which is located outside America. Figures 22 and 23 give the breakdown of the performance by considering three regions: Europe, North America and the other regions. We notice that Europe had a systematic positive contribution whereas North America has a systematic negative contribution whatever the period (2010–2013 and 2014–2019) and the currency (EUR and USD). If we consider optimized portfolios instead of sorted portfolios, results are similar[31]. Again, there is another transatlantic divide[32], implying that the location of the corporation is more important than the choice of currency in bond issuance. On average, ESG investing is a source of outperformance when it concerns IG bonds of European issuers, but it is also a source of underperformance when it concerns IG bonds of American issuers.

Figure 22: Contribution in bps to credit return (EUR IG, 2010–2019, $Q_1 - Q_5$ strategy)



(a) 2010–2013 (b) 2014–2019

Figure 23: Contribution in bps to credit return (USD IG, 2010–2019, $Q_1 - Q_5$ strategy)



(a) 2010–2013 (b) 2014–2019

[31] See Figures 49 and 50 on page 57.

[32] In the case of stocks, the divide concerns the Eurozone. Here, in the case of corporate bonds, the divide concerns Europe, and not only the Eurozone.

6 Conclusion

This research can be viewed as the companion article of Bennani *et al.* (2018a, 2018b) and Drei *et al.* (2019). Except some works done by professionals (Berg *et al.*, 2014, Polbennikov *et al.*, 2016, Dynkin *et al.*, 2018), there are few studies that consider the impact of ESG screening on corporate bonds from a mark-to-market point of view. In this article, we use this framework for analyzing the performance of active and passive management. Moreover, we concentrate on the 2010–2019 period since "*ESG investing was more of an anecdotal and exploratory investment idea, and was limited to a small number of players before the 2008 Global Financial Crisis*" (Bennani *et al.*, 2018b). This is particularly true for the bond market, which is less mature than the stock market in terms of ESG integration[33]. While results of active and passive management mainly concern ESG investors and the demand side of ESG assets, we also focus on ESG financing and the supply side of ESG assets. For that, we adapt the credit-ESG integrated model of Crifo *et al.* (2017) for corporate bonds and test the impact of **ESG** ratings on the cost of capital.

Our study initially concentrated on the EUR IG bond market. We retrieve some common patterns with the equity market. Indeed, we observe that the 2014–2019 period is more favorable to ESG investors than the 2010–2013 period. In the first period, we generally observe a negative alpha in terms of active management when ESG investors implement best-in-class versus worst-in-class bond selection, and an underperformance of **ESG** tilted portfolios. In the second period, the active management strategy creates a positive alpha and **ESG** optimized portfolios have a positive excess return with respect to the index benchmark. Contrary to equities, the outperformance is not very high but it is significant in the EUR IG corporate bond market. Of the different pillars, **S**ocial is the winning pillar. This is also one of the main conclusions reached by Drei *et al.* (2019) when analyzing the recent behavior of the stock market. Our study also exhibits an increasing relationship between ESG and credit ratings, demonstrating that there is an interconnectedness between extra-financial and financial risks. We also notice that ESG has a positive impact on the cost of debt and this relationship has become stronger in recent years. For instance, we estimate that the cost of capital difference is equal to 31 bps between a worst-in-class corporate and a best-in-class corporate.

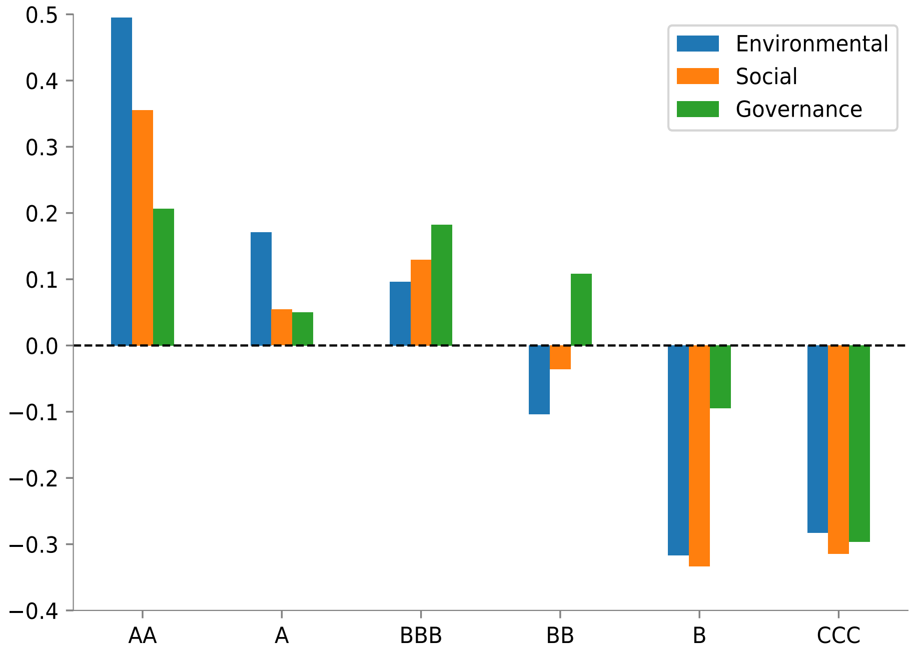
We have also tested if we obtain the same results with other investment universes. In the case of USD IG corporate bonds, we observe a trend that the cost of ESG investing has decreased over time. In recent years, the alpha of ESG active and passive management remains negative, but it is lower. We also confirm that ESG has a significative impact on the cost of debt, but it is reduced by a factor of two compared to EUR IG bonds. All these results indicate another transatlantic divide. Of course, we could guess that this pattern is mainly explained by the difference in terms of dynamics of ESG investing. However, looking forward, we can anticipate that ESG integration will be increasingly present in the USD IG bond market. In the case of high-yield bonds, results are less convincing and we also face some robustness issues. One of the problems is the coverage ratio of high-yield bonds by ESG rating agencies. There has been a lot of progress recently, and future years will be critical for developing ESG investing in these types of markets[34].

This study's final remark concerns **G**overnance, which may be the most discriminant pillar in the USD IG and EUR HY bond markets. Moreover, in Figure 24, we notice that

[33] According to the 2018 best practice report of CFA Institute and UNPRI, "*ESG integration in equities started gaining momentum at the beginning of the 21st century, while ESG integration in fixed income is still in its infancy, although expanding rapidly*" (Orsagh *et al.*, 2018).

[34] We face a similar issue with emerging markets, both in the stock and bond markets.

Figure 24: Average **E**, **S** and **G** score with respect to the credit rating (2010–2019)



Governance impacts more the HY segment than the IG segement of credit ratings[35]. It is true that academic research has mainly focused on this pillar when analyzing the transmission channel between ESG performance and financial performance in the fixed-income space. However, the results on EUR IG bonds show that **G**overnance is not the only significant pillar. Moreover, the asset pricing cycle that Drei *et al.* (2019) have observed in the stock market is inherent to all financial markets. At one time, if one pillar is perfectly priced by the market, investors will certainly turn to other pillars to discriminate good and bad risks. There is no reason for the corporate bond market to be an exception. The forthcoming years will be fascinating to understand how today's results will be confirmed and changed, and to analyze how the debt market will experience a green revolution. Because financing the environmental, social and governance transition depends first on the fixed-income markets. It is true that investors have generally preferred to implement ESG investment policies in their equity portfolios than in their bond portfolios until recently. However, being a true ESG actor also requires being an ESG fixed-income investor if investors want to have a significant impact on society and the world.

[35]For this later, **E**nvironmental and **S**ocial are more relevant.

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A Appendix

A.1 Additional results (EUR IG, 2010–2019)

1. Active management

   (a) Figure 25: Relative performance Q_1/Q_5 (EUR IG, 2010–2019, **ESG**)
   In this figure, we report the ratio of the performance of the Q_1 sorted portfolio to the Q_5 sorted portfolio when the screening is performed using the **ESG** score. Portfolio Q_1 outperforms (resp. underperforms) Portfolio Q_5 when the curve increases (resp. decreases). For instance, we observe that Portfolio Q_1 outperforms Portfolio Q_5 from mid-2012 to the end of 2015.

   (b) Figure 26: Relative performance Q_1/Q_5 (EUR IG, 2010–2019, **E**nvironmental)
   In this figure, the screening is performed using the **E**nvironmental score. Portfolios Q_1 and Q_5 posted similar performance in recent years since 2017.

   (c) Figure 27: Relative performance Q_1/Q_5 (EUR IG, 2010–2019, **S**ocial)
   In this figure, the screening is performed using the **S**ocial score.

   (d) Figure 28: Relative performance Q_1/Q_5 (EUR IG, 2010–2019, **G**overnance)
   In this figure, the screening is performed using the **G**overnance score. We observe that the outperformance of Portfolio Q_1 with respect to Portfolio Q_5 is not stable over time. Indeed, we observe some periods of strong outperformance followed by periods of strong underperformance.

2. Passive management

   (a) Figure 29: Contribution in bps to excess credit return (EUR IG, 2010–2019, **ESG**)
   This chart is similar to Figure 9 on page 19. It shows the contribution of the different sectors to the excess credit return.

   (b) Figure 30: Excess credit return in bps of optimized portfolios (EUR IG, 2010–2019)
   This chart is equivalent to Figure 11 on page 20 when the total return measure is replaced by the credit return measure. During the 2010–2013 period, all pillars underperform. Of the three pillars, **E**nvironmental is the best pillar and its excess return slides down until -22 bps when the targeted excess score is set to $+1$. **G**overnance is the worst pillar, and its excess return reaches -49 bps for the same tilt. After 2014, excess returns are between -3 and $+9$ bps. **S**ocial is the winning pillar and exhibits significant outperformance that peaks at $+9$ bps. Excess returns of **E**nvironmental and **G**overnance seem to be negatively correlated.

   (c) Figure 31: Tracking error in bps of **ESG** optimized portfolios (EUR IG, 2010–2019)
   As expected, the tracking error of optimized portfolios is higher when the risk measure is modified duration (MD) or duration-times-spread (DTS). Combining MD and DTS reduces it by a factor of two.

   (d) Figure 32: Excess total return in bps of **ESG** optimized portfolios (EUR IG, 2010–2019)
   In the 2010–2013 period, the excess total return of MD and DTS optimized portfolios fluctuates around 0 bps while it drops to -35 bps if we combine the two risk measures. After 2014, all excess returns are positive. MD and DTS

optimized portfolios reach 20 bps and outperform the optimized portfolio that takes into account both MD and DTS.

(e) Figure 33: Excess credit return in bps of **ESG** optimized portfolios (EUR IG, 2010–2019)
The performance using the credit return is very different from the performance based on the total return for the MD and DTS optimized portfolios. Indeed, it is now closer to the performance observed when we combine the two risk measures.

(f) Figure 34: Maximum drawdown in % of **ESG** optimized portfolios (Total return, EUR IG, 2010–2019)
The maximum drawdown is an increasing function of the excess score for the two periods and the three risk measures with a slight advantage for MD and DTS.

(g) Figure 35: Maximum drawdown in % of **ESG** optimized portfolios (Credit return, EUR IG, 2010–2019)
If we consider the credit return instead of the total return, we obtain different results. Indeed, we observe that the decreasing relationship between the excess score and the maximum drawdown is not valid for the 2010–2013 period for MD and DTS optimized portfolios.

(h) Figure 36: Excess credit spread in bps of **ESG** optimized portfolios (EUR IG, 2010–2019)
We notice that optimizing the portfolio with respect to the MD or DTS risk measure induces a bias in terms of credit spread. On the contrary, optimizing by combining MD and DTS keeps the excess credit spread around 0 bps.

(i) Figure 37: Excess duration in years of **ESG** optimized portfolios (EUR IG, 2010–2019)
Again, we notice that optimizing the portfolio with respect to the MD or DTS risk measure induces a bias in terms of duration, which is not the case if we combine the two risk measures.

3. Relationship between ESG and the cost of debt

(a) Table 16: **ESG** score with respect to the sector (2010–2019)
In this table, we report the statistics of the **ESG** score with respect to the sector. We verify that the standard deviation is close to one and does not significantly depend on the sector. However, we notice that the mean **ESG** score may depend on the sector. In particular, it is statistically significant for the following sectors: Banking, Basic and Capital Goods.

(b) Table 17: Results of the panel regression model (EUR IG, 2010–2019, Subordination)
The subordination has a high impact on the yield spread (47 bps between 2010 and 2013, and 66 bps between 2014 and 2019).

(c) Table 18: Results of the panel regression model (EUR IG, 2010–2019, Duration)
As expected, a higher duration increases the yield spread by 4 bps per one-year maturity between 2010 and 2013, and 6 bps per one-year maturity between 2014 and 2019.

(d) Table 19: Results of the panel data regression model (EUR IG, 2010–2019, Sector)
This table shows the estimated coefficients $\hat{\beta}_{\mathcal{S}ector}$ associated with the sector dummies. We note that all the betas are negative and significant at the 99% confidence level. However, the magnitude of $\hat{\beta}_{\mathcal{S}ector}$ has decreased after 2014. Special mention goes to the defensive Consumer Non-Cyclical sector.

(e) Table 20: Results of the panel data regression model (EUR IG, 2010–2019, Credit rating) Our results confirm that the spread of an **A**-rated bond is lower than the spread a **BBB**-rated bond.

Figure 25: Relative performance Q_1/Q_5 (EUR IG, 2010–2019, **ESG**)

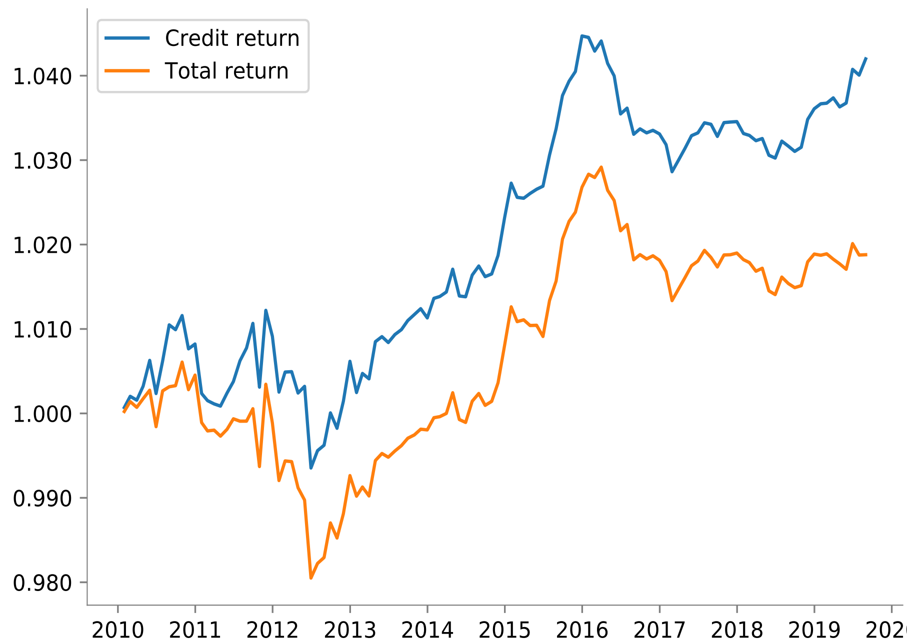


Figure 26: Relative performance Q_1/Q_5 (EUR IG, 2010–2019, **E**nvironmental)

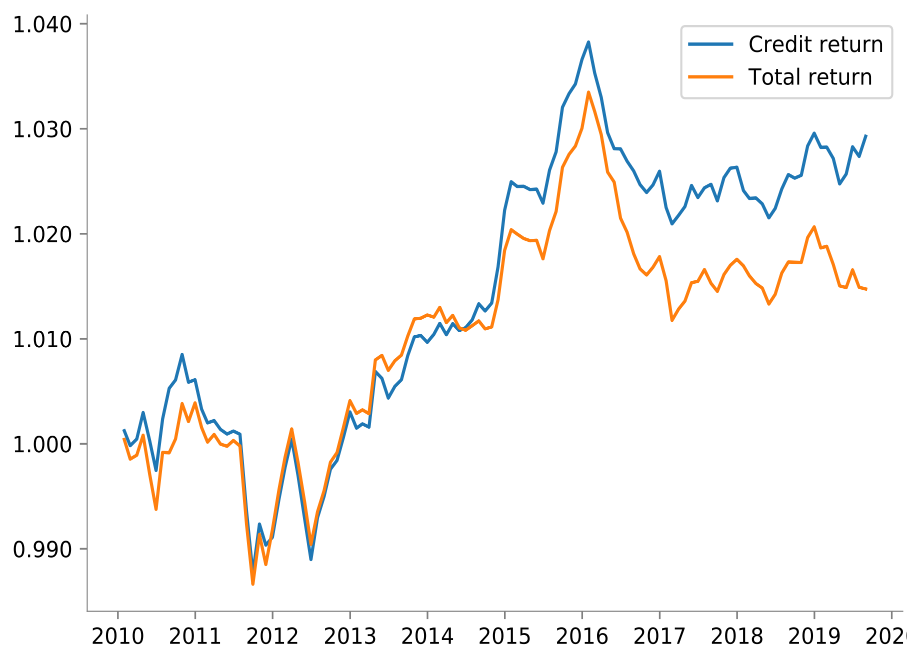


Figure 27: Relative performance Q_1/Q_5 (EUR IG, 2010–2019, **S**ocial)

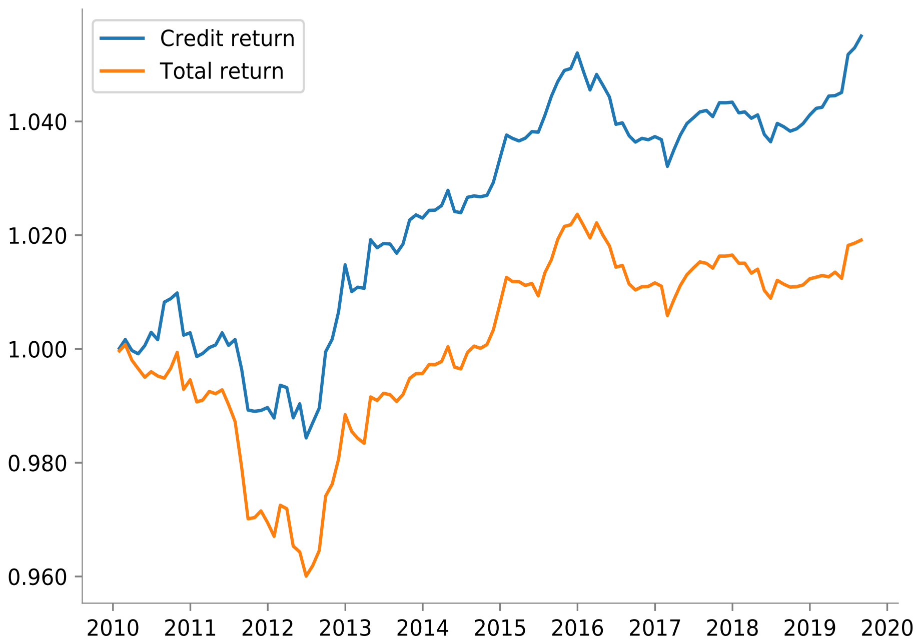


Figure 28: Relative performance Q_1/Q_5 (EUR IG, 2010–2019, **G**overnance)

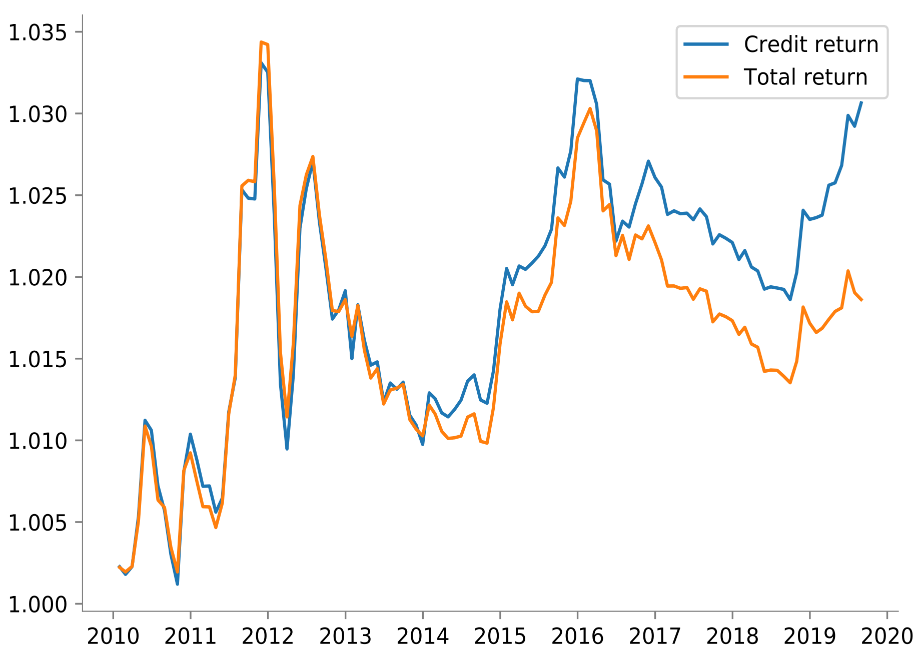
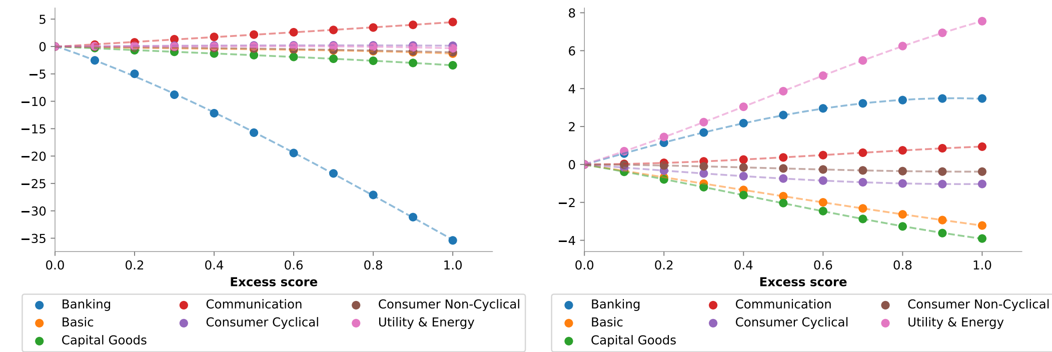
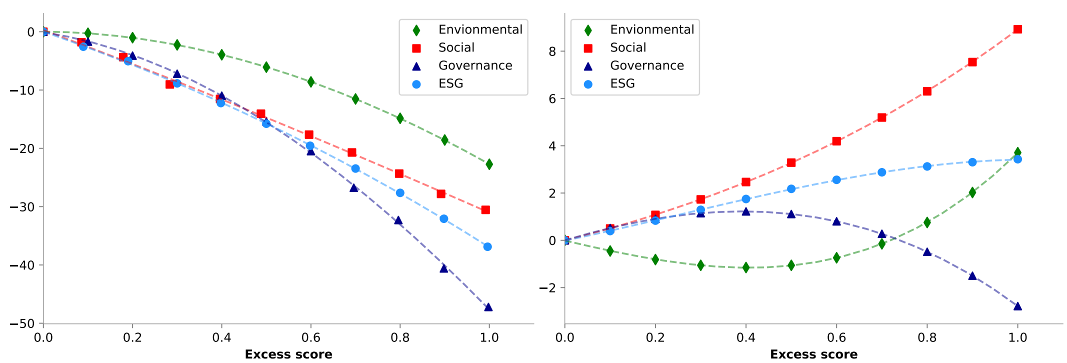


Figure 29: Contribution in bps to excess credit return (EUR IG, 2010–2019, **ESG**)



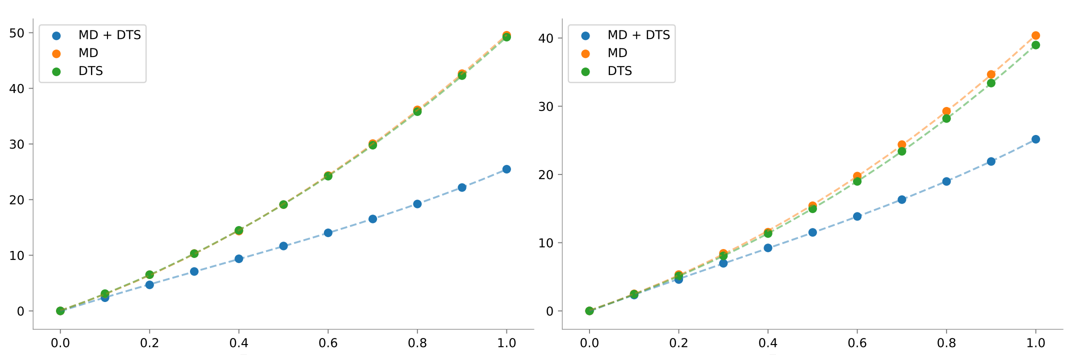
(a) 2010–2013 (b) 2014–2019

Figure 30: Excess credit return in bps of optimized portfolios (EUR IG, 2010–2019)



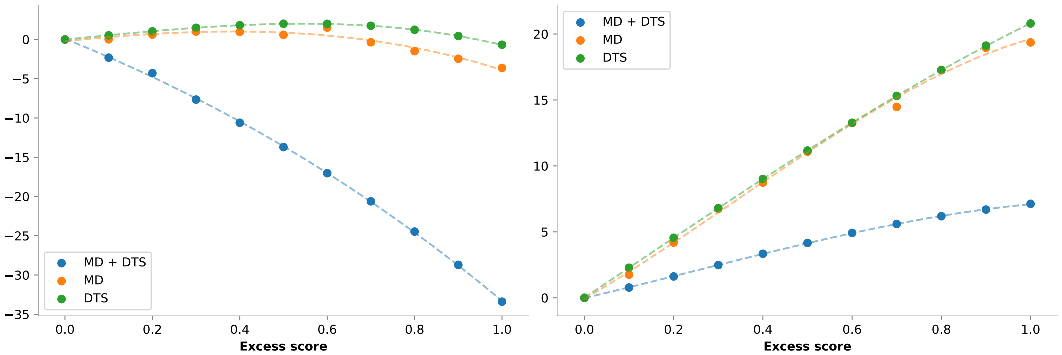
(a) 2010–2013 (b) 2014–2019

Figure 31: Tracking error in bps of **ESG** optimized portfolios (EUR IG, 2010–2019)



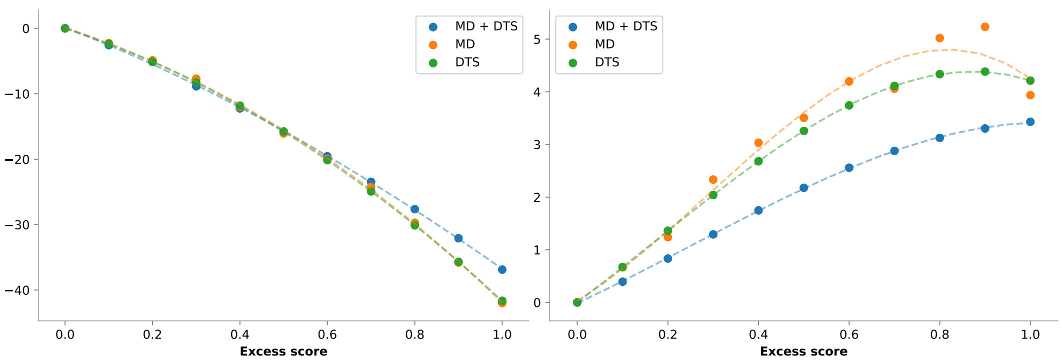
(a) Excess total return (b) Excess credit return

Figure 32: Excess total return in bps of **ESG** optimized portfolios (EUR IG, 2010–2019)



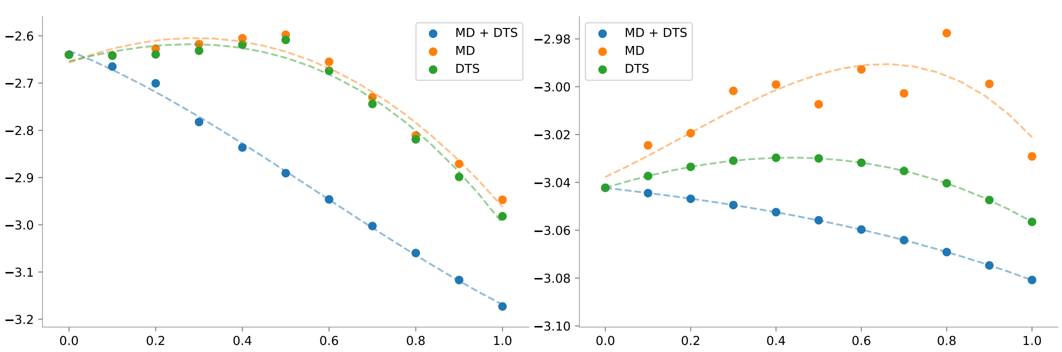
(a) 2010–2013 (b) 2014–2019

Figure 33: Excess credit return in bps of **ESG** optimized portfolios (EUR IG, 2010–2019)



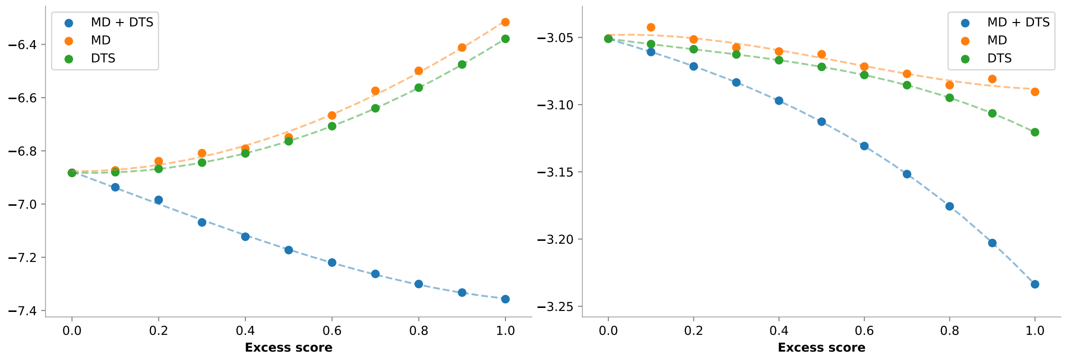
(a) 2010–2013 (b) 2014–2019

Figure 34: Maximum drawdown in % of **ESG** optimized portfolios (Total return, EUR IG, 2010–2019)



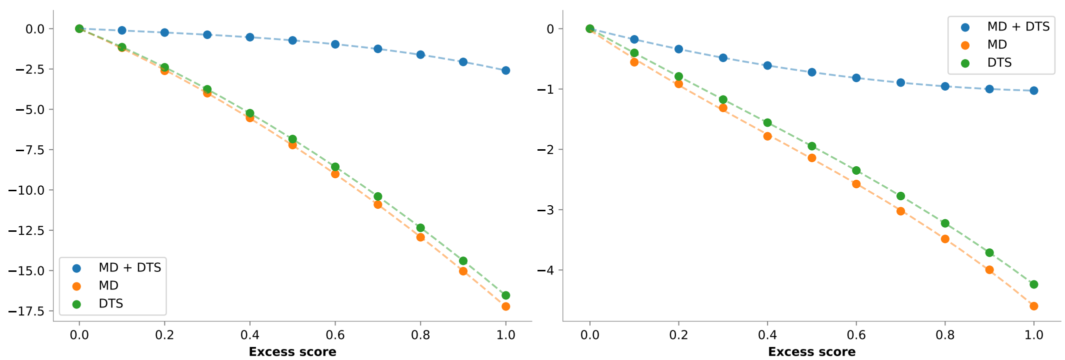
(a) 2010–2013 (b) 2014–2019

Figure 35: Maximum drawdown in % of **ESG** optimized portfolios (Credit return, EUR IG, 2010–2019)



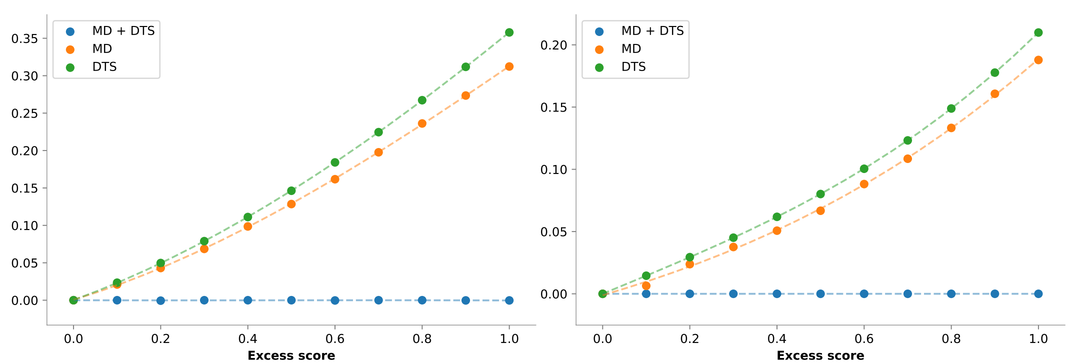
(a) 2010–2013 (b) 2014–2019

Figure 36: Excess credit spread in bps of **ESG** optimized portfolios (EUR IG, 2010–2019)



(a) 2010–2013 (b) 2014–2019

Figure 37: Excess duration in years of **ESG** optimized portfolios (EUR IG, 2010–2019)



(a) 2010–2013 (b) 2014–2019

Table 16: **ESG** score with respect to the sector (2010–2019)

Sector	Mean	Median	Stdev	Skewness	t-statistic
Banking	0.168	0.082	1.043	0.315	3.472
Basic	0.123	0.137	1.084	-0.248	1.728
Capital Goods	-0.096	-0.031	1.194	-0.221	-0.940
Communication	-0.079	-0.237	1.087	0.261	-0.815
Consumer Cyclical	0.009	-0.006	0.963	0.022	0.114
Consumer Non-Cyclical	0.036	0.037	0.882	0.004	0.616
Utility & Energy	-0.067	-0.161	0.973	0.306	-1.152
All sectors	0.046	0.000	1.031	0.092	1.804

Table 17: Results of the panel data regression model (EUR IG, 2010–2019, Subordination)

	2010–2013				2014–2019			
	ESG	**E**	**S**	**G**	**ESG**	**E**	**S**	**G**
$\hat{\beta}_{sub}$	0.47	0.46	0.46	0.46	0.66	0.66	0.66	0.64
t-statistic	104	102	102	104	259	252	254	246

Table 18: Results of the panel data regression model (EUR IG, 2010–2019, Duration)

	2010–2013				2014–2019			
	ESG	**E**	**S**	**G**	**ESG**	**E**	**S**	**G**
$\hat{\beta}_{md}$	0.04	0.03	0.03	0.03	0.06	0.06	0.06	0.06
t-statistic	62	61	61	62	229	225	224	222

Table 19: Results of the panel data regression model (EUR IG, 2010–2019, Sector)

	2010–2013				2014–2019			
	ESG	**E**	**S**	**G**	**ESG**	**E**	**S**	**G**
$\hat{\beta}_{\mathcal{S}ector}$								
Basic	-0.52	-0.53	-0.52	-0.53	-0.20	-0.23	-0.18	-0.18
Capital Goods	-0.39	-0.39	-0.38	-0.41	-0.18	-0.20	-0.17	-0.19
Communication	-0.47	-0.48	-0.47	-0.48	-0.18	-0.20	-0.18	-0.19
Consumer Cyclical	-0.42	-0.43	-0.42	-0.42	-0.13	-0.14	-0.10	-0.13
Consumer Non-Cyclical	-0.64	-0.63	-0.63	-0.65	-0.26	-0.26	-0.25	-0.25
Utility & Energy	-0.37	-0.36	-0.35	-0.39	-0.11	-0.15	-0.09	-0.12
t-statistic								
Basic	-87	-89	-86	-89	-67	-75	-60	-61
Capital Goods	-65	-65	-64	-69	-64	-70	-61	-65
Communication	-87	-87	-85	-89	-60	-65	-59	-63
Consumer Cyclical	-62	-62	-61	-62	-42	-44	-32	-41
Consumer Non-Cyclical	-121	-119	-119	-123	-103	-102	-96	-96
Utility & Energy	-87	-86	-83	-92	-50	-65	-38	-54

Table 20: Results of the panel data regression model (EUR IG, 2010–2019, Credit rating)

	2010–2013				2014–2019			
	ESG	**E**	**S**	**G**	**ESG**	**E**	**S**	**G**
$\hat{\beta}_{\mathcal{R}ating}$								
A	0.35	0.36	0.36	0.34	0.21	0.22	0.22	0.22
BBB	0.86	0.87	0.87	0.85	0.58	0.57	0.58	0.59
t-statistic								
A	87	92	90	86	82	83	83	82
BBB	189	191	190	186	221	214	220	220

A.2 Additional results (USD IG, 2010–2019)

1. Active management

   (a) Table 21: Sector breakdown of the benchmark (USD IG, 2010–2019)
   This table is the USD equivalent of the EUR results presented in Table 2 on page 8. We notice that the USD IG universe is more diversified than the EUR IG universe.

   (b) Tables 22 to 29: **ESG**, **E**, **S** and **G** sorted portfolios (USD IG, 2010–2019)
   Equivalent of Tables 3 to 10 on page 3.

   (c) Figures 38 to 38: Relative performance Q_1/Q_5 of **ESG**, **E**, **S** and **G** portfolios (USD IG, 2010–2019)
   For **ESG** and **G** scores, we notice a break in 2016. One explanation may be the behavior of the Utility & Energy sector. The relative performance has been generally flat since 2017 for the different pillars.

2. Passive management

   (a) Figure 42: Tracking error in bps of **ESG** optimized portfolios (USD IG, 2010–2019)
   Equivalent of Figure 6 on page 17.

   (b) Figure 43: Excess total return in bps of optimized portfolios (USD IG, 2010–2019)
   Equivalent of Figure 11 on page 20.

   (c) Figure 44: Excess credit return in bps of optimized portfolios (USD IG, 2010–2019)
   Equivalent of Figure 30 on page 41.

   (d) Figure 45: Excess credit spread in bps of optimized portfolios (USD IG, 2010–2019)
   This figure shows the excess credit spread of optimized portfolios with respect to the index. We notice that it is slightly negative.

Table 21: Sector breakdown of the benchmark (USD IG, 2010–2019)

Sector	Average Weight
Banking	36.90%
Basic	10.49%
Capital Goods	5.59%
Communication	10.83%
Consumer Cyclical	2.99%
Consumer Non-Cyclical	18.26%
Utility & Energy	14.95%

Table 22: **ESG** sorted portfolios (USD IG, 2010–2013)

	Benchmark	Q_1	Q_2	Q_3	Q_4	Q_5
		Credit return				
Return (%)	2.44	2.12	2.14	2.53	1.95	2.45
Volatility (%)	4.36	3.99	3.98	4.26	4.04	4.22
Sharpe Ratio	0.56	0.53	0.54	0.59	0.48	0.58
Skewness	-0.91	-1.12	-1.01	-1.02	-1.17	-1.03
Kurtosis	1.51	1.86	1.49	2.02	1.85	2.04
Max Drawdown (%)	-6.19	-6.19	-6.32	-5.97	-6.18	-6.65
Hit Ratio (%)			54	50	58	50
		Total return				
Return (%)	6.63	6.02	6.13	6.73	6.07	6.40
Volatility (%)	4.31	4.02	4.06	4.42	4.13	4.26
Sharpe Ratio	1.54	1.50	1.51	1.52	1.47	1.50
Skewness	-0.42	-0.42	-0.33	-0.49	-0.30	-0.46
Kurtosis	0.10	-0.02	-0.20	0.13	-0.07	0.18
Max Drawdown (%)	-4.83	-4.07	-4.32	-4.88	-4.88	-4.89
Hit Ratio (%)			50	46	48	44
		Metrics				
DTS	1186	1041	1092	1159	1130	1159
Duration	6.38	5.83	6.25	6.48	6.45	6.14
OAS	176	162	167	168	163	180

Table 23: **ESG** sorted portfolios (USD IG, 2014–2019)

	Benchmark	Q_1	Q_2	Q_3	Q_4	Q_5
		Credit return				
Return (%)	1.35	1.08	1.33	1.31	0.94	1.40
Volatility (%)	2.74	2.36	2.62	2.59	2.73	2.78
Sharpe Ratio	0.49	0.46	0.51	0.51	0.34	0.50
Skewness	0.33	0.14	0.37	0.28	-0.07	0.44
Kurtosis	0.73	0.43	1.30	0.95	1.92	1.11
Max Drawdown (%)	-4.98	-5.03	-4.58	-4.88	-6.76	-5.85
Hit Ratio (%)			50	38	53	53
		Total return				
Return (%)	5.35	4.89	5.22	5.34	4.80	5.31
Volatility (%)	3.72	3.42	3.66	3.71	3.63	3.63
Sharpe Ratio	1.44	1.43	1.43	1.44	1.32	1.46
Skewness	0.08	0.12	0.10	0.04	0.03	0.12
Kurtosis	0.34	0.49	0.52	0.30	0.36	0.20
Max Drawdown (%)	-3.56	-3.25	-3.47	-3.77	-3.56	-3.25
Hit Ratio (%)			51	40	57	50
		Metrics				
DTS	1041	889	959	999	1017	1064
Duration	6.77	6.20	6.57	6.77	6.53	6.61
OAS	132	119	123	127	136	141

Table 24: **E**nvironmental sorted portfolios (USD IG, 2010–2013)

	Benchmark	Q_1	Q_2	Q_3	Q_4	Q_5
			Credit return			
Return (%)	2.44	2.40	2.00	2.07	2.48	2.43
Volatility (%)	4.36	4.47	4.22	4.04	3.83	3.71
Sharpe Ratio	0.56	0.54	0.47	0.51	0.65	0.66
Skewness	-0.91	-0.89	-1.10	-0.99	-1.08	-1.21
Kurtosis	1.51	1.38	2.07	1.67	1.31	2.58
Max Drawdown (%)	-6.19	-7.02	-7.01	-5.03	-5.98	-5.68
Hit Ratio (%)			48	60	44	56
			Total return			
Return (%)	6.63	6.40	5.95	6.21	6.59	6.37
Volatility (%)	4.31	4.36	4.29	4.05	4.13	4.09
Sharpe Ratio	1.54	1.47	1.39	1.53	1.60	1.56
Skewness	-0.42	-0.31	-0.41	-0.32	-0.43	-0.53
Kurtosis	0.10	-0.02	-0.14	-0.11	-0.02	0.58
Max Drawdown (%)	-4.83	-4.30	-4.51	-4.33	-4.66	-5.17
Hit Ratio (%)			52	62	48	54
			Metrics			
DTS	1186	1127	1092	1113	1167	1134
Duration	6.38	6.02	6.23	6.32	6.43	6.23
OAS	176	174	164	163	169	176

Table 25: **E**nvironmental sorted portfolios (USD IG, 2014–2019)

	Benchmark	Q_1	Q_2	Q_3	Q_4	Q_5
			Credit return			
Return (%)	1.35	1.12	0.94	1.10	1.30	1.48
Volatility (%)	2.74	2.41	2.60	2.55	2.64	2.82
Sharpe Ratio	0.49	0.47	0.36	0.43	0.49	0.52
Skewness	0.33	0.38	0.28	0.25	0.20	0.15
Kurtosis	0.73	0.73	0.88	0.76	1.03	1.76
Max Drawdown (%)	-4.98	-4.80	-5.20	-5.52	-5.46	-6.36
Hit Ratio (%)			50	46	46	37
			Total return			
Return (%)	5.35	4.99	4.99	4.92	5.34	5.22
Volatility (%)	3.72	3.46	3.66	3.57	3.70	3.57
Sharpe Ratio	1.44	1.44	1.36	1.38	1.44	1.46
Skewness	0.08	0.09	0.15	-0.01	0.01	0.19
Kurtosis	0.34	0.27	0.40	0.49	0.37	0.22
Max Drawdown (%)	-3.56	-3.30	-3.64	-3.68	-3.57	-3.49
Hit Ratio (%)			47	53	46	40
			Metrics			
DTS	1041	910	971	960	1048	1037
Duration	6.77	6.33	6.67	6.54	6.76	6.25
OAS	132	120	121	125	136	146

Table 26: **S**ocial sorted portfolios (USD IG, 2010–2013)

	Benchmark	Q_1	Q_2	Q_3	Q_4	Q_5
			Credit return			
Return (%)	2.44	1.99	2.24	2.19	2.64	2.30
Volatility (%)	4.36	4.00	3.71	4.07	4.13	3.92
Sharpe Ratio	0.56	0.50	0.60	0.54	0.64	0.59
Skewness	-0.91	-1.08	-1.02	-1.28	-1.05	-0.99
Kurtosis	1.51	1.52	1.73	2.31	1.73	1.69
Max Drawdown (%)	-6.19	-6.60	-5.35	-6.27	-5.51	-6.08
Hit Ratio (%)			50	48	44	50
			Total return			
Return (%)	6.63	5.74	6.29	6.38	6.81	6.21
Volatility (%)	4.31	4.03	4.03	4.06	4.22	4.15
Sharpe Ratio	1.54	1.42	1.56	1.57	1.61	1.50
Skewness	-0.42	-0.41	-0.26	-0.40	-0.43	-0.40
Kurtosis	0.10	-0.10	-0.31	-0.08	0.27	0.17
Max Drawdown (%)	-4.83	-4.19	-4.21	-4.58	-4.90	-4.82
Hit Ratio (%)			46	50	42	48
			Metrics			
DTS	1186	1048	1043	1146	1161	1129
Duration	6.38	5.76	6.11	6.44	6.43	6.29
OAS	176	169	160	166	174	168

Table 27: **S**ocial sorted portfolios (USD IG, 2014–2019)

	Benchmark	Q_1	Q_2	Q_3	Q_4	Q_5
			Credit return			
Return (%)	1.35	1.30	1.18	1.09	1.02	1.42
Volatility (%)	2.74	2.52	2.47	2.70	2.81	2.61
Sharpe Ratio	0.49	0.52	0.48	0.40	0.36	0.54
Skewness	0.33	0.35	0.12	0.01	0.21	0.27
Kurtosis	0.73	0.92	0.72	2.25	0.74	0.65
Max Drawdown (%)	-4.98	-5.10	-4.72	-5.99	-7.11	-4.65
Hit Ratio (%)			63	63	50	50
			Total return			
Return (%)	5.35	5.06	5.13	4.90	4.93	5.39
Volatility (%)	3.72	3.45	3.52	3.70	3.64	3.62
Sharpe Ratio	1.44	1.47	1.46	1.32	1.36	1.49
Skewness	0.08	0.10	0.08	0.12	-0.01	0.10
Kurtosis	0.34	0.39	0.27	0.61	0.32	0.16
Max Drawdown (%)	-3.56	-3.17	-3.21	-3.61	-3.60	-3.23
Hit Ratio (%)			57	56	53	49
			Metrics			
DTS	1041	910	932	991	1085	1014
Duration	6.77	6.20	6.46	6.63	6.61	6.61
OAS	132	124	122	129	144	131

Table 28: **G**overnance sorted portfolios (USD IG, 2010–2013)

	Benchmark	Q_1	Q_2	Q_3	Q_4	Q_5
			Credit return			
Return (%)	2.44	2.30	2.18	2.37	2.31	2.18
Volatility (%)	4.36	3.53	3.61	4.13	4.44	4.47
Sharpe Ratio	0.56	0.65	0.60	0.57	0.52	0.49
Skewness	-0.91	-1.25	-1.03	-1.14	-1.08	-1.05
Kurtosis	1.51	2.20	1.60	1.76	2.52	1.66
Max Drawdown (%)	-6.19	-4.66	-5.21	-6.38	-7.00	-6.60
Hit Ratio (%)			44	46	46	52
			Total return			
Return (%)	6.63	6.25	6.18	6.62	6.28	6.11
Volatility (%)	4.31	3.88	3.87	4.19	4.47	4.40
Sharpe Ratio	1.54	1.61	1.59	1.58	1.40	1.39
Skewness	-0.42	-0.39	-0.52	-0.39	-0.38	-0.44
Kurtosis	0.10	0.03	0.42	0.06	0.25	-0.26
Max Drawdown (%)	-4.83	-4.27	-4.77	-4.63	-4.42	-4.89
Hit Ratio (%)			48	44	46	46
			Metrics			
DTS	1186	1025	1103	1135	1150	1172
Duration	6.38	5.98	6.43	6.44	6.31	6.08
OAS	176	159	161	167	172	181

Table 29: **G**overnance sorted portfolios (USD IG, 2014–2019)

	Benchmark	Q_1	Q_2	Q_3	Q_4	Q_5
			Credit return			
Return (%)	1.35	1.24	0.93	1.26	1.11	1.42
Volatility (%)	2.74	2.49	2.50	2.74	2.62	2.59
Sharpe Ratio	0.49	0.50	0.37	0.46	0.43	0.55
Skewness	0.33	0.26	0.14	0.05	0.28	0.36
Kurtosis	0.73	0.82	1.18	1.63	0.87	0.86
Max Drawdown (%)	-4.98	-4.96	-6.03	-5.99	-5.31	-4.96
Hit Ratio (%)			53	49	47	40
			Total return			
Return (%)	5.35	5.04	4.76	5.15	5.24	5.11
Volatility (%)	3.72	3.46	3.55	3.75	3.72	3.46
Sharpe Ratio	1.44	1.46	1.34	1.37	1.41	1.48
Skewness	0.08	0.19	0.00	0.09	0.17	0.00
Kurtosis	0.34	0.38	0.40	0.31	0.29	0.51
Max Drawdown (%)	-3.56	-3.02	-3.56	-3.54	-3.55	-3.40
Hit Ratio (%)			57	46	43	43
			Metrics			
DTS	1041	902	947	987	1016	1039
Duration	6.77	6.18	6.54	6.66	6.83	6.30
OAS	132	122	124	128	128	143

Figure 38: Relative performance Q_1/Q_5 (USD IG, 2010–2019, **ESG**)

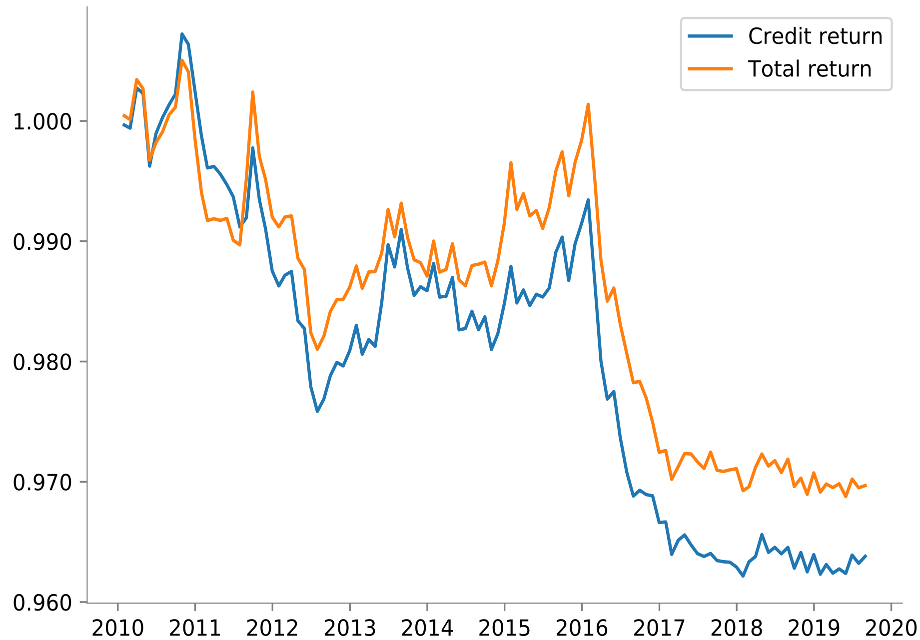


Figure 39: Relative performance Q_1/Q_5 (USD IG, 2010–2019, **E**nvironmental)

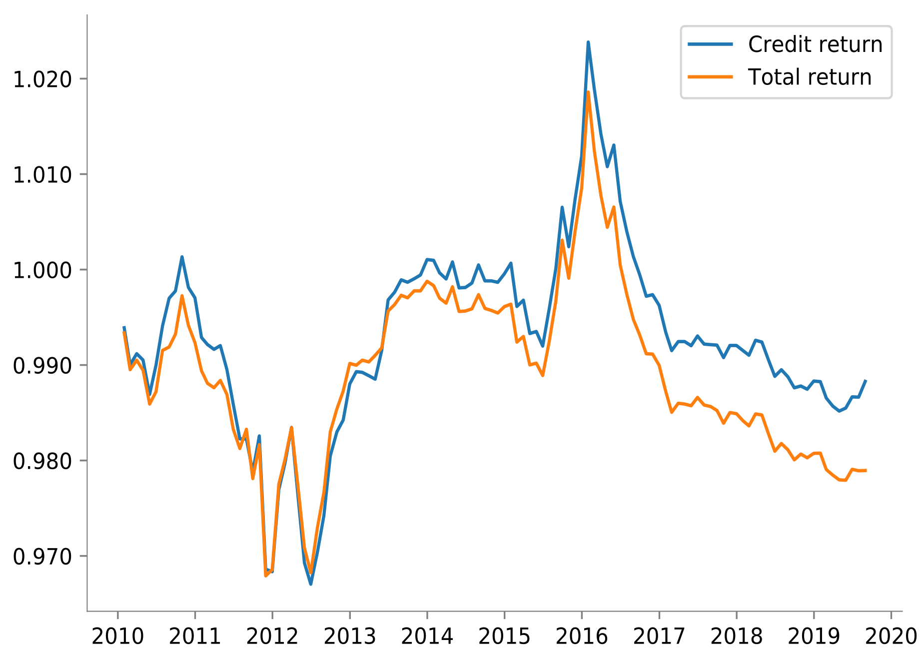


Figure 40: Relative performance Q_1/Q_5 (USD IG, 2010–2019, **S**ocial)

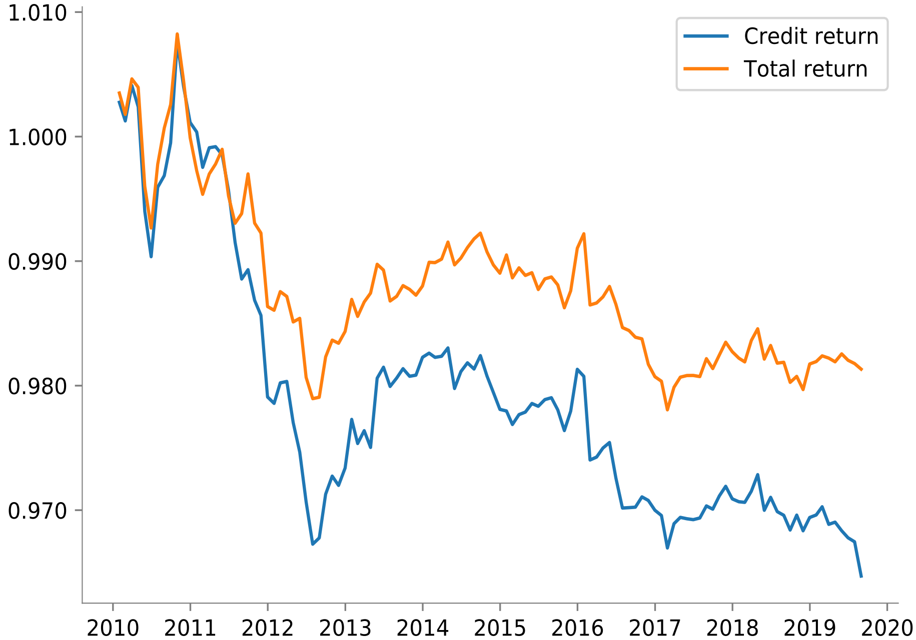


Figure 41: Relative performance Q_1/Q_5 (USD IG, 2010–2019, **G**overnance)

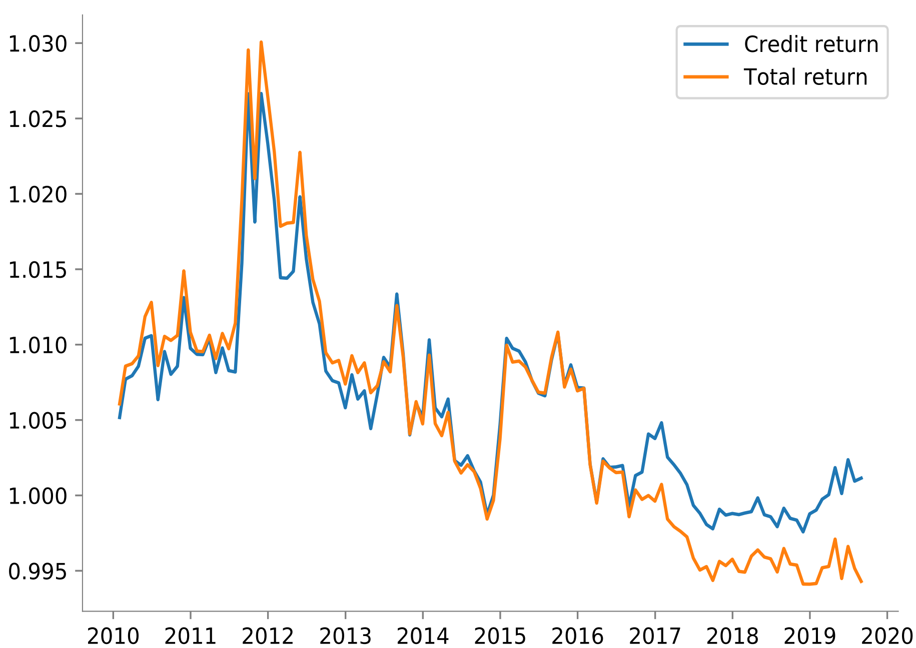


Figure 42: Tracking error in bps of **ESG** optimized portfolios (USD IG, 2010–2019)

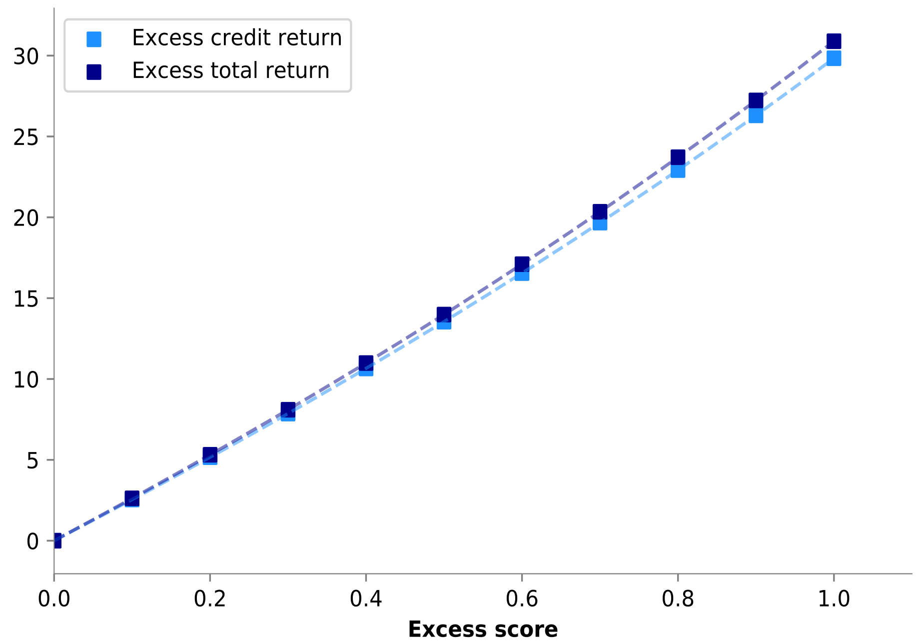
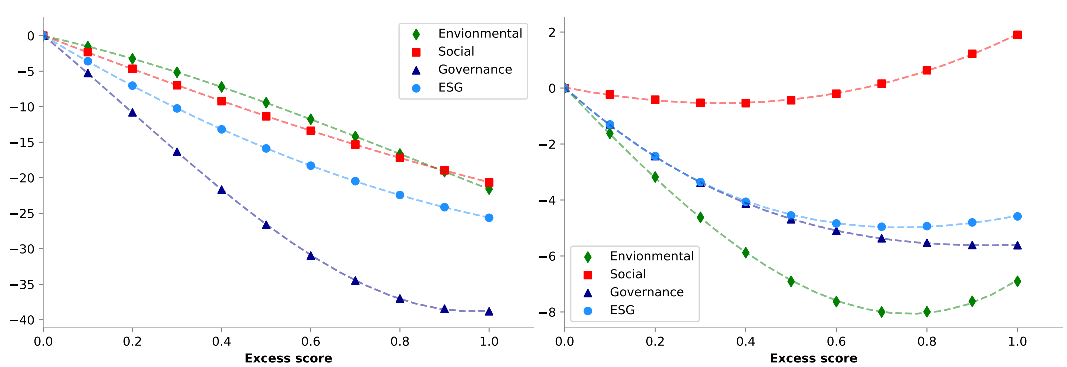
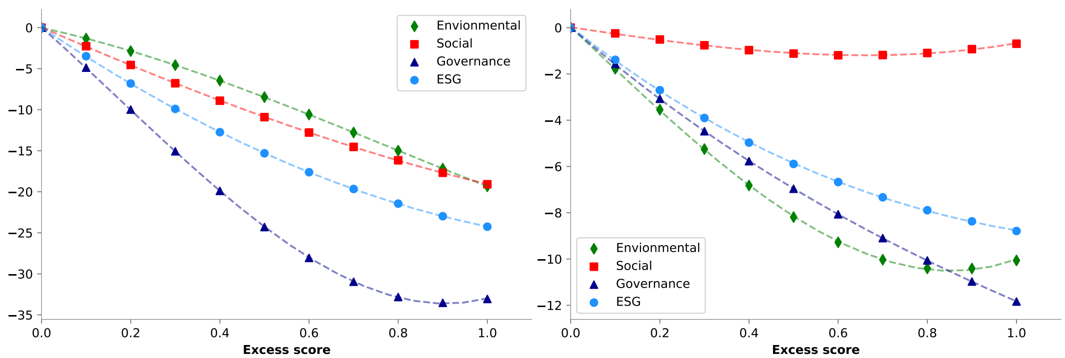


Figure 43: Excess total return in bps of optimized portfolios (USD IG, 2010–2019)



(a) 2010–2013 (b) 2014–2019

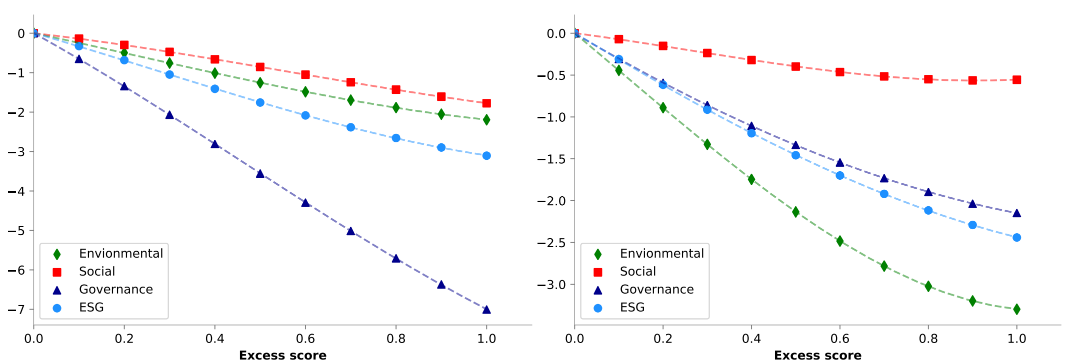
Figure 44: Excess credit return in bps of optimized portfolios (USD IG, 2010–2019)



(a) 2010–2013

(b) 2014–2019

Figure 45: Excess credit spread in bps of optimized portfolios (USD IG, 2010–2019)



(a) 2010–2013

(b) 2014–2019

A.3 Additional results (HY, 2010–2019)

1. Active management

   (a) Figure 46: **ESG** rated bonds (EUR and USD HY bonds)
   In Figure 46, we report the monthly number of bonds and the coverage ratio of **ESG** rated bonds for the high-yield universe (EUR + USD). We notice that the proportion of rated bonds increases from 20% in 2010 to 65% in 2019.

2. Passive management

   (a) Figure 47: Tracking error in bps of **ESG** optimized portfolios (EUR HY, 2010–2019)
   Equivalent of Figure 6 on page 17.

   (b) Figure 48: Tracking error in bps of **ESG** optimized portfolios (USD HY, 2010–2019)
   Equivalent of Figure 6 on page 17.

Figure 46: **ESG** rated bonds (EUR and USD HY bonds)

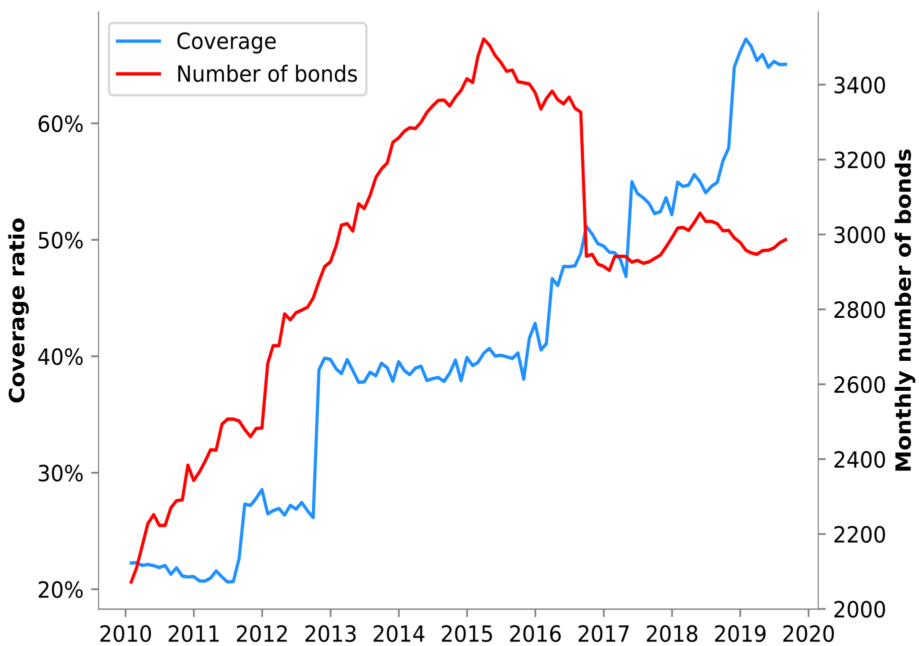


Figure 47: Tracking error in bps of **ESG** optimized portfolios (EUR HY, 2010-2019)

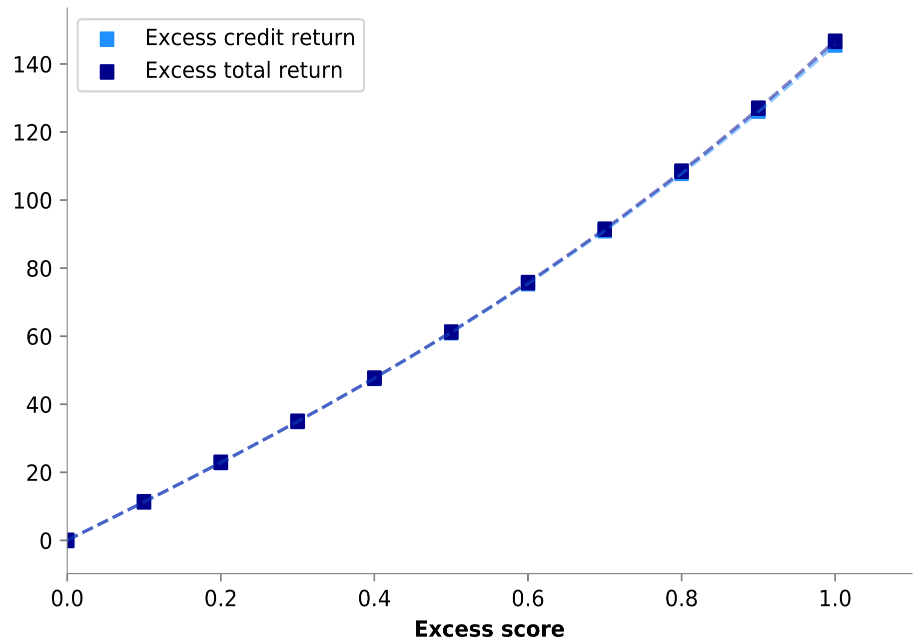
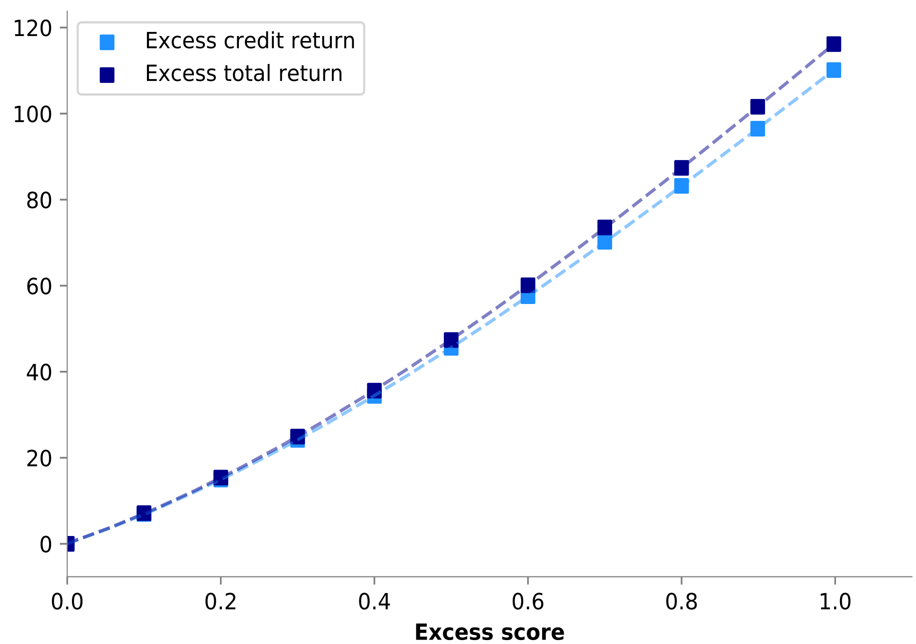


Figure 48: Tracking error in bps of **ESG** optimized portfolios (USD HY, 2010-2019)



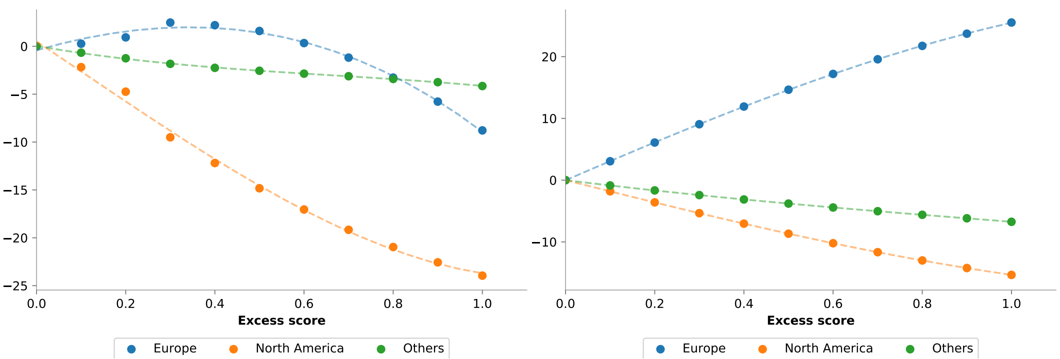
A.4 Additional results (Transatlantic divide, 2010–2019)

1. Passive management

   (a) Figure 49: Contribution in bps to excess credit return (EUR IG, 2010–2019, optimized portfolio)
   Breakdown of the excess credit return by regions.

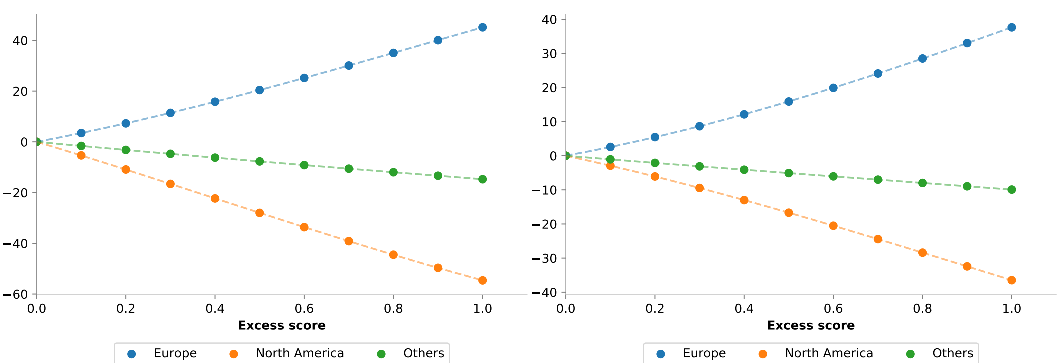
   (b) Figure 50: Contribution in bps to excess credit return (USD IG, 2010–2019, optimized portfolio)
   Breakdown of the excess credit return by regions.

Figure 49: Contribution in bps to excess credit return (EUR IG, 2010–2019, optimized portfolio)



(a) 2010–2013 (b) 2014–2019

Figure 50: Contribution in bps to excess credit return (USD IG, 2010–2019, optimized portfolio)



(a) 2010–2013 (b) 2014–2019

A.5 Computation of the cost of capital

For a given sector j and a given rating k, we have[36]:

$$\ln \mathrm{OAS}_i \approx \hat{\alpha} + \hat{\beta}_{esg} \cdot \mathcal{S}_i + \hat{\beta}_{md} \cdot \mathrm{MD} + \hat{\beta}_{\mathcal{S}ector}(j) + \hat{\beta}_{\mathcal{R}ating}(k)$$

It follows that the **ESG** cost of capital $\mathcal{C}$ is equal:

$$\begin{aligned}\mathcal{C} &= \mathrm{OAS}_1 - \mathrm{OAS}_2 \\ &= \varphi \cdot \left(e^{\hat{\beta}_{esg}\mathcal{S}_1} - e^{\hat{\beta}_{esg}\mathcal{S}_2}\right)\end{aligned}$$

where:

$$\varphi = \exp\left(\hat{\alpha} + \hat{\beta}_{md} \cdot \mathrm{MD} + \hat{\beta}_{\mathcal{S}ector}(j) + \hat{\beta}_{\mathcal{R}ating}(k)\right)$$

Since $\mathcal{S}_1 = -3$ corresponds to the worst-in-class bond and $\mathcal{S}_2 = +3$ corresponds to the best-in-class bond, we obtain:

$$\mathcal{C} = \varphi \cdot \left(e^{-3\hat{\beta}_{esg}} - e^{+3\hat{\beta}_{esg}}\right)$$

With this first method, we can calculate $\mathcal{C}$ for each sector $\times$ rating pair. Then, we can aggregate the different values of $\mathcal{C}$ by sector or rating. The computations[37] are reported in Tables 30 and 31.

Table 30: Theoretical **ESG** cost of capital per sector in bps (IG, 2014–2019)

	EUR		USD	
	$\mathcal{B}eta$-method	$\mathcal{M}ean$-method	$\mathcal{B}eta$-method	$\mathcal{M}ean$-method
Banking	61	58	26	26
Basic	50	51	23	28
Capital Goods	51	51	18	23
Communication	51	58	21	27
Consumer Cyclical	54	49	21	21
Consumer Non-Cyclical	47	47	18	22
Utility & Energy	55	55	24	31
Average	53	53	22	26

Table 31: Theoretical **ESG** cost of capital per rating in bps (IG, 2014–2019)

	EUR		USD	
	$\mathcal{B}eta$-method	$\mathcal{M}ean$-method	$\mathcal{B}eta$-method	$\mathcal{M}ean$-method
AA	39	41	13	17
A	49	47	19	22
BBB	70	69	32	38
Average	53	53	22	26

[36] We only consider the senior debt, meaning that $\mathrm{SUB}_i = 0$.
[37] We assume a duration equal to 7 years.

A second method uses the logarithm relationship:

$$\ln \mathrm{OAS}_1 - \ln \mathrm{OAS}_2 = \hat{\beta}_{esg} \left(\mathcal{S}_1 - \mathcal{S}_2 \right)$$

for two bonds of the same sector and with the same rating and the same duration. It follows that:

$$\mathrm{OAS}_1 = \overline{\mathrm{OAS}} \cdot e^{\hat{\beta}_{esg} \left(\mathcal{S}_1 - \bar{\mathcal{S}} \right)}$$

and:

$$\begin{aligned} \mathcal{C} &= \mathrm{OAS}_1 - \mathrm{OAS}_2 \\ &= \overline{\mathrm{OAS}} \cdot e^{-\hat{\beta}_{esg} \bar{\mathcal{S}}} \cdot \left(e^{-3\hat{\beta}_{esg}} - e^{+3\hat{\beta}_{esg}} \right) \end{aligned}$$

where $\overline{\mathrm{OAS}}$ and $\bar{\mathcal{S}}$ are the average yield spread and the average z-score for each sector $\times$ rating pair. Again, we can aggregate the different values by sector or rating. Results are reported in Tables 30 and 31. We observe that the two methods give coherent results. For EUR IG bonds, the **ESG** cost of capital $\mathcal{C}$ is equal to 53 bps on average, whereas it is equal to 24 bps for USD IG bonds. Moreover, we notice that some sectors are more sensitive than others, such that Banking and Utility & Energy, and we verify that the **ESG** cost of capital is an increasing function of the default risk.

Table 32: Empirical **ESG** cost of capital (IG, 2014-2019) - $\mathcal{B}eta$-method

	EUR				USD			
	AA	A	BBB	Average	AA	A	BBB	Average
Banking	24	47	68	46	11	19	33	21
Basic	9	25	43	26	5	14	29	16
Capital Goods	8	31	42	27	4	14	23	14
Communication		25	49	37	4	9	20	11
Consumer Cyclical	3	28	44	32	2	8	16	10
Consumer Non-Cyclical	15	29	31	25	5	10	17	11
Utility & Energy	12	32	56	33	8	12	27	16
Average	13	31	48	32	6	12	24	14

Table 33: Empirical **ESG** cost of capital (IG, 2014-2019) - $\mathcal{M}ean$-method

	EUR				USD			
	AA	A	BBB	Average	AA	A	BBB	Average
Banking	22	43	65	43	11	19	32	21
Basic	9	24	45	26	5	16	39	20
Capital Goods	8	32	42	27	7	16	29	17
Communication		27	47	37	6	12	25	14
Consumer Cyclical	3	24	41	23	2	7	17	9
Consumer Non-Cyclical	15	29	31	25	7	14	20	13
Utility & Energy	12	31	56	33	10	16	35	20
Average	11	30	47	30	7	14	28	16

Remark 4 *The previous calculations assume that* $\mathcal{S}_1 = -3$ *corresponds to the worst-in-class bond and* $\mathcal{S}_2 = +3$ *corresponds to the best-in-class bond. Nevertheless, these bounds are not necessarily reached because of the correlation between* ***ESG*** *ratings and credit ratings. This is why we consider a second approach where* $\mathcal{S}_1$ *and* $\mathcal{S}_2$ *corresponds to the empirical minimum and maximum* ***ESG*** *scores for a given rating*[38]*. Results are reported in Tables 32 and 33. On average, the* ***ESG*** *cost of capital is equal to* 31 *and* 15 *bps for EUR and USD IG bonds.*

[38] We have $\mathcal{S}_1 = \min \mathcal{S}_{i,t}$ and $\mathcal{S}_2 = \max \mathcal{S}_{i,t}$ for all $i \in \mathcal{R}ating\,(k)$. This means that $\mathcal{S}_1$ and $\mathcal{S}_2$ differ from one rating to another.

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