ESG and corporate credit spreads[1]

Florian Barth[†]
Friedrich-Alexander-Universität Erlangen-Nürnberg (FAU)

Benjamin Hübel[‡]
Friedrich-Alexander-Universität Erlangen-Nürnberg (FAU)

Hendrik Scholz[§]
Friedrich-Alexander-Universität Erlangen-Nürnberg (FAU)

First version: June 2018

This version: May 2019

[1]We are grateful for helpful comments and suggestions from Bert Scholtens, Ambrogio Dalò, Lammertjan Dam, Halit Gonenc, Auke Plantinga, Nassima Selmane, Wim Westerman, Tinang Nzesseu, Arjan Trinks and the participants of the EEF reserach seminar at University of Groningen. We gratefully acknowledge a research grant sponsored from Institute for quantitative investment research Europe (INQUIRE). In addition, we are very grateful to Marco Keidel from IHS Markit (https://ihsmarkit.com) for helpful comments on the data. We are responsible for all errors.

[†]Florian Barth, Friedrich-Alexander-Universität Erlangen-Nürnberg (FAU), Chair of Finance and Banking, Lange Gasse 20, 90403 Nürnberg, Germany, phone: +49 911 5302 162, e-mail: florian.barth@fau.de.

[‡]Benjamin Hübel, Friedrich-Alexander-Universität Erlangen-Nürnberg (FAU), Chair of Finance and Banking, Lange Gasse 20, 90403 Nürnberg, Germany, phone: +49 911 5302 405, e-mail: benjamin.huebel@fau.de.

[§]Hendrik Scholz, Friedrich-Alexander-Universität Erlangen-Nürnberg (FAU), Chair of Finance and Banking, Lange Gasse 20, 90403 Nürnberg, Germany, phone: +49 911 5302 649, e-mail: hendrik.scholz@fau.de.

ESG and corporate credit spreads

Abstract

This study examines how credit spreads of European firms are related to their environmental, social, and governance (ESG) performance.Our results indicate that firms with the worst environmental performance exhibit 25 basis points higher credit spreads while the remaining firms share similar CDS spreads. This could be due to environmental-friendly business practices resulting in lower firm risk. The opposite applies to social performance. Here, 22 basis points higher credit spreads of the most social firms could indicate a waste of valuable resources leading to higher firm risk. In a time-series analysis, we construct ESG factors to assess the time-varying market valuation of ESG. These factors significantly add explanatory power when explaining credit spread changes and thus point to the time-varying market valuation of ESG being a determinant of credit spread changes. These findings indicate that investors may improve their assessment and management of credit risk when considering the ESG performances of firms.[1]

Keywords: Corporate social responsibility (CSR); Enviromental, Social, Governance (ESG); Credit default swaps (CDS); Credit risk

[1] We are currently exenting the data to U.S. firms with MSCI ESG data and CDS spreads by Markit.

1 Introduction

Standard & Poor's reports that more than 1.000 of their credit rating decisions in the period from 2015 to 2017 were linked to environmental, social and governance concerns (see Standard & Poor's, 2017 and Thompson, 2019). The Financial Times concluded that credit rating agencies increasingly view risks through an ESG lens due to the rising awareness of investors for ESG risks (Thompson, 2019). ESG's sharply increasing popularity among investors and corporate executives raises the question, whether and to which extent fixed-income markets incorporate ESG information. We contribute to closing this gap by examining whether corporate credit spreads reflect the E, S and G profiles of firms.

There are contradictory views on ESG and firm risk. On the one hand, ESG might reduce firm risk via generating higher and/or less volatile cash flows. On the other hand, investments in ESG may be a waste of scarce resources resulting lower cash flows and higher firm risk (Goss and Roberts, 2011). Connections between ESG and firm risk should translate into the valuation of credit risk, i.e. a firm's probability of default. According to Merton (1974), higher and more stable cash flows due to ESG should, c. p., translate into higher asset values of firms resulting in lower probabilities of default and, thus, lower credit spreads. To examine the impact of ESG on credit risk, most studies either apply securities and figures related to tradable debt, such as corporate bonds and credit ratings (see, e.g., Menz, 2010 and Jiraporn et al., 2014), or non-tradable debt, including interest rates on bank loans or cost of capital estimates (see, e.g., Goss and Roberts, 2011 and Chava, 2014).[2]

In this study, we contribute to studies related to tradable debt by examining the link between ESG and the spreads of credit default swaps (CDS) of European firms. CDS

[2]A summary of the literature is provided in Section 2.

spreads are particularly interesting as they are highly standardized, more frequently traded than bonds and more often updated than credit ratings (Finnerty et al., 2013). Thus, CDS spreads provide a precise measure of credit risk that is easily comparable across firms and accounts for the majority of the firm-level determinants of default risk (e.g., Forte and Pena, 2009, and Tang and Yan, 2010). When assessing a firm's ESG performance, we distinguish between the E-, S- and G-ratings provided by Thomson Reuters. This allows us to reduce deflating effects compared to aggregated ESG ratings (e.g., Galema et al., 2008). In doing so, we contribute to two major strands of the empirical literature.

First, we add to the literature on the connection between ESG and credit risk. So far, studies on the U.S. corporate bond market mainly document a risk-reducing impact of ESG as shown through better credit ratings or lower bond yield spreads (see, e.g., Oikonomou et al., 2014 and Ge and Liu, 2015). In contrast, European studies only find a weak connection between aggregated ESG and corporate bonds in terms of yield spreads (Menz, 2010) and z-spreads (Stellner et al., 2015).[3] Since both studies employ aggregated ESG measures and corporate bond data, studying credit spreads and different ESG pillars can offer an interesting alternative, as CDS tend to be better suited for empirical research than bonds or credit ratings. For example, CDS markets exhibit higher liquidity than corporate bond markets (e.g., Ericsson et al., 2009 and Ederington et al., 2015) and are, per se, more frequently updated than credit ratings who have been shown to lag changes in CDS spreads (e.g., Finnerty et al., 2013). Moreover, CDS are standardized in terms of their features allowing us to compare credit risk across firms more easily (Norden and Weber, 2009). In contrast, bond prices can be affected by highly individual features such as embedded options or specific guarantees making

[3] Sustainable investing appears especially relevant from a European perspective. According to the GSIA (2016), 52.5% of all managed assets in Europe for 2016 were subject to considerations regarding sustainability, followed by Australia/New Zealand (50.6%) and Canada (37.8%).

comparisons across firms rather difficult (Zhang et al., 2009).

Second, we contribute to the literature on the determinants of CDS spreads. Main studies in this area by, among others, Ericsson et al. (2009) and Galil et al. (2014), report that variables such as credit rating, past stock return, stock return volatility, and firm leverage are significantly linked to credit spreads. Connecting to their findings, we find that different ESG aspects of firms can be considered as an additional determinant of credit spreads.

Our results based on Fama-MacBeth regressions (see Fama and MacBeth, 1973) show that better environmental ratings are connected to lower CDS spreads, i.e. less credit risk, after controlling for known determinants of CDS spreads. This finding supports the risk mitigation view, which connects ESG to lower firm risk (see Goss and Roberts, 2011).[4].

Linear Fama-MacBeth regression models might not be able to account for non-linear connections occurring often when investigating ESG (e.g., Barnett and Salomon, 2006; Lee et al., 2010; Mama and Fouquau, 2017). To investigate such possible connections, we sort CDS into groups based on their ESG ratings and analyze the residual CDS spreads of these groups individually. Residual CDS spreads represent CDS spread components that are unrelated to known determinants of CDS spreads. Residual CDS spreads appear to decline when moving from higher social ratings to lower ones. At first, this finding seems to support the overinvestment view which regards ESG as a waste of resources and, thus, links worse ESG performance to lower credit risk and vice versa. However, this pattern does not hold for the lowest social ratings where residual CDS spreads increase again. This could indicate that declines in social performance might only be related to lower credit risk until a certain level of social effort is reached. Efforts below that level

[4]The risk mitigation view is explained in more detail in Section 2.

might expose a firm to risks resulting from poor social performance and, hence, again increase credit risk. As an example, these risks might be linked to low levels of employee commitment or unfavorable media coverage.

Our results have important implications for investors and academics. From an investor's perspective, credit risk models can be improved when incorporating ESG ratings resulting in more efficient risk management and potential performance benefits. In addition, future academic research on CDS spreads may consider ESG when investigating determinants of CDS spreads. For instance, controlling for ESG in event studies may allow focusing on credit spread components that are related to firm-specific news and not due to common variation in the cross-section of firms.

The remaining study is structured as follows. Section 2 introduces the background to ESG, credit risk and CDS. Section 3 describes our data. Section 4 and 5 present the empirical analyses on the cross-sectional and time-series relationship between ESG ratings and CDS spreads, respectively. Section 6 concludes.

2 ESG, firm risk, and CDS

While many academic studies focus on ESG and financial performance in equity markets (see, e.g., Flammer, 2015 and Lins et al., 2017) or the mutual fund industry (see, e.g., Renneboog et al., 2008 and Borgers et al., 2015), a major strand of literature addresses the role of ESG in debt capital markets. In this respect, the prime question of interest is whether ESG is related to credit risk, i.e. a firm's ability to meet its financial obligations.

The literature distinguishes between two channels through which ESG performance can affect firm risk. The risk-mitigation view argues that improving ESG performance can reduce firm risk by generating higher and/or less volatile cash flows (Goss and

Roberts, 2011). For example, customers of sustainable firms might be willing to buy products at a price premium, suppliers could agree to longer payment terms or employees can potentially be recruited at lower cost (e.g., Albuquerque et al., 2018). Moreover, socially responsible firms could be less exposed to (spillover) risks stemming from natural disasters or changes in the regulatory environment (see, e.g., Renneboog et al., 2008).

In contrast, the overinvestment view considers investments in ESG as a waste of scarce resources, which leads to lower and/or more volatile cash flows and, thus, higher firm risk (e.g., Goss and Roberts, 2011). For example, large investments in ESG might provoke agency conflicts between managers, who might benefit from these overinvestments, and shareholders, who would have to carry the associated costs (see Goss and Roberts, 2011). Moreover, high levels of ESG performance require a costly maintenance of a multitude of relationships with stakeholders and increase a firm's fixed costs (e.g., Perez-Batres et al., 2012). In addition, managers might use ESG to distract from corporate misbehavior or accounting-related inaccuracies (see Kim et al., 2014). In summary, value-destroying overinvestments in ESG are assumed to tie up scarce (financial) resources which is why poorer ESG performance should be related to less credit risk and vice versa (see Goss and Roberts, 2011).

Connections between ESG and firm risk should translate into the valuation of credit risk, i.e. a firm's probability of default. According to Merton (1974), the value of a firm's debt depends on the value of a risk-free loan and a short put option on the firm's assets with the loan's nominal value as strike price. If the asset value drops below the loan's nominal value at maturity of the option, the shareholders would not repay the loan but exercise their option, i.e. default on the loan. If better ESG is connected to higher and more stable cash flows that translate into higher asset values, sustainable firms should, c. p., exhibit lower probabilities of default and, thus, lower credit spreads. The opposite would apply to firms with low ESG performance. In addition, other circumstances such as investor reputation or regulatory requirements may shift investors' focus towards high ESG firms (e.g., Franklin, 2008). This could lead to lower costs of capital for those firms and, consequently, to higher asset values and lower credit spreads (e.g., Chava, 2014).

Since we focus on CDS, our study is related to a strand of literature which mainly applies securities and figures related to trading in debt capital markets, including corporate bonds and credit ratings, to analyze the relationship between ESG and credit risk.[5] Table 1 shows that the literature in this research area focuses on corporate bond yields and credit ratings of U.S. firms and mainly finds evidence for the risk mitigation view, i.e. higher ESG performance is associated with lower credit risk. The European findings by Menz (2010) and Stellner et al. (2015) are rather inconclusive. Menz (2010) finds weak evidence for higher ESG being connected to higher bond yield spreads. Stellner et al. (2015) find no direct connection between ESG and bond yields, but do observe a risk-reducing impact on firms due to the moderating role of a country's level of ESG.[6]

Previous studies for Europe and the U.S. do hardly pay attention to credit spreads in this respect. Only Akdogu and Alp (2016) and Switzer et al. (2018) address the link between credit spreads and proxies for governance of firms. However, both studies do not focus on environmental and social performances of firms and do not employ ESG ratings. Such ESG ratings have become a standard approach to assess corporate social responsibility (CSR). A large body of literature focuses on the relationship between ESG ratings and past performance in equity markets (e.g., Kim et al., 2014; Nofsinger and Varma, 2014; Lins et al., 2017). In contrast, CDS allow us to investigate how markets perceive the *future* impact of ESG on credit spreads.

[5]Studies focusing on non-tradable debt include, among others, Sharfman and Fernando (2008), Chava et al. (2009), Goss and Roberts (2011), Baran and Zhang (2012), Izzo and Magnanelli (2012), and Chava (2014).

[6]Stellner et al. (2015) find no direct link between the z-spreads of corporate bonds and ESG performance. They only find a significant relation for bonds whose issuing firms operate in countries with above-average ESG performance, as determined by Bloomberg ESG ratings for countries, or if both the respective bond-issuing firm and country exhibit an above average ESG performance.

[Please insert Table 1 about here]

In our study, we focus on single-name CDS which are the most common type of credit derivative traded (see Longstaff et al., 2005 and Ericsson et al., 2009). They are similar to an insurance contract where the protection buyer receives compensation from the protection seller if a credit event takes place at the reference firm. In return, the buyer pays the seller annual spreads on a quarterly basis.

Most importantly, CDS have various advantages over bonds (and credit ratings) as a measure of credit risk. First, trading in CDS markets is more frequent than in corporate bond markets (see, e.g., Ericsson et al., 2009 and Ederington et al., 2015). Connecting to this, new information on changes in credit risk has been shown to be incorporated into CDS spreads faster than into bond prices or credit ratings (see Blanco et al., 2005, Zhu, 2006, and Norden and Weber, 2009). Second, most studies in Table 1 applying corporate bond data do not address whether the bond prices used are tradable or not. Bond prices, and thus yields, can often be indicative, meaning they are derived from the pricing of similar bonds. Indicative prices are therefore less likely to accurately reflect firm-specific information, including the bond issuing firm's level of ESG, but rather information relating to firms with similar bonds. We do not face these issues in CDS markets where indicative pricing is not common. Even if tradable bond prices were applied, CDS could still cover a larger number of firms because CDS can be available for firms without tradable bond prices. Third, CDS are standardized in terms of maturities, debt seniority levels, and restructuring events. In contrast, bond prices can be impacted by individual bond features, like embedded options or specific guarantees (see Zhang et al., 2009) which are hard to control for in terms of benchmarks. Therefore, CDS should allow us to precisely measure and compare credit risk across firms (see Norden and Weber, 2009).

CDS markets have seen a clear decline in trading volume after the global financial crisis (see, for example, Aldasoro and Ehlers, 2018) with the European CDS market being no exception, as suggested by a study of the International Capital Markets Association (ICMA) (see ICMA, 2018). Traded notional amounts of European single-name CDS referring to firms fell from around 335 billion U.S. dollars in 2010 to roughly 104 billion U.S. dollars in 2016. A similar development applies to the number of CDS trades.[7] Nonetheless, these numbers are still considerably larger than, for example, the notional amounts traded in the investment grade segment of the European corporate bond market, as addressed by another ICMA study covering the period 2013 to 2016 (see ICMA, 2016).[8] To sum up, the above-mentioned advantages of CDS in respect to empirical research should still hold even given the recent developments in CDS markets.

3 Data

3.1 Credit default swaps

Our monthly CDS data is obtained from Thomson Reuters Eikon for the period between July 31, 2009 and December 31, 2016.[9] We start our evaluation period after the global financial crisis to make sure that our results apply to general market conditions and are not potentially distorted in respect to CDS and ESG.[10] For instance, Galil et al. (2014)

[7] The report by ICMA (2018) provides an aggregate number for trade counts and does not break down this number on CDS for sovereigns and firms. The reported quarterly number of (all) trades fell from 142,000 at the end of 2010 to 60,000 at the end of 2016. Aldasoro and Ehlers (2018) link this development to, among other things, the rise of central clearing, the compression of redundant CDS positions, and an increased standardization of CDS markets.

[8] Over the period 2013 to 2016, ICMA (2016) reports traded notional amounts in European investment grade corporate bonds of around 50 to 60 billion euros per quarter. The corresponding number of trades lies at circa 2,800 per quarter. ICMA (2016) states that their analyses account for about 65% of all trades in European investment grade corporate bonds. Their numbers and figures do not cover high yield corporate bonds.

[9] The coverage of single-name CDS in Thomson Reuters Eikon starts in December 2007.

[10] The OECD-based recession indicator for the Euro Area indicates June 2009 as the last month of the global financial crisis. The indicator is provided by the Federal Reserve Bank of St. Louis and

document structural changes in the pricing of CDS over the course of the global financial crisis. As to ESG, Lins et al. (2017) reveal a temporary influence of ESG during the financial crisis, though a positive effect of ESG on stock returns faded over the following recovery phase.

In June 2016, the European Central Bank's (ECB) "corporate sector purchase program" began where corporate bonds were included in the ECB's asset purchase program (see ECB, 2016). These purchases are likely to affect corporate bond yields and potentially CDS spreads as well. However, our main findings do not change when we remove the relevant months between June 2016 and December 2016 from our sample period.[11]

We focus on single-name CDS which involve non-financial firms located in the Eurozone. All CDS have a maturity of five years, are denominated in euro, and refer to senior-unsecured debt. We obtain month-end mid spreads which are provided by Thomson Reuters as composite spreads across different pricing sources. These spreads are quoted on a daily basis and already include apportioned upfront payments. To ensure that our results are not driven by extreme values or data errors, we follow Zhang et al. (2009) and remove CDS spreads above 2,000 basis points. Zhang et al. (2009) argue that these spreads are often illiquid or associated with bilaterally arranged upfront payments.

3.2 Controls

Using Thomson Reuters Eikon, we collect month-end credit ratings from Standard & Poor's, Moody's and Fitch for unsecured debt. We always apply the last updated rating. If these ratings are not available, we use issuer ratings instead, similar to Norden and Weber (2009). In the case of firms defaulting, credit risk (or the probability of default)

available at: https://fred.stlouisfed.org/series/EUROREC.

[11]More detailed results are available upon request.

already amounts to 100%. Consequently, ESG should be irrelevant for credit risk at this stage. Default-rated observations are therefore removed from our sample.

We use credit rating as an integer variable by transforming ratings onto a linear scale that ranges from AAA (1) to C (21), as in, e.g., Jostova et al. (2013). However, changes in CDS spreads across ratings tend to be non-linear, as shown by, e.g., Galil et al. (2014). To account for these possible non-linearities in our following regression analyses (see Section 4), we first consider squared ratings as an additional explanatory variable to capture non-linear increases in CDS spreads with higher ratings (see, e.g., Güntay and Hackbarth, 2010). Second, we apply rating dummies which aggregate neighboring ratings into the same rating group.[12] In contrast to squared ratings, these dummy variables do not impose a functional form on changes in CDS spreads across ratings (see, e.g., Klock et al., 2005). Of course, these aggregations are inevitably followed by a loss in information that is captured in ratings. To minimize such loss, we select as few neighboring ratings into the same rating group as possible. Whenever possible, we apply a rating itself as a group. We require each rating group to comprise at least ten CDS in each month which results in the following five rating groups with the corresponding integer ratings in parentheses: AAA (1) to A (6), A- (7), BBB+ (8), BBB (9), and BBB- (10) or lower. If we lower the required number down to five CDS, we obtain the following six rating groups: AAA (1) to A+ (5), A (6), A- (7), BBB+ (8), BBB (9), and BBB- (10) or lower. We will consider both five and six rating groups in our empirical analyses (see Section 4).

Using the Eikon search functions, we match our CDS to stock ISINs. Based on these

[12] The aggregation of credit ratings into rating groups is common in the literature on bond and CDS markets. For example, Ericsson et al. (2009) distinguish between high and low ratings of CDS while Galil et al. (2014) aggregate CDS into five rating groups. The studies on corporate bond markets by Gebhardt et al. (2005) and Stellner et al. (2015) apply nine and seven rating groups, respectively. Klock et al. (2005) use dummy variables for seven rating groups as well as dummy variables for 21 ratings themselves (the 22nd rating is captured by a regression intercept) and obtain similar results under both settings.

ISINs, we use Thomson Reuters Datastream to download month-end and daily closing total return indexes in euro to compute total stock returns.[13] Using daily total returns, we further calculate month-end stock return volatilities based on the 180 trading days prior to the respective month-ends, similar to Campbell and Taksler (2003).

To calculate leverage ratios, we first extract month-end equity market values from Datastream using the stock ISINs. Equity market values are comprised of the market values of all listed shares and the book values of all non-listed shares. We further download month-end book values of debt which comprise long-term debt and short-term debt. Similar to Ericsson et al. (2009) and Galil et al. (2014), we determine leverage-ratios for firm i at the end of month t as

$$Leverage\ ratio_{i,t} = \frac{Book\ value\ of\ debt_{i,t}}{Equity\ market\ value_{i,t} + Book\ value\ of\ debt_{i,t}} \tag{1}$$

While equity market values change monthly according to (listed) stock prices, book values of debt are updated yearly depending on the respective firm's fiscal year. Hence, all variation in monthly leverage-ratios during a firm's fiscal year is due to stock price changes of listed shares.

3.3 ESG ratings

We obtain our ESG data from the widely used Thomson Reuters database which is available via Datastream (see, e. g., Cheng et al., 2014; Eccles et al., 2014, Ioannou and Serafeim, 2012).[14] Using our sample firms' stock ISINs, we download ESG ratings cover-

[13]We apply the usual adjustments as in Ince and Porter, 2003.

[14]Further information on the Thomson Reuters Asset4 database is provided online at https://financial.thomsonreuters.com/content/dam/openweb/documents/pdf/financial/esg-scores-methodology.pdf. Thomson Reuters recently discontinued its Asset4 database and now offers ESG ratings that are based on a different methodology that incorporates industry-adjustments of ESG

ing performance in the three different categories - environmental, social, and governance. Thomson Reuters calculates relative ESG ratings based on more than 400 firm-level ESG measures. A percentile rank methodology leads to ratings ranging from zero to 100 with higher values indicating better ESG performance. ESG ratings are updated on every first of January, i.e. they remain constant for twelve months. As suggested by Galema et al. (2008), we employ these ratings individually and do not compute an aggregate ESG rating.[15]

Since the literature also indicates possible non-linear patterns in the context of ESG (e.g., Barnett and Salomon, 2006; Lee et al., 2010; Mama and Fouquau, 2017), we use dummy variables that indicate groups of firms with similar ESG performance (see, e.g., Klock et al., 2005 and Lins et al., 2017). These dummy variables could reveal that ESG ratings may only matter to the CDS spreads of certain firms, such as to those with the best and worst ESG ratings. However, dummy variables depend on the break-points in ESG ratings that is used to indicate, for example, the best and worst firms every month. To ensure that our results do not stem from these sensitivities, we test a variety of dummy variables specifications.

In our empirical analyses, we therefore account for potential non-linear patterns regarding the connection between ESG ratings and CDS spreads. Like Klock et al. (2005), we first apply cross-sectional regressions that include ESG ratings (see Sections 4.1 and 4.2). Further, we also group CDS into quartiles based on their ESG ratings in the style of portfolio sorts and analyze these quartiles individually (see Section 4.3). This should allow us to investigate non-linearities between CDS spreads and ESG ratings that apply across these quartiles.

ratings and percentile-ranks to indicate ESG performance. We apply these new ratings in our analysis. Information on these new ESG ratings is provided in the web reference above.

[15]Galema et al. (2008) point out that the aggregation of individual ESG ratings can have confounding effects between individual dimensions of ESG.

3.4 Descriptive statistics

Our sample consists of 108 different CDS each referring to a single firm. The monthly cross-section contains between 80 and 99 CDS. Panel A of Table 2 shows that most of our sample firms are headquartered in France (34%) and Germany (22%). Panel B of Table 2 lists the industry concentration of our sample. Most of our sample firms are classified as industrials (19%), consumer cyclicals (18%), utilities (16%), and basic materials (15%).

[Please insert Table 2 about here]

Panel A of Table 3 presents descriptive statistics for all variables applied in our empirical analyses based on monthly observations (see Sections 3.1 to 3.3). The minimum and maximum values indicate that our variables do not seem to contain erroneous data entries that could distort our empirical results. Environmental and social ratings range between 26 and 99 averaging around 75. In comparison, our sample firms exhibit, on average, lower governnace performances indicated by an average governance rating of 55.

[Please insert Table 3 about here]

Panel B of Table 3 shows average monthly correlations among all variables. ESG ratings are highlighted in grey. Correlation coefficients larger than $|0.5|$ are bold. Correlations are high among ESG ratings which is especially the case for environmental and social ratings. Potential multicollinearity issues with regard to our following regression analyses will be addressed in the following section. ESG ratings, in general, are negatively correlated with CDS spreads indicating that firms with lower credit show higher ESG performance in our sample.

4 Cross-sectional analysis

4.1 Linear cross-sectional analysis of ESG and CDS spread levels

To examine the impact of ESG ratings on CDS spreads, we estimate different Fama-MacBeth regressions by running monthly cross-sectional regressions to obtain a time-series of coefficient values. The Fama-MacBeth estimator corresponds to the mean monthly coefficient value (see Fama and MacBeth, 1973). This approach is especially popular in empirical asset pricing in the context of panel data and used by, for example, Galil et al. (2015) to analyze the determinants of CDS spreads and by Galema et al. (2008) in the context of ESG performance and stock returns.[16] We base our t-statistics on the time-series of coefficient values with Newey and West (1987) adjusted standard errors (using twelve lags).[17] All variables represent month-end values (see Section 3).

As suggested by the literature, we use various determinants of CDS spreads as control variables in our cross-sectional regressions. In Models M1 to M3 (Eq. 1.1 to 1.3) we first examine whether those determinants apply to our European CDS sample in a way similar to that in Ericsson et al. (2009) and Galil et al. (2014) for U.S. firms. Starting with Model M1, *Rat* is an integer between one and 21 representing different credit ratings, *Vol* is the equity volatility, *Ret* is the equity return, and *Lev* is the leverage ratio. Model M2 contains the same control variables as Model 1 with the only difference being that *Ratsq* is added, which is the square of *Rat* and supposed to account for potential non-linear increases in CDS spreads when moving from lower to higher ratings, as similarly used by Klock et al. (2005). In Model M3, the intercept, *Rat*, and *Ratsq* are replaced by five dummy variables which represent five different rating groups instead. This specification

[16] An alternative approach would be the application of pooled regressions with fixed effects, as in, e.g., Chava (2014). Since we have an unbalanced panel with considerable variation in the number of monthly observations (between 80 and 99), panel regressions would place a higher weight on months with more observations (see Verbeek, 2017).

[17] Our findings are robust to six and 18 lags. More detailed results are available upon request.

is supposed to allow for non-linear differences in CDS spreads across ratings without imposing any functional form, such as with Ratsq.

$$M1 : S_{i,t} = \alpha_t + \beta_t^{Rat} Rat_{i,t} + \beta_t^{Vol} Vol_{i,t} + \beta_t^{Ret} Ret_{i,t} + \beta_t^{Lev} Lev_{i,t} + \epsilon_{i,t} \tag{1.1}$$

$$M2 : S_{i,t} = \alpha_t + \beta_t^{Rat} Rat_{i,t} + \beta_t^{Ratsq} Ratsq_{i,t} + \beta_t^{Vol} Vol_{i,t} + \beta_t^{Ret} Ret_{i,t} + \beta_t^{Lev} Lev_{i,t} + \epsilon_{i,t} \tag{1.2}$$

$$M3 : S_{i,t} = \sum_{j=1}^{5} \beta_t^{D_j} D_{i,t}^{j} + \beta_t^{Vol} Vol_{i,t} + \beta_t^{Ret} Ret_{i,t} + \beta_t^{Lev} Lev_{i,t} + \epsilon_{i,t} \tag{1.3}$$

Table 4 presents the results for Models M1 to M3. When looking at Model M1, our European findings seem similar to the results of Ericsson et al. (2009) and Galil et al. (2014) for the U.S. Higher credit ratings as well as higher volatilities and leverage ratios are significantly and positively related to higher CDS spreads while higher equity returns are significantly and negatively related to higher CDS spreads. The values of our estimated coefficients are also in a range similar to Ericsson et al. (2009) and Galil et al. (2014). When comparing Model M1 and Model M2, we find a clear increase in adjusted R2-values indicating that the squared rating variable seems to capture non-linear increases in CDS spreads with higher credit ratings. Another increase in adjusted R2-values can be achieved in Model M3, where rating dummies are employed to represent five different rating groups. Alternative models with four and six dummy variables to examine whether different specifications of the rating groups can explain more variation in CDS spreads. We do not find corresponding evidence.[18] Consequently, we base all following regressions to examine the relationship between CDS spreads and ESG ratings on Model M3.

[Please insert Table 4 about here]

[18]Detailed results are available upon request.

In Models M4 to M7 (Eq. 2.1 to 2.4), we augment Model M3 with the ESG pillar ratings. Due to the low correlation among relative ESG ratings (see Table 3) and unremarkable VIFs, we also estimate a model that includes all three relative ESG ratings at the same time.

$$M4 : S_{i,t} = \sum_{j=1}^{5} \beta_t^{D_j} D_{i,t}^{j} + \beta_t^{Vol} Vol_{i,t} + \beta_t^{Ret} Ret_{i,t} + \beta_t^{Lev} Lev_{i,t} + \beta_t^{ENV} ENV_{i,t} + \epsilon_{i,t} \quad (2.1)$$

$$M5 : S_{i,t} = \sum_{j=1}^{5} \beta_t^{D_j} D_{i,t}^{j} + \beta_t^{Vol} Vol_{i,t} + \beta_t^{Ret} Ret_{i,t} + \beta_t^{Lev} Lev_{i,t} + \beta_t^{SOC} SOC_{i,t} + \epsilon_{i,t} \quad (2.2)$$

$$M6 : S_{i,t} = \sum_{j=1}^{5} \beta_t^{D_j} D_{i,t}^{j} + \beta_t^{Vol} Vol_{i,t} + \beta_t^{Ret} Ret_{i,t} + \beta_t^{Lev} Lev_{i,t} + \beta_t^{CGV} CGV_{i,t} + \epsilon_{i,t} \quad (2.3)$$

$$M7 : S_{i,t} = \sum_{j=1}^{5} \beta_t^{D_j} D_{i,t}^{j} + \beta_t^{Vol} Vol_{i,t} + \beta_t^{Ret} Ret_{i,t} + \beta_t^{Lev} Lev_{i,t} + \\ + \beta_t^{ENV} ENV_{i,t} + \beta_t^{SOC} SOC_{i,t} + \beta_t^{CGV} CGV_{i,t} + \epsilon_{i,t} \quad (2.4)$$

It is important to note, that we do not account for possible industry effects in our regressions because of the small number of firms in certain industries (see Table 2) would not allow for meaningful industry dummies or industry fixed effects as in, for example, Bauer and Hann (2010). However, ESG ratings themselves are, industry-adjusted using a percentile ranking methodology with industry benchmarks. Therefore, we do not expect significant industry effects. In addition, many studies report that their results regarding the connection between ESG and credit risk seem to be robust to industry adjustments (see, e.g., Bauer and Hann, 2010, Chen et al., 2012, and Stellner et al., 2015).

[Please insert Table 5 about here]

Table 5 presents the results for Models M4 to M7 (see Eq. 2.1 to 2.4). When focusing on environmental ratings in Model M4, we find that, environmental ratings are significantly and negatively related to CDS spreads, after controlling for known determinants of CDS spreads. This indicates that better environmental performance is related to lower CDS spreads, i.e. less credit risk. This finding supports the risk mitigation view which maintains that ESG reduces firm risk, and thus credit risk. Social and governance ratings (Models M5 and M6) do not seem to be linearly connected to CDS spreads. Regression results from Model M7, which contains all relative ESG ratings at the same time, do not change our findings.

So far, our European findings are in line with the main literature on the U.S. market which documents that better environmental performance is connected to lower credit risk (see Table 1). Moreover, our findings can complement the studies by Menz (2010) and Stellner et al. (2015). Both apply aggregate ESG measures[19] and find a weak to no (direct) link between ESG and credit risk in European corporate bonds. Consequently, ESG might be related to credit risk (in Europe) on a more detailed level, such as captured in ESG pillar ratings, specifically focusing on environmental performance. This also supports Galema et al. (2008), who argue that ESG should not be applied as an aggregate measure comprising individual aspects of ESG.[20]

There are many reasons, why high environmental performance could be linked to lower credit risk, as indicated by our regression results. For example, environmentally friendly (or "green") firms might be at a competitive advantage compared to less environmentally friendly firms because green firms could attract new and loyal customers (see Flammer, 2015) or be less exposed to costs connected to current or future regulation of, e.g.,

[19]Menz (2010) employs Data from SAM which now operates as RobecoSAM (http://www.robecosam.com/de/). Stellner et al. (2015) apply aggregate ESG ratings based on ESG ratings provided by the Thomson Reuters' Asset4 database.

[20]Galema et al. (2008) point out that, for example, positive environmental news might be related to positive (stock) returns while positive social news might be related to negative (stock) returns. Aggregating environmental and social performance could therefore blur individual effects.

(excessive) emissions of greenhouse gases (see Chava, 2014).

Moreover, our findings are interesting against the background that previous literature observes credit ratings to be related to ESG (see Table 1). In addition, rating agencies themselves incorporate considerations regarding ESG into their rating decision. As an example, Standard & Poor's reports that more than 800 of their rating decisions in the last years were linked to environmental and climate concerns (see Standard & Poor's, 2017). Since we find a significant coefficient on environmental ratings after controlling for credit ratings, this might indicate that CDS markets value environmental performance differently than suggested by ratings.

4.2 Non-linear cross-sectional relationship of ESG and CDS spread levels

While our previous findings are based on regression analyses and, thus, the assumption of a linear relationship between CDS spreads and environmental ratings, non-linear relationships could still be the case. For example, our findings regarding environmental ratings and CDS spreads could be driven by i) higher CDS spreads only for lower ratings, ii) lower CDS spreads only for higher ratings, or iii) by both at the same time. Moreover, relationships between social or governance ratings and CDS spreads might be non-linear or characterized by asymmetric patterns, both of which are unlikely to be captured by our previous linear regression models.

To investigate such possible non-linearities between CDS spreads and ESG ratings, we replace ESG ratings in our Fama-MacBeth regressions with dummy variables indicating, the top and bottom quartiles of ESG ratings each month, as similarly done by Klock et al. (2005) and Goss and Roberts (2011).[21]

[21] Klock et al. (2005) examine the role of corporate governance in corporate bond markets and apply dummy variables indicating the best and worst quartiles of ESG performance in the context of, among other things, Fama-MacBeth regressions. Goss and Roberts (2011) address the connection

$$M8: S_{i,t} = \sum_{j=1}^{5} \beta_t^{D_j} D_{i,t}^j + \beta_t^{Vol} Vol_{i,t} + \beta_t^{Ret} Ret_{i,t} + \beta_t^{Lev} Lev_{i,t} + \\ + \beta_t^{ENV,top} D_{i,t}^{ENV,top} + \beta_t^{ENV,bottom} D_{i,t}^{ENV,bottom} + \epsilon_{i,t} \quad (3.1)$$

$$M9: S_{i,t} = \sum_{j=1}^{5} \beta_t^{D_j} D_{i,t}^j + \beta_t^{Vol} Vol_{i,t} + \beta_t^{Ret} Ret_{i,t} + \beta_t^{Lev} Lev_{i,t} + \\ + \beta_t^{SOC,top} D_{i,t}^{SOC,top} + \beta_t^{SOC,bottom} D_{i,t}^{SOC,bottom} + \epsilon_{i,t} \quad (3.2)$$

$$M10: S_{i,t} = \sum_{j=1}^{5} \beta_t^{D_j} D_{i,t}^j + \beta_t^{Vol} Vol_{i,t} + \beta_t^{Ret} Ret_{i,t} + \beta_t^{Lev} Lev_{i,t} + \\ + \beta_t^{CGV,top} D_{i,t}^{CGV,top} + \beta_t^{CGV,bottom} D_{i,t}^{CGV,bottom} + \epsilon_{i,t} \quad (3.3)$$

Here, the respective coefficients on these dummy variables indicate CDS spread components that are linked to high and low ESG ratings relative to median ESG ratings. Table 6 presents the results for the model M8 to M10 (see Eq. 3.1 to 3.3).

[Please insert Table 6 about here]

We find that environmental performances within the lowest quartile of firms are related to significantly lower CDS spreads compared to firms with median environmental performances. Exceeding a value of 25 basis points, this reduction is economically highly significant and may result from CDS markets perceiving low environmental performances as an indicator for higher credit risk. Concerning social performance, our results indicate that CDS spreads for the best social performances are not significantly different from median social performances. However, the best social performances are related CDS spreads which are 22 basis points higher than the median social performances.

between ESG and the cost of bank loans, and utilize dummy variables to indicate above-average ESG performance.

This result may stem from CDS markets regarding high social performances as a waste of resources increasing credit risk. Dummy variables for governance do not show any significant results.

In addition, we apply an approach that is similar to standard portfolio sorts. These sorts should allow us to conveniently examine different segments of ESG ratings individually as portfolios, including an intercept that has to be omitted as a reference segment when applying dummy variables.[22]

For this purpose, we utilize residual CDS spreads which correspond to the monthly residuals estimated from Model M3 (Eq. 1.3). By definition, the mean residual CDS spread is zero. More importantly, these residual CDS spreads should be cleansed from CDS spread components that are linked to the control variables in Model M3. Hence, residual CDS spreads should only contain spread components that relate to firm-specific information, noise, and ESG performance that is not captured by control variables.

Each month, we sort all CDS into equally sized quartiles (portfolios) based on their ESG ratings (low to high, i.e. worst to best). We choose quartiles as a compromise between the number of ESG segments and the amount of CDS in each segment to diversify firm-specific information and noise.[23] For each quartile, we first average the residual CDS spreads of its constituents for each month and then over time. By analyzing ESG quartiles individually, we allow for non-linearities across these quartiles and do not impose any functional form on the connection between CDS spreads and ESG ratings.

Table 7 presents the residual CDS spreads of quartiles that comprise CDS with similar ESG ratings. The first quartile comprises CDS with the lowest (worst) ESG ratings

[22] Among others, Cremers et al. (2007) apply portfolio sorts to analyze the link between governance mechanisms and bond prices.

[23] Each quartile contains between 20 and 25 CDS each month. Klock et al. (2005) also apply quartiles to construct dummy variables that are based on a governance index. We also tested quintiles and find similar results. Results are available upon request.

whereas the fourth quartile comprises CDS with the highest (best) ESG ratings. In addition, we report differences in residual CDS spreads between the first and fourth quartiles.

Focusing on environmental ratings, we find the highest residual CDS spreads for the first quartile and the lowest residual CDS spreads for the fourth quartile, both of which are significant. Moreover, the difference between both quartiles is the only significant one when compared to social and governance ratings. Importantly, the difference is also economically significant. After controlling for common CDS determinants, "green" firms pay, on average, 26 basis points lower spreads compared to brown firms. Consequently, the connection between environmental ratings and CDS spreads seems to stem from CDS with the best and worst environmental performance. This confirms our findings from the previous regression analyses and further supports the risk mitigation view (see Sections 4.1 and 4.2).

[Please insert Table 7 about here]

When looking at social ratings, we find a U-shaped pattern where residual CDS spreads are higher for the outer quartiles than for both middle quartiles. Specifically, significant and positive residual CDS spreads at the fourth quartile seem to decrease to significant and negative residual CDS spreads toward the second quartile. At first, these connections appear to support the overinvestment view, which connects lower ESG performances to lower credit risk (see Goss and Roberts, 2011). However, residual CDS spreads reverse for the lowest quartile where they are not significantly different from zero. Based on this, we assume that lower CDS spreads are connected to lower social ratings only up to a certain level, i.e. quartile two in our case. Firms with social ratings below that level might be exposed to risks that arise specifically due to their poor social efforts. These risk may result in CDS spreads 11 basis points higher than common determinants would suggest these firms. Such risk might include low levels of employee commitment or unfavorable media coverage. Consequently, these risks might increase credit risk and CDS spreads again. Finally, we find no residual CDS spreads with regard to governance ratings that are significantly different from zero. The negative correlation between governance ratings and CDS spreads (see Table 3) seems to be explained by the control variables such as credit ratings.

5 Time-series analysis

Our results on the previous Fama-MacBeth regressions indicate that ESG is priced by CDS markets, i. e. differing levels of ESG are c. p. associated with varying levels of credit spreads between firms. Each coefficient is derived as a time-series mean of coefficients resulting from cross-sectional regressions.

[Please insert Figure 1 about here]

Investigating these time-series in Figure 1, we find time-varyation of ESG coefficients in the cross-section of firms. This indicates that market's valuation of ESG's impact on credit risk appears to vary over time. In the market, the valuation of ESG may change due to various reasons. For instance, the rising sustainability awareness among investors and regulators imposes ESG related risks for firms (see e. g. Hübel and Scholz, 2019). Resulting changes in future cash flows and investors' behaviour may affect credit risk.

5.1 ESG factor construction

To asess the market's ESG valuation, we use a standard portfolio approach based on Fama and French (1993, 2015). We construct three ESG factors, one for each ESG pillar.

The ENV factor represents the spread of a portfolio with long positions in firms with high environmental ratings and short positions in firms with low environmental ratings. More precisely, to construct the ENV factor, we follow Fama and French (1993, 2015) and unconditionally sort firms into six portfolios based on their environmental rating and their credit ratings. We apply the terciles of the respective environmental ratings and the median credit rating as breakpoints. We calculate monthly equal-weighted spreads for the portfolios that contain the highest and lowest enviromental ratings. As all ESG ratings are updated on a yearly basis, we also update the sorting of the portfolios yearly. Finally, we obtain the spread of the ENV factor in month t as the difference between the average spread of the two high-ENV portfolios and the two low-ENV portfolios.

The ENV factor can be interpreted as time-varying market valuation of enviromental risks measured as the spread difference between green firms and brown firms. We construct the SOC factor and the CGV factor in the same way, however, based on social and governance ratings, respectively.

[Please insert Figure 2 about here]

Figure 2 shows the spreads of the three ESG factors over time. In line with our previous results, the ENV factor shows mainly negative spreads, indicating higher spreads for brown firms compared to green firms. The opposite is true for the social factor.

5.2 Time-series analysis of ESG and CDS spread changes

We intend to answer, whether the time-varying market valuation of ESG explains CDS spread changes. Therefore, we apply the ESG factors to explain changes in CDS spreads over time. When explaining CDS spread changes, literature by, among others, Ericsson et. al. (2009) and Galil et. al. (2014) suggest various potential control variables. Next to the firm specific variables stock return, stock return volatility and firm leverage, we apply a set of common variables, the Fama and French (2015) equity factors and the Chen, Roll and Ross (1986) factors.

Common variables include the 5yr German Treasury yield (Spot), 10y minus 2y German Treasury yield (Slope), Vstoxx volatility index (Vstoxx) and the change of the median CDS spread in the credit rating group of the firm (MRI). The Fama and French (2015) factors cover the market return (MKT), the size factor (SMB), the value factor (HML), the profitability factor (RMW) and the investment factor (CMA). In addition we include the momentum factor (UMD), as in Carhart (1996). Finally, the Chen, Roll and Ross (1986) factors cover the growth rate of industrial production in Europe (MP), unexpected inflation (UI), term premium (UTS, 20y minus 2y German Treasury yield) and default premium (UPR, Moody's Baa Corporate Bond Yield minus 10y German Treasury yield).

To measure the explanatory power of the variables regarding CDS spread changes, we use time-series regressions. We apply individual regressions for each firm and then average the estimated coefficients across all firms. The t-statistics are calculated based on the cross-section of the individual regression coefficients. Table 8 presents the results.

[Please insert Table 8 about here]

Model M1-all (first column) includes all variables. The model explains 51.19% of the variation in the CDS spread changes. However, many of the variables are insignificant (Vol, Lev, Slope, Vstoxx and most of the Fama and French (2015) factors). This indicates multicollinearity among the explanatory variables because most of the insignificant variables become significant when we investigate subsets of the explanatory variables (other models in the remaining columns).[24] Similar to Galil et. al. (2014) for the U.S. market,

[24]Descriptive statistics and correlations are listed in the appendix.

we find that firm-specific variables and the market factor MRI are needed to explain CDS spread changes (M2-firmspec and M3-com). In the last column, we calculate the model proposed by Galil et. al. (2014). This model becomes our base model for further calculations as it appears to best capture the variation in spread changes indicated by the highest adjusted R2. In this model, the spread changes are explained by stock returns, changes in volatility of stock returns, the equity HML factor and the change of the market factor MRI:

$$M11 : \Delta S_{i,t} = \beta_i^{Ret} Ret_{i,t} + \beta_i^{\Delta Vol} \Delta Vol_{i,t} + \beta_i^{HML} HML_{i,t} + \beta_i^{\Delta MRI} \Delta MRI_{i,t} + \epsilon_{i,t} \quad (4.1)$$

We augment model M11 by the three ESG factors to determine if those factors can add explanatory power. More specifically, we sort all firms into quintiles based on their ESG exposures. For each firm, we perform model M11 and report average coefficients for each of the quintile groups. Table 9 shows the results.

[Please insert Table 9 about here]

Panel A adresses the impact of adding the ENV factor. As we construct quintiles based on the firm's ENV exposures, we find increasing ENV exposures from Q1 to Q5. Concerning explanatory power, four out five adjusted R2 values increase. This indicates that adding the ENV factor contributes explanatory power. Especially in Q5 the increase of 5% suggests that a significant portion of credit spread variation is triggered by the time-varying market valuation of environmental risks. Similarly, Panel B and C adress the SOC and CGV factors. Again, we find the highest increases in adjusted R2 for Q5 (highest SOC and CGV exposure, respectively).

To conclude, adding ESG factors to common models explaining credit spreads changes increases explanatory power. This suggests that there is variation in spread changes that is driven by the time-varying market valuation of ESG.

6 Conclusion

This study examines how credit spreads of European firms vary with their sustainability performance. Sustainability is represented by industry-benchmarked ESG ratings covering environmental-, social-, and governance- (ESG) related performance.

Based on Fama-MacBeth regressions for a sample from July 2009 to December 2016, our findings indicate that, after controlling for known determinants of CDS spreads, environmental ratings are related to CDS spreads in the monthly cross-section. Specifically, better environmental performance seems to be connected to lower CDS spreads, i.e. less credit risk. This finding supports the risk mitigation view, which links better ESG performance to a reduction in firm-risk, and, thus, credit risk. We do not find significant connections with regard to social or governance ratings after controlling for common CDS determinants.

However, linear regressions might be unable to capture non-linear patterns between ESG ratings and CDS spreads. To consider this, we group CDS into quartiles based on their ESG ratings and analyze these quartiles individually in terms of their residual CDS spreads which correspond to CDS spread components that should be unrelated to known determinants of CDS spreads. Focusing on environmental ratings, we find the highest residual CDS spreads for the worst environmental ratings while the lowest residual CDS spreads seem to be the case for the best environmental ratings. This suggests that CDS with the best and worst environmental performance appear to drive our findings obtained from Fama-MacBeth regressions. Exceeding 25 basis points on average, the difference between the best and the worst environmental performances is also economically significant.

Focusing on social performance, we find that residual CDS spreads seem to decline from quartiles with higher social ratings toward quartiles with lower social ratings. At first, this finding appears to support the overinvestment view which connects poorer ESG performance to lower credit risk. However, the decline in residual CDS spreads does not hold for the lowest social ratings, where residual CDS spreads increase by 11 basis points on average. Firms in that quartile might be exposed to risks that could be directly connected to their poor social efforts and thus lead to increases in their credit risk and CDS spreads again. Such risks may include low levels of employee commitment or unfavorable media coverage.

From a time-series perspective, we also find an impact of ESG on credit spreads. To assess the time-varying market valuation of ESG, we construct three Fama and French (1993, 2015)-style ESG factors. These factors significantly enhance the explanatory power of standard models explaining credit spread changes. This suggests that the time-varying market valuation of ESG is a significant determinant of the variation in credit spread changes of firms.

In summary, our findings emphasize that firms' environmental and social performance seems to be connected CDS spreads, and thus to credit risk in Europe. These connections do not appear to be related to known determinants of CDS spreads, as suggested by the literature to date. As a result, the environmental and social performance of firms can potentially be considered as an additional determinant of their CDS spreads. Overall, our results on ESG and credit spreads should have three main implications for investors. First, credit analysts can improve their credit risk models when incorporating ESG ratings. Second, fixed-income portfolio managers can improve risk management and performance measurement when considering ESG ratings of their portfolio constituents. Third, potential time-variability of credit risk components related to ESG might be relevant for factor-based investment strategies in fixed income markets.

References

Aldasoro, I., Ehlers, T., 2018. The credit default swap market: What a difference a decade makes. BIS Quarterly Review June 2018, 1–14.

Ashbaugh-Skaife, H., Collins, D.W., LaFond, R., 2006. The effects of corporate governance on firms' credit ratings. Journal of Accounting and Economics 42, 203–243.

Baran, L.C., Zhang, C.X., 2012. KLD 400 index inclusion and corporate bonds. Working Paper, Kent State University.

Barnett, M. L., Salomon, R. M., 2006. Beyond dichotomy: The curvilinear relationship between social responsibility and financial performance. Strategic Management Journal 27, 1101–1122.

Bauer, R., Derwall, J., Hann, D., 2009. Employee relations and credit risk. Working Paper, Maastricht University.

Bauer, R., Hann, D., 2010. Corporate environmental management and credit risk. Working Paper, Maastricht University.

Bhojraj, S., Sengupta, P., 2003. Effect of corporate governance on bond ratings and yields: The role of institutional investors and outside directors. Journal of Business 76, 455–475.

Blanco, R., Brennan, S., Marsh, I.W., 2005. An empirical analysis of the dynamic relationship between investment-grade bonds and credit default swaps. Journal of Finance 60, 2255–2281.

Borgers, A., Derwall, J., Koedijk, K., ter Horst, J., 2015. Do social factors influence investment behavior and performance? Evidence from mutual fund holdings. Journal of Banking and Finance 60, 112–126.

Bradley, M., Chen, D., Dallas, G., Snyderwine, E., 2007. The Relation between corporate governance and credit risk, bond yields and firm valuation. Working Paper, Duke University.

Campbell, J.Y., Taksler, G.B., 2003. Equity volatility and corporate bond yields. Journal of Finance 58, 2321–2349.

Chava, S., 2014. Environmental externalities and cost of capital. Management Science 60, 2223–2247.

Chava, S., Livdan, D., Purnanandam, A., 2009. Do shareholder rights affect the cost of bank loans. Review of Financial Studies 22, 2973–3004.

Chen, H., Kacperczyk, M., Ortiz-Molina, H., 2012. Do nonfinancial stakeholders affect the pricing of risky debt? Evidence from unionized workers. Review of Finance 16, 347–383.

Cheng, B., Ioannou, I., Serafeim, G., 2014. Corporate social responsibility and access to finance. Strategic Management Journal 35(1), 1-23.

Cremers, K.J.M., Nair, V.B., Wei, C., 2007. Governance mechanisms and bond prices. Review of Financial Studies 20, 1359–1388.

Eccles, R. G., Ioannou, I., Serafeim, G., 2014. The impact of corporate sustainability on organizational processes and performance. Management Science 60(11), 2835-2857.

Ederington, L., Guan, W., Yang, L., 2015. Bond market event study methods. Journal of Banking and Finance 58, 281–293.

Ericsson, J., Jacobs, K., Oviedo, R., 2009. The determinants of credit default swap premia. Journal of Financial and Quantitative Analysis 44, 109–132.

European Central Bank (ECB), 2016. Decision (EU) 2016/948 of the European Central Bank of 1 June 2016 on the implementation of the corporate sector purchase programme (ECB/2016/16). Official Journal of the European Union, L 157/28–32.

Fama, E. F., French, K. R., 1993. Common risk factors in the returns on stocks and bonds. Journal of Financial Economics 33(1), 3–56.

Fama, E. F., French, K. R., 2015. A five-factor asset pricing model. Journal of Financial Economics 116(1), 1–22.

Fama, E.F., MacBeth, J.D., 1973. Risk, return and equilibrium: Empirical tests. Journal of Political Economy 81, 607–636.

Flammer, C., 2015. Does corporate social responsibility lead to superior financial performance? A regression discontinuity approach. Management Science 61, 2549–2568.

Forte, S., Pena, J. I., 2009. Credit spreads: An empirical analysis on the informational content of stocks, bonds, and CDS. Journal of Banking & Finance 33, 2013–2025.

Frooman, J., Zietsma, C., McKnight, B., 2008. There is no good reason not to be good. Administrative Science Association of Canada (ASAC), Halifax, Nova Scotia.

Galema, R., Plantinga, A., Scholtens, B., 2008. The stocks at sake: Return and risk in socially responsible investment. Journal of Banking and Finance 32, 2646–2654.

Galil, K., Shapir, O.M., Amiram, D., Ben-Zion, U., 2014. The determinants of CDS spreads. Journal of Banking and Finance 41, 271–282.

Ge, W., Liu, M., 2015. Corporate social responsibility and the cost of corporate bonds. Journal of Accounting and Public Policy 34, 597–624.

Gebhardt, W.R., Hvidkjaer, S., Swaminathan, B., 2005. The cross-section of expected corporate bond returns: Betas or characteristics? Journal of Financial Economics 75, 85–114.

Global Sustainable Investment Alliance (GSIA), 2016. Global sustainable investment review 2016.

Goss, A., Roberts, G.S., 2011. The impact of corporate social responsibility on the cost of bank loans. Journal of Banking and Finance 35, 1794–1810.

Graham, A., Maher, J.J., Northcut, W.D., 2001. Environmental liability information and bond ratings. Journal of Accounting, Auditing and Finance 16, 93–116.

Güntay. L., Hackbarth, D., 2010. Corporate bond credit spreads and forecast dispersion. Journal of Banking and Finance 34, 2328–2345.

Hübel, B., Scholz, H., 2019. Integrating sustainability risks in asset management: The role of ESG exposures and ESG ratings. Available at: https://ssrn.com/abstract=3091666.

Ince, O. S., Porter, R. B., 2006. Individual equity return data from Thomson Datastream: Handle with care!. Journal of Financial Research, 29(4), 463-479.

International Capital Markets Association (ICMA), 2016. Remaking the corporate bond market. Available at: https://www.icmagroup.org/assets/documents/Regulatory/Secondary-markets/Remaking-the-Corporate-Bond-Market-250716.pdf, Zurich, Switzerland, accessed 07/06/2018.

International Capital Markets Association (ICMA), 2018. The European corporate single name credit default swap market. Available at: https://www.icmagroup.org/assets/documents/Regulatory/Secondary-markets, Zurich, Switzerland, accessed 07/06/2018.

Ioannou, I., Serafeim, G., 2012. What drives corporate social performance? The role of nation-level institutions. Journal of International Business Studies, 43(9), 834-864.

Izzo, M.F., Magnanelli, B.S., 2012. Does it pay or does firm pay? The relation between ESG performance and the cost of debt. Working Paper, Luiss University.

Jiraporn, P., Jiraporn, N., Boeprasert, A., Chang, K., 2014. Does corporate social responsibility (ESG) improve credit ratings? Evidence from geographic identification. Financial Management 43, 505–531.

Jostova, G., Nikolova, S., Philipov, A., Stahel, C.W., 2013. Momentum in corporate bond returns. Review of Financial Studies 26, 1649–1693.

Kim, Y., Li, H., Li, S., 2014. Corporate social responsibility and stock price crash risk. Journal of Banking and Finance 43, 1–13.

Klock, M.S., Mansi, S.A., Maxwell, W.F., 2005. Does corporate governance matter to bondholders? Journal of Financial and Quantitative Analysis 40, 693–719.

Lee, D. D., Humphrey, J. E., Benson, K. L., Ahn, J. Y. , 2010. Socially responsible investment fund performance: the impact of screening intensity. Accounting & Finance 50(2), 351–370.

Lins, K.V., Servaes, H., Tamayo, A., 2017. Social capital, trust, and firm performance: The value of corporate social responsibility during the financial crisis. Journal of Finance 72, 1785–1824.

Longstaff, F.A., Mithal, S., Neis, E., 2005. Corporate yield spreads: Default risk or liquidity? New evidence from the credit default swap market. Journal of Finance 60, 2213–2253.

Mama, H. B., Fouquau, J. Nonlinear Financial Payoffs to Corporate Sustainability. Working Paper, ESCP Europe.

Menz, K.M., 2010. Corporate social responsibility: Is it rewarded by the corporate bond market? A critical note. Journal of Business Ethics 96, 117–134.

Newey, W.K., West, K.D., 1987. A simple, positive semi-definite, heteroskedasticity and autocorrelation consistent covariance matrix, Econometrica 55, 703–708.

Norden, L., Weber, M., 2009. The co-movement of credit default swap, bond and stock markets: An empirical analysis. European Financial Management 15, 529–562.

Oikonomou, I., Brooks, C., Pavelin, S., 2014. The effects of corporate social performance on the cost of corporate debt and credit ratings. Financial Review 49, 49–75.

Renneboog, L., Ter Horst, J., Zhang, C., 2008. The price of ethics and stakeholder governance: The performance of socially responsible mutual funds. Journal of Corporate Finance 14, 302–322.

Schneider, T.E., 2011. Is environmental performance a determinant of bond pricing? Evidence from the U.S. pulp paper and chemical industries. Contemporary Accounting Research 28, 1537–1561.

Sharfman, M.P., Fernando, C.S., 2008. Environmental risk management and the cost of capital. Strategic Management Journal 29, 569–592.

Standard & Poor's, 2017. How environmental and climate risks and opportunities factor into global corporate ratings - An update. Available at: https://www.spratings.com/documents/20184/1634005, accessed 09/21/2018.

Stellner, C., Klein, C., Zwergel, B., 2015. Corporate social responsibility and Eurozone corporate bonds: The moderating role of country sustainability. Journal of Banking and Finance 59, 538–549.

Sun, W., Cui, K., 2014. Linking corporate social responsibility to firm default risk. European Management Journal 32, 275–287.

Tang, D. Y., Yan, H., 2010. Market conditions, default risk and credit spreads. Journal of Banking & Finance 34, 743–753.

Thompson, Jennifer. Credit rating catches the ESG wave Thompson. Financial Times, London, 25 Feb 2019, p. 10.

Verbeek, M., 2017. A guide to modern econometrics. Chichester: John Wiley & Sons Ltd. Zhang, B.Y., Zhou, H., Zhu, H., 2009. Explaining credit default swap spreads with the equity volatility and jump risks of individual firms. Review of Financial Studies 22, 5099–5131.

Zhu, H., 2006. An empirical comparison of credit spreads between the bond market and the credit default swap market. Journal of Financial Services Research 29, 211–235.

Table 1: Literature overview

Authors	**Data**						**Evidence**
	Credit ratings	Corporate bonds	CDS	Period	Region	ESG pillar	
Frooman et al. (2008)	x			2006-2007	U.S.	ESG	Risk mitigation
Oikonomou et al. (2014)	x	x		1993-2008	U.S.	ESG	Risk mitigation
Ge and Liu (2015)	x	x		1992-2009	U.S.	ESG	Risk mitigation
Jiraporn et al. (2014)	x			1995-2007	U.S.	ESG	Risk mitigation
Sun and Cui (2014)	x			2008-2010	U.S.	ESG	Risk mitigation
Graham et al. (2001)	x			1986-1997	U.S.	E	Risk mitigation
Bauer and Hann (2010)		x		1995-2006	U.S.	E	Risk mitigation
Schneider (2011)		x		1994-2004	U.S.	E	Risk mitigation
Bauer et al. (2009)	x	x		1995-2006	U.S.	S	Risk mitigation
Chen et al. (2012)		x		1973-1998	U.S.	S	Risk mitigation
Klock et al. (2005)		x		1990-2000	U.S.	G	Risk mitigation
Ashbaugh-Skaife et al. (2006)	x			2002-2003	U.S.	G	Risk mitigation
Bradley et al. (2007)	x	x		2001-2007	U.S.	G	Risk mitigation
Bhojraj and Sengupta (2003)	x	x		1991-1996	U.S.	G	Risk mitigation
Cremers et al. (2007)	x	x		1990-1997	U.S.	G	Risk mitigation
Menz (2010)		x		2004-2007	Europe	ESG	Overinvestment (weak)
Stellner et al. (2015)		x		2006-2012	Eurozone	ESG	Risk mitigation (weak)
Akdogu and Alp (2016)			x	2001-2006	U.S.	G	Risk mitigation
Switzer et al. (2018)			x	2010-2012	World ex U.S.	G	Risk mitigation

This table lists studies analyzing the relationship between ESG and credit risk in the context of corporate bonds or credit ratings. The column "ESG" indicates whether ESG or more detailed measures covering environmental- (E), social- (S), or governance- (G) related aspects were applied. The "risk mitigation" view links better ESG performances to better credit ratings and lower bond yield spreads, whereas the "overinvestment" view asserts the reverse relationship.

Table 2: Country and industry concentration

	#	%
Panel A: Countries		
France	36	34
Germany	24	22
Netherlands	12	11
Italy	10	9
Spain	7	7
Finland	6	6
Austria	4	4
Belgium	3	3
Portugal	2	2
Greece	2	2
Ireland	1	1
Luxembourg	1	1
Total	**108**	
Panel B: Industries		
Industrials	20	19
Consumer Cyclicals	19	18
Utilities	17	16
Basic Materials	16	15
Telecommunications Services	11	10
Consumer Non-Cyclicals	10	9
Healthcare	5	5
Energy	5	5
Technology	5	5
Total	**108**	

This table shows the distribution of the firms in our CDS sample across countries (Panel A) and industries (Panel B).

Table 3: Descriptive statistics and correlations

Panel A: Descriptive statistics							
Variable	Mean	Median	Min.	5th pctl.	95th pctl.	Max.	Sd.
Spread (bp)	143.48	90.18	16.40	39.72	409.06	1988.09	174.42
Rating (AAA:1; CC:20)	8.45	8	2	5	12	20	2.41
Lev (%)	37.68	34.84	0.00	10.93	71.31	97.59	19.61
Ret (%)	1.06	0.96	-42.74	-11.17	13.54	66.03	7.87
Vola (%)	1.83	1.67	0.68	1.07	3.14	13.95	0.69
ENV	77.26	79.57	27.99	53.21	94.91	99.22	13.53
SOC	74.81	78.12	26.07	47.37	93.36	98.44	14.83
CGV	55.67	56.18	10.19	23.75	86.71	97.47	19.29

Panel B: Correlations							
	1)	2)	3)	4)	5)	6)	7)
1) Spread	1						
2) Rating	0.70	1					
3) Vola	0.63	0.57	1				
4) Return	-0.02	0.02	0.01	1.00			
5) Lev	0.42	0.37	0.33	-0.06	1		
6) ENV	-0.10	-0.19	-0.05	-0.01	-0.04	1	
7) SOC	-0.16	-0.35	-0.19	-0.01	-0.03	0.49	1
8) CGV	-0.09	-0.13	-0.06	0.00	-0.16	0.22	0.22

This table shows descriptive statistics for all variables used in our empirical analyses. Every firm is represented by one CDS. Variables are explained in Sections 3.1 to 3.3. The evaluation period covers July 2009 to December 2016.

Table 4: Determinants of credit spreads

	M1	M2	M3
Intercept	-302.89	41.49	
	(-7.51)	**(0.58)**	
Rat	29.57	-45.04	
	(4.70)	**(-2.78)**	
Ratsq		4.10	
		(3.54)	
Rat D1			-157.71
			(-8.76)
Rat D2			-168.06
			(-7.74)
Rat D3			-149.13
			(-6.71)
Rat D4			-143.38
			(-6.98)
Rat D5			-47.65
			(-1.77)
Vol	81.18	64.11	113.44
	(5.55)	**(4.65)**	**(6.05)**
Ret	-0.86	-0.88	-0.65
	(-2.10)	**(-2.44)**	(-1.44)
Lev	1.22	1.22	1.63
	(2.45)	**(2.79)**	**(2.38)**
N	8,370	8,370	8,370
Adj. R2	0.6176	0.7080	0.7560

This table shows results from regression analyses on the relationship between CDS spreads and determinants of CDS spreads as suggested by the literature (see Section 3). Results are obtained from Fama-MacBeth regressions. Coefficients are first estimated in the monthly cross-section and then averaged over time. The dependent variable is the monthly CDS spread. Each CDS refers to one firm. t-statistics are reported in parentheses and based on Newey and West (1987) standard errors (twelve lags) which are calculated from the time-series of coefficient values. Bold values indicate statistical significance at 10%. The evaluation period covers July 2009 to December 2016.

Table 5: The linear relationship between CDS spreads and ESG ratings

	M4	M5	M6	M7
Controls				
Rat D1	-107.46	-185.63	-156.96	-142.95
	(-4.84)	**(-5.99)**	**(-8.19)**	**(-4.41)**
Rat D2	-118.76	-196.48	-165.00	-151.92
	(-6.40)	**(-6.79)**	**(-6.76)**	**(-5.20)**
Rat D3	-103.46	-175.27	-147.55	-135.62
	(-5.04)	**(-6.19)**	**(-6.36)**	**(-4.66)**
Rat D4	-98.33	-167.82	-142.61	-128.01
	(-4.79)	**(-5.91)**	**(-6.77)**	**(-4.49)**
Rat D5	-1.61	-70.53	-45.60	-24.20
	(-0.05)	**(-2.13)**	**(-2.12)**	(-0.71)
Vol	114.39	113.88	112.47	114.12
	(6.12)	**(6.19)**	**(6.02)**	**(6.20)**
Ret	-0.62	-0.54	-0.60	-0.51
	(-1.34)	(-1.22)	(-1.42)	(-1.18)
Lev	1.61	1.61	1.62	1.52
	(2.37)	**(2.39)**	**(2.28)**	**(2.20)**
ESG variables				
ENV	-0.63			-0.98
	(-2.94)			**(-5.78)**
SOC		0.34		0.79
		(1.21)		**(2.98)**
CGV			0.01	0.04
			(0.06)	(0.25)
N	8,370	8,370	8,370	8,370
Adj. R2	0.7566	0.7586	0.7556	0.7587

This table shows results from regression analyses on the relationship between CDS spreads and relative ESG ratings while controlling for determinants of CDS spreads as suggested by the literature (see Section 3). Results are obtained from Fama-MacBeth regressions. Coefficients are first estimated in the monthly cross-section and then averaged over time. The dependent variable is the monthly CDS spread. Each CDS refers to one firm. t-statistics are reported in parentheses and based on Newey and West (1987) standard errors (twelve lags) which are calculated from the time-series of coefficient values. Bold values indicate statistical significance at 10%. The evaluation period covers July 2009 to December 2016.

Table 6: The non-linear relationship between CDS spreads and ESG ratings

	M8	M9	M10
Control variables			
Rat D1	-165.55	-167.99	-160.06
	(-8.39)	**(-8.80)**	**(-8.28)**
Rat D2	-175.81	-181.33	-168.06
	(-7.27)	**(-7.67)**	**(-7.30)**
Rat D3	-160.7	-155.08	-149.87
	(-6.47)	**(-6.61)**	**(-6.50)**
Rat D4	-155.93	-149.26	-144.39
	(-6.77)	**(-6.68)**	**(-6.81)**
Rat D5	-60.89	-52.14	-48.74
	(-2.11)	**(-1.78)**	**(-1.83)**
Vol	113.01	115.00	111.89
	(5.91)	**(6.38)**	**(5.92)**
Ret	-0.64	-0.67	-0.61
	(-1.40)	(-1.48)	(-1.43)
Lev	1.73	1.58	1.63
	(2.32)	**(2.43)**	**(2.25)**
ESG variables			
ENV top	4.32		
	(0.65)		
ENV bottom	25.77		
	(3.18)		
SOC top		22.47	
		(4.77)	
SOC bottom		1.96	
		(0.21)	
CGV top			8.34
			(1.46)
CGV bottom			7.51
			(1.07)
N	8,370	8,370	8,370
Adj. R2	0.7567	0.7576	0.7549

This table shows results from regression analyses on the relationship between CDS spreads and ESG ratings while controlling for determinants of CDS spreads as suggested by the literature (see Section 3). Instead of including ESG ratings, we use dummy variables assigning a value of one to firms belonging to the top or bottom E/S/G quartile in each month, respectively. Results are obtained from Fama-MacBeth regressions. Coefficients are first estimated in the monthly cross-section and then averaged over time. The dependent variable is the monthly CDS spread. Each CDS refers to one firm. t-statistics are reported in parentheses and based on Newey and West (1987) standard errors (twelve lags) which are calculated from the time-series of coefficient values. Bold values indicate statistical significance at 10%. The evaluation period covers July 2009 to December 2016.

Table 7: The relationship between residual CDS spreads and ESG quartiles

Quartile	Mean monthly residual CDS spreads		
	Environmental	Social	Governance
1 (Lowest ratings)	10.69	11.86	1.63
	(2.52)	(1.62)	(0.39)
2	-0.42	-11.14	3.00
	(-0.18)	**(-4.87)**	(1.02)
3	6.70	-8.89	-1.02
	(2.01)	(-1.18)	(-0.39)
4 (Highest ratings)	-15.92	7.28	-4.47
	(-4.37)	**(2.10)**	(-1.25)
4-1 (Difference)	-26.61	-4.58	-6.10
	(-3.79)	(-0.58)	(-0.81)

This table shows results from monthly sorts of CDS into quartiles based on their ESG ratings. For each quartile, reported values correspond to the residual CDS spreads of its constituents that are first averaged for each month and then over time. Residual CDS spreads are the residuals from monthly cross-sectional regressions according to Model M3 (Eq. 1.3) and should therefore be unrelated to the control variables used in this model. By definition, the mean monthly residual CDS spread is zero. **t**-statistics are reported in parentheses and indicate whether the reported values are significantly different from zero. Newey and West (1987) standard errors (twelve lags) are calculated from the time-series of monthly residual CDS spreads of the respective quartile. Bold values indicate statistical significance at 10%. The evaluation period covers July 2009 to December 2016.

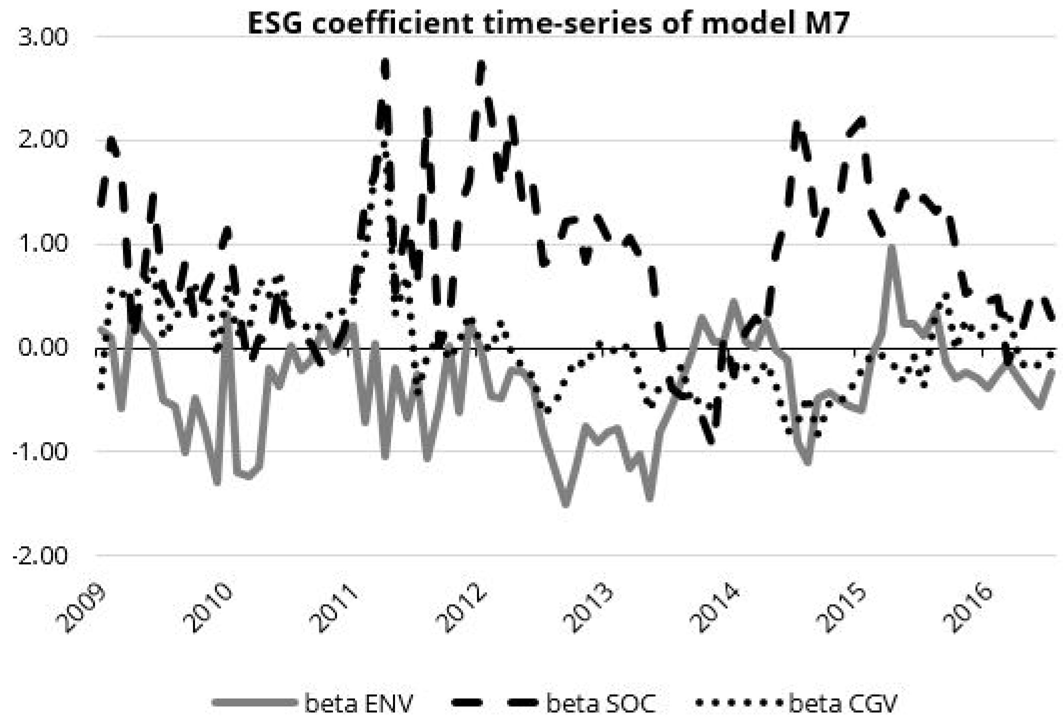

Figure 1: Time-series of ESG coefficients calculated from Fama-MacBeth regressions in model M7

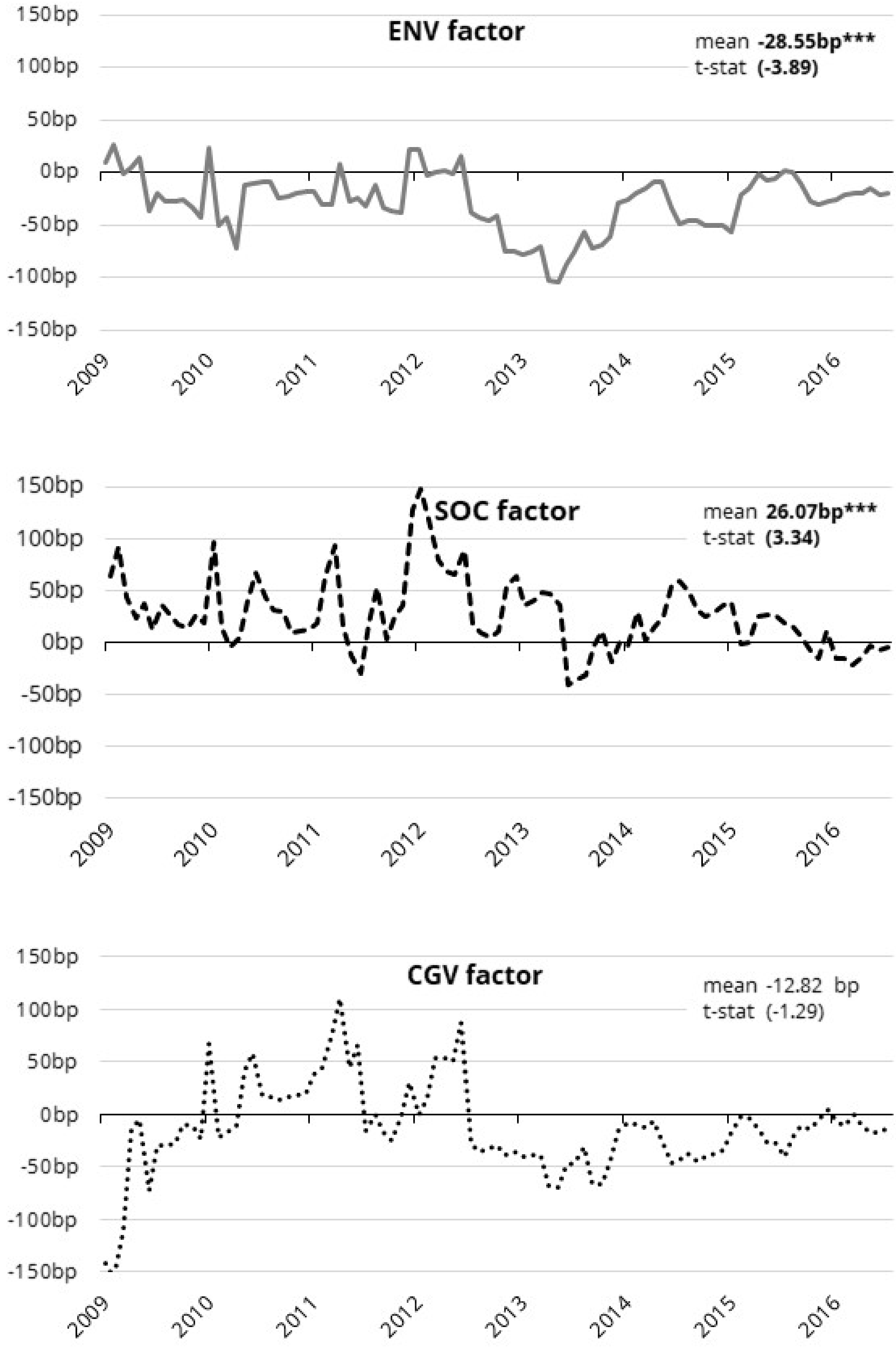

Figure 2: Time-varying spreads of credit-neutral ESG long-short factors

Table 8: The determinants of CDS spread● changes

	M1-all	M2-firmspec	M3-com	M4-FF	M5-CRR	M6-Galil et al.
Intercept	-0.15	1.00	0.00	2.01	0.45	0.82
	(-.35)	**(7.33)**	(.)	**(7.41)**	**(2.47)**	**(6.55)**
Ret	-0.78	-1.25				-0.91
	(-7.64)	**(-10.59)**				**(-9.34)**
ΔVol	-2.50	16.64				0.22
	(-.73)	**(5.62)**				(0.07)
ΔLev	0.35	0.92				
	(1.43)	**(2.97)**				
ΔSpot	-494.45		-170.90			
	(-3.02)		(-1.01)			
ΔSlope	-262.77		-508.65			
	(-.59)		**(-1.88)**			
ΔVstoxx	-0.10		0.66			
	(-.38)		**(4.12)**			
MKT	-0.30			-3.27		
	(-1.02)			**(-10.54)**		
SMB	0.11			-1.00		
	(.55)			**(-4.03)**		
HML	0.12			-1.94		-0.23
	(.57)			**(-9.75)**		(-1.62)
RMW	0.21			-0.69		
	(.73)			**(-2.8)**		
CMA	1.37			2.79		
	(3.19)			**(4.86)**		
UMD	0.60			0.26		
	(3.91)			**(2.14)**		
MP	41.04				111.57	
	(3.9)				**(6.06)**	
UI	28.55				44.43	
	(.48)				(1.41)	
ΔUTS	646.75				616.51	
	(2.34)				**(2.6)**	
ΔUPR	344.42				5928.22	
	(1.03)				**(10.43)**	
ΔMRI	0.62		0.71			0.64
	(11.81)		**(12.56)**			**(10.53)**
# firms	98	98	98	98	98	98
# months	90	90	90	90	90	90
adj. R2 (%)	51.19	25.01	40.93	32.45	10.72	46.93

This table shows results from regression analyses on the relationship between CDS spreads changes and determinants of CDS spreads changes as suggested by the literature (see Section 3). Results are obtained as average coefficients retrieved from time-series regressions on firm-level. t-statistics are reported in parentheses and based on Newey and West (1987) standard errors (twelve lags). Bold values indicate statistical significance at 10%. The evaluation period covers July 2009 to December 2016.

Table 9: The explanatory power of ESG factors when explaining CDS spread changes

	Q1 (low exp.)	Q2	Q3	Q4	Q5 (high exp.)
	Panel A: ENV exposure quintiles				
beta MRI	0.51	0.53	0.64	0.44	1.05
	(5.22)	**(21.91)**	**(7.59)**	**(9.25)**	**(12.32)**
adj. R2 (no ENV, %)	42.69	50.31	47.00	45.97	48.80
beta MRI	0.56	0.53	0.63	0.46	1.15
	(7.45)	**(21.93)**	**(7.61)**	**(9.71)**	**(11.73)**
beta ENV	-0.44	0.01	0.07	0.17	0.64
	(-2.44)	**(4.7)**	**(26.01)**	**(20.48)**	**(7.54)**
adj. R2 (with ENV, %)	44.00	49.86	47.71	48.18	53.80
chg adj. R2	1.32***	-0.46	0.71**	2.21***	5.00***
	Panel B: SOC exposure quintiles				
beta MRI	0.66	0.44	0.48	0.42	1.18
	(6.31)	**(13.2)**	**(6.27)**	**(7.91)**	**(15.08)**
adj. R2 (no SOC, %)	52.36	42.10	43.23	46.66	50.03
beta MRI	0.69	0.44	0.49	0.43	1.25
	(6.76)	**(13.22)**	**(6.31)**	**(8.35)**	**(16.21)**
beta SOC	-0.13	-0.01	0.02	0.09	0.37
	(-2.92)	**(-8.08)**	**(8.73)**	**(19.62)**	**(18.71)**
adj. R2 (with SOC, %)	53.32	41.36	42.86	47.86	53.91
chg adj. R2	0.96***	-0.75	-0.37	1.20***	3.88***
	Panel C: CGV exposure quintiles				
beta MRI	0.67	0.49	0.51	0.65	0.87
	(3.6)	**(13.86)**	**(19.13)**	**(8.15)**	**(12.98)**
adj. R2 (no CGV, %)	46.08	45.25	52.15	43.95	46.99
beta MRI	0.81	0.49	0.49	0.63	0.90
	(5.65)	**(13.63)**	**(18.48)**	**(8.55)**	**(12.83)**
beta CGV	-0.34	0.00	0.03	0.09	0.33
	(-1.9)	(1.38)	**(14.14)**	**(99.26)**	**(8.22)**
adj. R2 (with CGV, %)	47.67	44.41	52.28	45.91	50.71
chg adj. R2	1.59***	-0.84	0.13	1.96***	3.72***

This table shows results from regression analyses on the relationship between CDS spreads changes and determinants of CDS spreads changes as suggested by the literature (see Section 3). The base model M11 is augmented by the ESG factors. For brevity, we do not report coefficients of RET, VOL and HML as they do not vary across quintiles. Results are obtained as average coefficients retrieved from time-series regressions on firm-level. Firms are sorted into quintile groups based on their exposures to the ESG factors. t-statistics are reported in parentheses and based on Newey and West (1987) standard errors (twelve lags). Bold values indicate statistical significance at 10%. Significance levels for changes in adj. R2 are calculated based on one-sided F-tests . The evaluation period covers July 2009 to December 2016.

Appendix

Table 10: Descriptive statistics of changes of variables

Variable	Mean	Median	Min.	5th pctl.	95th pctl.	Max.	Sd.
ΔSpread (bp)	-0.79	-0.44	-1170.84	-36.75	37.04	1004.15	42.46
RET (%)	1.09	1.00	-42.74	-11.19	13.56	66.03	7.88
ΔVOL (%)	-0.02	-0.01	-10.72	-0.22	0.18	1.61	0.18
ΔLEV	-0.09	-0.11	-72.23	-2.90	2.84	53.86	2.29
ΔSpot	0.00	0.00	-0.01	0.00	0.00	0.01	0.00
ΔSlope	0.00	0.00	0.00	0.00	0.00	0.00	0.00
ΔVstoxx	-0.13	-0.61	-13.02	-7.16	8.16	11.78	4.82
MKT	0.93	1.25	-10.36	-5.26	6.86	9.00	3.60
SMB	0.23	0.30	-4.25	-2.65	3.31	4.82	1.75
HML	-0.16	-0.42	-4.43	-3.69	4.46	7.33	2.57
RMW	0.46	0.54	-3.90	-2.60	3.03	3.40	1.68
CMA	0.11	-0.07	-2.88	-2.10	2.13	3.16	1.21
UMD	1.15	1.52	-11.25	-3.13	5.60	7.16	3.03
QMJ	0.72	0.76	-5.69	-2.89	4.76	6.98	2.37
BAB	0.62	0.57	-5.61	-2.44	4.18	6.84	2.15
MP	0.00	0.00	-0.09	-0.03	0.03	0.09	0.02
UI	0.00	0.00	-0.02	-0.01	0.01	0.01	0.01
ΔUTS	0.00	0.00	-0.01	0.00	0.00	0.01	0.00
ΔUPR	0.00	0.00	-0.01	0.00	0.00	0.00	0.00
ΔMRI avg	-1.04	-2.02	-50.58	-30.58	25.48	64.29	17.31
ΔMRI groups	-1.29	-1.83	-67.79	-32.29	29.65	100.12	20.38
ΔENV factor	-0.32	0.74	-73.98	-34.26	35.83	66.15	20.35
ΔSOC factor	-0.76	0.82	-83.16	-49.30	44.73	92.11	28.85
ΔCGV factor	1.44	1.39	-115.18	-64.83	42.93	96.67	29.86

Table 11: Correlations of changes of variables

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
ΔSpread	1																			
RET	-0.38	1																		
ΔVOL	0.15	-0.14	1																	
ΔLEV	0.28	-0.68	0.11	1																
ΔSpot	-0.14	0.18	-0.12	-0.14	1															
ΔSlope	0.01	0.02	0.01	-0.03	0.34	1														
ΔVstox	0.27	-0.43	0.09	0.30	-0.33	-0.03	1													
MKT	-0.32	**0.54**	-0.20	-0.38	0.25	0.05	-0.74	1												
SMB	0.05	-0.17	0.02	0.09	0.07	0.08	0.38	-0.31	1											
HML	-0.19	0.28	-0.20	-0.22	0.47	0.10	-0.30	0.42	0.00	1										
RMW	0.16	-0.21	0.11	0.18	-0.44	-0.19	0.27	-0.37	-0.15	-0.82	1									
CMA	0.04	0.01	-0.11	-0.01	0.23	-0.02	0.04	-0.06	-0.07	0.50	-0.38	1								
UMD	0.15	-0.21	0.07	0.15	-0.23	-0.08	0.23	-0.33	-0.11	-0.58	**0.60**	-0.12	1							
MP	0.07	-0.05	0.01	0.05	-0.05	-0.22	0.15	-0.12	-0.06	0.00	0.12	0.13	0.12	1						
UI	-0.01	0.00	0.01	-0.02	0.10	0.09	-0.04	0.01	0.06	-0.02	0.05	-0.01	0.03	-0.06	1					
ΔUTS	-0.01	0.05	0.01	-0.05	0.44	**0.92**	-0.09	0.07	0.09	0.21	-0.29	-0.01	-0.16	-0.18	0.13	1				
ΔUPR	0.19	-0.25	0.26	0.19	-0.23	-0.15	0.23	-0.46	-0.11	-0.49	0.41	-0.11	0.38	0.03	-0.07	-0.16	1			
ΔMRI	0.40	-0.36	0.19	0.25	-0.26	0.08	**0.53**	-0.59	0.10	-0.33	0.28	0.06	0.18	0.10	-0.04	0.04	0.34	1		
ΔENV	0.11	-0.14	0.01	0.09	-0.04	-0.06	0.10	-0.21	0.03	-0.20	0.20	-0.04	0.17	0.12	-0.07	-0.12	0.15	0.03	1	
ΔSOC	0.06	-0.09	-0.06	0.06	-0.15	-0.07	0.11	-0.13	-0.02	-0.18	0.16	-0.06	0.19	0.25	-0.08	-0.04	0.16	-0.02	0.32	1
ΔCGV	0.10	-0.11	-0.03	0.08	-0.04	0.02	0.22	-0.19	0.11	-0.12	0.13	-0.03	-0.01	0.17	-0.06	0.00	-0.04	0.12	**0.63**	0.17