EUROPEAN CENTRAL BANK

EUROSYSTEM

# Working Paper Series

Kornelia Fabisik, Michael Ryf, Larissa Schäfer, Sascha Steffen

## Do debt investors care about ESG ratings?

ECB – Lamfalussy Fellowship Programme

No 2878

## ECB Lamfalussy Fellowship Programme

This paper has been produced under the ECB Lamfalussy Fellowship programme. This programme was launched in 2003 in the context of the ECB-CFS Research Network on “Capital Markets and Financial Integration in Europe”. It aims at stimulating high-quality research on the structure, integration and performance of the European financial system.

The Fellowship programme is named after Baron Alexandre Lamfalussy, the first President of the European Monetary Institute. Mr Lamfalussy is one of the leading central bankers of his time and one of the main supporters of a single capital market within the European Union.

Each year the programme sponsors five young scholars conducting a research project in the priority areas of the Network. The Lamfalussy Fellows and their projects are chosen by a selection committee composed of Eurosystem experts and academic scholars. Further information about the Network can be found at http://www.eufinancial-system.org and about the Fellowship programme under the menu point “fellowships”.

## Abstract

We study the effect of changes in firms' ESG ratings on the cost of debt of U.S. firms using a methodology change of an ESG rating provider. We find that loan spreads of downgraded ESG-rated firms in the secondary corporate loan market increase by about 10% compared to non-downgraded ESG-rated firms after the methodology change. The effect of ESG rating downgrades is not driven by the increase in the fundamental default risk of firms but rather by the premium charged by investors above the spread for default risk. The effect is stronger for firms that are more financially constrained, firms that are more exposed to ESG and, particularly, climate risk concerns as well as firms that are more held by climate-concerned lenders. We show that also loan spreads of private (unrated) firms in industries affected by ESG rating downgrades increase after the methodology change.



**JEL classification**: E44, G20, G24

**Keywords**: ESG ratings, Climate finance, Loan spreads, Private firms

## Summary

ESG assets are projected to increase to $53 trillion by 2025 or a third of global assets under management.[1] However, little is known about the extent to which debt investors incorporate ESG ratings into their investment decisions and the implications for the cost of debt for firms. To answer this question, we exploit a methodology-driven change in ESG ratings by one of the largest ESG rating providers - Refinitiv ESG. This allows us to study the effect of ESG rating changes on loan market-based credit spreads using a sample of secondary corporate loan market prices (see e.g., Saunders, Spina, Steffen, and Streitz (2021)).

The secondary syndicated loan market provides an ideal setting to study this question. The majority of loans traded in the secondary market are syndicated corporate loans that represent one of the most important sources of financing for large public and private firms. The annual secondary market trading volume reached $780 billion USD in 2021 (Saunders et al., 2021). Importantly, secondary market quotes for corporate loans are available on a *daily* frequency and thus we can track investor behavior in real-time. Moreover, they are less likely to be affected by shifts in the composition of issuers in the primary market over time.

For identification, we build on a key finding in Berg, Fabisik, and Sautner (2020), who show that Refinitiv ESG completely revised its ESG scoring methodology in April 2020.[2] As a consequence, virtually all ESG rating scores in the Refinitiv ESG database have been adjusted. Thirteen percent (13%) of ESG scores were "upgraded", i.e., the revised ESG score was higher than the initial ESG score. Even more remarkably, 87% of the observations were "downgraded". Refinitiv ESG applied the methodology change not just to newly created scores, but it also retroactively modified the historical scores in its

[1]Source: https://www.bloomberg.com/professional/blog/esg-assets-may-hit-53-trillion-by-2025-a-third-of-global-aum/; accessed on 11/30/2021.

[2]ESG scores by Refinitiv ESG have been used (or referenced) in more than 1,500 academic articles over the past 15 years. The ESG data provider has been used by e.g., BlackRock and other asset managers to manage their portfolios, or institutions such as the European Commission or OECD to shape their policy recommendations, see e.g., "BlackRock taps Thomson Reuters' ASSET4 for global ESG data," Responsible Investor, April 11, 2011.

database.

We use the revision of the ESG rating approach as a shock to firms' ESG ratings and study its effect on the spreads of syndicated corporate loans traded on the secondary market between December 1, 2019 and June 30, 2020. For our main analysis, we thus exploit the effect of changes in ESG ratings on the cost of debt for firms. Building on the work of Saunders et al. (2021), we use the loan market-based credit spread based on secondary market pricing information for individual loans to non-financial U.S. firms. As most firms experienced a downgrade, we define firms as being downgraded if the relative pre- and post-methodology change in ESG ratings is equal to or below the 75$^{\text{th}}$ percentile. To control for the fact that the COVID-19 crisis coincides with the time period at which the methodology change took place, we compare differences in loans spread within the same industry, rating category and month, as various industries might have been affected differently by the pandemic. We also add firm characteristics, loan or firm fixed effects as well as credit rating scale fixed effects.

We find that loans of firms that have been downgraded after the methodology change carry 10% higher loan spreads relative to non-downgraded firms within the *same industry, same rating category* and *month*. When we decompose the effect over time, we find that the spread increased for the following two months but declined afterwards, indicating that the effect was temporary. We perform a placebo test in which we shift the time period to show that our main results cannot be explained by the ongoing rewriting of the Refinitiv ESG data. To rule out confounding effects of the COVID-19 pandemic, we show that our result is robust when we control for market liquidity, stock market volatility, firm's distance to default or whether the firm was in a COVID-affected industry (Fahlenbrach, Rageth, and Stulz (2021)). Our main result remains unaffected when we use alternative definitions of downgraded firms, e.g., firms with an ESG rating change equal or below the 25$^{\text{th}}$ percentile or using just the continuous ESG rating change.

# 1. Introduction

ESG assets are projected to increase to $53 trillion by 2025 or a third of global assets under management.[1] However, little is known about the extent to which debt investors incorporate ESG ratings into their investment decisions and the implications for the cost of debt for firms. To answer this question, we exploit a methodology-driven change in ESG ratings by one of the largest ESG rating providers - Refinitiv ESG. This allows us to study the effect of ESG rating changes on loan market-based credit spreads using a sample of secondary corporate loan market prices (see e.g., Saunders, Spina, Steffen, and Streitz (2021)).

The secondary syndicated loan market provides an ideal setting to study this question. The majority of loans traded in the secondary market are syndicated corporate loans that represent one of the most important sources of financing for large public and private firms. The annual secondary market trading volume reached $780 billion USD in 2021 (Saunders et al., 2021). Importantly, secondary market quotes for corporate loans are available on a *daily* frequency and thus we can track investor behavior in real-time. Moreover, they are less likely to be affected by shifts in the composition of issuers in the primary market over time.

For identification, we build on a key finding in Berg, Fabisik, and Sautner (2020), who show that Refinitiv ESG completely revised its ESG scoring methodology in April 2020.[2] As a consequence, virtually all ESG rating scores in the Refinitiv ESG database have been adjusted. Thirteen percent (13%) of ESG scores were "upgraded", i.e., the revised ESG score was higher than the initial ESG score. Even more remarkably, 87% of the observations were "downgraded". Refinitiv ESG applied the methodology change not just to newly created scores, but it also retroactively modified the historical scores in its

[1] Source: https://www.bloomberg.com/professional/blog/esg-assets-may-hit-53-trillion-by-2025-a-third-of-global-aum/; accessed on 11/30/2021.

[2] ESG scores by Refinitiv ESG have been used (or referenced) in more than 1,500 academic articles over the past 15 years. The ESG data provider has been used by e.g., BlackRock and other asset managers to manage their portfolios, or institutions such as the European Commission or OECD to shape their policy recommendations, see e.g., "BlackRock taps Thomson Reuters' ASSET4 for global ESG data," Responsible Investor, April 11, 2011.

database.

We use the revision of the ESG rating approach as a shock to firms' ESG ratings and study its effect on the spreads of syndicated corporate loans traded on the secondary market between December 1, 2019 and June 30, 2020. For our main analysis, we thus exploit the effect of changes in ESG ratings on the cost of debt for firms. Building on the work of Saunders et al. (2021), we use the loan market-based credit spread based on secondary market pricing information for individual loans to non-financial U.S. firms. As most firms experienced a downgrade, we define firms as being downgraded if the relative pre- and post-methodology change in ESG ratings is equal to or below the $75^{\text{th}}$ percentile. To control for the fact that the COVID-19 crisis coincides with the time period at which the methodology change took place, we compare differences in loans spread within the same industry, rating category and month, as various industries might have been affected differently by the pandemic. We also add firm characteristics, loan or firm fixed effects as well as credit rating scale fixed effects.

We find that loans of firms that have been downgraded after the methodology change carry 10% higher loan spreads relative to non-downgraded firms within the *same industry, same rating category* and *month*. When we decompose the effect over time, we find that the spread increased for the following two months but declined afterwards, indicating that the effect was temporary. We perform a placebo test in which we shift the time period to show that our main results cannot be explained by the ongoing rewriting of the Refinitiv ESG data. To rule out confounding effects of the COVID-19 pandemic, we show that our result is robust when we control for market liquidity, stock market volatility, firm's distance to default or whether the firm was in a COVID-affected industry (Fahlenbrach, Rageth, and Stulz (2021)). Our main result remains unaffected when we use alternative definitions of downgraded firms, e.g., firms with an ESG rating change equal or below the $25^{\text{th}}$ percentile or using just the continuous ESG rating change.

Next, we explore potential channels for the temporary effect of ESG rating changes on firms' cost of debt. First, we test whether the effect is driven by changes in firm fundamentals or frictions in the secondary market. We decompose the loan spread into a default risk component based on firm fundamentals (which we term "predicted loan spread"), and a residual component that should capture the prices of risk above a default risk premium (which we term "excess loan spread"). Our findings reveal that our main effect is mostly explained by the excess loan premium that reflects potential temporary frictions of private debt investors in the secondary loan market.

Second, we investigate the role of financial constraints and informational frictions. We find that the effect is mostly driven by smaller and financially constrained firms, indicating that investors price in new information based on ESG score changes especially for opaque firms. Third, we find that the premium paid is higher for firms for which ESG seems to be more important based on their earnings calls, that have a higher exposure to carbon emissions, or to potential regulatory changes due to the climate risk. This suggests that ESG downgrades are especially informative for firms in areas sensitive to ESG, carbon emissions, or the climate risk topics.

Lastly, we explore potential spillover effects on private firms that are in industries with a large share of public firms that have experienced an ESG rating downgrade. As ESG scores are rarely available for private firms, we hypothesize that investors might learn about private firms' ESG exposure based on information about public firms in the same industry. Indeed, we find that private firms in affected industries experience a 9% increase in the loan spread relative to their average loan spread. The effect is especially pronounced for private firms without credit ratings for which additional information should play a larger role.

Our paper is related to the growing literature on the effects of ESG in capital markets. Professional investors seem to value sustainability, social responsibility or the climate when making investment decisions (Riedl and Smeets (2017), Hartzmark and Sussman (2019), Krueger, Sautner, and Starks (2020)). Empirical evidence shows that environmental risks also matter for pricing in equity markets (Ilhan, Sautner, and Vilkov (2021), Bolton and Kacperczyk (2021)), bond markets (Fatica, Panzica, and Rancan (2021), Painter (2020), Flammer (2021)) and real estate markets (Bernstein, Gustafson, and Lewis (2019), Baldauf, Garlappi, and Yannelis (2020)). We contribute to this literature by studying the value of ESG for professional investors in secondary loan markets.

Our paper mainly contributes to the literature on the effects of environmental factors on bank lending. Studies have shown that environmental risks, $CO_2$ emissions disclosure, exposure to climate change or sea-level rise result in higher loan spreads in corporate and mortgage credit markets (Chava (2014), Kleimeier and Viehs (2018), Ehlers, Packer, and de Greiff (2021), Javadi and Masum (2021), Nguyen, Ongena, Qi, and Sila (2020)). There is also evidence on the matching of firms and banks based on their ESG profiles. Literature documents that similarity in ESG and sustainability scores, environmental consciousness and ethical domains between banks and firms affects lending decisions and leads to more favorable loan pricing in primary markets (Kim, Surroca, and Tribó (2014), Hauptmann (2017), Houston and Shan (2020), Degryse, Goncharenko, Theunisz, and Vadasz (2021)). At the same time, Shin (2021) shows that low ESG banks attempt to improve their ESG profile by lending to high ESG firms at lower rates. In contrast, our paper focuses on the secondary market and explores the immediate impact of ESG rating downgrades on daily loan market prices.

# 2. Data

## 2.1. ESG data

We use Refinitiv ESG's methodology change as a shock to firms' ESG ratings.[3] We base our analysis on the methodology-change related data rewriting on two versions of the *same* Refinitiv ESG database, downloaded on February 27, 2020 and September 29, 2020 for the fiscal years 2018-2020. In the paper, we refer to the first ESG data version as the 02/2020 or "pre-methodology change" version and to the second ESG data version as the 09/2020 or "post-methodology change" version. The 02/2020 ESG data download covers the universe of firms in the database as of that date. In both data sets, we rely on the latest ESG score for each firm (usually 2019 or 2020), but for few cases when no

[3]Table A2 in Appendix provides a detailed description of Refinitiv ESG's methodology change.

later rating is available (indicated via "FY0" tag in the ESG data database), we rely on the rating from the fiscal year 2018. A lag in the ESG rating production is not unusual among ESG rating providers and the established practice is to rely on the ESG score displayed under "FY0" value of the *FinancialPeriodRelative* variable.[4]

To compute our main explanatory variable of interest that we label as *ESG Downgrade* throughout the paper, we first compute relative ESG score deviations for each firm based on the latest fiscal year observation common to both data versions as follows:

$$\Delta\, ESG\, Score = \left. \frac{ESG\, Score^{09/2020\ Data}}{ESG\, Score^{02/2020\ Data}} - 1 \right) . \tag{1}$$

We observe, in line with Berg et al. (2020), that the ESG scores for the *same* firm for the *same* year considerably vary between our pre- and post-methodology change data downloads (02/2020 and 09/2020). We find that due to the methodology change that took effect on April 6, 2020, not a single ESG score is the same. As shown by Berg et al. (2020), we similarly observe that most firms were subject to an ESG score downgrade. As a result, our indicator variable *ESG Downgrade* takes on a value of 1 for firms with an ESG rating difference (calculated according to Equation 1, i.e., pre- vs. post-methodology change) that is equal to or below the 75$^{\text{th}}$ percentile, and zero otherwise. The variable *ESG Downgrade* is based on quartiles calculated in the universe of firms with an ESG score for which we have data on both dates available prior to a merge with loan market data.

## 2.2. U.S. secondary syndicated loan market data

To study the effect of ESG rating downgrades on the cost of debt of U.S. firms, we use a dataset from the Loan Syndication and Trading Association (LSTA) comprised of daily secondary market quotes for corporate loans. With the creation of the LSTA in 1995, the secondary loan market grew to an active and liquid dealer-driven over-the-counter (OTC) market with an annual secondary market trading volume of $780 billion USD as

[4]We make sure that our comparison is for the same fiscal year, i.e., we always make sure to only compare within the same *FinancialPeriodAbsolute* variable.

of 2021. Similar to other debt securities OTC markets, we can observe daily price quotes for private claims that can be traded by banks and institutional investors legally even if in possession of material non-public information as they are not public securities under U.S. securities law (Taylor and Sansone, 2006). The majority of loans traded in the secondary market are syndicated corporate loans that constitute an important source of financing for public and private firms in the U.S..[5]

Similar to Saunders et al. (2021), we restrict our sample to term loans that are fully funded at origination and typically repaid at maturity. We further use only loans that can be linked to LPC's Dealscan database and have a remaining maturity of at least one year.[6] The initial dataset contains 1,531 loans for 825 non-financial U.S. firms during the September 1, 2019 and September 30, 2020 period. After merging the ESG rating database with the secondary markets data based on the Compustat ID (GVKEY), we obtain a sample of 415 loans for 260 publicly listed firms in the U.S.. For our main analysis, we restrict our sample to 3 months before and after the ratings restatement, *i.e.* between December 1, 2019 and June 30, 2020. As the first information about a future ratings change due to the methodology change was already announced on March 3, 2020, but was only officially made public on April 6, 2020 (the date when the change also came into effect), we use March either as our omitted category or exclude it from the analysis. Our final sample contains 394 loans for 246 firms (207 downgraded and 42 upgraded firms) and 41,818 observations.

To measure loan market-based credit spreads, our key dependent variable, we rely on the methodology by Saunders et al. (2021). In particular, we define the loan spread as the difference between a loan's implied yield to maturity and its risk-free equivalent yield to maturity. To calculate the yield to maturity for each loan in each period, we use a series of quarterly-paid cash flows based on the sum of the three-month LIBOR forward curve (obtained Bloomberg) and the term loan's fixed all-in-spread-drawn (obtained from Dealscan) for the respective period. We use the risk-free equivalent yield to maturity

[5] For more detailled discussion about the secondary loan market, refer to Saunders et al. (2021).

[6] We merge the primary and secondary syndicated market data relying on the Loan Identification Number (LIN) or on a combination of the borrower name, maturity dates, and the all-in-drawn spread.

based on zero-coupon Treasury yields with the same cash payment profile to account for a "duration mismatch".

Following Saunders et al. (2021), we define the loan spread as follows:

$$Loan\ Spread_{ijt} = y_{ijt} - y^f_{ijt}, \tag{2}$$

where $y_{ijt}$ is the implied yield to maturity of loan $j$ issued by firm $i$ in period $t$ based on the price of a loan promising a series of quarterly cash flows. $y^f_{ijt}$ is its risk-free equivalent yield to maturity of loan $j$ issued by firm $i$ in period $t$ based on a synthetic risk-free loan with the same cash-flow profile.

## 2.3. Additional data sources

### 2.3.1. ESG exposure measures

To create a measure of firms for which sustainability concerns likely play a role, we rely on transcripts of firms' earnings calls. We employ a simple researcher-defined measure as well as a measure with limited susceptibility to researcher-dependent bias. To construct the former, we take the following steps. In the first step, we parse earnings call transcripts (from Refinitiv) for the year 2020. In particular, we consider only earnings calls that took place prior to the date on which the methodology change came into effect (April 6, 2020) looking for mentions of the following phrases: 1)"climate risk/warming/change/concern", 2) "ESG rating/rater", 3) "ESG method/measure", 4) "global warming", 5) "carbon emissions/footprint", 6) "sustainability/sustainable", and 7) "ESG".[7] To construct our measure of ESG sensitivity we rely on all listed expressions. In the second step, we define the *ESG Phrases* as the number of phrases related to ESG mentioned in the earnings calls between January 1, 2020 and April 6, 2020

Our second measure, is the firm-level measure constructed by Sautner, van Lent, Vilkov, and Zhang (2020) similarly relying on earnings call transcripts. In our paper,

[7]We provide the exact regular expressions written in Python in Table A3 in the Appendix.

we employ the *regulatory* exposure measure, i.e., exposure to regulatory shocks (e.g., carbon taxes). The measure (*CCExposure Reg*) captures the relative frequency with which regulatory shocks related to climate change together with uncertainty and risk are mentioned in the transcripts of analyst conference calls.

While our simple measure stems from tractable count-based algorithm derived from our "climate change" library, the measure by Sautner et al. (2020) employs a machine learning algorithm (for more details, see King, Lam, and Roberts (2017)) that only requires that the researcher draws up a small set of sets of words and is thus less susceptible to human error.

Finally, we use S&P Global Trucost data to identify industries with the highest carbon emissions in 2019, the year prior to the methodology change. Subsequently, we define an indicator variable "Top Carbon" as the top quartile of 4-digit SIC industries with the highest carbon emissions in the respective year.

## 2.4. Sample summary statistics

In Table 1, we report the summary statistics of the variables used in the paper. Our main variable of interest, the loan spread, has a mean (median) of 0.04 (0.03) and a sample standard deviation of 0.03. The average ESG Score as of February 2020, was around 48, while the average ESG Score as of September 2020, was around 40. Based on our downgrade definition, 84% of firms had an ESG rating difference (calculated according to Equation 1, i.e., pre- vs. post-methodology change) that is equal to or below the 75$^{\text{th}}$ percentile.

Firms in our sample have a debt ratio (*Debt/Assets*) of 46%, hold 8% of total assets in cash (*Cash/Assets*), spend 3% of total assets on capital expenditures (*Capex/Assets*), are profitable (with *EBIT/Assets* equal to 8%) and their tangible assets represent one quarter of their total assets (measured as *PP&E/Assets*), on average. Consistent with a typical composition of secondary trading market, we see that 79% of the firms have a B-Letter S&P rating, while only 4% of firms have an A-letter rating and 2% of firms have a B-letter rating. The remaining firms are unrated.

[Table 1 here]

Next, we provide a comparison of summary statistics between Compustat and loan sample used in our paper. The sample covers non-financial U.S. firms in the fiscal year 2019 (i.e., dropping firms with SIC codes 6000-6999), as this is the year for which we compute control variables. We report the differences in Table 2. We find that U.S. firms with syndicated loans traded in the secondary market tend to be much larger than the average firm in the Compustat sample of all non-financial firms. The average book leverage (*Debt/Assets*) is with 46% much higher than that of the average firm in the Compustat universe which has book leverage of 26%. Similar magnitudes can be found for median book leverage. The mean and median capital expenditures scaled by total assets (*Capex/Assets*) range in both samples between 2-4%. Firms in our loan sample tend to hold on average less cash (*Cash/Assets* of 8% as compared to 25%), but tend to be much more profitable. In particular, median *EBIT/Assets* is 7% in our loan sample as compared to 0% in the remaining Compustat universe. Lastly, there is no difference in tangibility (*PP&E/Assets*) across these samples in terms of medians.

[Table 2 here]

# 3. Results

To establish the relevance of the Refinitiv ESG score methodology change, we begin our analysis in Section 3.1 with a test of the stock market reaction of U.S. public firms in our sample around the day on which the scoring methodology change became effective. In Section 3.2, we study the effect of the ESG methodology change on U.S. public firms' costs of debt.

### 3.1. Event study around ESG methodology change

Refinitiv's methodology change became effective and thus visible to all subscribers of the data on April 6, 2020 which we use as our event day.

To measure the stock market reaction to the ESG score methodology change, we first calculate abnormal returns on the event day using both the four-factor Fama-French-Carhart model (Fama and French, 1993; Carhart, 1997) as well as the market model, which we use as dependent variables in the regression. To predict normal performance, we run regressions over an estimation window spanning over 250 trading days preceded by a gap of 100 days.

We estimate abnormal returns of each firm under the four-factor Fama-French-Carhart model:

$$r_{it} - r_{ft} = \alpha + \beta_{i,MKT}(r_{mt} - r_{ft}) + \beta_{i,HML}HML_t + \beta_{i,SMB}SMB_t + \beta_{i,UMD}UMD_t + \epsilon_{it} \tag{3}$$

and under the market model:

$$r_{it} - r_{ft} = \alpha + \beta_{i,MKT}(r_{mt} - r_{ft}) + \epsilon_{it}, \tag{4}$$

where $r_{it}$ is the daily stock return, $r_{ft}$ is the return on the risk-free asset (one-month Treasury bill rate), $r_{mt}$ is the CRSP value-weighted return on all NYSE, NYSE MKT, Nasdaq, and Arca stocks, $HML$, $SMB$, and $UMD$ are the value, size, and momentum factors, and $\epsilon_{it}$ is the error term. The sample includes firms for which we have syndicated loan data during the September 1, 2019 to October 1, 2020 period. A firm must have a minimum of 100 return observations in the estimation period to be included in the analysis.

The abnormal return, $AR_{it}$ used as the dependent variable in Table 3 is computed as the difference between the realized return on the announcement day and the expected return calculated using the factor loadings from Equation 3 and Equation 4, respectively. Since we are interested in the stock market reaction to the downgrade in firms' ESG ratings on the announcement day, we use a one-day window [0;0]. In columns (1) and

(2), we show the regression results under the four-factor model and in columns (3) and (4), we show the same for the single-factor model. All specifications include industry fixed effects and standard errors clustered at the industry level. In even-numbered columns, we include firm-level control variables in addition to industry fixed effects.

We estimate the following regressions:

$$\Delta AR_i = \beta \, ESG \, Downgrade_i + \gamma X_i' + \delta_j + \epsilon_i \tag{5}$$

where $AR_i$ is a firm's abnormal return on the announcement day. *ESG Downgrade* is an indicator variable showing whether the firms's Refinitiv ESG score has been downgraded as defined above. The vector $X_i$ includes *Ln(Assets)*, *Debt/Assets*, *Capex/Assets*, *Cash/Assets*, *EBIT/Assets*, and *PP&E/Assets* measured as of the last fiscal year. The variable $\delta_j$ represents industry fixed effects.

[Table 3 here]

Table 3 presents our results. We show that downgraded firms experienced a negative stock market reaction to the ESG rating change in comparison to other firms. The economic magnitude of the announcement return corresponds to -0.9% to -0.8% under the Fama-French-Carhart model and -1.0% to -0.9% under the market model. Although we do not want to over-interpret these event-study results, our ARs are consistent with changes in the portfolio allocation of some ESG investors. For example, investors that overweight firms with high-ESG scores may have sold (bought) firms experiencing large negative changes (increases/small negative changes) in their ESG scores. Alternatively, the negative ARs may reflect that investors obtained new information about the inherent ESG quality of firms.

## 3.2. The effect of the ESG methodology change on public firms' cost of debt

### 3.2.1. Methodology

Our goal is to estimate the effect of the methodology-driven rewriting of ESG scores on April, 2020 on firms' cost of debt. In order to gauge the immediate effect of an ESG score downgrade on firms' costs of debt, we exploit the secondary market for syndicated loans and calculate a daily loan spread measure. We hypothesize that loans of firms that experienced a large change in their ESG score are traded at higher loan spreads after the methodology change. Our main identification challenge to cleanly identify the effect of ESG downgrades on firms' costs of debt is the official onset of the worldwide COVID-19 pandemic in March 2020 and its differential effect on various industries. We introduce a battery of fixed effects to control for unobserved time-invariant firm characteristics as well as time-varying industry and credit rating differences. Importantly, we can compare the effect of the ESG downgrade on loan spreads of firms in the *same* industry, *same* credit rating category, and *same* month which allows us to isolate our main effect from possible confounding effects of the COVID-19 pandemic. We estimate the following regression:

$$Loan\,Spread_{ijt} = \alpha_j + \alpha_{ct_m} + \alpha_r + \beta ESG\,Downgrade_i \times Post_t + \gamma X'_{it} + \epsilon_{ijt}, \qquad (6)$$

where the $Loan\,Spread_{ijt}$ is the loan spread of loan $j$ for firm $i$ on day $t$. $ESG\,Downgrade_i$ is equal to one if firm $i$ experiences a downgrade in its ESG score after the Refinitiv ESG's methodology change on April 6, 2020, and zero otherwise. $Post_t$ is equal to one after April 6, 2020 and zero otherwise.[8] $X'_{it}$ stands for a vector of firm characteristics lagged by one year as in Equation 5. For a definition of firm characteristics see Table A1 in the Appendix. $\alpha_j$ stands for loan fixed effects, $\alpha_{ct_m}$ stands for firm cluster $\times$ month fixed effects and $\alpha_r$ stands for rating scale fixed effect. A firm cluster is defined as the Fama French 12 industry of a firm and the credit rating category based on S&P ratings

[8] We drop observations between April 1, 2020 and April 5, 2020 such that $Post_t$ is subsumed by the time fixed effects. Our main results are not affected if we add back these five days.

from Capital IQ (A-letter, B-letter, C-letter rating or unrated), following Acharya, Eisert, Eufinger, and Hirsch (2018). Loan fixed effects control for loan characteristics and firm characteristics when the loan was issued in the primary market. If not possible otherwise, for example, when we add non-time varying firm characteristics, we use firm fixed effects instead of loan fixed effects.

We also estimate a dynamic regression to better understand the effect over time:

$$Loan\,Spread_{ijt} = \alpha_j + \alpha_{ct_m} + \alpha_r + \sum_{\tau=-3}^{\tau=+3} \beta_\tau ESGDowngrade_i \times D_t^\tau + \epsilon_{ijt}, \tag{7}$$

where $D_t^\tau$ stands for each month before and after the downgrade and all other variables are defined as above.

### 3.2.2. Main result

[Table 4 here]

The results are reported in Table 4. In Panel A of Table 4, we estimate Equation 6 in columns (1) to (4), sequentially adding different fixed effects and controls, and Equation 7 in column (5). In all our specifications, we find that the loan spread significantly increased after the Refinitiv ESG rating change announcement. In column (1) we add time fixed effects, in column (2), we add firm cluster × month and rating scale fixed effects, in column (3), we include loan fixed effects, while in column (4), we introduce firm controls. In our main specification in column (3) that includes the full set of fixed effects, we find that loans of firms that have been downgraded after the methodology change carry 10% higher loan spreads relative to the average loan spread of 4%. When we decompose the effect in column (5) with the same set of fixed effects, we find that the effect is strongest, at 17.5% relative to the average, two months after the event and quickly declines gradually afterwards. In Section 5, we explore potential channels that might explain the temporary nature of the effect.

[Figure 1 here]

**Parallel trends**. In Figure 1, we show the coefficient from Equation 7 between September 1, 2019 and September 30, 2020, where we use March 2020 as the omitted category as the announcement of an upcoming ratings change was already made available internally on March 6, but the final ESG scores were not available until one month later. The figure reveals that before the announcement the difference between loan spreads of downgraded and not downgraded firms was relatively close to zero, while after the ratings change, the loan spread increased for the following 2 months and declined afterwards until it became insignificant in the fifth month after the event. We explore possible explanations for the temporary nature of the effect in Section 5.

**Placebo test**. In Panel B of Table 4, we conduct a placebo test of our main result from Panel A of Table 4 for which we use a different time period. We study the time period between November 2020 and May 2021, with the event date assumed to take place in the middle of the studied time period, i.e., in February 2021. For our analysis, we use data downloads of the ESG scores in September 2020 and February 2021 to create a "placebo" *ESG Downgrade* dummy. We find that the effect is not significant and substantially varies in magnitude for different specifications. In unreported results, we experiment with other time periods and find similarly unstable and insignificant results. This suggests that our main effect indeed captures a large impact of Refinitiv ESG rating change.

**Alternative measures**. In Table 5, we repeat our main specification in column (3) of Panel A of Table 4, using alternative definitions of downgraded firms. We show that our main result remains robust when we define downgraded firms as firms with an ESG rating change below or equal to the $25^{\text{th}}$ percentile and upgraded firms as firms with a rating change above the $75^{\text{th}}$ percentile; we decompose the downgraded dummy into ESG rating changes in the $25^{\text{th}}$, $50^{\text{th}}$ and $75^{\text{th}}$ percentiles, leaving firms above the $75^{\text{th}}$ percentile as the omitted category; we define downgraded firms only as firms with negative changes in ESG ratings; we just use the difference between post- and pre-methodology ESG ratings to define downgraded firms and, lastly, when we directly use the continuous difference between the post- and pre-methodology ESG ratings.

# 4. Robustness

In this section, we present robustness of our main results. In particular, we address the concern related to the evidence that Refinitiv has rewritten its ESG data at different points in time in Section 4.1. Next, we show that our results cannot we explained by loan market liquidity, heightened credit risks, stock market volatility or the effect of the COVID-19 crisis in Section 4.2.

## 4.1. Rewriting rating data

One major potential caveat against the use of Refinitiv ESG data is the rewriting of data by Refinitiv. Berg et al. (2020) show that data rewriting of current as well as historical ESG scores might have occured after the methodology change in April 2020.[9] To address the concern that our results are affected by a rewriting of ESG scores rather than the downgrade through the methodology change, we perform two analyses.

First, we study the size of the ESG score changes across four ESG data samples. Recall that our *ESG Downgrade* indicator variable is calculated based on the 02/2020 and 09/2020 ESG data downloads. To answer the question to what extent our study could be affected by the findings of Berg et al. (2020), we plot ESG score changes in four scenarios: 1-2) twice during pre-methodology change, 3) post-methodology change, and 4) in our sample, i.e. pre- vs. post-methodology change. To study 1-2), we rely on a comparison of the 09/2018 and 02/2020 ESG data downloads as well as a comparison of the 02/2020 and 03/2020 ESG data downloads. To study 2), we rely on a comparison of the 09/2020 and 02/2021 ESG data downloads. To study 3), we rely on 02/2020 and 09/2020 ESG data downloads.

[Figure 2 here]

[9] They document that rewriting might have happened prior to the methodology change, but this data is not available to us.

In Figure 2, we show the histogram of absolute ESG score differences between the downloads. We show the histogram for the last fiscal year observation that is available in both data downloads, but our results remain unaffected if we instead incorporate the entire overlapping firm-year history. For example in the first subfigure, the x-axis shows the "absolute ESG score difference" defined as $ESG\,Score^{New\,Data}$ - $ESG\,Score^{Old\,Data}$, where in the first graph, new data refers to 09/2020 data and the old data refers to the 02/2020 data. The ESG score difference in the remaining comparisons is constructed accordingly. We find that by far the largest data rewriting took place at the time of the methodology change in April 2020.

When we focus our attention on the fraction of firms that experience an absolute change in their ESG score of at least 5, we find that 72.9% of firms experienced such a change between our 02/2020 and 09/2020 ESG data downloads. When we look at the ongoing data rewriting in the pre-methodology change period that spans between 09/2018 and 02/2020, we see that the fraction of firms that experience an absolute change in their ESG score of at least 5 equals to 11%. The shorter pre-methodology change period spanning between 02/2020 and 03/2020, however reveals that only 0.3% of ESG scores changed to such an extent. In the post-methodology change period, it is as low as 2.4%. We observe that rankings of firms might change when data are rewritten. However, we document that rewriting does usually *not* change the rating score that we rely on to construct our *ESG Downgrade* indicator variable and that is used in our regressions.

Second, we perform a placebo test of our main result from Table 4 in which we shift the time period. In the placebo test, we study the time period between November 2020 and May 2021, with the event date assumed to take place in the middle of the studied time period.

## 4.2. Other robustness tests

Table 6 presents several robustness tests of our main result. In column (1), we include the median daily bid ask spread over industries as a measure of loan-market liquidity and find that our results are not affected. In column (2), we add a "naive distance to default measure" based on Bharath and Shumway (2008) to control for heightened credit risk of firms at the onset of the COVID-19 pandemic. While the coefficient is negative and significant as expected, our results remain robust. In column (3), we add the VIX to account for possible increases in the loan spread due to higher uncertainty around the COVID-19 pandemic.[10] As expected, higher uncertainty is associated with higher spreads, however, our main coefficient remains virtually unchanged. In column (4), we interact our main coefficient with an indicator for industries *most* affected by COVID-19 pandemic to show that our main effect is not driven by increases in loan spreads of COVID-affected industries. We access the list of NAICS three-digit industries that identifies the most affected industries based on cumulative COVID-19 crisis returns from Fahlenbrach et al. (2021).

[Table 6 here]

# 5. Channels

In Section 5.1, we explore different potential channels explaining the effect of the ESG downgrade on a firm's cost of debt. In Section 5.3, we study potential spillover effects on private firms in industries with a high number of public downgraded firms.

## 5.1. Channels explaining the effect on firms' cost of debt

So far, we have presented consistent evidence that the methodology-driven change in ESG scores leads to higher costs of debt for downgraded public firms. In this section, we investigate channels that have the potential to explain the temporary effect of ESG rating changes on firms' cost of debt documented in the previous section. In Section 5.1.1, we test whether the effect is driven by changes in firm fundamentals or frictions in the secondary

[10] The VIX index provided by the Chicago Board of Exchange (CBOE) nonparametrically approximates the expected future realized volatility of the SP 500 returns over the next 30 days (Bardgett, Gourier, and Leippold, 2019).

market. In Section 5.1.2, we explore whether financial constraints and the associated informational frictions that firms face might explain the main effect. In Section 5.1.3, we analyze whether investors are pricing ESG downgrades differently for firms with higher exposure to ESG related topics, carbon emissions or climate change risks.

[Table 7 here]

### 5.1.1. Loan spread decomposition

As the first possible channel, we try to understand how much of our effect is driven by potential changes in firm fundamentals and/or frictions in the secondary market. We decompose the loan spread into two components (Gilchrist and Zakrajšek, 2012): i) a component that captures changes in default risk based on firm fundamentals ("predicted loan spread"), and ii) a residual that captures the price of risk above a default risk premium, i.e., the "excess loan premium" (ELP). The idea behind the decomposition is that after predicting the fundamental components of the loan spread based on borrower default risk and contract terms, the residual component should capture potential frictions arising in the secondary market. The predicted component, on the other hand, captures the variation in the loan spread due to changes in firm fundamentals. We expect the residual component that proxies for frictions among investors in the secondary markets rather than firm fundamentals to be driving our main result.

Table 7 estimates Equation 6, replacing the dependent variable with the predicted loan spread in column (1) and the ELP in column (2). Column (3) shows the first stage regression in which we regress the loan spread on firm's distance to default risk, the volatility of its distance to default risk, contract terms as well as the loan type, industry and rating scale fixed effects. While there is no economic or statistically significant effect of *ESG Downgrade* in the post period on the predicted loan spread, for the ELP, the coefficient is the same in magnitude as our main specification in column (3) of Table 4. Figure 3 plots the decomposition of the loan spread into its predicted and residual components, showing that the rise in the loan spread after the ESG downgrade event is fully explained by the ELP.

[Figure 3 here]

The result confirms our prediction that our main effect is driven by frictions among investors and not by long-term changes in firm fundamentals. We argue that this explains the temporary nature of our effect as investors respond to changes in ESG scores of firms and adjust their portfolio accordingly, putting downward price pressure on downgraded firms. This in turn leads to temporary higher loan spreads for downgraded firms.

### 5.1.2. Financing constraints

As another possible channel, we investigate the importance of financing constraints. We hypothesize that the effect could be driven by existing or anticipated future financing constraints of firms that might be aggravated once a lower ESG score is given to a firm. To analyze the former, we use multiple existing measures proxying for financial constraints and present the results in Table 8. We expect the effect to be weaker for less financially constrained firms (e.g., larger and/or older).

**Measures.** We proxy financing constraints via the KZ-index of Kaplan and Zingales (1997) as well as the Size-Age-index of Hadlock and Pierce (2010). We construct the KZ-index following Lamont, Polk, and Saaá-Requejo (2015). The Size-Age-index of Hadlock and Pierce (2010) is calculated as:

$$\textit{Size-Age-index} = (0.737 \times \textit{Size}) + (0.043 \times \textit{Size}^2) - (0.040 \times \textit{Age}). \tag{8}$$

We compute both measures as of fiscal year 2019. In the paper, we do not rely on the raw measures, but rather on their extreme quartiles. We construct an indicator variable "KZ" which is equal to one if the firm's KZ-index is in the top quartile of the distribution, and zero otherwise. Similarly, the indicator variable "HP" is equal to one if the firm's Size-Age-index is in the top quartile of the distribution, and zero otherwise. To calculate quartiles for both measures, we rely on the universe of firms in our loan sample.[11] We also include other measures such as firm size, as well as the firms' credit rating status. The indicator variable "Large" is equal to one if the lagged assets of a firm are above the median firm for the overall sample, and zero otherwise. "Old" is equal to one if the age of a firm based on the IPO year is above the median firm for the overall sample, and zero otherwise.

**Results.** We first test simple measures such as firm size, as well as the firms' age on a stand-alone basis. As noted by Hadlock and Pierce (2010), while firm size and firm age emerge as useful predictors of constraints, their combination is superior to using the two measures alone as their role in explaining financial constraints is nonlinear. Lastly, we also include the KZ-index of Kaplan and Zingales (1997) constructed following Lamont et al. (2015).

In column (1), we interact our main coefficient with a dummy for large firms. We find that the loan spread of larger firms is lower than for smaller firms after the ESG downgrade. The total effect is almost equal to zero for large firms, suggesting that only small firms that are more likely to be opaque experience an increase in their loan spreads. In column (2), we find no differential effect for firm age. When we interact our main coefficient with the Size-Age-index of Hadlock and Pierce (2010), we again find a negative effect for larger and older firms relative to smaller and younger firms, which is, however, not statistically significant. Lastly, we interact our post downgrade dummy with the KZ-index, finding that the effect of the downgrade is especially pronounced for financially constrained firms. All in all, the evidence in this section suggests that the ESG score downgrade effect was especially pronounced in a subsample of smaller and financially constrained firms.

[Table 8 here]

[11] To view the differences between the Compustat universe and our sample in fiscal year 2019, refer to Table 2.

### 5.1.3. Importance of ESG risks, carbon emissions and climate change risks

Next, we analyze whether after an ESG score downgrade investors penalize firms for which ESG-related aspects seem to play a more prominent role. These firms include e.g., firms that are in an industry with higher carbon emissions or that have a higher exposure to climate change risks. As described in the Section 2.3.1, we measure exposure to ESG-related topics by analyzing earnings calls from January to April 2020. We define industries with higher carbon emissions as firms in the top quartile of 4-digit SIC industries with the highest carbon emissions. The climate change risk measure is based on Sautner et al. (2020).

Table 9 presents the results. Results shown in column (1) suggest that firms that have more emphasis placed on ESG-related topics during their Q1 2020 earnings calls, experience a larger increase in loan spreads after the ESG downgrade. Similarly, in column (2), we find that firms with higher carbon emissions are penalized more following an ESG downgrade. Lastly, results in column (3) reveal that firms exposed to regulatory climate change risks face higher loan spreads after their ESG score has been downgraded. While our main effect is not fully explained by the different measures, the results indicate that ESG downgrades are especially informative for firms in ESG-, carbon-emission- or climate-risk-sensitive areas.

We also investigate whether ESG concerns of the investors drive for our results. It is possible that firms, which are more exposed to investors with ESG concerns are more likely to experience a rise in loan spreads. To test the hypothesis, we match our sample of firms with data on CLOs that held our sample of firms during the years 2019 and 2020. CLOs represent the largest share of investors in the secondary market and thus we should be able to capture at least the direction of investors' preferences.

We interact our ESG downgrade measure with four different measures for ESG concerns of investors. First, we check whether the main fund of the CLO manager mentions ESG on the homepage; second, whether the CLO applies negative exclusions of certain industries in the portfolio management practices and third, whether the fund is a UN

Principles for Responsible Investment (PRI) signatory. For the last measure, we also collect the year in which the fund signed the PRI since becoming a member was tied to minimum requirements only after 2018. We thus create a fourth measure of funds that signed the PRI post 2018. For each measure, we count the number of CLOs that, for example, signed the PRI, and held a certain firm and divide this number by the total number of CLOs that held the firm between 2019 and 2020.

Table 10 presents the results. We observe that once we condition on the share of funds that signed the UN PRI after 2018 the effect becomes highly significant and our main effect loses its significance and becomes even negative, indicating that a large part of the increase in the loan spreads might be driven by ESG-concerned investors.

[Table 10 here]

## 5.2. Effects on the costs of debt

In this section, we study whether the temporary higher spreads in the secondary loan market had also an effect on the costs of debt on the primary syndicated loan market. The temporary nature of our main results and the fact that our results are not driven by an increase in the fundamental default risk of firms, already lends support to the hypothesis that the downgrade event might have not affected the costs of debt of firms.

For our analysis, we take all loans issued on the primary syndicated loan market of our sample of firms one year before and after the ESG downgrade event. We are able to match 143 firms and 299 loans. We then regress our main explanatory variable on the natural logarithm of the all-in-spread drawn at loan issuance. Table 11 shows that downgraded firms did not experience differences in the loan spread after the ESG downgrade event.

## 5.3. Spillover effects on private firms

In this section, we explore potential spillover effects on private firms that are in the industries with a high share of downgraded public firms. We define affected firms as private firms in a Fama-French 17 industry that has been in the bottom quartile of downgraded firms after the ESG methodology change. We use our secondary market data to extract loan spreads for private firms and regress it on a dummy variable of affected industries after the ESG downgrade for public firms. As private firms are less likely to receive an ESG rating, the downgrade of public firms in the same industry might be also informative about the ESG quality of private firms. As a result, we expect that private firms in highly affected industries will also face higher loan spreads after ESG downgrades of public firms in the same industry.

As hypothesized, column (1) of Table 12 reveals that private firms in affected industries experience a 9% increase in their loan spread relative to their average loan spread. The effect is economically meaningful but smaller in size than the main effect as would intuitively be the case for spillover effects on private firms. Figure 4 decomposes the effect into three months before and after the ESG downgrade of private firms. The plot shows that the effect for private firms only kicks in during the second month after the ESG downgrade. When we control for industries highly affected by the COVID-19 pandemic in column (2), the effect remains to hold, suggesting that our results are not driven by confounding events. In column (3), we show that the spillover effect is mostly driven by opaque firms without a credit rating. This suggests that the information about ESG downgrades in public firms in the same industry is also reflected in loan spreads of private firms.

[Table 12 here]

[Figure 4 here]

# 6. Policy implications

Showing that an ESG rating methodology change can have an effect on the spreads of syndicated U.S. corporate loans traded in the secondary market provides additional evidence on the real-world importance of ESG ratings. Policymakers and regulators have already started to make the first steps to regulate the ESG ratings market.[12] Quantifying the real-effect of ESG ratings might provide ground for future polices as the market for ESG data is fraught with conflicts of interest that might need world-wide regulator attention.

# 7. Conclusion

We use a major ESG rating agency's methodology change to firms' ESG ratings to study its effect on the spreads of syndicated U.S. corporate loans traded in the secondary market. We find that loan spreads temporarily increase by 10% relative to the average spread of 4%. The effect is robust to the ongoing rewriting of ESG ratings by Refinitiv as well as other robustness tests.

We explore multiple channels that could explain the effect of the ESG downgrade on firms' cost of debt. When we decompose the loan spread into a component that captures changes in firm fundamentals and a residual that captures potential frictions arising in the secondary market, we show that higher loans spreads are mostly driven by the latter which is in line with the temporary nature of the effect. Next, we find some evidence that the effect is stronger for smaller and financially constrained firms, but not for younger firms. We also find that investors penalize firms for which ESG-related aspects seem to play a more prominent role.

Lastly, when we explore potential spillover effects on private firms that are in the same industry as the downgraded firms, we find evidence supporting this channel. We find that private firms in highly affected industries face higher loan spreads after ESG downgrades of public firms in the same industry, suggesting that investors of private (unrated) firms also price in ESG downgrades of public firms.

Overall, we show that ESG rating changes can have real effects on the spreads observed in the secondary market trading. It is therefore likely, that the effect is also present for new loans, which is an avenue that we will explore in the future versions of this paper.

[12] https://eur-lex.europa.eu/legal-content/EN/TXT/?uri=CELEX%3A52023PC0314.

# References


Acharya, V. V., T. Eisert, C. Eufinger, and C. Hirsch (2018). Real effects of the sovereign debt crisis in Europe: Evidence from syndicated loans. *Review of Financial Studies 31*(8), 2855–2896.

Baldauf, M., L. Garlappi, and C. Yannelis (2020). Does climate change affect real estate prices? only if you believe in it. *Review of Financial Studies 33*(3), 1256–1295.

Bardgett, C., E. Gourier, and M. Leippold (2019). Inferring volatility dynamics and risk premia from the sp 500 and vix markets. *Journal of Financial Economics 131*(3), 593–618.

Berg, F., K. Fabisik, and Z. Sautner (2020). Is history repeating itself? The (un)predictable past of ESG ratings. Working Paper.

Bernstein, A., M. T. Gustafson, and R. Lewis (2019). Disaster on the horizon: The price effect of sea level rise. *Journal of financial economics 134*(2), 253–272.

Bharath, S. and T. Shumway (2008). Forecasting default with the merton distance to default model. *Review of Financial Studies 21*(3), 1339–1369.

Bolton, P. and M. Kacperczyk (2021). Do investors care about carbon risk? *Journal of Financial Economics*.

Carhart, M. M. (1997). On persistence in mutual fund performance. *Journal of Finance 52*(1), 57–82.

Chava, S. (2014). Environmental externalities and cost of capital. *Management science 60*(9), 2223–2247.

Degryse, H., R. Goncharenko, C. Theunisz, and T. Vadasz (2021). When green meets green.

Ehlers, T., F. Packer, and K. de Greiff (2021). The pricing of carbon risk in syndicated loans: which risks are priced and why? *Journal of Banking & Finance*, 106180.

Fahlenbrach, R., K. Rageth, and R. M. Stulz (2021). How valuable is financial flexibility when revenue stops? Evidence from the COVID-19 crisis. *Review of Financial Studies 34*(11), 5474–5521.

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

Fatica, S., R. Panzica, and M. Rancan (2021). The pricing of green bonds: are financial institutions special? *Journal of Financial Stability 54*, 100873.

Flammer, C. (2021). Corporate green bonds. *Journal of Financial Economics 142*(2), 499–516.

Gilchrist, S. and E. Zakrajšek (2012, June). Credit spreads and business cycle fluctuations. *American Economic Review 102*(4), 1692–1720.

Hadlock, C. J. and J. R. Pierce (2010, 03). New evidence on measuring financial constraints: Moving beyond the KZ index. *Review of Financial Studies 23*(5), 1909–1940.

Hartzmark, S. M. and A. B. Sussman (2019). Do investors value sustainability? a natural experiment examining ranking and fund flows. *Journal of Finance 74*(6), 2789–2837.

Hauptmann, C. (2017). Corporate sustainability performance and bank loan pricing: It pays to be good, but only when banks are too. *Saïd Business School WP 20*.

Houston, J. F. and H. Shan (2020). Corporate esg profiles and banking relationships.

Ilhan, E., Z. Sautner, and G. Vilkov (2021). Carbon tail risk. *Review of Financial Studies 34*(3), 1540–1571.

Javadi, S. and A.-A. Masum (2021). The impact of climate change on the cost of bank loans. *Journal of Corporate Finance 69*, 102019.

Kaplan, S. N. and L. Zingales (1997, 02). Do investment-cash flow sensitivities provide useful measures of financing constraints? *Quarterly Journal of Economics 112*(1), 169–215.

Kim, M., J. Surroca, and J. A. Tribó (2014). Impact of ethical behavior on syndicated loan rates. *Journal of Banking & Finance 38*, 122–144.

King, G., P. Lam, and M. E. Roberts (2017). Computer-assisted keyword and document set discovery from unstructured text. *American Journal of Political Science 61*(4), 971–988.

Kleimeier, S. and M. Viehs (2018). Carbon disclosure, emission levels, and the cost of debt.

Krueger, P., Z. Sautner, and L. T. Starks (2020). The importance of climate risks for institutional investors. *Review of Financial Studies 33*(3), 1067–1111.

Lamont, O., C. Polk, and J. Saaá-Requejo (2015, 06). Financial Constraints and Stock Returns. *Review of Financial Studies 14*(2), 529–554.

Nguyen, D. D., S. Ongena, S. Qi, and V. Sila (2020). Climate change risk and the costs of mortgage credit. *Swiss Finance Institute Research Paper* (20-97).

Painter, M. (2020). An inconvenient cost: The effects of climate change on municipal bonds. *Journal of Financial Economics 135*(2), 468–482.

Refinitiv (2020). Refinitiv enhances ESG scoring methodology to reflect sustainable industry developments and market changes. April 15, https://www.refinitiv.com/en/media-center/press-releases/2020/april/refinitiv-enhances-esg-scoring-methodology-to-reflect-sustainable-industry-developments-and-market-changes. Accessed on: 2020-10-12.

Riedl, A. and P. Smeets (2017). Why do investors hold socially responsible mutual funds? *Journal of Finance 72*(6), 2505–2550.

Saunders, A., A. Spina, S. Steffen, and D. Streitz (2021). Corporate loan spreads and economic activity. Working Paper.

Sautner, Z., L. van Lent, G. Vilkov, and R. Zhang (2020). Firm-level climate change exposure. Working Paper.

Shin, D. (2021). Corporate ESG profiles, matching, and the cost of bank loans. Working Paper.

Taylor, A. and A. Sansone (2006). *The Handbook of Loan Syndications and Trading.* McGraw-Hill and the Loan Syndications and Trading Association (LSTA).

# Appendix

**Table A1: Variable Definitions**
This table defines the variables used in the analysis.

| Variable | Description |
|---|---|
| ESG Variables | |
| *ESG Score* | Overall score of a firm's ESG performance. The score covers a firm's environmental (E), social (S) and corporate governance (G) performance. The score ranges between 0 (minimum) and 100 (maximum score). *ESG Score*$^{02/2020\ Data}$ is the data set downloaded in February 2020 (pre-methodology change), and *ESG Score*$^{09/2020\ Data}$ is the data set downloaded in September 2020 (post-methodology change). |
| $\Delta$ *ESG Score* | Percentage deviation in a firm's overall ESG score between two versions of the ESG data. For example, for the methodology-related rewriting, the score deviation is computed for each firm-year combination as *ESG Score*$^{09/2020\ Data}$ divided by *ESG Score*$^{02/2020\ Data}$ minus one, times 100. |
| *ESG Score Downgrade* | Indicator variable equal to one if a firm experiences a downgrade in its ESG score after the Refinitiv ESG's Methodology Change on April 6, 2020, and zero otherwise. |
| *ESG Sum Phrases* | Measure constructed based on firm's earnings calls between January 1, 2020 and April 5, 2020 looking for mentions of the following phrases: 1)"climate risk/warming/change/concern", 2) "ESG rating/rater", 3) "ESG method/measure", 4) "global warming", 5) "carbon emissions/-footprint", 6) "sustainability/sustainable", and 7) "ESG". The search is not case-sensitive. |
| Loan Spread Variables | |
| *Loan spread* | The difference between the loan's implied yield to maturity and its risk-free equivalent yield to maturity, winsorized at the 1% and 99% levels. |
| *Predicted Loan Spread* | Predicted component of the loan spread that captures changes in default risk based on firm fundamentals. |
| *Excess Loan Premium* | Residual component of the loan spread that captures the price of risk in excess of default risk. |
| Loan Characteristics | |
| *Ln(AISD)* | Natural logarithm of all-in spread drawn (AISD) at loan issuance. Winsorized at the 1% and 99% levels. |
| *Ln(Amount)* | Natural logarithm of one plus the dollar loan amount at loan issuance. Winsorized at the 1% and 99% levels. |

| Variable | Description |
|---|---|
| *Secured* | Indicator variable equal to one if a loan is secured by collateral, and zero otherwise. |
| *Covenant* | Indicator variable equal to one if a loan contract includes covenants, and zero otherwise. |

| Firm Characteristics | |
|---|---|
| *Ln(Assets)* | Logarithm of total assets. The variable is constructed using Compustat data item *at*. Winsorized at the 1% and 99% levels. |
| *Debt/Assets* | Ratio of total debt in current liabilities plus total long-term debt to total assets. The variable is constructed using Compustat data items $(dlc + dltt)/at$. Winsorized at the 1% and 99% levels. |
| *Capex/Assets* | Ratio of capital expenditures to total assets. The variable is constructed using Compustat data items $capx/at$. Winsorized at the 1% and 99% levels. |
| *Cash/Assets* | Ratio of cash plus short-term investments divided by total assets. The variable is constructed using Compustat data items $che/at$. Winsorized at the 1% and 99% levels. |
| *EBIT/Assets* | Ratio of earnings before interest and taxes to total assets. The variable is constructed using Compustat data items $ebit/at$. Winsorized at the 1% and 99% levels. |
| *PP&E/Assets* | Ratio of property, plant and equipment to total assets. The variable is constructed using Compustat data items $ppent/at$. Winsorized at the 1% and 99% levels. |

| Additional variables | |
|---|---|
| *Post* | Indicator variable equal to one after April 6, 2020, and zero otherwise. |
| *Bid Ask Spread* | Daily median bid-ask spread over industries in the secondary market. |
| *Distance to Default* | Naive distance to default based on Bharath and Shumway (2008). |
| *Vol(Distance to Default)* | Daily volatility of the distance to default across firms. |
| *VIX* | Index measuring the volatility of the S&P 500 index retrieved from the Federal Reserve Bank of St. Louis (FRED). |
| *Covid Ind* | Indicator variable equal to one if a firm has been in the bottom 20-NAICS 3-digit industry sorted by cumulative excess return from February 3, 2020 until March 23, 2020 as in Fahlenbrach et al. (2021). |
| *Large* | Indicator variable equal to one if the lagged assets of a firm lie above the median, and zero otherwise. |
| *Ln(Age)* | Natural logarithm of firm age determined from the year of the IPO. |
| *HP* | The Size-Age index of Hadlock and Pierce (2010). |
| *KZ* | The Kaplan and Zingales (KZ) index, which we construct following Lamont et al. (2015). |

| Variable | Description |
| --- | --- |
| *Top Carbon* | Indicator variable equal to one if a firm has been in top quartile of 4-digit SIC industries with the highest carbon emissions, and zero otherwise. |
| *CCExposure Reg* | The earnings call-based measure of Sautner et al. (2020) capturing exposure related to regulatory shocks associated with climate change (scaled up by $10^3$). |
| *Unrated* | Indicator variable equal to one if the firm does not have Standard & Poor's credit rating, and zero otherwise. |
| *Affected Ind* | Indicator variable equal to one if a firm is private and is in an industry (Fama-French 17) that has been in the bottom quartile of downgraded public firms after the Refinitiv ESG's Methodology Change, and zero otherwise. |

**Table A2: Description of Changes to the ESG Scoring Methodology**

The table cites the description of the changes to Refinitiv ESG's scoring methodology (Refinitiv, 2020).

| Change name | Description provided by Refinitiv |
|---|---|
| (1) Change to Materiality Matrix | "Refinitiv enhanced ESG scores further takes into account that not all metrics have the same importance to every industry. The Refinitiv ESG magnitude matrix is developed as a proprietary model and is applied at the category level. Importantly, the magnitude values are automatically and dynamically adjusted as ESG corporate disclosure evolves and matures. For Boolean metrics, levels of data disclosure can act as a proxy for investor driven pressure on company reporting. Levels of disclosure inform the relative 'weight' of data points for each industry. For measurable numeric metrics, we use our data to determine which sectors contribute most and the proportion of the contribution to the total is used as a proxy for the level of materiality for that sector. For example, the more a given sector contributes to carbon emissions, the more material are carbon emissions data points to companies in that sector. Refinitiv proprietary "magnitude matrix" assesses materiality, showing the weight, from 1 to 10, of data points for each industry." |
| (2) Change to Transparency/ Investment Grade Scores | "The previous ESG scoring methodology allocated a score of 0.5 to companies which didn't report on metrics, essentially giving them the 'benefit of the doubt'. However, as this may disincentivize companies to report on their ESG performance, the enhanced methodology assigns a score of zero to companies who don't report on metrics relevant to the industry. This new approach encourages company disclosure and transparency." |

### Table A3: Regular expressions in Python

This table shows the regular expressions in Python that we use in parsing quarterly earnings call transcripts. We set the algorithm to be case-insensitive.

**Python code 1** Phrases

```
# Phrase 1
regexp = re.compile(r"(climate(.{1,2}|.{1,2}\n|\n)(risk|warming|change|concern))(.*)",
flags=re.IGNORECASE)

# Phrase 2
regexp = re.compile(r"(esg(.{1,2}|.{1,2}\n|\n)(rating|rater))(.*)", flags=re.IGNORECASE)

# Phrase 3
regexp = re.compile(r"(esg(.{1,2}|.{1,2}\n|\n)(method|measure))(.*)", flags=re.IGNORECASE)

# Phrase 4
regexp = re.compile(r"(global(.{1,2}|.{1,2}\n|\n)(warming))(.*)", flags=re.IGNORECASE)

# Phrase 5
regexp = re.compile(r"((co(|2)|carbon)(.{1,3}|.{1,2}\n|\n)(emissions|footprint))(.*)",
flags=re.IGNORECASE)

# Phrase 6
regexp = re.compile(r"(sustainability|sustainable)(.*)",

# Phrase 7
regexp = re.compile(r"(esg)(.*)", flags=re.IGNORECASE)
```

# Figures

**Figure 1: Loan Spread around Refinitiv ESG's Methodology Change: Parallel trends**

The figure plots the coefficients from regressing loan spreads on a dummy for downgraded firms interacted with a monthly dummy sixth months before and after the downgrade event on April 6, 2020. We include loan fixed effects, firm cluster × time fixed effects as well as rating scale fixed effects. Firm cluster is defined as risk category (investment grade, non-investment grade, unrated)× industry (Fama-French 12-Industry Classification). The corresponding 95% confidence intervals are based on standard errors that are clustered at the firm × time level.

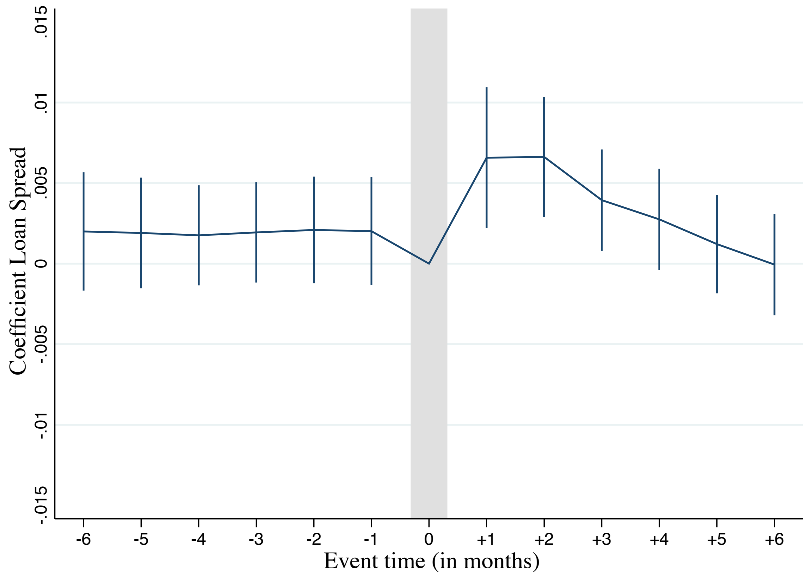
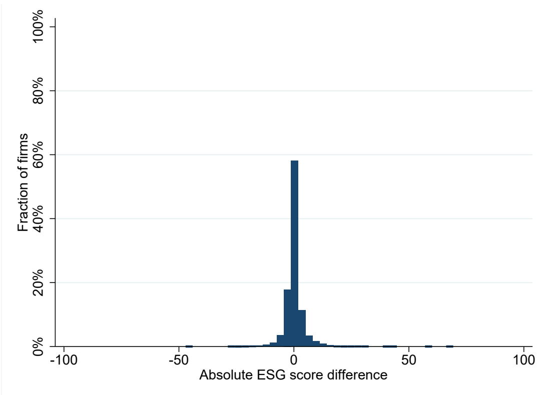
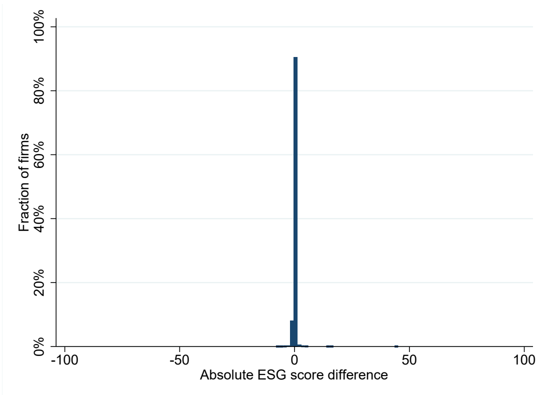


**Figure 2: Distribution of ESG score changes between various Refinitiv ESG data downloads**

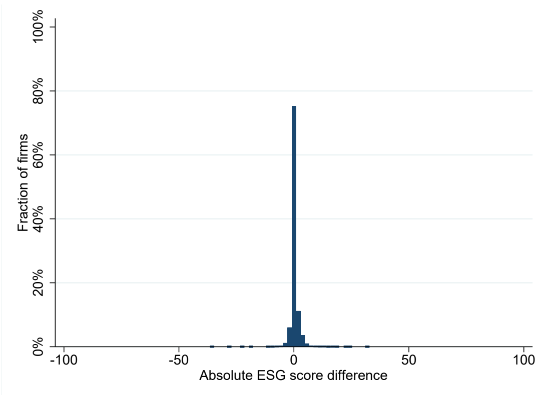
The figure shows the distribution of ESG score changes between various Refinitiv ESG data downloads in scenarios when the data downloads take place during the pre- and/or post-methodology change by Refinitiv ESG. Figure (a) shows the distribution of ESG score changes between Refinitiv ESG data downloads from the first pre-methodology change time period (09/2018 and 02/2020) for which we have data available. Figure (b) shows the distribution of ESG score changes between Refinitiv ESG data downloads from the second pre-methodology change time period (02/2020 and 03/2020) for which we have data available. Figure (c) shows the distribution of ESG score changes between Refinitiv ESG data downloads from the post-methodology change time period (09/2020 and 02/2021) for which we have data available. Figure (d) shows the distribution of ESG score changes between Refinitiv ESG data downloads from the pre- and post-methodology change time period (02/2020 and 09/2020) for which we have data available. The x-axis shows the "absolute ESG score difference" defined as *ESG Score*$^{new}$ minus *ESG Score*$^{old}$ where "new" and "old" are chronologically defined as outlined above, and the y-axis shows the fraction of firms in the sample that fall within a given histogram bin.



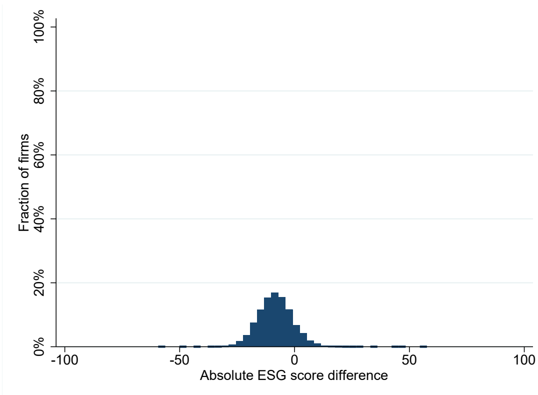

(a) Pre-methodology change (09/2018 and 02/2020)




(b) Pre-methodology change (02/2020 and 03/2020)




(c) Post-methodology change (09/2020 and 02/2021)




(d) Pre- vs. post-methodology change (02/2020 and 09/2020)

**Figure 3: Loan Spread Decomposition around Refinitiv's ESG Methodology Change**

The figure plots the loan spread, the predicted loan spread and the excess loan premium between January 1, 2019 and December 21, 2020. The predicted loan spread and the excess loan spread are the result of a regression in which we decompose the loan spread into a default risk component based on firm fundamentals ("predicted loan spread"), and a residual component that should capture the prices of risk above a default risk premium ("excess loan spread").

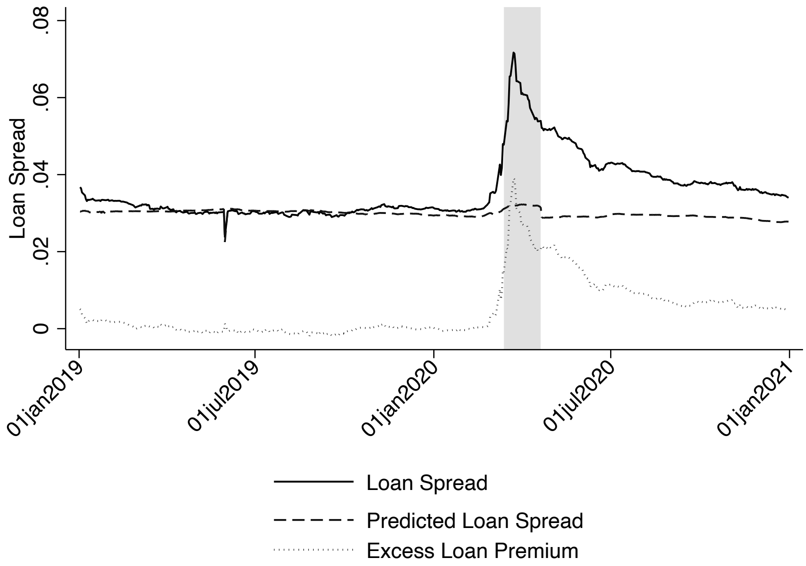
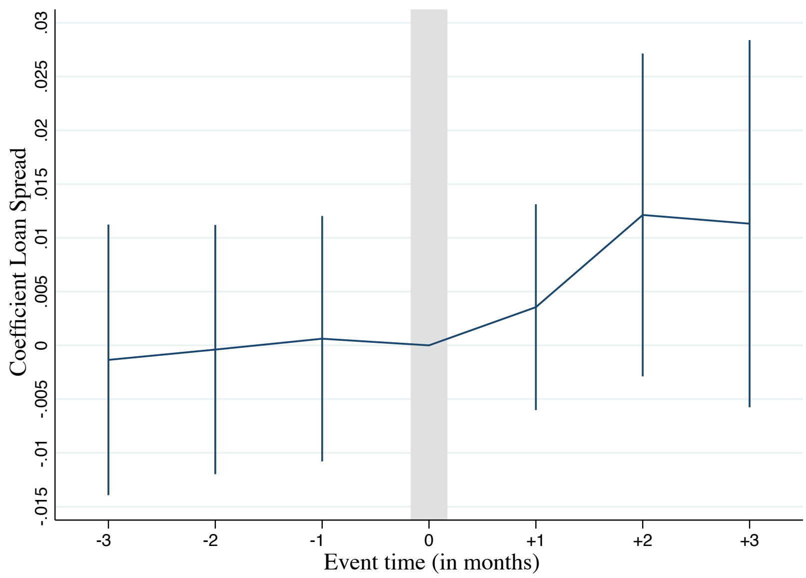


**Figure 4: Loan Spreads around Refinitiv ESG's Methodology Change for Affected Industries**

The figure plots the coefficient from regressing the loan spread on a dummy for private firms that are in a Fama French industry hat has been in the bottom quartile of downgraded public firms interacted with a month dummy three months before and after the downgrade event on April 6, 2020. We include firm fixed effects as well as firm cluster $\times$ time fixed effects. Firm cluster is defined as risk category (rated, unrated) $\times$ industry (Fama-French 12-Industry Classification). The corresponding 95% confidence intervals are based on standard errors that are clustered at the industry (Fama-French 17-Industry Classification) $\times$ time level.



# Tables

**Table 1: Summary Statistics**

This table reports summary statistics for our loan sample. It includes U.S. non-financial firms with secondary market data during the period between between December 1, 2019 and June 30, 2020 for which we have Refinitiv ESG ratings from February and September 2020 available. Column abbreviated "SD" reports the standard deviation. Columns abbreviated "25%" and "75%" report the 25$^{\text{th}}$ and 75$^{\text{th}}$ percentile, respectively. The abbreviation "S&P" stands for Standard & Poor's. The variables are constructed as described in the Appendix in Table A1.

| Variable | Observations | Mean | SD | 25% | Median | 75% |
|---|---|---|---|---|---|---|
| *Dependent variable* | | | | | | |
| Loan Spread | 41,818 | 0.04 | 0.03 | 0.02 | 0.03 | 0.05 |
| *ESG firm characteristics* | | | | | | |
| ESG Score$^{02/2020\text{ Data}}$ | 41,818 | 47.77 | 15.79 | 35.51 | 45.08 | 60.56 |
| ESG Score$^{09/2020\text{ Data}}$ | 41,818 | 40.44 | 16.94 | 26.64 | 38.02 | 52.28 |
| $\Delta$ ESG Score$^{\text{Rel.}}$ | 41,818 | -0.17 | 0.68 | -0.33 | -0.23 | -0.11 |
| ESG Downgrade | 41,818 | 0.84 | 0.37 | 1.00 | 1.00 | 1.00 |
| ESG Sum Phrases | 37,037 | 1.03 | 1.77 | 0.00 | 0.00 | 2.00 |
| *Other firm characteristics* | | | | | | |
| Log(Assets) | 33,085 | 8.57 | 1.35 | 7.74 | 8.39 | 9.38 |
| Capex/Assets | 33,614 | 0.03 | 0.04 | 0.01 | 0.02 | 0.04 |
| Cash/Assets | 33,614 | 0.08 | 0.08 | 0.02 | 0.05 | 0.10 |
| Debt/Assets | 33,038 | 0.46 | 0.17 | 0.35 | 0.45 | 0.56 |
| EBIT/Assets | 33,614 | 0.07 | 0.05 | 0.03 | 0.06 | 0.09 |
| PP&E/Assets | 33,614 | 0.24 | 0.22 | 0.08 | 0.15 | 0.37 |
| A-Letter Grade S&P Rating | 41,818 | 0.04 | 0.19 | 0.00 | 0.00 | 0.00 |
| B-Letter Grade S&P Rating | 41,818 | 0.79 | 0.41 | 1.00 | 1.00 | 1.00 |
| C-Letter Grade S&P Rating | 41,818 | 0.02 | 0.14 | 0.00 | 0.00 | 0.00 |
| Unrated by S&P | 41,818 | 0.16 | 0.36 | 0.00 | 0.00 | 0.00 |

**Table 2: Sample Comparison: Loan Sample vs. Compustat**

This table reports a comparison of summary statistics between Compustat and loan sample used in our paper. The sample covers non-financial U.S. firms in the fiscal year 2019, as this is the year for which we compute control variables. The variables are constructed as described in the Appendix in Table A1. The column labelled "Loan Sample" contains firms that constitute our loan sample. The column labelled "Compustat" contains all Compustat non-financial firms. All continuous variables are winsorized at the 1% and 99% levels, respectively. ***, **, and * indicate statistical significance of the underlying coefficient at the 1%, 5%, and 10% levels, respectively (based on a t-test allowing for unequal variances, and a non-parametric Mann-Whitney-Wilcoxon rank-sum test of equality of distributions, respectively).

| | Means | | Medians | |
|---|---|---|---|---|
| Variables | Loan Sample | Compustat | Loan Sample | Compustat |
| Log(Assets) | 8.46 | 5.49*** | 8.33 | 5.76*** |
| Debt/Assets | 0.46 | 0.26*** | 0.45 | 0.23*** |
| Capex/Assets | 0.04 | 0.04** | 0.03 | 0.02*** |
| Cash/Assets | 0.08 | 0.25*** | 0.06 | 0.11*** |
| EBIT/Assets | 0.07 | -0.55*** | 0.07 | 0.00*** |
| PP&E/Assets | 0.27 | 0.30* | 0.19 | 0.18 |

**Table 3: Event Study around Refinitiv ESG's Methodology Change**

This table reports a regression of abnormal returns (AR) for firms around Refinitiv ESG's methodology change announcement on an indicator variable "ESG Score Downgrade" and a set of firm characteristics. The event date is April 6, 2020 that corresponds to the date the ESG ratings change became effective. The sample is composed of firms that make up our loan sample of non-financial U.S. firms. "ESG Downgrade" is equal do one if a firm experiences a downgrade in its ESG score after the Refinitiv ESG's Methodology Change on April 6, 2020, and zero otherwise. To be included in a portfolio, a firm must have a minimum of one hundred return observations in the estimation period. We estimate normal performance over an estimation window spanning over 250 trading days. The gap between the estimation and event periods equals 100 trading days. We use the Fama-French-Carhart four-factor model (in Columns 1 and 2) as well market model (in Columns 3 and 4) as the normal performance return models. $t$-statistics, based on standard errors clustered at industry level (Fama-French 17-Industry Classification), are reported in parentheses. The control variables include Log(Assets), Debt/Assets, Capex/Assets, Cash/Assets, EBIT/Assets, and PP&E/Assets, which are defined in the Appendix in Table A1. All continuous variables are winsorized at the 1% and 99% levels, respectively. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

| | Fama-French-Carhart model | | Market model | |
|---|---|---|---|---|
| Dependent variable | AR [0,0] | AR [0,0] | AR [0,0] | AR [0,0] |
| | (1) | (2) | (3) | (4) |
| ESG Score Downgrade | -0.008** | -0.009* | -0.009** | -0.010* |
| | (-2.19) | (-1.77) | (-2.19) | (-1.91) |
| Observations | 229 | 175 | 229 | 175 |
| Adj. R-squared | 0.08 | 0.10 | 0.08 | 0.08 |
| Controls | No | Yes | No | Yes |
| Industry FE | Yes | Yes | Yes | Yes |

**Table 4: Loan Spreads around Refinitiv ESG's Methodology Change**

This table reports regressions of an ESG score downgrade on loan spreads in the secondary syndicated loan market at the daily loan - firm - level for the period between December 2019 and June 2020 in Panel A and for a placebo sample period between November 2020 to May 2021 in Panel B. Loan spread is defined as the difference between the loan's implied yield to maturity and its risk-free equivalent yield to maturity. For Panel A (B), "ESG Downgrade" is equal do one if a firm experiences an actual downgrade in its ESG score after the Refinitiv ESG's methodology change on April 6, 2020 (on February 1, 2021), and zero otherwise. In particular, we use the difference in latest ESG scores available downloaded as of February 2020 and September 2020 (September 2020 and February 2021). "Post" is equal to one after April 6, 2020 (February 1, 2021) and zero otherwise for Panel A (B). In column (5) of Panel A (B), we use monthly dummies for 3 months around the main event, where March 2020 (February 2021) is the omitted category. Firm Controls are defined in the Appendix in Table A1. Firm cluster is defined as risk category (A-letter, B-letter, C-letter rating or unrated) × industry (Fama-French 12-Industry Classification). *t*-statistics, based on standard errors clustered at firm level × time, are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Main Sample Period

| | Loan Spread | | | | |
|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) |
| ESG Downgrade × Post | 0.006** | 0.006** | 0.004*** | 0.004*** | |
| | (2.23) | (2.44) | (4.21) | (3.06) | |
| ESG Downgrade × -3 | | | | | 0.002 |
| | | | | | (1.24) |
| ESG Downgrade × -2 | | | | | 0.002 |
| | | | | | (1.30) |
| ESG Downgrade × -1 | | | | | 0.002 |
| | | | | | (1.22) |
| ESG Downgrade × +1 | | | | | 0.007*** |
| | | | | | (3.26) |
| ESG Downgrade × +2 | | | | | 0.007*** |
| | | | | | (4.03) |
| ESG Downgrade × +3 | | | | | 0.004*** |
| | | | | | (2.85) |
| Firm Controls | No | No | No | Yes | No |
| Time FE | Yes | No | No | No | No |
| Loan FE | No | No | Yes | Yes | Yes |
| Firm Cl. × Month FE | No | Yes | Yes | Yes | Yes |
| Rating Scale FE | No | Yes | Yes | Yes | Yes |
| $R^2$ | 0.123 | 0.498 | 0.859 | 0.857 | 0.859 |
| N | 41,818 | 41,818 | 41,818 | 32,509 | 41,818 |

Panel B: Placebo Sample Period

| | Loan Spread | | | | |
|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) |
| ESG Downgrade × Post | -0.005 | 0.000 | 0.005 | 0.001 | |
| | (-0.61) | (0.02) | (1.41) | (1.20) | |
| ESG Downgrade × -3 | | | | | -0.012 |
| | | | | | (-1.42) |
| ESG Downgrade × -2 | | | | | -0.009 |
| | | | | | (-1.19) |
| ESG Downgrade × -1 | | | | | -0.004 |
| | | | | | (-0.63) |
| ESG Downgrade × +1 | | | | | -0.005 |
| | | | | | (-0.98) |
| ESG Downgrade × +2 | | | | | -0.005 |
| | | | | | (-0.86) |
| ESG Downgrade × +3 | | | | | -0.003 |
| | | | | | (-0.41) |
| Firm Controls | No | No | No | Yes | No |
| Time FE | Yes | No | No | No | No |
| Loan FE | No | No | Yes | No | Yes |
| Firm Cl. × Month FE | No | Yes | Yes | Yes | Yes |
| Rating Scale FE | No | Yes | Yes | Yes | Yes |
| $R^2$ | 0.002 | 0.220 | 0.906 | 0.968 | 0.906 |
| N | 25,476 | 25,476 | 25,476 | 25,023 | 25,476 |

**Table 5: Loan Spreads around Refinitiv ESG's Methodology Change: Alternative Downgrade Measures**

This table reports regressions of an ESG score downgrade on loan spreads in the secondary syndicated loan market at the daily loan - firm - level. The table repeats the specification in column (3) of Panel A of Table 4, using alternative downgrade definitions. Loan spread is defined as the natural logarithm of the difference between the loan's implied yield to maturity and its risk-free equivalent yield to maturity. "ESG Downgrade 25th" is equal do one if a firm experiences an ESG ratings change below or equal to the 25$^{th}$ percentile and zero for an ESG ratings change above the 75$^{th}$ percentile. "ESG Downgrade 1st Qrtl", "ESG Downgrade 2nd Qrtl", and "ESG Downgrade 3rd Qrtl" equal one if a firms' ESG ratings change lies in the 25$^{th}$, 50$^{th}$ or 75$^{th}$ percentiles, leaving firms above the 75$^{th}$ percentile as the omitted category. "ESG Downgrade Neg." is equal to one if a firm experiences negative changes in ESG ratings and zero otherwise. "ESG Downgrade Alt." is equal to one if a firm experiences a difference between post- and pre-methodology ESG ratings that is below or equal to the 75$^{th}$ and zero otherwise. "Δ ESG Score" is defined as the continuous difference between the post- and pre-methodology ESG ratings. Firm cluster is defined as risk category (A-letter, B-letter, C-letter rating or unrated) × industry (Fama-French 12-Industry Classification). The sample period is between December 2019 and June 2020. $t$-statistics, based on standard errors clustered at firm level × time, are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

| | Loan Spread | | | | |
|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) |
| ESG Downgrade 25th × Post | 0.004*** | | | | |
| | (2.73) | | | | |
| ESG Downgrade 1st Qrtl× Post | | 0.004*** | | | |
| | | (2.65) | | | |
| ESG Downgrade 2nd Qrtl × Post | | 0.004*** | | | |
| | | (3.14) | | | |
| ESG Downgrade 3rd Qrtl × Post | | 0.005*** | | | |
| | | (3.85) | | | |
| ESG Downgrade Neg. × Post | | | 0.005*** | | |
| | | | (3.34) | | |
| ESG Downgrade Alt. × Post | | | | 0.004*** | |
| | | | | (3.20) | |
| Δ ESG Score × Post | | | | | -0.002*** |
| | | | | | (-4.72) |
| Firm Controls | No | No | No | No | No |
| Time FE | No | No | No | No | No |
| Loan FE | Yes | Yes | Yes | Yes | Yes |
| Firm Cl. × Month FE | Yes | Yes | Yes | Yes | Yes |
| Rating Scale FE | Yes | Yes | Yes | Yes | Yes |
| $R^2$ | 0.889 | 0.859 | 0.859 | 0.859 | 0.859 |
| N | 18,410 | 41,818 | 41,818 | 41,818 | 41,818 |

**Table 6: Loan Spreads around Refinitiv ESG's Methodology Change: Robustness**

This table reports regressions of an ESG score downgrade on loan spreads in the secondary syndicated loan market at the daily loan - firm - level. Loan spread is defined as the natural logarithm of the difference between the loan's implied yield to maturity and its risk-free equivalent yield to maturity. "ESG Downgrade" is equal do one if a firm experiences a downgrade in its ESG score after the Refinitiv ESG's Methodology Change on April 6, 2020, and zero otherwise. In particular, we use the difference in latest ESG scores available downloaded as of February 2020 and September 2020. "Post" is equal to one after April 6, 2020 and zero otherwise. "Bid Ask Spread" is equal to the median daily bid ask spread per industry. "Distance to Default" is equal to the natural logarithm of the Merton Distance to Default. "VIX" is equal to the natural logarithm of the VIX. "Covid Ind" is equal to one if a firm is in a Covid affected 3-digit NAICS industry as defined in Fahlenbrach et al. (2021). Firm cluster is defined as risk category (A-letter, B-letter, C-letter rating or unrated) × industry (Fama-French 12-Industry Classification). The sample period is between December 2019 and June 2020. *t*-statistics, based on standard errors clustered at firm level × time, are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

| | Loan Spread | | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| ESG Downgrade × Post | 0.005*** | 0.005*** | 0.005*** | 0.004*** |
| | (4.23) | (4.22) | (4.24) | (3.95) |
| Bid Ask Spread | -0.004** | | | |
| | (-2.38) | | | |
| Distance to Default | | -0.013*** | | |
| | | (-9.59) | | |
| VIX | | | 0.012*** | |
| | | | (14.63) | |
| ESG Downgrade × Post × Covid Ind | | | | 0.004 |
| | | | | (1.10) |
| Loan FE | No | Yes | Yes | Yes |
| Firm FE | Yes | No | No | No |
| Firm Cl. × Month FE | Yes | Yes | Yes | Yes |
| Rating Scale FE | Yes | Yes | Yes | Yes |
| $R^2$ | 0.800 | 0.857 | 0.865 | 0.859 |
| N | 41,818 | 35,906 | 41,818 | 41,818 |

**Table 7: Loan Spread Decomposition around Refinitiv ESG's Methodology Change**

This table reports regressions of an ESG score downgrade on the decomposed loan spreads in the secondary syndicated loan market at the daily loan - firm - level. We decompose the loan spread into the "Predicted Loan Spread" that is defined as a component that captures changes in default risk based on the fundamentals of the borrower in column (1) and the "Excess Loan Premium" that is defined as a residual that captures the price of risk above a default risk in column (2). "ESG Downgrade" is equal do one if a firm experiences a downgrade in its ESG score after the Refinitiv ESG's Methodology Change on April 6, 2020, and zero otherwise. In particular, we use the difference in latest ESG scores available downloaded as of February 2020 and September 2020. "Post" is equal to one after April 6, 2020 and zero otherwise. Firm cluster is defined as risk category (A-letter, B-letter, C-letter rating or unrated) × industry (Fama-French 12-Industry Classification). The sample period is between December 2019 and June 2020. In column (3), we show the first stage regression of the determinants of the loan spread based on Gilchrist and Zakrajšek (2012) for the sample period between January 2019 and December 2019. $t$-statistics, based on standard errors clustered at firm level × time, are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

| | Second Stage | | First Stage |
|---|---|---|---|
| | Predicted Loan Spread | ELP | Loan Spread |
| | (1) | (2) | (3) |
| ESG Downgrade × Post | 0.000 | 0.005*** | |
| | (0.97) | (4.31) | |
| Distance to Default | | | -0.000*** |
| | | | (-6.90) |
| Vol(Distance to Default) | | | 0.000*** |
| | | | (3.19) |
| Ln(AISD) | | | 0.035*** |
| | | | (53.84) |
| Ln(Age) | | | 0.000*** |
| | | | (2.68) |
| Ln(Amount) | | | 0.001*** |
| | | | (5.01) |
| Secured | | | -0.002*** |
| | | | (-4.07) |
| Covenant | | | 0.000 |
| | | | (1.35) |
| Loan Type FE | No | No | Yes |
| Industry FE | No | No | Yes |
| Loan FE | Yes | Yes | No |
| Firm Cl. × Month FE | Yes | Yes | No |
| Rating Scale FE | Yes | Yes | Yes |
| $R^2$ | 0.996 | 0.745 | 0.868 |
| N | 35,766 | 35,766 | 59,668 |

**Table 8: Loan Spreads around Refinitiv ESG's Methodology Change: Financial Constraints**

This table reports regressions of an ESG score downgrade on loan spreads in the secondary syndicated loan market at the loan - firm - level. Loan spread is defined as the natural logarithm of the difference between the loan's implied yield to maturity and its risk-free equivalent yield to maturity. "ESG Downgrade" is equal do one if a firm experiences a downgrade in its ESG score after the Refinitiv ESG's Methodology Change on April 6, 2020, and zero otherwise. In particular, we use the difference in latest ESG scores available downloaded as of February 2020 and September 2020. "Post" is equal to one after April 6, 2020 and zero otherwise. "Large" is equal to one if the lagged assets of a firm are above the median firm for the overall sample. "Old" is equal to one if the firm's age is above the median firm for the overall sample. "KZ" is equal to one if the firm's KZ-index is in the top quartile of the distribution and set to zero otherwise. "HP" is equal to one if the firm's Size-Age-index of Hadlock and Pierce (2010) is in the top quartile of the distribution and set to zero otherwise. Firm cluster is defined as risk category (A-letter, B-letter, C-letter rating or unrated) × industry (Fama-French 12-Industry Classification). The sample period is between December 2019 and June 2020. $t$-statistics, based on standard errors clustered at firm level × time, are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

| | Loan Spread | | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| ESG Downgrade × Post | 0.009*** | 0.006*** | 0.005*** | 0.002 |
| | (5.19) | (2.80) | (4.41) | (1.49) |
| ESG Downgrade × Post × Large | -0.011*** | | | |
| | (-3.72) | | | |
| ESG Downgrade × Post × Old | | -0.001 | | |
| | | (-0.32) | | |
| ESG Downgrade × Post × HP | | | -0.004 | |
| | | | (-1.33) | |
| ESG Downgrade × Post × KZ | | | | 0.010*** |
| | | | | (3.42) |
| Loan FE | Yes | Yes | Yes | Yes |
| Firm Cl. × Month FE | Yes | Yes | Yes | Yes |
| Rating Scale FE | Yes | Yes | Yes | Yes |
| $R^2$ | 0.859 | 0.865 | 0.859 | 0.863 |
| N | 33,085 | 26,718 | 41,818 | 41,818 |

**Table 9: Loan Spreads around Refinitiv ESG's Methodology Change: ESG Firms**

This table reports regressions of an ESG score downgrade on loan spreads in the secondary syndicated loan market at the loan - firm - level. Loan spread is defined as the natural logarithm of the difference between the loan's implied yield to maturity and its risk-free equivalent yield to maturity. "ESG Downgrade" is equal do one if a firm experiences a downgrade in its ESG score after the Refinitiv ESG's Methodology Change on April 6, 2020, and zero otherwise. In particular, we use the difference in latest ESG scores available downloaded as of February 2020 and September 2020. "Post" is equal to one after April 6, 2020 and zero otherwise. "ESG Phrases" measures the number of phrases related to ESG mentioned in the earnings calls between January 1, 2020 and April 6, 2020. "Top Carbon" is equal to one if a firm has been in top quartile of 4-digit SIC industries with the highest carbon emissions. "CCExposure Reg" is equal to the average relative frequency with which bigrams that capture regulatory shocks related to climate change occur in the transcripts of analyst conference calls (scaled up by $10^3$). Firm cluster is defined as risk category (A-letter, B-letter, C-letter rating or unrated) $\times$ industry (Fama-French 12-Industry Classification). The sample period is between December 2019 and June 2020. $t$-statistics, based on standard errors clustered at firm level $\times$ time, are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

| | Loan Spread | | |
|---|---|---|---|
| | (1) | (2) | (3) |
| ESG Downgrade × Post | 0.005*** | 0.005*** | 0.005*** |
| | (3.69) | (4.20) | (4.30) |
| ESG Downgrade × Post × ESG Phrases | 0.001** | | |
| | (2.31) | | |
| ESG Downgrade × Post × Top Carbon | | 0.012*** | |
| | | (3.25) | |
| ESG Downgrade × Post × CCExposure Reg | | | 0.045*** |
| | | | (4.34) |
| Firm FE | Yes | Yes | Yes |
| Firm Cl. × Month FE | Yes | Yes | Yes |
| Rating Scale FE | Yes | Yes | Yes |
| $R^2$ | 0.799 | 0.805 | 0.801 |
| N | 37,037 | 29,997 | 35,735 |

**Table 10: Loan Spreads around Refinitiv ESG's Methodology Change: ESG CLOs**

This table reports regressions of an ESG score downgrade on loan spreads in the secondary syndicated loan market at the loan - firm - level. Loan spread is defined as the natural logarithm of the difference between the loan's implied yield to maturity and its risk-free equivalent yield to maturity. "ESG Downgrade" is equal do one if a firm experiences a downgrade in its ESG score after the Refinitiv ESG's Methodology Change on April 6, 2020, and zero otherwise. In particular, we use the difference in latest ESG scores available downloaded as of February 2020 and September 2020. "Post" is equal to one after April 6, 2020 and zero otherwise. "ESG Homepage" measures the share of CLOs that mention ESG on their homepage out of all CLOS that held a firm during our sample period. "ESG Neg. Exlusion" measures the share of CLOs that use negative ESG exclusions out of all CLOs that held a firm during our sample period. "ESG PRI Signatory" measures the share of CLOs that signed the PRI Signatory out of all CLOs that held a firm during our sample period. "ESG PRI Signatory 2018" measures the share of CLOs that signed the PRI Signatory after 2018 out of all CLOs that held a firm during our sample period. Firm cluster is defined as risk category (A-letter, B-letter, C-letter rating or unrated) × industry (Fama-French 12-Industry Classification). The sample period is between December 2019 and June 2020. *t*-statistics, based on standard errors clustered at firm level × time, are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

| | Loan Spread | | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| ESG Downgrade × Post | 0.001 | 0.007** | -0.013 | -0.004 |
| | (0.23) | (2.49) | (-1.13) | (-0.89) |
| ESG Downgrade × Post × ESG Homepage | 0.017 | | | |
| | (1.27) | | | |
| ESG Downgrade × Post × ESG Neg. Excl. | | -0.011 | | |
| | | (-0.89) | | |
| ESG Downgrade × Post × ESG PRI Sign. | | | 0.022 | |
| | | | (1.57) | |
| ESG Downgrade × Post × ESG PRI Sign. 2018 | | | | 0.018** |
| | | | | (2.11) |
| Loan FE | Yes | Yes | Yes | Yes |
| Firm Cl. × Month FE | Yes | Yes | Yes | Yes |
| Rating Scale FE | Yes | Yes | Yes | Yes |
| $R^2$ | 0.852 | 0.852 | 0.852 | 0.852 |
| N | 36,003 | 36,003 | 36,003 | 36,003 |

**Table 11: Primary market loan interest rates around Refinitiv ESG's Methodology Change**

This table reports regressions of an ESG score downgrade on primary market loan interest rates at the loan - firm - level for loans issued one year before and after the ESG downgrade event. Loan interest rate is defined as the natural logarithm of the all-in-spread drawn (in basis points) at loan issuance in the primary syndicated loan market. "ESG Downgrade" is equal do one if a firm experiences a downgrade in its ESG score after the Refinitiv ESG's Methodology Change on April 6, 2020, and zero otherwise. In particular, we use the difference in latest ESG scores available downloaded as of February 2020 and September 2020. "Post" is equal to one after April 6, 2020 and zero otherwise. Firm cluster is defined as risk category (A-letter, B-letter, C-letter rating or unrated) × industry (Fama-French 12-Industry Classification). The sample period is between December 2019 and June 2020. *t*-statistics, based on standard errors clustered at firm level × time, are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

| | Loan Interest Rate | | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| ESG Downgrade × Post | 0.057 | -0.079 | -0.177 | 0.017 |
| | (0.29) | (-0.41) | (-0.81) | (0.09) |
| Loan Controls | No | No | No | Yes |
| Year FE | Yes | Yes | No | No |
| Firm Cl. × Month FE | No | No | Yes | Yes |
| Rating Scale FE | No | Yes | Yes | Yes |
| $R^2$ | 0.187 | 0.359 | 0.732 | 0.781 |
| N | 286 | 283 | 226 | 226 |

**Table 12: Loan Spreads around Refinitiv ESG's Methodology Change for Affected Industries**

This table reports regressions of affected industries on loan spreads in the secondary syndicated loan market at the loan - firm - level. Loan spread is defined as the natural logarithm of the difference between the loan's implied yield to maturity and its risk-free equivalent yield to maturity. "Affected" is equal to one if a firm is private and in an industry (FF 17) that has been in the bottom quartile of downgraded public firms after the Refinitiv ESG's Methodology Change on April 6, 2020, and zero otherwise. "Post" is equal to one after April 6, 2020 and zero otherwise. "Covid" is equal to one if a firm has been in the bottom 20-NAICS 3-digit industry sorted by cumulative excess return from Feb 3, 2020 until March 23, 2020 as in Fahlenbrach et al. (2021). "Unrated" is equal to one if the firm is unrated. Firm cluster is defined as risk category (rated, unrated) × industry (Fama-French 12-Industry Classification). The sample period is between December 2019 and June 2020. *t*-statistics, based on standard errors clustered at industry (Fama-French 17-Industry Classification) × time , are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

| | Loan Spread | | |
|---|---|---|---|
| | (1) | (2) | (3) |
| Affected Ind × Post | 0.010** | 0.010** | -0.000 |
| | (2.04) | (1.99) | (-0.13) |
| Affected Ind × Post × Covid | | -0.004 | |
| | | (-0.41) | |
| Affected Ind × Post × Unrated | | | 0.015** |
| | | | (2.44) |
| Firm FE | Yes | Yes | Yes |
| Firm Cl. × Month FE | Yes | Yes | Yes |
| $R^2$ | 0.824 | 0.824 | 0.823 |
| N | 173,955 | 173,955 | 173,955 |

**Acknowledgements**

The contribution by Kornelia Fabisik has been prepared under the Lamfalussy Fellowship Programme sponsored by the ECB.
Any views expressed are only those of the authors and do not necessarily represent the views of the ECB or the Eurosystem.

**Kornelia Fabisik**
University of Bern, Bern, Switzerland; email: kornelia.fabisik@unibe.ch

**Michael Ryf**
University of Bern, Bern, Switzerland; email: michael.ryf@unibe.ch

**Larissa Schäfer**
Frankfurt School of Finance & Management, Frankfurt am Main, Germany; email: l.schaefer@fs.de

**Sascha Steffen**
Frankfurt School of Finance & Management, Frankfurt am Main, Germany; email: s.steffen@fs.de



Postal address 60640 Frankfurt am Main, Germany
Telephone +49 69 1344 0
Website www.ecb.europa.eu



PDF ISBN 978-92-899-6255-1 ISSN 1725-2806 doi:10.2866/318913 QB-AR-23-115-EN-N