The Influence of ESG Ratings on Idiosyncratic Stock Risk:

The Unrated, the Good, the Bad, and the Sinners

Matthias Horn[a*]

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This study analyzes two questions. First, do stocks of companies with Environmental Social Governance (ESG) rating show lower idiosyncratic risk? Second, do stocks of ESG-rated companies subject to a negative screen show lower idiosyncratic risk than comparable stocks of ESG-rated companies not subject to a negative screen? The main analysis covers 898,757 company-month observations of US stocks in the period from 1991 to 2018 and controls for stocks' exposure to liquidity, mispricing, innovations in volatility risk, investor sentiment, and analysts' forecast divergence. The main findings are that stocks of companies with an ESG rating show significantly lower idiosyncratic risk than stocks of companies without an ESG rating. Furthermore, stocks subject to a negative screen show lower idiosyncratic risk during recessions and since the last financial crisis than comparable stocks with an ESG rating but without a negative screen. The results support the notion that the receipt of an ESG rating decreases uncertainty regarding future stock risk and return, provide further empirical support for the defensive nature of sin stocks, and show that ESG ratings and negative screens individually influence stock risk and, therefore, should be considered separately.

Key words: ESG Rating, Idiosyncratic Risk, ESG Investments, Sin stocks

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1 Introduction

Empirical evidence shows that stocks with higher idiosyncratic risk, on average, exhibit significantly lower returns than stocks with lower idiosyncratic risk (see Ang et al. 2006, 2009). Stambaugh et al. (2015) show that arbitrage asymmetry is a reason for this puzzle. As long as arbitrage asymmetry prevails, market participants will have difficulties to arbitrage that relation between idiosyncratic stock risk and stock return away. In consequence, investors only holding a limited number of stocks with high idiosyncratic risk, may significantly harm their investment performance (see Levy 1978, Adler/Kritzman 2008).

Market participants following Environmental Social Governance (ESG) investment approaches may be substantially exposed to idiosyncratic risk, even with portfolios of several hundred stocks (see Barnett/Salomon 2006, Geczy et al. 2005, Statman 2000). ESG approaches limit the number of investable stocks by prohibiting investments in certain “sin”, “vice”, or “controversial” industries or companies associated with unethical products (usage of negative screens), or only allow investments in the most sustainable companies of a peer group (best-in-class approach) (see Oehler et al. 2018). ESG ratings provide orientation for the steadily rising share of market participants that considers ESG criterions in their investment decisions (see Renneboog et al. 2008, Oehler 2013, Riedl/Smeets 2017) and, consequently, significantly influence investment flows (see Benson/Humphrey 2008, Bialkowski/Starks 2016, Hartzmark/Sussman 2019, Latino et al. 2021).

However, only few studies analyze the relationship between ESG ratings and idiosyncratic stock risk and the role of ESG ratings remains ambiguous: On the one hand, Cao et al. (2019) and Bofinger et al. (2020) show that the focus of ESG investors on ratings may lead to significant mispricing among high ESG-rated stocks, i.e., potentially higher idiosyncratic risk. Becchetti et al. (2015) provide empirical support that stocks of companies with higher ESG ratings show higher idiosyncratic volatility. With a focus on changes in ESG ratings, Glück et al. (2021) hardly find a significant impact of ESG rating changes on idiosyncratic volatility. On the other hand, previous studies generally hypothesize (see e.g. Bouslah et al. 2018 for a theoretical framework, see also Friede et al. 2015) and followingly find that stocks of companies with higher ESG ratings show lower idiosyncratic risk than stocks of companies with lower ESG ratings.

However, most of the previous studies cover only short observation periods[1] or focus on companies' legal risk[2]. Exceptions are studies by Mishra/Modi (2013), Becchetti et al. (2015), Sassen et al. (2016), Bouslah et al. (2013, 2018), Dunn et al. (2018), Giese et al. (2019), and Monti et al. (2019).[3] Nevertheless, there is a gap in the literature on the relation between ESG ratings and idiosyncratic stock risk, as the cited studies only consider the subsample of stocks corresponding to companies with an ESG rating, while ignoring the remaining stocks without an ESG rating.

Focusing only on stocks of companies with an ESG rating might miss some aspects of the general impact that ESG ratings have on stock prices, particularly since many of the listed companies worldwide did not receive an ESG rating during the last decade. Studies on ESG disclosure find that better ESG transparency improves firm value by decreasing reputational risk, information asymmetries, agency costs, capital constraints, and ultimately, capital costs (Cheng et al. 2014, Erragragui 2018,

[1] Lins et al. (2017) find a negative correlation between their CSR measure and idiosyncratic risk for the period from August 2008 through March 2009. Lee/Faff (2009) find a negative relation between corporate social performance and idiosyncratic risk in the years 1998-2002, Luo/Bhattachary (2009) in the years 2002 and 2003. Chen et al. (2018) analyze Taiwanese stocks from 2010 to 2014 and find a negative relation between CSR and idiosyncratic risk.

[2] See Gidfrey et al. (2009), Hong et al. (2016).

[3] Jo/Na (2012) analyze stocks over a longer period (1991 to 2010), however, do not specifically focus on idiosyncratic risk and only include companies of controversial industries.

Ng/Rezaee 2015, Yu et al. 2018, Ghoul et al. 2011). ESG disclosure even decreases capital cost, when the disclosed information displays weak ESG performance (Eliwa et al. 2021). Not having an ESG rating can be interpreted as very low ESG transparency and, therefore, negatively affects firm value (Wong et al. 2021), i.e., is an idiosyncratic risk. From an investor's point of view, it could also be argued that while an ESG rating provides an orientation regarding the ESG risk of a company (and hence enables to properly assess expected stock risk and return), the absence of an ESG rating is equivalent to major uncertainty regarding a company's ESG risk. Considering that uncertainty has a significant impact on expected stock returns that is not covered by standard systematic risk measures (Anderson et al. 2009, Bali/Zhou 2016, Brenner/Izhakian 2018), the absence of an ESG rating can be interpreted as an idiosyncratic firm risk when risk and return expectations are formed. Hence, there are several reasons why the receipt of an ESG rating should reduce idiosyncratic risk. However, empirical evidence on this issue is missing and it is not clear whether idiosyncratic stock risk decreases after the receipt of an ESG rating and whether stocks of companies with an ESG rating generally show lower idiosyncratic risk than stocks of unrated companies.

Furthermore, it is important to notice that ESG ratings are also provided for stocks of companies subject to a negative screen, i.e., companies associated with unethical products or "sin", "vice", or "controversial" industries. However, many previous studies do not differentiate between stocks of companies not subject to a negative screen and stocks of companies subject to a negative screen although negative sceens are of particular interest due to their ambiguous standing in ESG approaches. On the one hand, firms participating in sin industries must pay higher costs of equity (Chava 2014, Hong/Kacperczyk 2009, Ghoul et al. 2011, Killins et al. 2020), higher costs for loans

(Chava 2014, Goss/Roberts 2011, Kim et al. 2014, Nandy/Lodh 2012), and face capital constraints (see e.g., initiatives like Net Zero Asset Managers). On the other hand, avoiding doing business in or with whole industry sectors might lead to a lack of firm business model diversification and thus depicts an idiosyncratic risk. The latter should be particularly relevant in market downturns when idiosyncratic risk rises with market risk (Bartram et al. 2016) and stocks of sin companies may profit from their defensive nature (Richey 2020).

ESG investment approaches are ambiguous when it comes to negative screens. While some ESG approaches apply negative screens to ban the affected stocks from the investable universe, some best-in-class approaches ignore negative screens and invest in stocks from all industries to allegedly harvest higher abnormal returns. Empirical evidence regarding the profitability of these strategies is mixed. While early studies assume that the higher capital costs of sin stocks translate into higher abnormal returns (see e.g. Fabozzi et al. 2008), more recent studies find that the documented alphas can be explained by the exposure to certain systematic asset pricing factors (see e.g. Blitz/Fabozzi 2017). Applying a more differentiated research design, Zerbib (2020) shows that exclusionary screening (i.e., avoiding stocks subject to negative screens) and ESG integration (i.e., overweighting stocks with high ESG ratings) are two distinct investment approaches that both have an individual influence on (expected) stock returns. Hence, negative screens and ESG ratings not adjusted for negative screens (as is the case for the MSCI ratings used in this analysis) should be considered as independent influential factors of stock returns. According to Zerbib (2020), the mean premium earned by holding sin stocks is significantly positive ("the exclusion effect"). However, 10 out of the 52 sin stocks analyzed showed a negative exclusion effect. The latter finding underlines the idiosyncratic risk associated with sin stocks. Taken together, it seems that generally the idiosyncratic risk of higher costs of capital associated with negative screens is in balance with the benefits of diversification. In market downturns, however, the latter benefits should outweigh the higher capital costs associated with negative screens. Yet, specific empirical evidence on the relation between ESG ratings, negative screens and idiosyncratic risk is still missing.

The present study contributes to the literature by answering two questions of fundamental practical importance for investors when considering an ESG investment[4] approach:

(a) Do stocks of companies with ESG rating show lower idiosyncratic risk than stocks of companies without ESG rating?

(b) Do stocks of ESG-rated companies subject to a negative screen show lower idiosyncratic risk in recessions than otherwise comparable stocks of ESG-rated companies not subject to a negative screen?

The analysis spans the period from 1991 to 2018, covering a survivorship bias-free sample of the stocks listed in the MSCI North America All Cap index during this time period, applying ESG ratings from MSCI ESG KLD Stats and multiple widely recognized monthly factor and index data to control for market-wide liquidity (see Pástor/Stambaugh 2003), mispricing (see Stambaugh/Yuan 2017), investor sentiment and NBER recessions (see Baker/Wurgler 2006), and innovation in volatility risk (see Ang et al. 2006).

[4] It is important to notice, though, that (some) ESG investors would keep investing solely in ESG assets even if these assets showed a financial underperformance (see Bauer et al. 2019). The reason is that ESG investments may additionally provide some non-financial utility (see Renneboog et al. 2008, El Ghoul/Karoui 2017). Furthermore, investments in ESG assets may have a lower systematic risk (see Albuquerque et al. 2019).

The contribution of this paper is threefold. First, I provide empirical evidence that stocks of companies with an ESG rating show lower idiosyncratic risk than stocks of companies without an ESG rating. Moreover, the results of an event study and a difference-in-differences analysis show that idiosyncratic stock risk decreases after the receipt of an ESG rating. Second, by showing that stocks subject to a negative screen show lower idiosyncratic risk during recessions and since the last financial crisis than comparable stocks with an ESG rating but without a negative screen, this study shows that ESG ratings and negative screens have an individual influence on stock risk. This finding complements the notion of Zerbib (2020) that a company's ESG rating and negative screen individually influence stock returns. Hence, ESG ratings and negative screens should be considered separately. Third, I show that the previously found relation between ESG ratings and idiosyncratic stock risk is not driven by stocks' exposure to market-wide liquidity, mispricing, investor sentiment, NBER recession periods, and innovations in volatility risk or stocks' negative screens. Hence, I enhance the robustness of the finding that companies with higher ESG ratings show lower idiosyncratic stock risk (see e.g. Monti et al. 2019).

2 Data and Methodology

I focus on US stocks and respective MSCI/KLD ESG ratings. The advantage of this focus is that these ratings were provided several years before other rating providers entered the market.[5] Therefore, it is very likely that the MSCI/KLD ESG rating is the first ESG rating a US company received. Furthermore, MSCI/KLD ESG ratings are considered the most comprehensive and widely-used data source for ratings in ESG

[5] Other ESG rating providers like Refinitiv, ISS, Sustainalytics, and VIego Eiris started providing ESG ratings for US companies between 2002 and 2010. However, none of these providers did reach a coverage comparable to MSCI until the year 2015.

research (Bouslah et al. 2013). The analysis employs MSCI/KLD ESG ratings on a yearly basis from 1991 to 2018.[6] To check the obtained results for robustness as well as to derive potential implications, I also include Canadian stocks into the analysis. For Canadian stocks, the ESG ratings are available from 2013 to 2018. The applied ESG ratings contain eight rating categories: *Community, Corporate Governance, Diversity, Employee Relations, Environment, Human Rights, Product,* and *Other*. Negative screens are pooled in the rating category *Other* and are not inclusive in the ESG rating. The influence of a company being subject to a negative screen on idiosyncratic risk is controlled for by adding a dummy variable to the regression analyses, which equals one if a company is subject to any negative screen (*NegativeScreen*). To control for the influence of companies' ESG rating, I compute the ESG rating with the approach used by Lins et al. (2017), however, including all seven remaining rating categories instead of only applying five. For each category I compute a score which is the sum of strength divided by the maximum number of strengths possible for that category in that year minus the sum of concerns divided by the maximum number of concerns possible. The overall ESG rating (*ESGRating*) is the sum of the seven category scores and may range between +7 and -7. As negative screens are not inclusive in the ESG rating, companies subject to a negative screen can still reach the best possible ESG rating of +7.

I use daily total return and stock price data from Thomson Reuters Datastream from January 1991 to the end of 2018. Stocks with a price lower than five US Dollars at the beginning of a month are excluded for that month (see Pástor/Stambaugh 2003,

[6] Ratings for most non-US stocks have been available only since 2013 (see MSCI 2016, p. 12f.).

Stambaugh et al. 2015).[7] The idiosyncratic stock risk per month is based on daily returns and the Carhart (1997) four-factor model, which is defined as

$$R_{it} - R_{Ft} = \beta_{1i} * R_{Mt} + \beta_{2i} * SMB_t + \beta_{3i} * HML_t + \beta_{4i} * WML_t + \alpha_i + \varepsilon_{i,t}. \qquad (1)$$

where R_{it} is the return of stock i and R_{Ft} is the risk-free return on day t. R_{Mt}, SMB_t, HML_t, are the three factors defined by Fama/French (1992). WML_t is the momentum factor introduced by Carhart (1997). $\varepsilon_{i,t}$ is the residual per day t. Idiosyncratic risk of stock i measured as daily idiosyncratic volatility per month m ($IVOL_{i,m}$; in the remainder of the paper referred to as IVOL for better readability) is defined as $\sqrt{var(\varepsilon_{i,t})}$ for all days t of month m (see Bouslah et al. (2018) for this approach).[8] All results for IVOL are presented in percent. As robustness check, $IVOL_{i,m}$ is also computed with the Fama/French (2015) five factor model and trimmed and winsorized to minimize the influence of outliers. The daily North American factors for the four- and five-factor model are from Kenneth French's homepage.[9]

T-tests, an event study approach, and panel regressions with company and time fixed/random effects and robust standard errors clustered by company are provided to analyze differences in IVOL of stocks with and without ESG rating. Previous studies as well as the present study are based on two assumptions. First, that stock markets are information-efficient and, second, that the ESG ratings actually reflect the ESG risk exposure of the rated companies. Consequently, the actual idiosyncratic risk of the companies matches the idiosyncratic stock risk and the actual ESG risk of a company

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[7] Stocks with tickers C:SMU.UN, C:WRG, US:ACER, US:AMEH, US:APDN, US:ARWR, US:BLNK, US:ELOX, US:HROW, US:IDEX, US:IDRA, US:LFVN, US:LLEX, US:MAMS, US:OCAT, US:OTRK, US:PLX, US:PZZ, US:RIBT, US:SAUC, US:SRNE, US:SVRA, US:TEUM, US:TXMD, US:VTNR, US:XELB, and US:ZYXI are dropped because of data errors.

[8] I abstain from additionally computing idiosyncratic risk with downside measures (lower partial moments, LPM) since Bouslah et al. (2018) report that results for LPM1 through LPM3 are similar to those for IVOL computed with the four-factor model.

[9] http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

matches its ESG rating. Particularly the second assumption is hard to proof. Mild support of the robustness of these assumptions is that earnings forecasts for stocks with higher ESG ratings are more precise (Becchetti et al. 2013) and that companies with lower ESG ratings are more likely to become bankrupt (Cooper/Uzun 2019). Stronger support is found by Serafeim and Yoon (2021), showing that ESG ratings predict future company-specific ESG news and – with some constraints – proxy for market expectations of future ESG news.

Moreover, endogeneity effects may influence the results of the panel regressions. To address this concern, a matching and difference-in-differences approach for causal analysis with varying treatment time and duration is employed as robustness check to control for endogeneity effects (see Dettmann et al. 2020). Due to the weaknesses associated with propensity score matching (King/Nielsen, 2019), the approach is based on coarsened exact matching (see Blackwell et al. 2009).

Since companies' business models, and therefore companies' classification regarding negative screens, are easily observable and usually do not exhibit frequent and sudden changes, endogeneity concerns play a negligible role for the analysis of negative screens. Hence, differences between the IVOL of stocks subject to a negative screen and otherwise comparable stocks not subject to a negative screen are solely analyzed with panel regressions including company and time fixed/random effects as well as robust standard errors clustered by company, to account for ESG rating differences. As the ESG ratings are provided on a yearly basis, there are no changes over the twelve monthly observations of each year, causing the R^2 of the regression analyses to remain rather low. Nevertheless, I choose the monthly panel regression approach since the regressions apply multiple factors from different models to capture systematic time-series variations in realized returns (see Stambaugh/Yuan 2017) that may appear on monthly time horizons and only temporarily influence idiosyncratic stock risk. The applied factors control for liquidity risk (*InnovLiq*; see Pástor/Stambaugh 2003; also referred to as the non-traded liquidity factor to capture innovations in market liquidity and to estimate an asset's liquidity risk, see Pástor/Stambaugh 2019)[10], mispricing (*SMB_Mispricing*, *MGMT_Mispricing*, *PERF_Mispricing*; see Stambaugh/Yuan 2017)[11], and investor sentiment[12] (*Sentiment*; see Baker/Wurgler 2006, Stambaugh et al. 2012). Furthermore, due to their impact on stock returns and idiosyncratic risk, analyst forecast divergences[13] (*Deviation_Analysts*; see Boehme et al. 2009, Diether et al. 2002), industry sectors[14] (*Industry_Sectors*; see Moskowitz/Grinblatt 1999), NBER recessions[15] (*USREC*; see Bozhkov et al. 2020), and innovations in volatility risk proxied as changes in the S&P 500 VIX (Δ*VIX*; see Ang et al. 2006) are also included. As further robustness check, I split the dataset in observations before and after the end of the financial crisis to control for its impact (see Lins et al. 2017 and SIF 2018).

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[10] The factor data is from Robert Stambaugh's homepage http://finance.wharton.upenn.edu/~stambaug/.

[11] The factor data is from Robert Stambaugh's homepage http://finance.wharton.upenn.edu/~stambaug/.

[12] The factor data is from Jeffrey Wurgler's homepage http://people.stern.nyu.edu/jwurgler/.

[13] Stock price instead of earnings forecasts are used as companies' profitability, and hence earnings, is already captured in the factor models. The applied standard deviation of analysts' price forecasts is from the Institutional Brokers Estimate System (I/B/E/S). The standard deviation of analysts' price forecasts is divided by the stock price to adjust for price effects.

[14] A vector of nine dummy variables is used to reflect firms' industrial sector according to the MSCI Global Industry Classification Standard (GICS). The tenth sector *Communication* is omitted as basis vector because this is the sector with the fewest observations in the sample.

[15] The data is from https://fred.stlouisfed.org/series/USREC.

3 Main Results

The main results are based on the sample of US stocks, which covers 898,757 company-month observations. Table 1 provides descriptive statistics of these companies' ESG ratings and IVOL.

Please insert Table 1 about here

ESG ratings are available for 516,569 observations in an unbalanced panel. The ESG ratings have a mean (median) value of .07 (.00) and range between -3.25 and 5.9. Companies subject to a negative screen on average have a .05 points higher ESG score than companies not subject to a negative screen. This difference is significant at the one per mill level and again underlines the importance to differentiate between negative screens and the remaining ESG aspects (see Zerbib 2020). The mean IVOL of the full sample is 1.99 percent with a standard deviation of 1.92 percent. When the full sample is split up in stocks of companies with and without ESG rating, the mean IVOL of stocks with ESG rating is .85 percentage points lower than the IVOL of stocks with no ESG rating. Figure 1 shows the difference in IVOL of stocks with and without ESG rating per month in the period from January 1991 to December 2018. Stocks with ESG rating on average show a lower IVOL in every month of the 28-year long observation period. T-tests with Welch's (1947) formula show that the IVOL differences are significant at the one per mill level in each month.

Please insert Figure 1 about here

The t-tests only show that the IVOL of stocks of companies that already received an ESG rating is lower. But of particular interest is the question whether receiving an ESG rating by itself leads to lower idiosyncratic stock risk or whether rating providers are biased in their selection and, thus, only rate companies with already lower idiosyncratic risk (see e.g., Krueger (2015) for a discussion of the comparable reverse causality issue regarding ESG ratings). This question is analyzed with an event study approach. Stocks of 1,840 companies received an ESG rating for the first time in the years 1993 to 2014 and have been traded on the market for at least two years before and at least four years after the receipt of their first ESG rating. The IVOL of these stocks is compared to the IVOL of all other stocks (i.e. a sample of stocks with and without an ESG rating). The month of the receipt of the ESG rating is set as t=0.

The upper part of Figure 2 shows the mean difference in IVOL of stocks around the receipt of their first ESG rating and the IVOL of all other stocks. Please note that due to the construction of the employed dataset, market participants might actually have got the information regarding the new rating up to twelve months later than t=0. In the months -24 to 0 the mean IVOL of stocks that will receive an ESG rating in t=0 is not different from the mean IVOL of the remaining stocks at statistically significant levels (see the respective p-values of t-test per month in the lower part of Figure 2). In the months 0 to twelve, when the information about the received rating spreads among market participants, the mean IVOL of newly rated stocks is significantly decreasing compared to the IVOL of the remaining stocks. In months twelve to 48, the mean IVOL of the stocks that received an ESG rating is on average 15 percentage points lower than the mean IVOL of all other stocks. The latter difference is statistically significant at the one per mill level in each month of the period from months twelve to 48. Furthermore, the distribution of stocks' IVOL clearly becomes narrower when the respective companies received an ESG rating. This is in line with the conjecture that the receipt of an ESG rating decreases uncertainty regarding future risk and return. The mean standard deviation of the difference between the IVOL of newly rated stocks and the mean IVOL of all other stocks is 1.66 percent in months -24 to -1, 1.22 percent in months 0 to eleven, and 1.13 in months twelve to 48. Hence, results of the event study approach show that the receipt of an ESG rating does not only decrease a stock's mean idiosyncratic risk, but also narrows the width of a stock's IVOL distribution.

Please insert Figure 2 about here

To analyze the causal relationship between the receipt of an ESG rating and idiosyncratic stock risk in further detail, I apply stepwise panel regressions. The regression results presented in Table 2 support the results of the t-tests and the event study approach; ESG-rated stocks show lower IVOL than stocks of companies without a rating. The coefficient of the respective dummy variable (*HasESGRating*) is significant at the one per mill level in all model specifications. In recessions, the effect of an ESG rating on idiosyncratic stock risk is only about half as large, while remaining its significance. Results of the full regression model show that the risk decreasing effect of an ESG rating cannot be explained by exposure to liquidity risk, mispricing, innovations in volatility risk, investor sentiment, and analysts' forecast divergence.

Please insert Table 2 about here

In the subsample of ESG-rated stocks, 48,798 company-month observations are tagged with a negative screen. The results of the stepwise panel regression analyses presented in Table 3 show that stocks of companies subject to a negative screen do in general not exhibit lower IVOL at a statistically significant level. When information about recessions is included, however, the regression analyses yield an about .20 percentage points lower IVOL for stocks subject to a negative screen during periods of recession, i.e., stocks of sin companies profit from their defensive nature (see Richey 2020). In addition, the results support the previously found negative relation between a company's ESG rating and its IVOL (see Mishra/Modi (2013), Sassen et al. (2016), Bouslah et al. (2018), Dunn et al. (2018), and Giese et al. (2019)). Both findings hold when controlled for liquidity risk, mispricing, innovations in volatility risk, investor sentiment, analysts' stock price forecast divergence, and industry sectors in the full model. Hence, the lower idiosyncratic stock risk of sin companies with higher ESG ratings is not driven by these stocks' exposure to the analyzed systematic factors.

Please insert Table 3 about here

4 Robustness Checks

To address the issue that outliers may drive the results, the values of IVOL are winsorized at the lowest (five percent) and highest (95 percent) percentile each month. The coefficients for *HasESGRating* as reported in Table 2 only change by .02 (.05) percentage points after this treatment and remain statistically significant at the one per mill level. The coefficients and statistical significance of *ESGRating* as reported in Table 3 remain the same. The magnitude of the coefficients of *NegativeScreen*USREC* decreases by four percentage points at the most while the statistical significance stays unchanged. Trimming the values of $IVOL_{i,m}$ at the lowest and highest percentile each month has the same effect on the regression results as winsorizing values.

Instead of using the four-factor model of Carhart (1997), some investors may assess idiosyncratic risk rather by applying the more recent five-factor model of Fama/French (2015). Hence, I additionally compute $IVOL_{i,m}$ (denoted as $IVOL_{i,m}^{5F}$) with this model.[16]

[16] Please note, however, that the mispricing factors of Stambaugh/Yuan (2017) also include information captured in the factors RMW and CMA.

Compared to the previous analyses, the untabulated results for $IVOL_{i,m}^{5F}$ as dependent variable are almost identical[17] and therefore robust with regard to the applied factor model.

As reported by Lins et al. (2017), stocks of companies with high ESG ratings earned a premium during the financial crisis. Thereafter, investments in ESG mutual funds soared (see SIF 2018), indicating that market participants' investment approaches may have been subject to change, leading to an increased awareness – and, thus, an increased demand – with regard to ESG investment approaches[18]. Therefore, I split the dataset in observations before and after the end of the financial crisis and repeat the regression analyses for the latter subsample. Following NBER data on economic cycles, July 2009 is set as the end of the financial crisis (first month not marked as a recession since the beginning of the financial crisis). The respective results presented in Table 4 show that the IVOL of stocks with and without rating converges, but is still significantly higher for stocks without an ESG rating. Within the subsample of stocks with an ESG rating, stocks with a higher ESG rating still show lower IVOL although the magnitude of this effect decreases. In contrast to the analysis covering the full sample, stocks of companies subject to a negative screen show lower IVOL with a statistical significance at the one per mill level when all control variables are included. Nevertheless, a better ESG rating of sin firms still decreases their firm risk (see also Jo/Na 2012). An interpretation of these results could be that investors' preferences have shifted to ESG investment approaches during the financial crisis. As a consequence, the litigation risk associated with sin investments (see Hong/Kacperczyk 2009) has been fully priced in, leading to an equilibrium where the prices of sin stocks

[17] Tabulated detailed results of the respective regression analyses are available from the author upon request.
[18] Please note that this might also lead to an undiversifiable risk in prices, however rather as a systematic risk (see Ben-David et al. 2018).

and remaining stocks fully reflect the new aggregated ESG preferences of investors. In the absence of any further large preference shifts until the end of the year 2018, sin companies did not suffer from further litigation risk discounts and instead profited from their broader access to business opportunities and defensive nature.[19] This interpretation also reflects the assessment of mainstream investment organizations depicting negative screening is the least beneficial approach for investment performance (Amel-Zadeh/Serafeim 2018).

Please insert Table 4 about here

To address endogeneity issues regarding the companies' first receipt of an ESG rating, i.e., whether rating providers are biased in their selection and only rate companies with already lower idiosyncratic risk, I provide a matching and difference-in-differences approach for causal analysis with varying treatment time and duration (see Dettmann et al. 2020). The considered time window for the matching approach spans the years 2000 to 2018. The reasons for this choice are that MSCI significantly expanded the rating coverage in the years 2001 and 2003 by about 1,750 companies and that the popularity of ESG investment approaches soared after the financial crisis. The matching of the stocks is based on two sets of matching criteria. The first set includes industry sector and firm size measured as market capitalization, due to their important role in the ESG rating process and their influence on ESG scores (see e.g., Monti et al. 2019 and Drempetic et al. 2020). The second set covers stocks' loadings on the five factors of the Fama/French (2015) model in month t to capture stocks' exposure

[19] It is an interesting question for further research whether the COVID-19 pandemic induced a further large preference shift towards ESG investments. The data currently at hand, unfortunately, does not enable such an analysis. Furthermore, it still needs to be analyzed whether a systematic COVID-19 factor exists to correctly disentangle systematic and idiosyncratic risks during the pandemic.

to systematic risk factors at the time just before an ESG rating has been assigned. Companies that receive an ESG rating in month t for the first time are matched with companies that do not receive an ESG rating in month t according to the matching criteria in month t-1. The difference-in-differences approach compares the IVOL of the matched companies in month t-1 with their IVOL in months t+13, t+24, and t+36. The robustness of the conditional difference-in-differences is checked with a fixed effects panel regression to compute the total treatment effect for the treated companies within a two-way fixed effects model. Due to the significant role of the financial crisis, as before, the dataset is split in observations before and after the end of the financial crisis.[20]

The results of the difference-in-differences analysis are presented in Table 5 and Table 6. Unsurprisingly, not all companies that receive their first ESG rating can be matched with an unrated company. Depending on the analyzed time window and employed matching criteria, 63 to 96 percent of the newly rated companies can be matched. Results for stocks matched by market capitalization and industry sector are presented in Table 5. The IVOL of the stocks that received their first ESG rating on average decreased by -.13 to -.53 percentage points when compared to the IVOL in the month before the receipt of the first rating. This reduction in IVOL is .14 to .52 larger than the reduction comparable stocks without an ESG rating experienced. The conditional difference-in-differences is significant at the one per mill level before the financial crisis. Statistical significance after the financial crisis is lower, but still reaches the one percent level for the 36 months observation period. The total effect of the ESG rating receipt in a two-way fixed effects model with robust standard errors also is negative. However,

[20] If the event window for a company would cover parts of both observation periods, e.g., when the first ESG rating of a company was received five months before the end of the financial crisis, the company is excluded from the difference in differences analysis.

only in the model covering observations before the financial crisis in a 24-month period, the respective coefficient is statistically significant at the one per mill level. Results for stocks matched by factor loadings according to the Fama/French (2015) five factor model are shown in Table 6. The results are similar to those based on the market capitalization and industry sector-matching. The only noteworthy exception is that the negative total effect of the ESG rating receipt on IVOL in the two-way fixed effects model is significant at the five percent level in the models covering observations after the financial crisis in a 24-month and 36-month period. Hence, the results of the difference-in-differences analysis are further support that the receipt of an ESG rating decreases idiosyncratic stock risk.

Please insert Table 5 about here

Please insert Table 6 about here

I check whether the findings can be confirmed in other countries by analyzing Canadian stocks (results are not tabulated in this paper). ESG ratings are available for 14,428 of 23,169 company-month observations in the years 2013 to 2018. The ESG ratings have a mean (median) value of .73 (.45) and range between -1.5 and 5.7. The mean $IVOL_{i,m}$ of the full Canadian sample is 1.55 percent with a standard deviation of 1.27 percent. A fixed effects panel regression with $IVOL_{i,m}$ as dependent and a dummy that indicates whether a stock is rated (*Dummy_HasESGRating*) as independent variable yields a coefficient for the dummy of -.11 percentage points and a statistical significance at the one per mill level; supporting the findings on the US sample. Due to the small number of only 1,415 company-month observations that are tagged with a negative screen, I do not perform an analysis covering the effect of negative screens on the Canadian sample.

5 Discussion

Within the Neoclassical finance paradigm, including corner stone theories such as the Capital Asset Pricing Model by Sharpe (1964), Lintner (1965), and Mossin (1966), expected stock returns do not depend on idiosyncratic risk. In spite of what is predicted by the theoretical framework, more recent findings show that stocks with higher IVOL, on average, exhibit significantly lower returns than stocks with lower IVOL (see Ang et al. 2006, 2009, Stambaugh et al. 2015). Moreover, investors employing ESG approaches may be substantially exposed to idiosyncratic risk and thereby suffer from weak investment performance (see Barnett/Salomon 2006, Geczy et al. 2005, Statman 2000, Levy 1978, Adler/Kritzman 2008). The results of the present study show a statistically significant influence of ESG ratings on IVOL. Whether the magnitude of the documented relation is large enough to be of economic significance has yet to be discussed.

When stocks receive an ESG rating, the magnitude of the negative effect on IVOL varies, depending on the methodology, between .94 (see Table 2, model (9)) and .14 (see Table 5, conditional difference-in-differences, see also event study in Figure 2) percentage points. When considering that the mean IVOL of stocks with ESG rating is .85 percentage points lower than the IVOL of stocks with no ESG rating, a certain selection bias of the rating providers has to be considered. The selection of rated companies is based on index membership and market capitalization. Over time, the ESG ratings usually have been provided for those stocks listed in the MSCI KLD 400 Social Index, MSCI USA Index, MSCI USA IMI Index, as well as the 1000 largest US companies. By design of the employed asset pricing factors, stocks with lower market capitalization are more likely to have higher IVOL – and they more likely do not receive an ESG rating. The economic magnitude of the receipt of an ESG rating should, therefore, be closer to the .14 percentage points derived by the methods that focus on the longitudinal profile than to the .94 percentage points as derived by methods with an emphasis on the cross section. Compared to the mean IVOL of the full sample of 1.99 percent with a standard deviation of 1.92 percentage points, a reduction in IVOL of .14 percentage points does not initially seem economically meaningful. However, for listed companies the costs associated with receiving an ESG rating are negligible. Since studies on ESG disclosure find that better ESG transparency improves firm value and decreases capital costs (Cheng et al. 2014, Erragragui 2018, Ng/Rezaee 2015, Yu et al. 2018, Ghoul et al. 2011), even when the disclosed information displays weak ESG performance (Eliwa et al. 2021), getting an ESG rating appears to resemble free lunch – although small – for listed companies and their equity investors. Therefore, the risk-reducing effect of an ESG rating is economically significant.

Although stocks subject to a negative screen show statistically significant lower idiosyncratic risk during recessions as well as since the last financial crisis, than comparable stocks with an ESG rating but without a negative screen, the magnitude of the difference is hardly economically significant. In recessions, the IVOL of stocks subject to a negative screen is .18 percentage points lower than the IVOL of stocks without a negative screen (see Table 3, model (9)). It is important to notice that only 29 months in the dataset actually cover periods of recessions. Corresponding to less than a tenth of the observation period. Consequently, the average risk reducing effect of sin stocks in times of recessions seems economically marginal over the entire observation period. Even combined with sin stocks' .08 percentage points lower IVOL since the last financial crisis, it is hardly justified stating that stocks subject to a negative screen show economically significant lower IVOL. On the flipside, the analysis does not provide any evidence that excluding sin stocks might reduce investors' risk.

Whether investors shall push companies to improve their ESG ratings in order to make use of the negative relation between the ESG rating score and IVOL is an issue worth discussing. Standardized coefficients in a simple OLS regression indicate that an one-standard-deviation-increase of the ESG rating score leads to a .11 to .14 percentage points decrease in IVOL. This is in line with the results in Table 1 (standard deviation of ESG ratings of .81) and Table 3, model (9) (coefficient of *ESGRating* of -.10), according to which an one-standard-deviation-increase of the ESG rating leads to a 0.81*.10 = 0.08 percentage points decrease in IVOL. This decrease does not seem economically meaningful compared to a mean IVOL of 1.63 (median: 1.32) with a standard deviation of 1.20 in the subsample of rated stocks. Also, when considering the typical IVOL of stocks in the portfolios formed by Stambaugh et al. (2015), the stocks with an ESG rating are unlikely to be in the highest-IVOL-portfolios. As the differences in the benchmark-adjusted returns of the two portfolios with the next lowest IVOL are rather negligible, it is unlikely that a decrease in IVOL triggered by a higher ESG rating has an economically meaningful impact on expected stock returns. It is important to notice that a better ESG performance – and consequently a higher ESG rating – might nevertheless have a positive influence on expected stock performance (see Liang/Renneboog 2020 for a review on this issue), however, unlikely via the influence of idiosyncratic risk on stock prices. On the flipside, the analysis provides no evidence that a better ESG rating might hurt investment performance.

6 Conclusion

This paper contributes to the literature by providing empirical support on three important issues regarding the influence of ESG ratings on idiosyncratic stock risk. First, after the receipt of an ESG rating, idiosyncratic stock risk decreases and stocks of rated companies show statistically and economically significantly lower idiosyncratic risk than stocks of companies with no ESG rating. Second, stocks subject to a negative screen show statistically significant lower idiosyncratic risk during recessions as well as since the last financial crisis, than comparable stocks with an ESG rating but without a negative screen. Nevertheless, a stronger ESG engagement of firms subject to a negative screen still decreases their idiosyncratic stock risk. Hence, as ESG ratings and negative screens individually influence stock risk, they should be considered separately. Third, both effects are robust over time, statistically significant for US and Canadian stocks, and cannot be explained by exposure to liquidity risk, mispricing, innovations in volatility risk, investor sentiment, and analysts' forecast divergence. Hence, the analysis shows that the previously found negative relation between stocks' IVOL and ESG ratings is robust to the stocks' exposure to liquidity risk, mispricing, innovations in volatility risk, investor sentiment, and analysts' forecast divergence and also holds for sin stocks.

These findings have practical implications. The lower idiosyncratic risk of ESG-rated stocks – and of stocks with good ESG rating in particular – is not only good news for ESG investors or investors thinking about following an ESG investment approach, but also relevant for the remaining market participants. A lot of companies in developed and particularly in developing markets are not rated by an ESG rating agency yet. These companies should strive for receiving an ESG rating – even though the company might show a rather low ESG performance. Just the receipt of an ESG rating significantly reduces idiosyncratic stock risk. As the mere receipt of an ESG rating is hardly associated with noteworthy costs for listed companies, investors should push companies to get rated.

Barber/Odean (2000, 2001), Polkovnichenko (2005), and Goetzmann/Kumar (2008) show that many investors (most probably not only ESG investors) are under-diversified and suffer from associated idiosyncratic risks. If investors are not willing to minimize their exposure to idiosyncratic risk by buying index funds (Oehler/Wanger 2020), they may have a better investment performance by investing in stocks of companies with high ESG ratings. Hereby, investors likely benefit from avoiding negative screening approaches as companies subject to a negative screen usually have lower idiosyncratic risk, particularly in economic downturns. However, although statistically significant in the cross sections of stocks, the economic magnitude of the effects of higher ESG ratings and negative screens is rather small and may not justify the reallocation of an existing portfolio and the respective transaction costs. But it may be worthwhile considering these effects when establishing a new portfolio from the scratch.

An advantage of the dataset employed in this study is the long history of ESG ratings. Yet, particularly since the financial crisis and especially in Europe, several rating agencies have become popular. Their rating approaches differ significantly from each other, sometimes leading to different assessments regarding the ESG performance of a company (Berg et al. 2019). I do not assume that this has an influence on the results of this study, as MSCI/KLD had provided ESG ratings for US stocks even before some of the European rating agencies have been founded and therefore has the position of an old bull. Nevertheless, as differences in opinion (a proxy for uncertainty) significantly influence stocks' IVOL (Diether et al. 2002, Anderson et al. 2009), further research might analyze the impact of ESG rating dispersion on IVOL. When doing so, researchers should consider ESG ratings and negative screens as independent from each other, as both have an individual influence on stock risk.

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Figure 1: Mean $IVOL_{i,m}$ per month in percent for US stocks without and with ESG rating

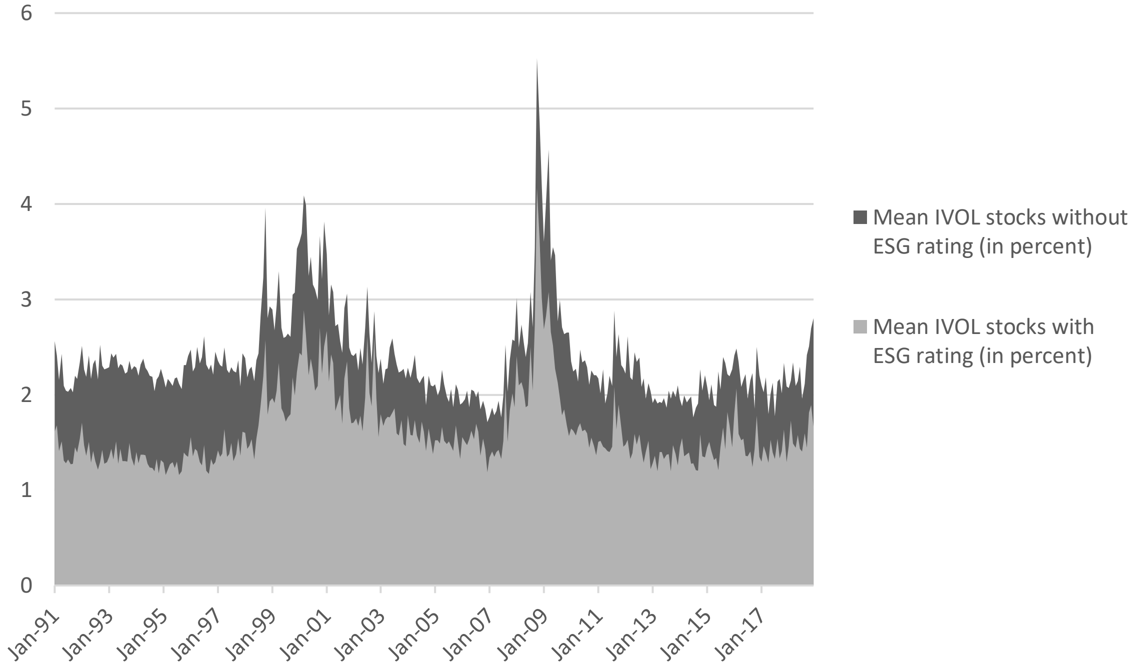

Figure 2: Mean difference of IVOL of stocks receiving their first ESG rating and IVOL of all stocks in the period spanning 24 months before and 48 months after the rating receipt

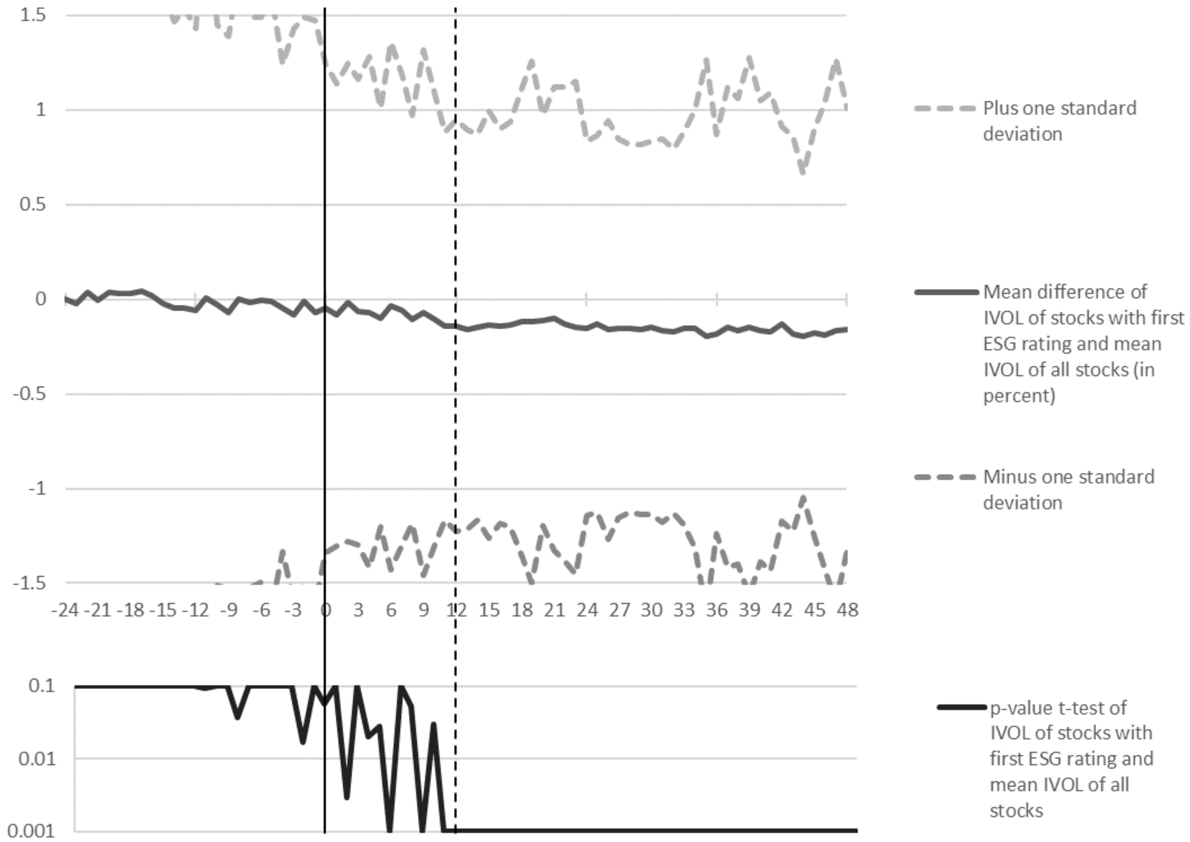

Table 1: Descriptive statistics of the companies' ESG ratings and $IVOL_{i,m}$

	ESGRating			$IVOL_{i,m}$			
	Mean	Median	Std. Dev.	Mean	Median	Std. Dev.	N
Observations without ESG rating				2.47	1.93	2.51	382,188
Observations with ESG rating	.07	.00	.81	1.63	1.32	1.20	516,569
thereof							
without negative screen	.06	.00	.79	1.63	1.32	1.20	467,771
with negative screen	.11	.00	1.01	1.39	1.16	0.95	48,798

Table 2: Panel regressions on $IVOL_{i,m}$ in percent for US stocks without and with ESG rating

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
HasESGRating	-.75**** (.02)	-.79**** (.02)	-.73**** (.02)	-.73**** (.02)	-.74**** (.02)	-.71**** (.02)	-.95**** (.02)	-.72**** (.02)	-.94**** (.02)
HasESGRating*USREC		.40**** (.03)							.56**** (.04)
USREC		.54**** (.03)							.36**** (.03)
InnovLiq			-1.55**** (.03)						-.91**** (.04)
SMB_Mispricing				.57**** (.08)					.17* (.07)
MGMT_Mispricing				1.73**** (.08)					1.81**** (.08)
PERF_Mispricing				.78**** (.04)					-.25**** (.04)
ΔVIX					.02**** (.00)				.02*** (.00)
Sentiment						.06**** (.01)			-.01 (.01)
Deviation_Analysts($x10^{-6}$)							3.55* (1.61)		3.13* (1.56)
Industry_Sectors	No	No	No	No	No	No	No	Yes	Yes
Fixed/random effects	fixed	fixed	fixed	fixed	fixed	fixed	fixed	random	random
β_0	2.41**** (.01)	2.37**** (.01)	2.41**** (.01)	2.40**** (.01)	2.41**** (.01)	2.38**** (.01)	2.56**** (.02)	2.67**** (.08)	2.70**** (.07)
R^2	.05	.06	.05	.05	.05	.06	.05	.11	.17
N	898,666	898,666	898,666	822,452	892,433	898,666	529,538	789,488	422,123

Notes: I provide coefficients, robust standard errors (in parentheses) clustered by company, and R^2 for fixed-/random-effects panel regression analysis with the model

$$IVOL_{i,m} = \beta_{1i} * \mathrm{HasESGRating}_{i,m} + \sum_{j=2}^{10} \beta_{j,i} * X_{j,m} + \gamma * IS_i + \beta_{0,i} + u_{i,m},$$

where $IVOL_{i,m}$ is the idiosyncratic risk of stock i measured as daily idiosyncratic volatility per month m in percent, $\mathrm{HasESGRating}_{i,m}$ is a dummy variable indicating whether a stock i has an ESG rating in month m, $X_{2,m}, \ldots, X_{10,m}$ are the factors HasESGRating*USREC, USREC, InnovLiq, SMB_Mispricing, MGMT_Mispricing, PERF_Mispricing, ΔVIX, Sentiment, and Deviation_Analysts, and IS_i is vector of nine dummy variables to reflect firms' industrial sector. The symbols ****, ***, **, and * denote significance at the one per mill, five per mill, one percent, and five percent level, respectively. Coefficients with p-values >= .05 are not labeled as significant. Example: Regressing $IVOL_{i,m}$ on the dummy variable $\mathrm{HasESGRating}_{i,m}$ (model (1)) yields a coefficient of -.75 with a p-value < .001 for this dummy variable.

Table 3: Panel regressions on $IVOL_{i,m}$ per month in percent for ESG-rated US stocks subject and not subject to negative screens

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
NegativeScreen	-.03 (.03)	.02 (.03)	-.02 (.03)	-.03 (.03)	-.03 (.03)	-.03 (.03)	-.05 (.03)	-.05 (.03)	-.01 (.03)
NegativeScreen*USREC		-.21**** (.04)							-.18**** (.04)
ESGRating	-.14**** (.00)	-.09**** (.00)	-.12**** (.00)	-.14**** (.01)	-.14**** (.00)	-.14**** (.00)	-.14**** (.00)	-.14**** (.00)	-.10**** (.00)
ESGRating*USREC		.00 (.03)							.02 (.03)
USREC		.94**** (.02)							.93**** (.02)
InnovLiq			-1.82**** (.03)						-.69**** (.04)
SMB_Mispricing				.72**** (.07)					.16* (.07)
MGMT_Mispricing				2.85**** (.07)					2.57**** (.08)
PERF_Mispricing				.92**** (.04)					-.06 (.04)
ΔVIX					.02**** (.00)				.01**** (.00)
Sentiment						-.05**** (.01)			-.08**** (.01)
Deviation_Analysts(x10^{-6})							2.68**** (.27)		2.41**** (.24)
Industry_Sectors	No	No	No	No	No	No	No	Yes	Yes
Fixed/random effects	fixed	fixed	fixed	fixed	fixed	fixed	fixed	random	random
β_0	1.64**** (.00)	1.54**** (.00)	1.65**** (.00)	1.63**** (.00)	1.64**** (.00)	1.64**** (.00)	1.64**** (.00)	1.95**** (.05)	1.83**** (.06)
R^2	.02	.06	.02	.02	.02	.02	.02	.07	.13
N	516,478	516,478	516,478	454,386	515,322	516,478	447,311	472,825	357.752

Notes: I provide coefficients, robust standard errors (in parentheses) clustered by company, and R^2 for fixed-/random-effects panel regression analysis with the model

$$IVOL_{i,m} = \beta_{1i} * \text{NegativeScreen}_{i,m} + \beta_{2i} * \text{ESGRating}_{i,m} + \sum_{j=3}^{12} \beta_{j,i} * X_{j,m} + \gamma * IS_i + \beta_{0,i} + u_{i,m},$$

where $IVOL_{i,m}$ is the idiosyncratic risk of stock i measured as daily idiosyncratic volatility per month m in percent, $\text{NegativeScreen}_{i,m}$ is a dummy variable indicating whether a stock i is subject to a negative screen in month m, $\text{ESGRating}_{i,m}$ is the ESG rating of stock i in month m, $X_{3,m}, \ldots, X_{12,m}$ are the factors NegativeScreen*USREC, ESGRating*USREC, USREC, InnovLiq, SMB_Mispricing, MGMT_Mispricing, PERF_Mispricing, ΔVIX, Sentiment, and Deviation_Analysts, and IS_i is vector of nine dummy variables to reflect firms' industrial sector. The symbols ****, ***, **, and * denote significance at the one per mill, five per mill, one percent, and five percent level, respectively. Coefficients with p-values >= .05 are not labeled as significant. Example: Regressing $IVOL_{i,m}$ on regression model (1) yields a coefficient of -.14 with a p-value < .001 for the companies' ESG ratings as independent variable.

Table 4: Panel regressions on $IVOL_{i,m}$ per month for observations from July 2009 and later

	(1)	(2)	(3)	(4)
HasESGRating	-.31**** (.03)	-.40**** (.03)		
NegativeScreen			-.05* (.02)	-.08**** (.02)
ESGRating			-.05**** (.00)	-.06**** (.00)
InnovLiq		-.08 (.06)		.00 (.06)
SMB_Mispricing		-.41**** (.10)		-.54**** (.09)
MGMT_Mispricing		1.44**** (.14)		1.35**** (.12)
PERF_Mispricing		.08 (.07)		.04 (.06)
ΔVIX		.01**** (.00)		.01**** (.00)
Sentiment		-.29**** (.01)		-.26**** (.01)
Deviation_Analysts(x10^{-6})		16.0* (7.26)		-7.89 (14.5)
Industry_Sectors	No	Yes	No	Yes
Fixed/random effects	fixed	random	fixed	random
β_0	1.88**** (.02)	2.05**** (.07)	1.50**** (.00)	1.70**** (.06)
R^2	.03	.09	.02	.08
N	359,615	213,325	276,562	191,692

Notes: I provide coefficients, robust standard errors (in parentheses) clustered by company, and R^2 for fixed-/random-effects panel regression analysis with the model ((1) and (2))

$$IVOL_{i,m} = \beta_{1i} * \text{HasESGRating}_{i,m} + \sum_{j=2}^{8} \beta_{j,i} * X_{j,m} + \gamma * IS_i + \beta_{0,i} + u_{i,m},$$

where $IVOL_{i,m}$ is the idiosyncratic risk of stock i measured as daily idiosyncratic volatility per month m in percent, $\text{HasESGRating}_{i,m}$ is a dummy variable indicating whether a stock i has an ESG rating in month m, $X_{2,m}$, …, $X_{8,m}$ are the factors InnovLiq, SMB_Mispricing, MGMT_Mispricing, PERF_Mispricing, ΔVIX, Sentiment, and Deviation_Analysts, and IS_i is vector of nine dummy variables to reflect firms' industrial sector. Models (3) and (4) are

$$IVOL_{i,m} = \beta_{1i} * \text{NegativeScreen}_{i,m} + \beta_{2i} * \text{ESGRating}_{i,m} + \sum_{j=3}^{9} \beta_{j,i} * X_{j,m} + \gamma * IS_i + \beta_{0,i} + u_{i,m},$$

where $\text{NegativeScreen}_{i,m}$ is a dummy variable indicating whether a stock i is subject to a negative screen in month m, $\text{ESGRating}_{i,m}$ is the ESG rating of stock i in month m. The symbols ****, ***, **, and * denote significance at the one per mill, five per mill, one percent, and five percent level, respectively. Coefficients with p-values >= .05 are not labeled as significant. Example: Regressing $IVOL_{i,m}$ on $\text{HasESGRating}_{i,m}$ in model (1) yields a coefficient of -.31 with a p-value < .001 for this dummy variable.

Table 5: Difference-in-differences approach applied on IVOL of stocks receiving their first ESG rating (i.e. the treatment) and IVOL of stocks without ESG rating (control group) based on CEM-Matching by market capitalization and industry sector

	(1)	(2)	(3)	(4)	(5)	(6)
Time period	Jan 1999 – June 2009	Jan 1999 – June 2009	Jan 1999 – June 2009	July 2009 – Dec 2018	July 2009 – Dec 2018	July 2009 – Dec 2018
Mean difference treated	-.38	-.41	-.53	-.13	-.43	-.49
Mean difference controls	-.17	-.27	-.35	.01	-.05	.03
Conditional difference-in-differences (standard error of differences between treated and control group in parentheses)	-.21**** (.03)	-.14**** (.04)	-.18**** (.04)	-.14 (.12)	-.39* (.15)	-.52** (.20)
Total treatment effect for the treated within two-way fixed effects model (robust standard error in parentheses)	-.13 (.10)	-.38**** (.11)	-.14 (.14)	-.04 (.22)	-.36 (.21)	-.29 (.24)
N treated matched	1585	1387	1248	540	406	305
N controls matched	565	464	385	584	478	373
N treated unmatched	75	95	87	17	15	12
Matching variables included:						
Market capitalization	Automatic	Automatic	Automatic	Automatic	Automatic	Automatic
Industry sector	Cutpoints	Cutpoints	Cutpoints	Cutpoints	Cutpoints	Cutpoints
Time period of pre-treatment outcome relative to treatment in months	1	1	1	1	1	1
Length of time period after treatment included in months	13	24	36	13	24	36

Notes: I provide results for a Coarsened Exact Matching-matching and subsequent difference-in-differences approach with $IVOL_{i,m}$ as dependent variable. Relative matching time is the month before the treatment, i.e. the receipt of an ESG rating. The information provided for the matching variables shows whether coarsening was performed based on fixed cutpoints ("Cutpoints") or automatically ("Automatic") for each included variable. The symbols ****, ***, **, and * denote significance at the one per mill, five per mill, one percent, and five percent level, respectively. Coefficients with p-values >= .05 are not labeled as significant.

Table 6: Difference-in-differences approach applied on IVOL of stocks receiving their first ESG rating (i.e. the treatment) and IVOL of stocks without ESG rating (control group) based on CEM-Matching by Fama-French-five-factor-loadings

	(1)	(2)	(3)	(4)	(5)	(6)
Time period	Jan 1999 – June 2009	Jan 1999 – June 2009	Jan 1999 – June 2009	July 2009 – Dec 2018	July 2009 – Dec 2018	July 2009 – Dec 2018
Mean difference treated	-.25	-.25	-.37	-.09	-.43	-.49
Mean difference controls	-.04	-.07	-.22	-.11	-.10	.01
Conditional difference-in-differences (standard error of differences between treated and control group in parentheses)	-.20**** (.04)	-.17**** (.04)	-.16**** (.04)	.02 (.13)	-.33* (.16)	-.50* (.23)
Total treatment effect for the treated within two-way fixed effects model (robust standard error in parentheses)	-11 (.11)	-14 (.13)	-.00 (.14)	-.03 (.16)	-.44* (.20)	-.46* (.24)
N treated matched	1095	947	840	483	362	273
N controls matched	453	364	304	501	408	318
N treated unmatched	565	535	495	74	59	44
Matching variables included:						
Mkt_Loading	Automatic	Automatic	Automatic	Automatic	Automatic	Automatic
SMB_Loading	Automatic	Automatic	Automatic	Automatic	Automatic	Automatic
HML_Loading	Automatic	Automatic	Automatic	Automatic	Automatic	Automatic
RMW_Loading	Automatic	Automatic	Automatic	Automatic	Automatic	Automatic
CMA_Loading	Automatic	Automatic	Automatic	Automatic	Automatic	Automatic
Time period of pre-treatment outcome relative to treatment in months	1	1	1	1	1	1
Length of time period after treatment included in months	13	24	36	13	24	36

Notes: I provide results for a Coarsened Exact Matching-matching and subsequent difference-in-differences approach with $IVOL_{i,m}$ as dependent variable. Relative matching time is the month before the treatment, i.e. the receipt of an ESG rating. The information provided for the matching variables shows whether coarsening was performed based on fixed cutpoints (“Cutpoints”) or automatically (“Automatic”) for each included variable. The symbols ****, ***, **, and * denote significance at the one per mill, five per mill, one percent, and five percent level, respectively. Coefficients with p-values >= .05 are not labeled as significant.