Environmental Disclosure and Idiosyncratic Risk in the European Manufacturing Sector

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Abstract

We study the impact of environmental disclosure on the idiosyncratic risk of European manufacturing firms. Utilizing a panel data set of 288 firms from 17 European countries during the period from 2005 to 2016, we provide evidence that environmental disclosure reduces idiosyncratic risk of investment. Our findings show that this relationship can best be justified by the *stakeholder* and the *legitimacy theories*. By contrast, predictions based on *managerial opportunism* appear to be unsupported by our data. In addition, results reveal that the effect of environmental disclosure on idiosyncratic risk varies significantly across the conditional distribution of idiosyncratic risk. Results remain robust under three different econometric methods; namely, (i) panel data techniques, (ii) dynamic panel data and (iii) quantile regressions.

Keywords: Environmental Disclosure; Idiosyncratic Risk; Panel data
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1 Introduction

For the past several years, great consideration has been given to economic implications of corporate environmental responsibility, not only by companies' stakeholders including investors, managers, suppliers and employees, but also by researchers (Zhang, 2017). Importantly, the disclosure of environmental information is crucial for shaping future actions of regulators (Qiu et al., 2016). Particularly, in an attempt to monitor rising temperatures, the European Parliament has underlined the importance of corporate environmental disclosure for identifying sustainability risks and for helping to increase both investors' and consumers' trust (EU Commission., 2014). Reporting transparent environmental information not only mitigates information asymmetries, but also helps to create an informative network within society, which is crucial for dealing with climate change (Stern, 2007; Aggarwal and Dow, 2012; IPCC, 2014). In this paper, we add to the discussion on climate change by examining whether the disclosure of environmentally sensitive information by European manufacturing firms is conducive to less risky investments in the stock market.

Environmental disclosure[1] is the information pertaining to environmental performance that is publicly disclosed by firms (Al-Tuwaijri et al., 2004; Luo et al., 2012; Matsumura et al., 2014). Transparent environmental information has the potential to appease investors' expectations because firms signal their smooth transition to the new climate era (Benlemlih et al., 2018). In turn, from the investors' point of view, this signalling can have important implications not only for the financial performance of the firms but also for the financial risk (King and Lenox, 2001; Endrikat et al., 2014; Misani and Pogutz, 2015). Therefore, asking whether disclosure of such information reduces financial risk of investment is of paramount importance for a company's stakeholders, financial regulators, policymakers and researchers. To be more explicit, the risk of financial investment can be decomposed into the systematic and idiosyncratic components. In this study, we concentrate on the latter because it is shaped by firm-specific characteristics and is driven by corporate policy. Making the right corporate decisions should diminish idiosyncratic risk. In retrospect, given the importance of idiosyncratic risk for investment decision making (e.g., Merton, 1987; Ang et al., 2006; Lin et al., 2014), this study investigates whether environmental disclosure affects idiosyncratic risk.

The effects of environmental disclosure on the risk of financial investment is founded on a complex theoretical framework (Brooks and Oikonomou, 2017). On the one hand, environmental disclosure promotes a strategy that values environmental issues. Thus, investors might be attracted by firms that commit to disclos-

[1] One example of transparent environmental disclosure is when firms report greenhouse gases, energy consumption, renewable energy consumption and total waste.

ing environmentally-sensitive information and are more likely to benefit from lower financial risk (Jiang et al., 2009; Molina-Azorin et al., 2009), as predicted by both the *legitimacy* and the *stakeholder theories*. On the other hand, environmental disclosure can be detrimental (Friedman, 1970; Jensen and Meckling, 1976) because firms are exposed to not necessarily fair criticism and high pollution-abatement costs (Wagner et al., 2002; Lee et al., 2015), as *managerial opportunism* advocates. In this regard, we investigate whether different levels of idiosyncratic risk affect both the strength and the sign of this relationship across firms.

Empirical studies conducted over the years have substantially improved our knowledge about the effects of environmental disclosure on firm performance. These studies imply that disclosure in general decreases the information asymmetries between firms and investors and thus it is negatively related to financial risk (Ferreira and Laux, 2007; Benlemlih et al., 2018; Qiu et al., 2016). However, information about climate change typically conveys a negative tone, and investors might be sceptical concerning "green" future investment decisions (Cormier and Magnan, 2015). This is apparent from the body of research that examines the relationship between environmental and financial performance, and reports inconclusive results. For instance, meta-analytic papers (Horvathova, 2010; Dixon-Fowler et al., 2013; Albertini, 2013; Endrikat et al., 2014) suggest that the controversy of the results is attributed to intense endogeneity. This endogeneity arises either because (i) the independent variable (i.e. environmental performance) correlates with the random disturbance term in the regression model, or (ii) there is simultaneous causality between financial and environmental performance, or (iii) the regression model is suffering from an omitted variable bias (Delmas et al., 2015; Misani and Pogutz, 2015; Nollet et al., 2016; Trumpp and Guenther, 2017; Brooks and Oikonomou, 2017). It should also be noted that while the aforementioned studies examine this relationship by utilizing profitability measures (e.g., ROA, ROE, Sales), research, which is centred on whether and, if so, how financial risk is influenced by environmental disclosure, remains underwhelming (Orlitzky and Benjamin, 2001; Benlemlih et al., 2018).

The main objective of this study is to examine how environmental disclosure affects firm risk. We focus on the idiosyncratic risk of financial investments. We further outline the controversial predictions of economic theory and evaluate the relevance of the specific theories for explaining the financial risk-disclosure nexus. Another important aim of our study is to investigate if the level of idiosyncratic risk moderates the effect of environmental disclosure. Thus far, studies focus only on the mean of idiosyncratic risk (e.g., Mishra and Modi, 2013). If only the mean value was adequate, forming portfolios by sorting on idiosyncratic risk should not provide the investor with different expected returns. However, Ang et al. (2006) prove that by sorting portfolios based on idiosyncratic risk, portfolio's exposure to different factors can vary substantially. Thus, our understanding how risk is driven outside of the mean, in the tails of a distribution, remains embryonic. Finally, we evaluate the effect of environmental disclosure on a sample of manufacturing firms that are subject to stringent environmental regulations (Mallin and Ow-Yong, 2012).

Our study offers four important contributions. First, although prior studies have examined the effects of environmental disclosure on idiosyncratic risk (Lee and Faff, 2009; Salama et al., 2011; Oikonomou et al., 2012; Cai et al., 2016; Diemont et al., 2016; Utz, 2017; Linciano et al., 2018), we test the said relationship under the competing theories, and we shed light on the relevance of these theories. Second, in contrast to previous literature that uses the traditional capital asset pricing model, and on some occasions the Carhart four factor model (Mishra and Modi, 2013; Bouslah et al., 2013), we utilize both the four- and five-factor models to estimate idiosyncratic risk. Third, by focusing on the idiosycnratic risk distribution, we provide additional insights into the relationship between environmental disclosure and idiosyncratic risk. Specifically, we show that environmental disclosure of a portfolio has a heterogeneous financial risk effect at different idiosyncratic risk levels, an important yet under-researched area of the empirical finance literature (Ang et al., 2006). Fourth, this study offers new evidence from the highly regulated EU manufacturing sector.

It is worth noting that our study is closely related to the work of Benlemlih et al. (2018). In particular, we extend their work as we address their call to offer an in-depth discussion on the connection between environmental disclosure and idiosyncratic risk. We do so in the following ways. First, while they explore the effect of social and environmental disclosures on different types of firm risk, our research centres on environmental disclosure and idiosyncratic risk. Second, they estimate idiosyncratic risk by employing a standard CAPM model, whereas we use both the four and five-factor models. Third, their sample comprises UK firms, whereas we analyze a sample of 17 EU countries including the UK. Fourth, unlike Benlemlih et al. (2018), we scrutinise portfolios with different risk levels (ranked on idiosyncratic risk). Finally, we only consider manufacturing firms because their operations are particularly instrumental for climate change. On a final note, our findings agree with Benlemlih et al. (2018) that indeed environmental disclosure decreases idiosyncratic risk.

By utilizing a framework of multiple regressions in a strongly balanced data set of 288 manufacturing firms from 17 European countries during the period from 2005 to 2016, we find significant evidence that environmental disclosure reduces idiosyncratic risk. This finding lends support to both the *stakeholder* and *legitimacy theories* and emphasizes the importance of transparent environmental disclosure as a management practice for risk-reduction. After controlling for endogeneity within a dynamic panel data model, results remain robust. Additionally, consistent with (Ang et al., 2009), quantile regressions show an asymmetric relationship between idiosyncratic risk and environmental disclosure. Specifically, disclosure exerts a stronger effect on stock market investments with high rather than low idiosyncratic risk. Thus, our results suggest that investors perceive transparent environmental practices of EU firms as risk-reducing, in line with Ziegler et al. (2011). However, as expected (Boehme et al., 2009), a perfectly diversified portfolio does not seem to price in environmental disclosure, in the sense that the systematic risk effect is insignificant. Finally, in line with Benlemlih et al. (2018), we also show that environmental disclosure has a stronger link with idiosyncratic risk rather than other risk types.

This research has profound implications for CEOs, portfolio managers and investors. First, the negative environmental disclosure - idiosyncratic risk nexus can be perceived by CEOs as a signal to pledge to more transparent environmental policies, which will be rewarded by the stock market in terms of lower idiosyncratic risk of investment. Second, because idiosyncratic risk can be diversified away, the negative effect of environmental disclosure on idiosyncratic risk helps portfolio managers and investors to identify stocks of companies that offer greater diversification benefits. Indeed, our results imply that investing in a portfolio with potentially more environmentally transparent than opaque stocks can help portfolio managers and investors to diversify the risk of portfolio investment. Third, if the volume of financial transactions is proportional to transaction costs, then a portfolio made up of fewer stocks may be associated with lower transaction costs.

The remainder of the paper is organized as follows. In Section 2, we present the main hypotheses. Section 3 describes the data and the methodology. In Section 4, we report the empirical results. We then conclude with Section 5.

2 Hypotheses Development

The aim of this section is to present the hypotheses of the study, which directly stem from the theoretical framework that describes the link between environmental disclosure and idiosyncratic risk. Starting with *signalling theory* (Connelly et al., 2011), information asymmetry between stakeholders and firms can be mitigated when firms provide transparent information about their practises. More specifically, environmental disclosure can strengthen bonds with investors, customers, suppliers and regulators (*legitimacy theory*) and thus firms can be less vulnerable to both external and internal shocks. In turn, a good firm-stakeholder relationship (*stakeholder theory*) serves as a safeguard that helps firms sustain their competitive advantage and attain their financial objectives. However, the practice of transparent environmental information does not necessarily translate into "good" environmental performance (Al-Tuwaijri et al., 2004) and it might be adopted merely for symbolic purposes. To be more explicit, in line with the *managerial opportunism* theory, increased disclosure could potentially increase risk in financial markets instead of reducing it. Overall, there are three main scenarios associated with the contribution of environmental disclosure to financial risk. First, conveying environmental information reduces risk because informed stakeholders can make rational decisions by holding well-diversified portfolios. Second, conveying environmental information increases idiosyncratic risk as firms become exposed to the critics of climate change. Finally, the relationship may be more complex, implying that the disclosure might abnormally influence portfolios with different levels of idiosyncratic risk.

2.1 Positive association between Disclosure and Risk

We begin by considering the positive relationship between environmental disclosure and risk. The positive association is founded on the view that providing environmental information can be costly (Cormier and Magnan, 2015). Specifically, it is costly for the firm to design, operate and maintain a reporting mechanism. Additionally, environmental disclosure can increase the cost of capital because it provides information to competitors about firm's specific environmental strategies and it might be a negative sign for various shareholders (Peters and Romi, 2014). The positive association between disclosure and risk receives support from the *managerial opportunism theory* (e.g., Bouslah et al., 2013). To elaborate, this theory refers to the principal-agent problem, which suggests that agents act according to their own preferences disregarding the principals' objectives (Jensen and Meckling, 1976). Particularly, managers might over-disclose merely for symbolic purposes or because they aspire to be seen as being environmentally-sensitive managers. In other words, managers might increase environmental expenditure ineffectively. Since increased cost shrinks profits, it is implied that environmental disclosure increases risk. Another important reason supporting the positive association between disclosure and risk is the role of environmental regulations (Commission Regulation (EU) No 601/2012), which coerce firms to disclose. Environmental disclosure can reduce the risk provided that firm's environmental performance is outstanding. If not, it becomes a cause for concern for stakeholders and translates into heightened risk (Brown and Deegan, 1998; Lee et al., 2015). Manufacturing firms in particular would have to bear considerably high environmental costs in order to be able to operate "green" (Wagner, 2005). Therefore, there is in fact a direct trade-off between cost and benefit, suggesting that manufacturing firms will eventually face a competitive disadvantage, which informs **Hypothesis 1 (H1):**

Hypothesis 1 (H1): In line with *managerial opportunism*, high environmental disclosure has a positive impact on idiosyncratic risk.

It should be noted that very few existing studies document a positive association between idiosyncratic risk and transparency (Lin et al., 2014; Wu et al., 2016). In fact, the majority of the studies argue in favour of a negative association (Ferreira and Laux, 2007; Mishra and Modi, 2013; Cai et al., 2016; Utz, 2017).

2.2 Negative association between Disclosure and Risk

Turning to the negative-association theoretical framework, environmental disclosure reduces asymmetric information and signals that firms place particular emphasis on their environmental practices. That is, on one hand, environmental disclosure minimises the risk of damaging the reputation of the firm, while on the other hand, governments are able to exercise less regulatory environmental pressure (Reinhardt and Stavins, 2010). This negative association between disclosure and risk is predicted by the *stakeholder theory*. This theory advocates that a green firm is more efficient, enjoys increased visibility, reduces its operational costs, as well as, develops strong bonds with ethical-investors, employees, consumers and government (Jones, 1995). Salama et al. (2011) and Oikonomou et al. (2012) identify that social actions significantly decrease systematic risk and raise concerns about the potential impact on idiosyncratic risk.

In addition, the principal assumption of the negative-association framework is that firms operate within a society where they have to contribute and inform the public about their environmental actions. In turn, the ethical side of the relationship is best described by the *legitimacy theory*. According to this theory, reporting environmental information would help to legitimise corporate actions and abate the demands from society (Guthrie and Parker, 1989). For instance, disclosing a firm's environmental performance could result in alleviating external pressure for climate change. Furthermore, transparent information regarding environmental performance implies that firms have to become eco-friendly in order to make their environmental sensitivity known and hence boost their profitability (Ben-Amar and McIlkenny, 2015). For this reason, according to the *legitimacy theory*, any firm which informs both its investors and the society should be rewarded because (i) it legitimises its actions and (ii) it diminishes asymmetric information.

There are numerous studies that examine the impact of environmental disclosure on stock performance (Al-Tuwaijri et al., 2004; Dawkins and Fraas, 2011; Matsumura et al., 2014; Nollet et al., 2016). All these studies opine that higher levels of disclosure improve firms' financial performance. On a parallel note, there are also studies that examine whether both corporate social strengths and concerns are linked with idiosyncratic risk (Salama et al., 2011; Bouslah et al., 2013; Mishra and Modi, 2013; Cai et al., 2016; Diemont et al., 2016). These studies underscore that social activities might positively affect the investment climate. For instance, Lins et al. (2017) show that social investments can reduce idiosyncratic risk. During turbulent periods, when trust wanes, symmetric environmental information acts as insurance policy for investors and thus investors may place a valuation premium on these firms. Perhaps the only existing article which is related to the present study in this respect is Benlemlih et al. (2018). These authors, examine the effect of corporate and environmental disclosures on idiosyncratic, systematic and total risk utilizing a sample of British companies. Their findings further support that disclosure significantly decreases idiosyncratic risk, but not systematic risk. Overall, the majority of the empirical literature accords with the negative association between corporate actions and risk. In this regard, we formulate our **Hypothesis 2 (H2):**

Hypothesis 2 (H2): In line with both the *legitimacy* and the *stakeholder theories*, high environmental disclosure has a negative impact on idiosyncratic risk.

2.3 Ranking on Idiosyncratic risk

Existing relevant literature highlights the fact that the level of environmental engagement can affect the financial performance of the firm by solely focusing on the mean of the financial performance distribution (e.g, Misani and Pogutz, 2015; Qiu et al., 2016; Trumpp and Guenther, 2017; Lewandowski, 2017). Conversely, Tzouvanas et al. (2019) demonstrate that investigating the tails of the financial performance distribution could offer different results. Along a similar vein, we argue that disclosure might affect differently investment-portfolios with high and low risk. If capital asset pricing models correctly price risk, then portfolios with different idiosyncratic risk should provide homogeneous expectations regarding returns and/or other risk exposure factors. Nonetheless, Ang et al. (2006) and Ang et al. (2009) provide a multitude of empirical examples to show that portfolios with different idiosyncratic risk are heterogeneously affected by different risk exposure factors. Notwithstanding, this result cannot be explained by traditional financial theory. In fact, sorting portfolios on idiosyncratic risk could provide additional insights on the risk exposure factors that cannot be captured by traditional asset pricing models, such as, the dispersion of opinions in the financial markets (Miller, 1977), liquidity risk (Boehme et al., 2009) or the effect from other economic variables (Ang et al., 2009). In this regard, we expect that transparent information about climate change should have a heterogeneous effect on the idiosyncratic risk distribution. This expectation informs our **Hypothesis 3 (H3):**

Hypothesis 3 (H3): Environmental disclosure can heterogeneously affect idiosyncratic risk at different levels of idiosyncratic risk.

3 Research Design

3.1 Sample and Data

The sample consists of 288 European firms of the manufacturing sector that are included in the STOXX Europe 600 Index across 17 countries of the European region, covering a 12 year period from 2005 to 2016 (see Table 1). Those firms are chosen because the unavailability of data creates constrains for investigating larger sample. In addition, manufacturing firms have been highly criticized because they emit large amounts of carbon, which by turn triggers climate change. For this reason, the EU environmental regulations[2] have enforced firms to disclose essential information about their climate change actions and at the same time firms are monitored for the reliability of the data. 2005 has been chosen as the initial year as it was the year when the EU emissions trading scheme was launched and Kyoto Protocol was set into force.

INSERT TABLE [1]

3.2 Variables of the Study

3.2.1 Idiosyncratic risk

To answer the hypotheses, idiosyncratic risk needs to be constructed. Previous studies (e.g., Ferreira and Laux, 2007; Fu, 2009) define idiosyncratic risk as the standard deviation of the residuals of the pricing models. The capital asset pricing model, three-factor (Fama and French, 1993) and four-factor (Carhart, 1997) models have been used for this type of examination extensively. We compute our measure of idiosyncratic risk based on the four-factor model following Ang et al. (2006), Mishra and Modi (2013), Bouslah et al. (2013) and Cai et al. (2016).

$$R_{i,d} - R_{f,d} = \alpha_i + \beta_{i,1}(R_{m,d} - R_{f,d}) + \beta_{i,2}SMB_d + \beta_{i,3}HML_d + \beta_{i,4}MOM_d + u_{i,d} \quad (1)$$

[2] Commission Regulation (EU) No 601/2012 of 21 June 2012 on the monitoring and reporting of greenhouse gas emissions pursuant to Directive 2003/87/EC of the European Parliament and of the Council. During the second compliance cycle of the greenhouse gas emissions trading scheme, covering the years 2008 to 2012, industrial operators, aviation operators, verifiers and competent authorities have gained experience with monitoring and reporting pursuant to Commission Decision 2007/589/EC of 18 July 2007 establishing guidelines for the monitoring and reporting of greenhouse gas emissions pursuant to Directive 2003/87/EC of the European Parliament and of the Council. The rules for the third trading period of the Union's greenhouse gas emission allowance trading scheme which begins on 1 January 2013 and for the following trading periods should build on that experience.

The left part of the equation corresponds to the excess stock return, alpha (α_i) shows the performance of a stock relative to the market portfolio, $(R_{m,d} - R_{f,d})$ is the excess return on the market portfolio, the second factor (SMB_d) measures the return of small over large stocks, (HML_d) the return of value over growth stocks, the momentum factor measures the portfolio returns of winner over loser stocks (MOM_d) and $u_{i,d}$ is the residuals. $R_{m,d}, R_{f,d}, SMB_d, HML_d$ and MOM_d values for the European market are retrieved from Kenneth R. French website. Data on stock prices is obtained from Datastream. Moreover, log-returns, $R_{i,d}$, are computed by means of $R_{i,d} = \log P_{i,d} - \log P_{i,d-1}$, where $P_{i,d}$ is the price of stock i in time d. All the aforementioned values are on a daily frequency (d) for all 288 firms for the 12 year period. We next run ordinary least squares (OLS) regressions to Equation (1) by assuming that the residuals are normally distributed with zero mean and constant variance. We repeat this procedure for each year of the sample in order to obtain 12 different variances for every firm. Then, we define the idiosyncratic risk ($Risk$) as the annualized standard deviation of the residuals ($Risk = \sigma(u_{i,d}) \times \sqrt{K} \times 100\%$) (Boehme et al., 2009), where k corresponds to trading days of any year given with $k \approx 251$).

3.2.2 Environmental disclosure

Answering the hypotheses, environmental disclosure score ($Disc$) is used. Disclosure is produced by Bloomberg database and it measures the quality and magnitude of the environmental information disclosed by each firm. While previous studies use binary or low range scores to account for the disclosure (see, Fisher-Vanden and Thorburn, 2011; Barnett and Salomon, 2012; Hsu and Wang, 2013; Matsumura et al., 2014), our score takes values from 0 to 100 with the lowest values corresponding to lack of climate change information. This indicates that our examination might vary substantially across different quantiles. The fact that contemporaneous literature has a growing interest in Bloomberg's scores strengthens the appropriateness of this variable as a proxy of environmental disclosure (Nollet et al., 2016; Broadstock et al., 2018; Petitjean, 2019). As examined by Qiu et al. (2016) and Benlemlih et al. (2018), the score weights the information provided by firms for 60 different environmental actions and it is normalized according to the mean disclosure of the industry where firms operate (see more about environmental disclosure in Appendix).

3.2.3 Other Control Variables

We employ a set of different variables that affect the idiosyncratic risk (Table 2). First, the probability of default measured by Altman's Z-score (Z), low values correspond to higher probability of default and should induce higher idiosyncratic risk (Bouslah et al., 2013). Z-score sums up five weighted measures in order to classify firms according to their financial distress and it uses both accounting and market based indicators. Firms with high probability of default are closely tied to idiosyncratic risk (Lopez, 2004). In contrast to default risk, leverage (Lev) is debt to equity ratio which is measured by summing the short and long term liabilities divided by the market value. Leverage is a proxy of financial risk and it is expected to be positive because risky firms hold usually more debt (Ang et al., 2006; Psillaki et al., 2010; Mallin and Ow-Yong, 2012). High leverage implies that stakeholders bear a high amount of cash flow risk and therefore volatility of the stock return increases.

Furthermore, larger firms have diversified activities and hence less idiosyncratic risk. We use as a size proxy the logarithm of the total assets ($LogTa$) (Lee and Faff, 2009; Mishra and Modi, 2013; Cai et al., 2016). Profitability is linked to risk. Return on assets (ROA) measures the ability of the firm to generate profits from its assets and it is used as a proxy for financial profitability. High profitability might act as signal to investors about the soundness of the firm (Mishra and Modi, 2013). Another profitability proxy is the the annual growth rate of total sales ($Growth$); $Growth$ displays the firm's cash flows and so it is expected to decrease risk (Ang et al., 2006).

Additionally, the future prosperity can be represented by intangible assets ($Inta$). They cannot be easily collateralized but they add value to the firm (Psillaki et al., 2010). Intangible assets have characteristics of Research and Development ($R\&D$) and it might either generate future profits or losses (Elsayed and Paton, 2005). Intangibility is generally expected to have negative association with risk. Also, tangible assets ($Tang$) can be a proxy for the collateral of the firm. Negative relation between risk and tangibility is expected because creditors can liquidate assets easily and thus they face less risk (Konar and Cohen, 2001).

An important aspect of the investigation is to control for the slack resources of the firms. Slack resources may be a consequence of good financial performance, leading to excess resources, which yield additional funds that can be invested in environmentally and socially responsible activities, or it can also be the result of bad planning (Nohria and Gulati, 1996). Slack resources can either be *unabsorbed* or *absorbed*. *Unabsorbed* slack ameliorates the financial performance of firms, while *absorbed* slack refers to bad planning. The former would indicate that slack decreases idiosyncratic risk because resources can be re-deployed for other organizational purposes, while the latter increases idiosyncratic risk because resources cannot be re-deployed for other activities (Symeou et al., 2019). In either case, slack resources should affect idiosyncratic risk (Ang et al., 2006). Slack resources can be measured as a liquidity ratio (Liq) (Bansal, 2005; Aguilera-Caracuel et al., 2015); that is, the ratio between current assets and current liabilities.

Finally, we include year (Year), industry (Industry) and country (Country) dummies to control for the unobserved firm heterogeneity. Different industries have been observed to have different risk and different countries affect dis-similarly the idiosyncratic risk of their firms (Chen and Wang, 2012; Mishra and Modi, 2013; Wu et al., 2016).

INSERT TABLE [2]

3.3 Descriptive Statistics and Correlations

We now turn to present some descriptive statistics and correlations of the variables employed in the regressions. Firstly, our final sample numerates 3,465 firm-year observations. Having a closer look at panel A in Table 3, disclosure is the variable with the most missing values comparing to the rest of the data-set with 2788 valid observations. In a pooled sample of 901,728 firm-daily observations, we extract 3389 annual idiosyncratic risk values, which have a mean (median) of 26.96 (24.11) with the highest value being 115.08 and standard deviation of 10.62. In terms of the distribution of the variables $Disc$, $Inta$, ROA and $LogTA$ are very close to satisfy the normality conditions (Skewness=0 and Kurtosis=3). While $Risk$, Z, Lev, $Tang$, $Growth$ and Liq have a leptokurtic distribution and they also have fat upper tails apart from Lev with a thick lower tail. Panel B reports the correlations. Pairwise correlations provide some preliminary view of the effect of independent variables on $Risk$. Note that most of the examined variables have a negative and very low correlation with $Risk$. Particularly, disclosure negatively correlates with $Risk$ at a rate of 22.3%.

INSERT TABLE [3]

If high environmental disclosure decreases (increases) idiosyncratic risk, then the theory of finance will imply that lower (higher) risk should be followed by lower (higher) returns (Merton, 1987). Hence, our investigation would be only meaningful for investors who want to shift their risk-taking levels. However, Table 4 shows that this is not the case. In line with the empirical literature, high idiosyncratic risk portfolios exhibit lower returns and low idiosyncratic risk portfolios have higher returns (Miller, 1977; Ang et al., 2006). Sharpe ratio and alpha (α) also exhibit that investments in low idiosyncratic risk portfolios have better performance than investments in high idiosyncratic risk portfolios. We now proceed to econometrically test whether indeed disclosing environmental information can decrease the idiosyncratic risk of a portfolio.

INSERT TABLE [4]

3.4 Empirical Model

This subsection presents three different types of econometric techniques. (1) Panel, (2) dynamic panel and (3) quantile regressions. We are trying to capture all different aspects of risk-disclosure relationship since there is no extensive literature on this particular topic. The methodology aims to deal with the endogenous and non-linear estimates and at the same time to provide insights into the overall effect of environmental disclosure on the financial risk.

3.4.1 Panel Data Model

Having discussed about how environmental disclosure and risk are connected, we now proceed to estimate their relationship. Following previous studies (e.g., Delmas et al., 2015; Nollet et al., 2016) we employ panel data methodology and we stress disclosure in risk regressions as shown below:

$$Risk_{i,t} = a_0 + a_1 Disc_{i,t} + \mathbf{X}'_{i,t}\phi + \sum_{t=2}^{T} \delta_t Year_t + \sum_{m=2}^{M} \delta_m Industry_m + \sum_{j=2}^{J} \delta_j Country_j + e_{i,t} \tag{2}$$

Where the subscripts i and t correspond to firm and year respectively, $i = 1, 2, ..., n$ and $t = 1, 2, ..., T$ and $e_{i,t}$ the error term. $Risk$ denotes the idiosyncratic volatility and $\mathbf{X}'$ is a vector that contains control variables (Z, Lev, $Inta$, $Tang$, ROA, $LogTa$, $Growth$ and Liq). We also control for year, industry and country fixed effects, so a_0 intercept is refereed to the base year (2005), industry (Technology) and country (Germany) where $m = 1, 2, ..., M$ and $j = 1, 2, ..., J$. Particular attention should be placed on the variable of interest which is $Disc$ and the coefficient we should observe is a_1. According to the first hypothesis (**H1**), we perform one-tailed test, so the null hypothesis is $H1_0 : a_1 \leq 0$ and alternative $H2_1 : a_1 > 0$. Similarly to answer hypothesis 2 (**H2**), $H2_0 : a_1 \geq 0$ and alternative $H2_1 : a_1 < 0$.

The results are presented under the pooled OLS, fixed effects and random effects models. For all different specifications, we use robust standard errors. Fixed effects model is appropriate when we focus on a specific firm characteristics (c_i) and therefore $e_{i,t}$= $v_{i,t} + c_i$ with $v_{i,t}$ being a time-varying error component. Note that in case of fixed effects model industry and country dummies are dropped from the model to avoid multicollinearity. Random effect model represents random draws from the population so that c_i allows for individual effects. In contrast with the previous models, pooled OLS estimates constant coefficients ($c_i = c$). Finally, we report likelihood ratio redundant fixed effects and Hausman test in order to identify if the individual effects c_i are unobserved and are correlated with explanatory variables (Baltagi, 2008; Oikonomou et al., 2012).

3.4.2 Dynamic Panel Data Model

The problem of endogeneity which has been reported continuously should be carefully considered (Tamazian and Bhaskara Rao, 2010; Coban and Topcu, 2013; Albertini, 2013; Endrikat et al., 2014; Busch and Lewandowski, 2018). Endogeneity arises due to simultaneity or omitted variable bias. Riskier firms normally undertake more environmental projects and thus risk and disclosure are endogenous (Orlitzky and Benjamin, 2001). This is because it involves a commitment to financially support environmental actions. Therefore, risk might influence the environmental disclosure of firms. Endogeneity in panel data is commonly controlled with generalized method of moments model (GMM) or with two-stage least squares (2SLS). The main advantage of GMM is that it can treat all control variables as endogenous as well as there is no need to identify exogenous instruments. Identifying exogenous variables to instrument the endogenous variable may be challenging task and eventually may never be exogenous precisely (Broadstock et al., 2018). For this reason, GMM relies on internal instruments (lagged values or internal transformation). For example, it may not be the current environmental disclosure that affects idiosyncratic risk, but rather the previous year's disclosure could be playing a significant role.

A system of generalized method of moments (Sys-GMM), which is proposed by Blundell and Bond (1998) can control for endogeneity in our estimations. Hence, equation 2 is now tested with dynamic panel model:

$$
\begin{aligned}
Risk_{i,t} = a_0 + a_1 Disc_{i,t} + \beta_1 Risk_{i,t-1} + \mathbf{X}'_{i,t}\phi + \sum_{t=3}^{T} \delta_t Year_t \\
+ \sum_{m=2}^{M} \delta_m Industry_m + \sum_{j=2}^{J} \delta_j Country_j + e_{i,t}
\end{aligned}
\tag{3}
$$

Equation 3 is instrumented with lagged values of the explanatory variables. However, lagged values are usually weak instruments and thus Sys-GMM combines the first-difference estimator with the estimator in levels in order to efficiently deal with endogeneity. The description of the variables is as above and again $e_{i,t} = v_{i,t} + c_i$ is referred to the typical fixed effects components of the error term, with the assumption that $E(v_{i,t}) = E(c_i) = E(v_{i,t}c_i) = 0$, for $i = 1, .., n$ and $t = 2, .., T$. The model is appropriate to re-address the hypotheses 1 and 2 (**H1** and **H2**).

In order to satisfy the orthogonality condition, we collapse instruments as proposed by Roodman (2009) because large number of instruments would lead to finite sample bias and therefore we assume that $E(Risk_{i,t-1}\Delta v_{i,t}) = E(\Delta Risk_{i,t} v_{i,t-1})=0$. We collapse instruments after two lags. Also, Hansen's (1982) J-test measures the validity of instruments. We also use two-step Sys-GMM which is based on corrected standard errors (Windmeijer, 2005).

3.4.3 Non-parametric Model

In order to ascertain how disclosure influences idiosyncratic risk of firms with different risk levels we employ quantile regression model, which was introduced by Koenker and Bassett (1978). We investigate parameters that describe the 5%, 25%, median, 75% and 95% of the conditional distribution. The main advantage of this method is that it captures the abrupt changes of $Disc$ on $Risk$. It can be linearly represented as:

$$Risk_{i,t} = \pi(\tau) + \gamma(\tau)Disc_{i,t} + \mathbf{Y}'_{i,t}\theta(\tau) + \varepsilon_{i,t}, \quad \tau \in (0,1) \tag{4}$$

Where $Risk$ is the dependent variable, π is the intercept, $\mathbf{Y}$ is a vector that contains all explanatory variables, $\theta(\tau)$ is the parameters, ε signifies the error term and τ refers to the part the of $Risk$ distribution. We assume that the error is equal to zero at the conditional τ^{th} quantile $[Q_\varepsilon(\tau|\mathbf{Y}, Disc) = 0]$. Also, the parameter γ for any given quantile τ for a sample of N observations can be calculated with linear programming as follows:

$$\hat{\gamma}(\tau) = arg \min_{\gamma} \frac{1}{N \times T} \sum_{i=1}^{N} \sum_{t=1}^{T} \rho_\tau[Risk_{i,t} - \pi(\tau) - \gamma(\tau)Disc_{i,t} - \mathbf{Y}'_{i,t}\theta(\tau)]$$

where check function $\rho_\tau(.)$ is defined as:

$$\rho_\tau(\varepsilon) = \begin{cases} \tau\varepsilon_{i,t}, & \text{if } \varepsilon_{i,t} \geq 0; \\ (\tau-1)\varepsilon_{i,t}, & \text{if } \varepsilon_{i,t} < 0 \end{cases}$$

We use bootstrap estimates of $\gamma(\tau)$ in order to calculate the covariance matrix. We compute standard errors with 1000 bootstrap replications and thus we obtain asymptotically normally distributed estimators which are valid under heteroskedasticity.

In order to investigate the Hypothesis 3 (**H3**: Disc heterogeneously affects Risk), we consider that γ coefficients do not vary across the conditional distribution. Therefore jointly equality test is performed. The null hypothesis is that the slope of disclosure is the same across quantiles and can be written as $H3_0$: $\gamma_{0.05} = \gamma_{0.25} = \gamma_{0.50} = \gamma_{0.75} = \gamma_{0.95}$, otherwise disclosure unequally influences risk.

4 Results

4.1 Panel Data Models

Results relating to Hypotheses 1 and 2 are reported in Table 5. Columns 1, 2 and 3 report the pooled-OLS, fixed effects and random effects models respectively. Concerning the control variables, $Inta$, $Tang$, ROA and $LogTa$ reduce idiosyncratic risk; finding which is in line with our expectations and previous literature (Konar and Cohen, 2001; Mishra and Modi, 2013; Cai et al., 2016), while higher Lev and Liq unexpectedly increase idiosyncratic risk (Ang et al., 2006; Psillaki et al., 2010). Z and $Growth$ do not appear to have a significant effect on the idiosyncratic risk. The results from the three models support **Hypothesis 2** and clearly reject **Hypothesis 1**. Hence, transparent information about climate change significantly decreases the idiosyncratic risk of EU manufacturing firms. This finding is in line with both the *legitimacy* and *stakeholder theory*. Overall, it provides additional support to existing literature, which acknowledges the benefits from social corporate actions (Lee and Faff, 2009; Salama et al., 2011; Oikonomou et al., 2012; Mishra and Modi, 2013; Cai et al., 2016).

INSERT TABLE [5]

It is worth noting that $Disc$ significantly adds to the explanatory power of our benchmark model. This highlights the importance of environmental disclosure as determinant of idiosyncratic risk. We should underline that the goodness of fit of the models reaches 60%, which indicates that the chosen variables can explain a high proportion of the idiosyncratic risk of stock returns. Also, the likelihood ratio specifies that the pooled-OLS model is not appropriate in this examination due to the fact that firms have different characteristics. We cannot reject though that pooled-OLS provides with unbiased results since we have controlled for a set of different attributes. On a final note, the Hausman test indicates that the random effects model is preferable relative to the fixed effects in this instance. This indicates that our sample is representative for all manufacturing firms in the EU.

Regarding the dynamic panel results, column 4 of Table 5 reports the two-step Sys-GMM of Equation 3. Dynamic panel regressions are appropriate to address the problem of endogenous variables and consequently to re-address Hypotheses 1 and 2. In this regard, we cannot reject **Hypothesis 2** that the $Disc-Risk$ relationship is negative; consistent with the previous estimates. Even if $Risk$ and $Disc$ are bidirectionally related (Orlitzky and Benjamin, 2001), results demonstrate that environmental disclosure is tied up with a risk-reduction hypothesis.

It is important to underline the validity of the model. Hansen J-test reports p-values of 48%, signifying the validity of the instruments. AR(1) and AR(2) related to the first differenced equation denote that there is first order autocorrelated disturbances and no second order autocorrelation. Windmeijer (2005) affirms that the two-step estimator with the finite sample correction for standard errors provides unbiased results. As expected the autoregressive term for $Risk$ is positive and highly statistically significant, underlining the memory of the idiosyncratic risk (Ang et al., 2006).

Interestingly, the panel estimates report larger coefficients in comparison with the Sys-GMM. An explanation is that the autoregressive term in the Sys-GMM model absorb a large proportion of the systematic influence of the control variables. Also, we cannot reject that panel estimates are affected by endogeneity. Nevertheless, $Disc$ remains negative and statistically significant at 1% level. This finding is in line with the majority of empirical studies (Ziegler et al., 2011; Salama et al., 2011; Oikonomou et al., 2012; Mishra and Modi, 2013; Cai et al., 2016; Utz, 2017) and therefore we provide evidence supporting the negative theoretical framework for European firms. At the same time, results do reveal that environmental disclosure could be a rational managerial decision to reduce firm's specific risk and it is also evident that environmental disclosure can be priced in financial markets.

4.2 Non-parametric Model

The use of quantile regressions help us to analyze the dependence between $Disc$ and $Risk$. Panel and dynamic panel regressions estimate the average effect of $Disc$ on $Risk$. In turn, quantile regressions are able to estimate the tails of the idiosyncratic risk distribution (see, e.g., Ang et al., 2006). Table 6 considers 5 different quantiles based on Equation 4.

INSERT TABLE [6]

The results of quantile regressions are interpreted in a very similar way to OLS regressions, except that quantile regressions can predict not only the mean of the dependent variable but also different quantiles. This gives us the capability of sorting portfolios on idiosyncratic risk and detect the effects of different variables on these sorted portfolios. Similar to the parametric models; Int, $Tang$, ROA and $LogTa$ appear to significantly decrease idiosyncratic risk for the largest part of the conditional distribution. In particular, tangible assets significantly contribute to the $Risk$ in the upper part of the distribution, whereas intangible assets are insignificant at the upper tail only. Also, Z, Lev and $Growth$ are insignificant for the whole distribution, while Liq appears positive across the distribution. Another important aspect of the model is that it explains from 31 to 41% of the variability of $Risk$ (see, Pseudo R^2).

INSERT FIGURE [1]

Turning to **Hypothesis 3**, quantile regressions reveal that $Disc$ and $Risk$ exhibit a negative and heterogeneous association, which lends support to our Hypothesis 3. Table 6 shows that higher environmental disclosure significantly reduces $Risk$. This is apparent at the upper part of the distribution, while the lower tail is insignificant with a coefficient close to null. The lower tail represents firms with low idiosyncratic risk and therefore perfectly diversified activities; such investments are unaffected by the environmental disclosure. To visualize this, Figure 1 displays a downward trend of environmental disclosure coefficients (Y-axis) as idiosyncratic risk increases (X-axis). The practical implications of this finding are particularly interesting. Environmental disclosure is valued by the investors and thus higher degree of diversification can be attained with a portfolio of disclosing firms. However, investors should not value environmental disclosure in a well-diversified portfolio. Confirming the above, equality test shows that environmental disclosure coefficients have statistical differences across the conditional distribution. Therefore, we cannot reject that environmental disclosure heterogeneously affects idiosyncratic risk (**H3**).

Overall, by testing the three hypotheses the following conclusions can be drawn: (1) environmental disclosure has a significant and negative impact on idiosyncratic risk; (2) the effect of environmental disclosure on idiosyncratic risk varies significantly across the conditional distribution of idiosyncratic risk; (3) this finding confirms Hypotheses 2 and 3 and hence the negative theoretical framework allowing for heterogeneous effects is more appropriate to model the relationship.

4.3 Robustness checks

In order to check the sensitivity and accuracy of the results, we substitute some variables from the benchmark model (see Equation 2) and we repeat the same regression procedure. In particular, we use two alternative dependent variables. First, firm's total risk also matters as indicated by Bouslah et al. (2013) and Benlemlih et al. (2018). Total risk ($T.Risk$) includes both the systematic and idiosyncratic risk components and can be measured as the annualized standard deviation of the daily stock returns. Second, we also consider an alternative approach to measure idiosyncratic risk. Fama and French (2015) propose a five factor capital asset pricing model. In Equation (1), the authors remove the MOM_d component and add two new terms as shown bellow:

$$\begin{aligned} R_{i,d} - R_{f,d} = \alpha_i + \beta_{i,1}(R_{m,d} - R_{f,d}) + \beta_{i,2}SMB_d + \beta_{i,3}HML_d + \beta_{i,4}RMW_d \\ + \beta_{i,5}CMA_d + u_{i,d}, \end{aligned} \tag{5}$$

where RMW_d is the difference of stock returns between robust and weak profitability firms and CMA_d is the return of low over high investment firms. By running OLS regressions to Equation (5), the five-factor idiosyncratic risk ($5.Risk$) is the annualized standard deviation of the residuals.

Additionally, previous literature commonly uses accounting profitability ratios to examine the disclosure-performance relationship; instead of ROA, we add Tobin's Q (Q) as a measurement of market-based profitability indicator (measured as the market value of a firm to the replacement costs of its assets) (Konar and Cohen, 2001; Broadstock et al., 2018). Lastly, intangible assets attempted to capture a part of $R\&D$ expenses, which have been argued to be of a major importance of the examination (Konar and Cohen, 2001; Elsayed and Paton, 2005; Duqi et al., 2015). $R\&D$ was not included in our primary analysis due to the high number of missing values (similarly to Delmas et al., 2015).

INSERT TABLE [7]

Table 7 presents the robustness checks, columns 1, 2 and 3 report the random effect, Sys-GMM and median regression results respectively and the denotation a and b indicates that the dependent variable is either the idiosyncratic risk from the 5-factor model or the total risk. In terms of the idiosyncratic risk of the 5-factor model, our results are qualitatively similar to the previous estimations. Interestingly, results cannot support a relationship between environmental disclosure and total risk. Since we have established that disclosure has an impact on idiosyncratic risk, it can be implied that disclosure and the systematic risk component are irrelevant (Benlemlih et al., 2018). We extend our analysis by excluding British firms. This is mainly done because the sample is over-represented by British firms and it is rational to consider a post-Brexit scenario. Previous literature shows that British firms are environmentally sensitive (Salama et al., 2011) and thus this is how the negative sign ($Disc-Risk$) dominates. However, results reported in Table 8 remain robust for the rest of the European firms.

INSERT TABLE [8]

5 Conclusion

This paper examines the environmental disclosure - idiosyncratic risk relationship for a panel of 288 EU manufacturing firms. In the main analysis, we use four factor model (Carhart, 1997) to extract the idiosyncratic risk of the firms, while the environmental disclosure score has been retrieved from Bloomberg database. Relevant empirical literature along with the economic theory suggest that environmental actions and financial performance exhibit an endogenous and non-linear relationship (Tzouvanas et al., 2019). For this reason, panel, dynamic panel and quantile regressions with the inclusion of different set of control variables attempt to shed light on the examination.

Our empirical investigation confirms the generic hypothesis that it is less risky to be informative. Particularly, the findings demonstrate that environmental disclosure heterogeneously reduces idiosyncratic risk. This result is robust under different specifications and it is consistent with a large part of literature that acknowledges the importance of high environmental visibility (Dawkins and Fraas, 2011; Matsumura et al., 2014; Ben-Amar and McIlkenny, 2015). For this reason, regulators should further advance environmental sensitivity and firms should be encouraged to increase their environmental transparency because eventually this engagement can be described as a "win-win" situation; monitoring climate change risk (Stern, 2007) and decreasing idiosyncratic risk.

Furthermore, our results underline the prominent role of transparent information on the financial markets. The comprehensive and articulated picture of environmental disclosure on idiosyncratic risk suggests that the negative theoretical framework is more suitable to frame the relationship. Therefore, it can be extracted that management should consider to provide transparent environmental information as a means of risk reduction. At the same time, environmental disclosure seems to reveal a unique dimension of idiosyncratic risk which can potentially enhance our understanding about the information content of idiosyncratic risk (e.g., Fu, 2009; Wu et al., 2016).

The main limitation of the study is that the score of environmental disclosure is assumed to be objective (Nollet et al., 2016; Benlemlih et al., 2018). Future studies should investigate the quality of environmental actions that are disclosed by firms. An alternative interesting avenue for future research would be to construct an environmental disclosure index and conduct a similar examination controlling for a larger number of countries and industries. Moreover, a greater number of risk measurements (as dependent variables) might be dis-similarly correlated with a larger number of environmental performance variables (as independent variables) (see for example meta-analyses, Horvathova, 2010; Albertini, 2013; Endrikat et al., 2014).

In turn, future studies could concentrate on investigating the relationship between environmental disclosure and systematic risk. On a final note, our study motivates further research related to the diversification benefits of portfolios with symmetric environmental information (see, Merton, 1987; Ang et al., 2006; Fu, 2009).

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Table 1: Industry and Country Composition

Panel A: Industry Composition		
Industry	**Frequency**	**Percent**
Technology	11	3.82
Telecommunications	12	4.17
Consumer Discretionary	56	19.44
Consumer Staples	40	13.89
Industrials	88	30.56
Basic Material	40	13.89
Energy	17	5.9
Utilities	24	8.33
Panel B: Country Composition		
Country	**Frequency**	**Percent**
Germany	36	12.5
United Kingdom	71	24.65
France	47	16.32
Italy	14	4.86
Spain	14	4.86
Netherlands	15	5.21
Switzerland	18	6.25
Sweden	24	8.33
Norway	8	2.78
Austria	4	1.39
Belgium	6	2.08
Denmark	5	1.74
Finland	14	4.86
Ireland	7	2.43
Czech Republic	1	0.35
Portugal	3	1.04
Luxemburg	1	0.35
Total	288	100

Firms are allocated to industries according to the Industry Classification Benchmark (ICB).

Table 2: Variable description and source of data

Variables	Concept	Source
Risk	(Idiosyncratic risk) Annualized standard deviation of 4-factor model's residuals	Kenneth French[a]
5.Risk	(Idiosyncratic risk) Annualized standard deviation of 5-factor model's residuals	Kenneth French[a]
T.Risk	(Total risk) Annualized standard deviation of stock returns	Datastream
Disc	Environmental disclosure score	Bloomberg
Z	(Default risk) Altman's Z = 1.2*(WC/ TA)+1.4* (RE/ TA)+3.3* (EBIT/ TA) +(Sales/ TA)+0.6* (MV/ TL), higher score denotes lower probability of default	Datastream, Bloomberg
Lev	Leverage = total debt/total equity	Datastream
Inta	Intangible assets/TA	Bloomberg
Tang	Tangible assets/ TA	Bloomberg
ROA	Return on assets	Bloomberg
LogTa	Log of TA	Datastream
Growth	Annual growth rate of total sales	Bloomberg
Liq	Liquidity ratio = current assets / current liabilities	Datastream
Q	Tobin's Q = (MV + TL + PE + MI) / TA	Bloomberg
R&D	Log of research and development expenses	Datastream
[WC, TA, EBIT, RE, MV, TL, PE, MI][b]	Variables for calculations , WC= working capital, TA= total assets, EBIT= earnings before interest and taxes, RE= retained earnings, MV= market value, TL= total liabilities, PE= preferred equity, MI= minority interest	Datastream, Bloomberg

[a] The factors (SML, HML, MOM, RMW, CMA, R_M and R_f) to calculate idiosyncratic risk are retrieved from Kenneth R. French Data library (http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.
[b] All money-based indicators for all countries, for each given year, are adjusted into current Euro.

Table 3: Descriptive statistics and correlations of the main variables

Panel A: Descriptive statistics

	(1) Risk	(2) Disc	(3) Z	(4) Lev	(5) Inta	(6) Tang	(7) ROA	(8) LogTA	(9) Growth	(10) Liq
Obs	3389	2788	3232	3437	3282	3349	3341	3437	3390	3393
Mean	26.96	35.68	4.86	90.25	0.22	0.80	6.06	9.06	9.03	1.49
Std	10.62	16.21	9.97	601.48	0.19	0.22	5.34	1.46	66.81	1.57
Min	10.62	2.33	-0.52	-22583.33	0.00	0.00	-9.03	3.41	-91.06	0.00
1st Q	19.75	23.96	2.32	34.98	0.06	0.68	2.83	8.04	-1.25	0.96
Med	24.11	37.21	3.46	64.57	0.18	0.85	5.21	9	5.09	1.25
3rd Q	31.30	47.29	4.99	114.72	0.35	0.96	8.43	10.15	12.56	1.67
Max	115.08	75.97	328.07	10020.93	1.16	2.72	28.28	12.9	2290.13	46.15
Skew	1.90	-0.09	19.83	-20.69	0.92	-0.08	0.94	0.04	27.66	15.40
Kurt	9.14	2.31	524.37	872.52	3.29	8.84	4.93	2.62	868.33	353.29

Panel B: Correlations

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
(1)	1									
(2)	-0.2229*	1								
(3)	0.0563*	-0.1365*	1							
(4)	-0.0153	0.0291	-0.0244	1						
(5)	-0.0914*	-0.0895*	-0.0841*	0.0203	1					
(6)	-0.0005	-0.0192	0.1034*	-0.0091	0.0051	1				
(7)	-0.1165*	-0.1282*	0.1882*	-0.0411*	-0.03	-0.0242	1			
(8)	-0.2501*	0.4932*	-0.2642*	0.0543*	-0.0054	-0.0909*	-0.3482*	1		
(9)	0.0599*	-0.0485*	0.034	0.0149	0.0282	-0.0045	0.0721*	-0.0487*	1	
(10)	0.1389*	-0.0920*	0.5864*	-0.0248	-0.1644*	0.0326*	0.1071*	-0.2627*	0.0200	1

All variables are defined in Table 2. * denotes 10% level of significance. Std= standard deviation, Q= quartile, Med=median, Skew= skewness and Kurt= kurtosis.

Table 4: Variables sorted by idiosyncratic risk

	1 Low	2	3	4	5	6 High	1-6
Disc	43.527	39.925	36.612	34.665	32.038	26.849	16.678
T.Risk	0.172	0.212	0.256	0.316	0.440	0.663	-0.491
r	0.084	0.092	0.096	0.096	-0.092	-0.281	0.365
α	0.027	0.025	0.020	0.016	-0.036	-0.046	0.073
β_1	0.420	0.499	0.563	0.637	0.621	0.643	-0.223
Sharpe	0.517	0.448	0.391	0.329	-0.150	-0.354	0.872

Quantile portfolios "1" to "6" from Low to High idiosyncratic risk. Portfolios are sorted according to the idiosyncratic risk distribution (q), with "1", "2", "3", "4", "5" and "6" correspond to $q \leq 5\%$, $5\% < q \leq 25\%$, $25\% < q \leq 50\%$, $50\% < q \leq 75\%$, $75\% < q \leq 95\%$, and $q > 95\%$, respectively. Portfolio "1-6" represents a strategy that goes long the lowest idiosyncratic quantile and short the highest idiosyncratic quantile. Alpha (α) measures the performance of a stock compared with the market portfolio. The variable r denotes the annual excess return ($R_{i,t} - R_{f,t}$) of the portfolio and β_1 is the systematic risk (the coefficient of $R_{m,d} - R_{f,d}$) from the Carhart four-factor model. Sharpe ratio ($\frac{R_{i,t}-R_{f,t}}{\sigma_{i,t}}$) measures the annual financial performance (returns) of portfolios adjusted for risk.

Table 5: Regression results for Idiosyncratic risk

	Pooled OLS		Fixed effects	Random effects	Sys-GMM
	(1a)	(1b)	(2)	(3)	(4)
$Risk_{t-1}$					0.528***
					(0.0844)
Disc		-0.0508***	-0.0601***	-0.0558***	-0.0220**
		(0.0111)	(0.0220)	(0.0179)	(0.0108)
Z	0.0530	0.0545	-0.0647	-0.0425	0.0497
	(0.0591)	(0.05864)	(0.0729)	(0.0588)	(0.0214)
Lev	0.000302*	0.000316*	0.000316**	0.000315**	0.000107
	(0.0001542)	(0.000169)	(0.000143)	(0.000148)	(0.000288)
Inta	-4.0194***	-4.146***	-7.424***	-6.400***	-1.911**
	(0.717)	(0.7136)	(2.515)	(1.456)	(0.761)
Tang	-0.1048**	-0.1045***	-0.149	-0.121**	-0.0671***
	(0.048)	(0.046)	(0.419)	(0.0479)	(0.0219)
ROA	-0.411***	-0.388***	-0.381***	-0.374***	-0.235***
	(0.0478)	(0.048)	(0.0664)	(0.0624)	(0.0488)
LogTa	-1.558***	-1.248***	-2.659***	-1.581***	-0.504**
	(0.1241)	(0.143)	(0.736)	(0.261)	(0.194)
Growth	0.005**	0.0045*	0.0035	0.0034	0.0029
	(0.00223)	(0.00236)	(0.0027)	(0.0026)	(0.0022)
Liq	1.673***	1.675***	-0.466	0.505*	0.779***
	(0.2899)	(0.2870)	(0.454)	(0.266)	(0.208)
Cons	37.29***	35.09***	49.98***	39.90***	18.85***
	(1.88)	(1.97)	(6.76)	(3.19)	(3.604)
Year	Yes	Yes	Yes	Yes	Yes
Industry	Yes	Yes	No	Yes	Yes
Country	Yes	Yes	No	Yes	Yes
Likelihood ratio			7.44 [0]		
Hausman $\chi^2_{(d.f)}$				$18.5_{(20)}$ [0.48]	
AR(1)					[0]
AR(2)					[0.132]
Instr					65
H-J					[0.270]
R^2	0.561	0.565	0.603	0.600	
Obs	2580	2580	2580	2580	2528

Standard errors are in parenthesis, p-values in brackets. Standard errors are robust correcting for heterogeneity. Idiosyncratic risk (Risk) is the dependent variable for all models. Disclosure's significance is based on one-tailed test. Hansen J-test (H-J) reports the instrument validity. AR(1) and AR(2) show the first and second order auto-correlation respectively. The number of instruments (Instr) is reported. All variables listed are defined in Table 2. ***,**,* significance level at 1%, 5%, 10%.

Table 6: Quantile regressions for Idiosyncratic Risk

τ	0.05	0.25	0.50	0.75	0.95
	(1)	(2)	(3)	(4)	(5)
Disc	-0.0135	-0.0241**	-0.0264***	-0.0510***	-0.0770***
	(0.00995)	(0.0102)	(0.00813)	(0.0170)	(0.0254)
Z	-0.0858	-0.112	-0.0847	-0.0333	-0.0506
	(0.0678)	(0.109)	(0.0639)	(0.0724)	(0.0953)
Lev	0.0000449	0.000199	0.000340**	0.0000607	0.000637
	(0.000384)	(0.000218)	(0.000171)	(0.000204)	(0.000649)
Inta	-1.707**	-3.225***	-2.847***	-3.419***	-2.192
	(0.669)	(0.834)	(0.676)	(0.974)	(1.792)
Tang	-0.00115	0.0262	-0.0314	-0.125	-0.528
	(0.0498)	(0.0848)	(0.0616)	(0.0785)	(0.551)
ROA	-0.164***	-0.224***	-0.310***	-0.421***	-0.637***
	(0.0447)	(0.0477)	(0.0333)	(0.0406)	(0.0902)
LogTA	-0.901***	-1.026***	-1.048***	-1.113***	-1.848***
	(0.104)	(0.128)	(0.104)	(0.182)	(0.371)
Growth	0.00598	0.00349	0.00599**	0.00584	0.00806
	(0.00372)	(0.00259)	(0.00285)	(0.00532)	(0.0111)
Liq	1.006***	1.093***	1.488***	1.580***	2.539***
	(0.231)	(0.343)	(0.253)	(0.261)	(0.912)
Cons	23.68***	30.24***	32.89***	35.78***	50.89***
	(1.321)	(1.508)	(1.514)	(2.224)	(8.669)
Year	Yes	Yes	Yes	Yes	Yes
Industry	Yes	Yes	Yes	Yes	Yes
Country	Yes	Yes	Yes	Yes	Yes
Pseudo R^2	0.312	0.347	0.379	0.41	0.411
Obs	2580	2580	2580	2580	2580

Significance based on bootstrap standard errors (1000 replications). Idiosyncratic risk (Risk) is the dependent variable for all models. Disclosure's significance is based on one-tailed test. τ denotes the different quantiles. All variables listed are defined in Table 2. Equality test of the environmental disclosure coefficients reports p-value = 0.042 [F(4, 2537)= 2.48]. ***,**,* significance level at 1%, 5%, 10%.

Table 7: Robustness checks I. Full-sample

	Random effects		Sys-GMM		Quantile(.50)	
	(1a)	(1b)	(2a)	(2b)	(3a)	(3b)
Variable	5.Risk	T.Risk	5.Risk	T.Risk	5.Risk	T.Risk
$5.Risk_{t-1}$			0.4137***			
			(0.084)			
$T.Risk_{t-1}$				0.900***		
				(0.115)		
Disc	-0.0650***	-0.0674**	-0.0831**	-0.0384	-0.0326***	-0.0361*
	(0.0249)	(0.0282)	(0.0365)	(0.0519)	(0.0117)	(0.0188)
Z	-0.904***	-0.863***	-0.604*	-0.356	-0.759***	-0.663***
	(0.211)	(0.217)	(0.310)	(0.310)	(0.171)	(0.179)
Lev	0.0002	0.00025	-0.00005	-0.00025	0.0001	-0.00005
	(0.00016)	(0.00017)	(0.00008)	(0.00015)	(0.00013)	(0.0002)
$R\&D$	0.0354	0.1289	-0.200	0.827	-0.0071	0.141
	(0.269)	(0.297)	(0.689)	(0.720)	(0.104)	(0.192)
Tang	0.335***	0.350***	0.188	0.057	0.320**	0.313**
	(0.118)	(0.123)	(0.147)	(0.158)	(0.142)	(0.153)
Q	-1.278**	-0.646	-1.935**	-3.255***	-0.812**	-0.945
	(0.563)	(0.634)	(0.859)	(1.05)	(0.398)	(0.576)
LogTA	-1.793***	-1.063**	-0.651	-1.579***	-1.459***	-0.814***
	(0.379)	(0.448)	(0.928)	(0.569)	(0.167)	(0.290)
Growth	-0.0107	-0.00845	-0.0059	0.00288	-0.0127	-0.0038
	(0.0231)	(0.0195)	(0.0183)	(0.0212)	(0.0112)	(0.011)
Liq	0.258	0.265	-0.184	0.387	1.219*	1.591**
	(0.201)	(0.227)	(0.203)	(0.65)	(0.952)	(0.712)
Cons	45.92***	36.78***	39.40***	16.64	39.82***	31.53***
	(3.88)	(4.33)	(12.36)	(13.86)	(2.63)	(3.66)
Year	Yes	Yes	Yes	Yes	Yes	Yes
Industry	Yes	Yes	Yes	Yes	Yes	Yes
Country	Yes	Yes	No	No	Yes	Yes
AR(1)			[0]	[0]		
AR(2)			[0.373]	[0.524]		
Instr			50	50		
H-J			[0.169]	[0.161]		
R^2	0.597	0.682			0.386	0.424
Obs	1708	1708	1668	1668	1708	1708

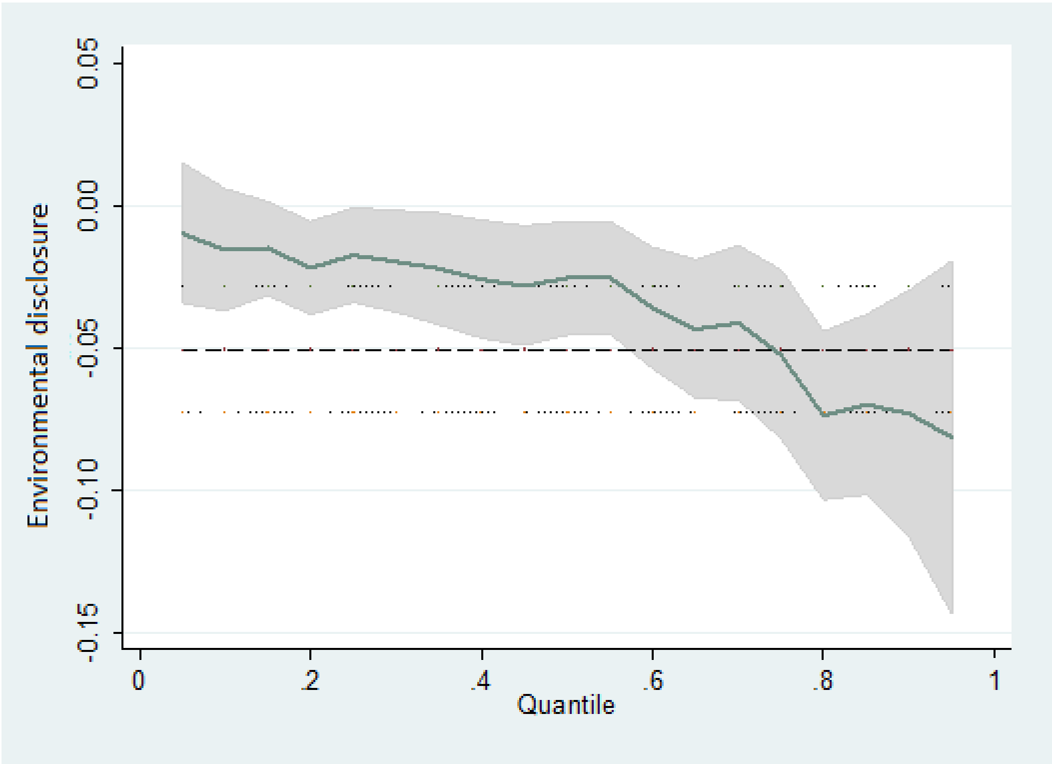
Standard errors are in parenthesis, p-values in brackets. Standard errors are robust correcting for heterogeneity. Disclosure's significance is based on one-tailed test. Hansen J-test (H-J) reports the instrument validity. AR(1) and AR(2) show the first and second order auto-correlation respectively. The number of instruments (Instr) is reported. All variables listed are defined in Table 2. ***,**,* significance level at 1%, 5%, 10%. Column 2, which reports Sys-GMM estimations, does not use country dummies because the over-identifying restrictions were not valid.

Table 8: Robustness checks II. Sub-sample without British firms.

	Random effects		Sys-GMM		Quantile(.50)	
	(1a)	(1b)	(2a)	(2b)	(3a)	(3b)
	5.Risk	T.Risk	5.Risk	T.Risk	5.Risk	T.Risk
$5.Risk_{t-1}$			0.498***			
			(0.104)			
$T.Risk_{t-1}$				0.498***		
				(0.0905)		
Disc	-0.0750***	-0.0638**	-0.0526***	-0.0204	-0.0461***	-0.0265
	(0.0270)	(0.0320)	(0.0162)	(0.0321)	(0.0161)	(0.0180)
Z	-0.982***	-0.962***	-0.375	-0.309	-0.759***	-0.873***
	(0.280)	(0.293)	(0.292)	(0.285)	(0.200)	(0.194)
Lev	0.00211	0.00273	0.00275	0.00382	0.000477	0.00133*
	(0.00312)	(0.00326)	(0.00297)	(0.00237)	(0.00118)	(0.000736)
$R\&D$	0.432	0.486	0.253	0.315	0.457***	0.620***
	(0.307)	(0.332)	(0.184)	(0.213)	(0.141)	(0.204)
Tang	0.365**	0.403**	0.126	0.128	0.334**	0.411**
	(0.156)	(0.163)	(0.145)	(0.143)	(0.133)	(0.165)
Q	-1.486**	-0.802	-1.078**	-1.559***	-1.308***	-1.412**
	(0.658)	(0.714)	(0.505)	(0.546)	(0.486)	(0.556)
LogTA	-2.224***	-1.432***	-0.967***	-0.904**	-2.020***	-1.643***
	(0.450)	(0.533)	(0.319)	(0.413)	(0.283)	(0.338)
Growth	-0.0301*	-0.0244	-0.0160	-0.00432	-0.0183	0.00003
	(0.0156)	(0.0163)	(0.0164)	(0.0186)	(0.0169)	(0.0177)
Liq	0.843	1.046	0.612	0.634	1.285**	2.058***
	(0.621)	(0.701)	(0.500)	(0.660)	(0.513)	(0.599)
Cons	45.40***	40.48***	26.15***	26.70***	40.87***	35.74***
	(4.58)	(5.14)	(4.24)	(5.69)	(2.35)	(3.56)
Year	Yes	Yes	Yes	Yes	Yes	Yes
Industry	Yes	Yes	Yes	Yes	Yes	Yes
Country	Yes	Yes	Yes	Yes	Yes	Yes
AR(1)			0	0		
AR(2)			0.266	0.978		
Instr			65	65		
H-J			0.315	0.115		
R^2	0.602	0.684			0.398	0.439
Obs	1325	1325	1291	1291	1325	1325

Standard errors are in parenthesis, p-values in brackets. Standard errors are robust correcting for heterogeneity. Disclosure's significance is based on one-tailed test. Hansen J-test (H-J) reports the instrument validity. AR(1) and AR(2) show the first and second order auto-correlation respectively. The number of instruments (Instr) is reported. All variables listed are defined in Table 2. ***,**,* significance level at 1%, 5%, 10%.

Figure 1: Environmental disclosure on Risk distribution



The grey area corresponds to confidence intervals calculated with 1,000 bootstrap replications. The dash line represents the OLS estimations with its confidence intervals (dot lines). The control variables are not reported for brevity but are available upon request.

Appendix

Advised by the study of Qiu et al. (2016), Bloomberg environmental disclosure has been constructed by 60 different items that have been retrieved by annual reports, sustainability reports and company websites. The overall score is standardized by industry. The 60 environmental items are not equally weighted, items appeared in the top of Table 9 receive relatively higher weights than items in the bottom. So, the score captures both the quantity and quality of the disclosures.

Table 9: Environmental disclosure items

#		#	
1	Direct CO2 Emissions	31	Paper Recycled
2	Indirect CO2 Emissions	32	Fuel Used (Th Litres)
3	Travel Emissions	33	Raw Materials Used
4	Total CO2 Emissions	34	% Recycled Materials
5	CO2 Intensity (Tonnes)	35	Gas Flaring
6	CO2 Intensity per Sales	36	Number of Spills
7	GHG Scope 1	37	Amount of Spills (Th Tonnes)
8	GHG Scope 2	38	Nuclear % Total Energy
9	GHG Scope 3	39	Solar % Total Energy
10	Total GHG Emissions	40	Phones Recycled
11	NOx Emissions	41	Environmental Fines #
12	SO2 Emissions	42	Environmental Fines $
13	SOx Emissions	43	ISO 14001 Certified Sites
14	VOC Emissions	44	Number of Sites
15	CO Emissions	45	% Sites Certified
16	Methane Emissions	46	Environmental Accounting Cost
17	ODS Emissions	47	Investments in Sustainability
18	Particulate Emissions	48	Energy Efficiency Policy
19	Total Energy Consumption	49	Emissions Reduction Initiatives
20	Electricity Used (MWh)	50	Environmental Supply Chain
21	Renewable Energy Use	51	Management Green
22	Water Consumption	52	Green Building Policy
23	Water/Unit of Prod (in Litres)	53	Waste Reduction Policy
24	%Water Recycled	54	Sustainable Packaging
25	Discharges to Water	55	Environmental Quality Management Policy
26	Waste Water (Th Cubic Metres)	56	Climate Change Policy
27	Hazardous Waste	57	New Products - Climate Change
28	Total Waste	58	Biodiversity Policy
29	% Waste Recycled	59	Environmental Awards Received
30	Paper Consumption	60	Verification Type

These 60 items should not be strictly disclosed by every firm. For instance, the item "Phones Recycled" is only relevant for telecommunications industry and so firms from different industries are not penalized for not disclosing it.