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Corporate social performance and financial risk: Further empirical evidence using higher frequency data

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ABSTRACT

Using a unique dataset of corporate social responsibility rating – available on a monthly basis – we shed new light on the relationship between corporate social performance (CSP) and firm risk. Where previous studies use annual (at best) measures of CSP, assuming that a change in CSP leads a change in risk, we formally test the direction of the relationship using Granger causality. Looking at large UK companies over 2002–2018 (for a total number of 19,832 firm-months), we reject any causality (either way) between CSP and financial risk (both systematic and idiosyncratic risk). This shows that the CSP-risk relationship is not an endogenous one, contrary to what previous evidence has found. Given the structure of our panel data (long T and short N), we apply GLS based estimator to correct for serial correlation in our panel regressions. We find strong evidence that CSP has a negative impact on idiosyncratic risk; however, the effect of CSP on systematic risk is not statistically significant. The existence of a contemporaneous, rather than lagged relationship doesn't fare well with established CSP theories. Overall, our original approach has opened a new door to further the study of the link between CSP, financial performance and financial risk.

1. Introduction

Attracting great attention since the 1970s, corporate social responsibility (CSR) has never been more prevalent than in the last ten years. Since the global financial crisis, companies have been forced to adjust their corporate governance mechanisms through increased regulation and mandatory reforms, as well as a surge in shareholder activism. This ultimately led to a shift towards the voluntary adoption of socially responsible practices aimed at enhancing the value-creation process and restoring public confidence (Alexandridis, Antypas, & Travlos, 2017). Evidence to date suggests that companies investing in environmental, social and governance (ESG) activities tend to create value for their shareholders, through higher financial performance and lower financial risk (Huang, Sim, & Zhao, 2020; Luo & Bhattacharya, 2009). One caveat to extant evidence is that, for many studies, the relationship is not statistically significant, which is likely due to the low frequency of the data used. Indeed, all published papers on the topic rely on annual (at best) data to measure corporate social performance (CSP), when firm risk and return can drastically vary over a year. We address this major limitation by investigating the relationship (both dependency and causality) between CSP and financial risk using an original dataset of monthly ESG scores.

According to the stakeholder theory (Freeman, 1984) and the risk management theory (Godfrey, 2005), ESG activities should increase the value of the firm through the good management of stakeholders and moral capital, respectively. On the contrary, the managerial opportunism theory argues that money spent on CSR activities is a waste of resources and does not lead to the maximisation of shareholders' wealth (Farag, Meng, & Mallin, 2015; Preston & O'Bannon, 1997). In this context, financial performance and financial risk are both important determinants of firm value, as managers can increase the value for shareholders by maximising future cash flows (driving financial performance) and/or minimising the cost of capital (intrinsically related to risk). Financial risk can be broadly defined as the potential of losing firm value as a result of uncertainty about future outcomes (Chang, Kim, & Li, 2014; Orlitzky & Benjamin, 2001). In the finance literature, market risk is usually measured as the volatility of stock returns (total risk) which can be split into systematic risk (volatility of returns due to broad movements in the stock market) and idiosyncratic risk (volatility of returns due to firm-specific events).

Interestingly, the literature investigating the CSP-risk relationship is much sparser than the one looking at the CSP-performance relationship.

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There is a consensus in the literature that a firm's CSP is negatively related to its market risk, whether total risk (Chang et al., 2014; Harjoto & Laksmana, 2018; Sassen, Hinze, & Hardeck, 2016), systematic risk (Boutin-Dufresne & Savaria, 2004; Oikonomou, Brooks, & Pavelin, 2012; Salama, Anderson, & Toms, 2011) or idiosyncratic risk (Luo & Bhattacharya, 2009; Sassen et al., 2016). But again the relationship is often weak (statistically and/or economically) and its statistical strength depends on the sample period (Bouslah, Kryzanowski, & M'Zali, 2018; Salama et al., 2011). What is more puzzling is the causality between CSP and risk. Most aforementioned papers simply assume that causality runs from CSP to risk, when theoretically the causality can go either way or not exist at all.

Our study contributes to this strand of literature by identifying and addressing a major gap. All published papers to date rely on annual (at best) data to measure CSP, the most commonly used ESG datasets being MSCI (KLD) rating in the USA (Chahine, Fang, Hasan, & Mazboudi, 2019; Chang et al., 2014; Lin, Li, Cheng, & Lam, 2021; Oikonomou et al., 2012) and Thomson Reuters ASSET4 rating in European/international studies (Chollet & Sandwidi, 2018; Sassen et al., 2016). There are several issues with using annual data for this type of study, noise being the most obvious one. It is very difficult to assess the dependency and causality between CSP and risk on a yearly basis, and as such many studies assume a causality running from CSP to risk. The need for higher frequency data analysis is particularly striking when considering market risk, as volatility is time-varying and time-dependent by definition. Using monthly ESG data to calculate CSP, and three different measures of financial risk (total market risk; systematic and idiosyncratic risk), we investigate the relationship between CSP and firm risk (both sign and causality) on a large sample of 19,832 firm-months over the period 2002–2018. Interestingly our Granger causality tests do not reveal any systematic causality either way between CSP and risk, which is in contrast with previous literature. That being said, a strong negative dependency exists between CSP and idiosyncratic risk, i.e., better CSP is related (contemporaneously) to lower firm-specific risk. We do not find any statistically significant relationship between CSP and systematic risk. Our original approach of using monthly CSP data represents a significant contribution to the empirical literature where the evidence to date is highly inconsistent.

The rest of the paper is structured as follows. Section 2 presents the current state of the literature, both theoretical and empirical, and develops our research hypotheses. Section 3 describes our methodological framework while Section 4 explains the data collection. In Section 5, we present and discuss our empirical results, and we offer concluding remarks in Section 6.

2. Literature review and hypotheses development

2.1. Conceptual framework

Theoretically, the relationship between CSP and financial risk – both systematic and firm-specific – can go both ways and can be either positive or negative. The most popular strand of literature argues that better social performance leads to lower idiosyncratic risk and this idea is supported by three main arguments. First, the stakeholder theory, developed by Ed Freeman in the 1980s, argues that firms have a responsibility to all stakeholders who are directly affected by the firm's actions, and not only its shareholders (Freeman, 1984; Harrison & Wicks, 2013). Stakeholder theory provides the underpinning for the good management theory (Waddock & Graves, 1997) suggesting that good management of relationships with various stakeholders results in stronger corporate performance. By meeting and maximising demands and interests of various stakeholders, such as customers, suppliers, employees, public interest groups, etc., managers will reduce uncertainty and enhance firm value (Donaldson & Preston, 1995; Sassen et al., 2016). Hence, ESG initiatives aimed at satisfying different stakeholders will minimise the likelihood of a lawsuit, a product recall, a strike, etc., and as a consequence, help decrease the firm's risk, particularly its idiosyncratic risk. Indeed, the effects of ESG initiatives on carbon footprint, waste management and product safety are very much firm specific. For instance, ESG engagement has been found to *(i)* increase brand recognition and identification from consumers (Brown & Dacin, 1997; Krasnikov, Mishra, & Orozco, 2009; Sen & Bhattacharya, 2001), *(ii)* enhance job satisfaction and productivity of employees (Aguilera, Rupp, Williams, & Ganapathi, 2007), and *(iii)* minimise disruptions in the supply chain (Carter, 2000; Modi & Mishra, 2011). According to the resource-based view of the firm, these valuable resources provide the firm with a competitive advantage, lower firm-specific uncertainty about future cash flows and ultimately decrease idiosyncratic risk. This is consistent with market segmentation, i.e., the idea that investors prefer certain types of stocks (e.g. stocks with high CSP) and neglect others (e.g. stocks with low CSP). In this case, firms with lower CSP will have higher idiosyncratic risk (Lee & Faff, 2009).

Second, ESG activities help reduce information asymmetry, which in turn affects idiosyncratic risk. Pastor and Veronesi (2003, 2009) develop a general model where an improvement in the quality of information about firm profitability leads to lower information asymmetry and lower idiosyncratic risk. In the context of CSR practices, firms with better ESG engagement are likely to produce more transparent and better-quality financial reporting (Dhaliwal, Li, Tsang, & Yang, 2011), mitigating information asymmetry about their financial performance and reducing their stock price volatility (Cho, Lee, & Pfeiffer Jr, 2013; O'Hara, 2003; Rajgopal & Venkatachalam, 2011).

The third argument is based on the risk management theory (Godfrey, 2005) and argues that good companies – i.e., with better CSP – will attract/retain more investors as they can generate positive moral capital. This moral capital alleviates sanctions against the firm and therefore leads to less volatile future cash flows, thereby reducing firm idiosyncratic risk (Chang et al., 2014; Luo & Bhattacharya, 2009). Also, by attracting more investors, these firms would have to rely less on other sources of funding such as debt (Cheng, Ioannou, & Serafeim, 2014). This has a direct impact on the financial leverage and risk of the firm, i.e., better CSP leads to lower idiosyncratic risk.

Another strand of literature asserts that CSP can also impact the systematic risk of the firm. Combining marketing and economics literature, Albuquerque, Koskinen, and Zhang (2018) argue that ESG engagement is a product differentiation strategy, and that better CSP leads to higher pricing power and higher profit margins. From the perspective of a risk-averse investor, higher profit margins lead to lower elasticity of profits to aggregate shocks, and hence lower systematic risk (Albuquerque et al., 2018). Hence a firm's CSP is negatively related to its systematic risk through lower earning sensitivity to market movements.

Albeit the plethora of arguments supporting a negative relationship between CSP and risk, there is an argument that higher CSP could lead to higher risk for companies (Bouslah, Kryzanowski, & M'Zali, 2013; Preston & O'Bannon, 1997). According to managerial opportunism theory, ESG engagement can be considered as a principal-agent relation between managers and shareholders. In that vein, Barnea and Rubin (2010) argue that affiliated insiders (managers and block-holders) have an interest in overinvesting in CSP if doing so provides private benefits of reputation building as good social citizens, possibly at a cost to non-affiliated shareholders (to the extent that such overinvestment will destroy value and increase risk). Assuming that both systematic and idiosyncratic risk matter for shareholders, such managerial entrenchment will impact both types of risks. On the contrary, managers who are motivated by short-term profits might decide to underinvest in CSP to cash in whenever financial performance is high; thereby disregarding risks that occur in the long run (Sassen et al., 2016). Similarly, investors and analysts may perceive strong ESG engagement as riskier or more likely to be subject to information asymmetry (Chollet & Sandwidi, 2018).

There is also an argument for a reverse causality, i.e., lower risk will lead to better CSP. According to the slack resources theory (Waddock &

Table 1
Conceptual framework.

Causality (direction of the relationship)	Dependency (sign of the relationship)	Theoretical argument	Empirical evidence
CSP → Idiosyncratic risk	Negative	Stakeholder theory (Freeman, 1984) and good management theory (Waddock & Graves, 1997) Information asymmetry (Pastor & Veronesi, 2003, 2009) Risk management theory (Godfrey, 2005)	Better CSP leads to lower firm-specific risk
CSP → Systematic risk	Negative	Product differentiation strategy (Albuquerque et al., 2018)	Better CSP leads to lower systematic risk
CSP → Idiosyncratic risk	Positive	Managerial opportunism (Preston & O'Bannon, 1997)	Better CSP leads to higher firm-specific risk
CSP → Systematic risk	Positive	Managerial opportunism (Preston & O'Bannon, 1997)	Better CSP leads to higher systematic risk
Idiosyncratic risk → CSP	Negative	Slack resources theory (Waddock & Graves, 1997)	Lower firm-specific risk leads to better CSP
Systematic risk → CSP	Negative	Slack resources theory (Waddock & Graves, 1997)	Lower systematic risk leads to better CSP
No Causality	No dependency	Moderating or intermediary variables (Ullmann, 1985)	No statistical relationship between CSP and risk

Graves, 1997), firms with lower risk may have higher valuations and more resources to spend in ESG efforts; or have fewer growth options and again more resources to dedicate to CSP (Albuquerque et al., 2018). Alternatively, firms with lower risk (both idiosyncratic and systematic) may be more prone to developing more rigorous CSR policies. Indeed, firms with lower risk face less financial uncertainty, so their managers have greater discretion to improve ESG engagement (Chollet & Sandwidi, 2018).

The final strand of literature argues that ESG activities are not systematically correlated with the economic fundamentals of corporations so that there is no obvious and direct relationship between CSP and risk (Orlitzky, 2013). On average and all things being equal, the marginal benefits of ESG will be offset by the marginal costs (Curran & Moran, 2007; McWilliams & Siegel, 2001). This argument is consistent with the existence of moderating or intermediary variables driving the relationship (Ullmann, 1985; Waddock & Graves, 1997), so that ESG efforts impact differently the risk of different firms. As Waddock and Graves (1997) explain for the CSP-performance link: "there are so many intervening variables between social and financial performance that there is no reason to expect a relationship to exist, except possibly by chance". Therefore, CSP and financial risk do not lead each other but may both be impacted by other variables. For instance, authors have drawn upon marketing literature to argue that customer boycotts, advertising spending and firm reputation are significant moderators in the link between CSP and firm-specific risk (Fornell, Mithas, Morgeson III, & V., & Krishnan, M. S., 2006; Luo & Bhattacharya, 2009). In the finance literature, other significant moderators include financial leverage (Mishra & Modi, 2013), earnings forecast accuracy (Becchetti, Ciciretti, & Hasan, 2015) or the firm's legal environment (Benlemlih & Girerd-Potin, 2017). In summary, there shouldn't be any statistical causality or dependency between CSP and risk.

Table 1 summarizes our conceptual framework by presenting the different arguments pertaining to the relationship (both sign and causality) between CSP and financial risk, distinguishing idiosyncratic and systematic risk.

2.2. Empirical evidence and hypotheses

Empirically, early studies focus on the US market and show a bidirectional and negative relationship between CSP and financial risk, although at the time only systematic risk was taken into account (see Orlitzky and Benjamin (2001) for a review of the literature before 1995).[1] Also, different measures of CSP were adopted making the results difficult to compare (Sassen et al., 2016). More recent US evidence still suggests that a firm's engagement in ESG activities helps reduce its financial risk, whether total risk (Chang et al., 2014; Harjoto & Laksmana, 2018), systematic risk (Chang et al., 2014; Luo & Bhattacharya, 2009; Oikonomou et al., 2012) or idiosyncratic risk (Fatemi, Fooladi, & Wheeler, 2009; Lee & Faff, 2009; Luo & Bhattacharya, 2009). Mishra and Modi (2013) distinguish positive and negative CSR, and report that positive (negative) CSR significantly decreases (increases) idiosyncratic risk accordingly. While all aforementioned papers are based on annual data, Ferreira and Laux (2007) conduct a "higher frequency" analysis of CSP and financial risk, using a comprehensive panel of monthly data over 12 years and across 1248 US firms. Focusing on antitakeover-related governance provisions as their CSP measure, they find a strong negative (lagged) relation between CSP and firm-specific risk. But again their main variable CSP is only available at a low frequency and they simply interpolate the index to obtain monthly data.[2] Although previous findings support the stakeholder theory and the product differentiation argument, it is worth mentioning that the relationship is sometimes weak and its statistical strength depends on the sample period (Bouslah et al., 2018). Most importantly, these studies do not actually test for the existence of a causal relationship, instead simply lag (or not) the independent variable, i.e., CSP.

Consistent with the risk management hypothesis, several studies find that ESG engagement can lower the firm's cost of equity (Chava, 2014; Dhaliwal et al., 2011; El Ghoul, Guedhami, Kwok, & Mishra, 2011; Sharfman & Fernando, 2008) as well as their financial leverage (Fatemi et al., 2009). There is also evidence that CSP significantly reduces the credit risk of the firm, proxied by its credit rating (Hsu & Chen, 2015; Sun & Cui, 2014). Also, in the context of the global financial crisis, ESG activities were found to be useful in terms of managing risk and described as an "insurance" against idiosyncratic risk (Lins, Servaes, & Tamayo, 2017).

[1] None of the studies considered by Orlitzky and Benjamin (2001) have looked at idiosyncratic risk, as 30 years ago investors were considered to hold well-diversified portfolios so that only systematic risk would matter.

[2] "We construct the index for each sample firm for the years 1990, 1993, 1995, 1998, and 2000 from observations on a set of antitakeover-related governance provisions (…) When we need to specify a governance index for a particular month *t*, we use the most recently announced level."

Table 2
Comparison of ESG criteria used by Covalence and MSCI.

	Covalence rating		MSCI (KLD) rating	
Environment	Environmental impacts of products	Emissions/Energy consumption/Environmental impact of transport	Climate change	Carbon emissions/Product carbon footprint/Financing environmental impact/Climate change vulnerability
	Resources	Water management/Biodiversity	Natural resources	Water stress/Biodiversity & land use/Raw material sourcing
	Emissions, effluents & waste	Pollution/Waste management	Pollution & waste	Toxic emissions & waste/Packaging material & waste/Electronic waste
			Environmental opportunities	Clean tech/Green building/Renewable energy
Social	Labour Practices and Decent Work	Wages/Employee benefits/Trade unions/Health & safety/Training & education/Diversity/Discrimination	Human capital	Labour management/Health & safety/Human capital development/Supply chain labor standards
	Product Responsibility	Product safety/Product labelling/Marketing communications/Customer privacy/Product compliance/Social impact of products	Product liability	Product safety & quality/Chemical safety/Financial product safety/Privacy & data security/Responsible investment/Health & demographic risk
	Human Rights	Human rights policy/Child labour/Forced labour/Indigenous rights	Stakeholder opposition	Controversial sourcing
	Society/Community	Local sourcing/local hiring/Infrastructures/Local communities/Humanitarian action	Social opportunities	Access to communications/Access to finance/Access to healthcare/Nutrition & health
Governance	Management	Board independence & diversity/Fiscal contributions/Competition/Corruption/Lobbying	Corporate governance	Board/Pay/Ownership & control/Accounting
	Remuneration	Sustainable compensation		
	Shareholders	Shareholders rights		
	Sustainability strategy	Mission statements & codes of conduct	Corporate behaviour	Business ethics/Anti-competitive practices/Tax transparency/Corruption & instability/Financial system instability

Contrary to previous evidence, Becchetti et al. (2015) document a positive relationship between CSP and idiosyncratic risk, i.e., firms with higher CSP display significantly higher firm-specific risk. This is because CSR introduces additional constraints and reduces the firm's capacity to smooth earnings in the presence of productivity shocks, in line with the presence of managerial opportunism.

Very few studies investigate non-US markets, and most international evidence tends to support the idea of a negative (contemporaneous) association between CSP and risk, either systematic or idiosyncratic, although the significance is often economically, if not statistically, weak (Benlemlih & Girerd-Potin, 2017; Boutin-Dufresne & Savaria, 2004; Salama et al., 2011; Sassen et al., 2016).[3] To the best of our knowledge, only a handful of papers tests for statistical causality between CSP and risk (again using annual data), and results differ significantly. On one side, Benlemlih and Girerd-Potin (2017) find evidence of a unidirectional causality from CSP to financial risk across a sample of 25 countries and 11 years (2001–2011). They show that a firm's CSP does Granger-cause its risk (both systematic and idiosyncratic); however neither systematic nor idiosyncratic risk Granger-causes CSP. The relationship is significantly negative and supports our first two lines of arguments (first two rows in Table 1). On the other side, Chollet and Sandwidi (2018) also evidence a one-way causality from CSP to systematic risk, but the relationship is significantly positive, i.e., firms with better CSP actually record higher levels of systematic risk, consistent with the existence of agency problems. Interestingly, they demonstrate the existence of a two-way causality and a negative relationship between CSP and idiosyncratic risk. Using a sample of 3787 firms over 10 years (2003–2012) and 67 countries, they find that stronger CSP generates lower firm-specific risk, which in turn stimulates their social performance. This is consistent with the idea of a virtuous circle between CSP and firm-specific risk (Waddock & Graves, 1997).

Finally, another strand of literature documents no significant relationship between CSP and financial risk, whether idiosyncratic risk (Humphrey, Lee, & Shen, 2012; Kim, 2010) or systematic risk (Benlemlih, Shaukat, Qiu, & Trojanowski, 2018; Sassen et al., 2016). These results are in line with most recent evidence supporting the moderating or intermediary variables hypothesis.

In light of the theory and empirical evidence to date, firm-specific risk seems to matter more than systematic risk with regards to social responsibility. On one side, there is a consensus on the existence of a negative relationship (direct or indirect) between CSP and idiosyncratic risk, although the causality, if any, is still unclear. Hence it is important to test the following hypotheses using monthly CSP data:

H1. There is no statistical causality (either way) between CSP and idiosyncratic risk.

H2. There is a negative and statistically significant relationship between CSP and idiosyncratic risk.

On the other side, the evidence regarding the CSP-systematic risk relationship is mixed and tends to suggest that there is no statistical or systematic relationship between the two. Our intention is to shed new light on the evidence using higher frequency data:

H3. There is no statistical causality (either way) between CSP and systematic risk.

H4. There is no statistical dependency between CSP and systematic risk.

3. Methodology and empirical framework

3.1. *Corporate social performance (CSP)*

In the literature, a firm's CSP has been measured using two main ways. Some studies have collected environmental, social and governance (ESG) data using surveys (Amel-Zadeh & Serafeim, 2018) and others have based their analysis on ratings (Barnea & Rubin, 2010; Benlemlih & Girerd-Potin, 2017). One of the main disadvantages of using surveys is that they are subject to a response bias and selection bias (Amel-Zadeh & Serafeim, 2018). Another limitation that is particularly

[3] Benlemlih and Girerd-Potin (2017) find a negative and significant relationship between CSP and risk (both systematic and idiosyncratic) using a large sample across 25 countries. Boutin-Dufresne and Savaria (2004) find a negative association between CSP and idiosyncratic risk on a sample of Canadian stocks. In the UK, Salama et al. (2011) find that a firm's environmental performance (measured with survey data) is inversely related to its systematic risk. Sassen et al. (2016) report a negative relationship between CSP (mainly environmental performance) and idiosyncratic risk for a large sample of European companies.

relevant here is the irregularity of survey data. Using ratings, on the contrary, is considered to be more reliable and consistent as each company is rated in the same way, applying similar criteria (Andersen & Dejoy, 2011; Benlemlih & Girerd-Potin, 2017). Despite certain criticism of using ratings, such as validity of measures applied (Chatterji & Levine, 2006), a lot of academics continue to base their research on these ratings (e.g. Wang & Berens, 2015).

Since we are investigating the link between CSP and financial risk, we need an ESG measure that is objective, consistent over time, and directly available to investors in a timely manner, i.e., with the highest possible frequency. In our case, a composite ESG score available on a monthly basis is the best proxy for CSP. In this study we use an original database of ESG scores provided by Covalence SA. Their rating methodology is based on a variety of information from company websites, NGO websites, news sources, CSR reports, annual reports, etc. Covalence uses 50 ESG criteria inspired by the Global Reporting Initiative's sustainability reporting guidelines as well as by international norms and conventions – such as the United Nations' Sustainable Development Goals and Global Compact Principles. The 50 criteria are distributed across various Environment, Social and Governance categories (see Table 2 for a classification of the main criteria). Given the methodology and criteria used by Covalence, this independent rating is similar to ESG scores published by Thomson Reuters (previously ASSET4) and MSCI (previously KLD) and extensively used in previous literature (Table 2 also provides, for comparison, a classification of ESG criteria used by MSCI). However, contrary to those, Covalence ESG scores are available and updated on a monthly basis. For each company, ESG data is collected throughout the month and the final score is calculated at the end of the month as the average across the different ESG categories. Scores can range from 0 (lowest CSP) to 100 (highest CSP).

3.2. Financial risk

Financial risk can be measured as the variability of accounting data (e.g. standard deviation of ROA) or market data (e.g. standard deviation of stock returns). Since we are interested in the point of view of shareholders (and potential investors), and because accounting data is only available on a yearly basis, we use in this study a range of market-based risk measures. In this context, our first measure of financial risk is the total risk of the stock i defined as the month t volatility (standard deviation) of daily stock returns r_{id}:

$$\sigma_{it} = \sqrt{Var\left(r_{id,t}\right)} \tag{1}$$

Total risk can then be divided into systematic risk and idiosyncratic risk (or firm-specific risk). Systematic risk is the sensitivity of the stock price to the movement of the whole market, usually measured with the market beta:

$$\beta_i = \frac{Cov(r_i, r_m)}{Var(r_m)} \tag{2}$$

Monthly betas for each stock β_{it} are estimated from the market model using daily returns over the past 24 months (Luo & Bhattacharya, 2009; Oikonomou et al., 2012; Salama et al., 2011):

$$\left(r_{id,t} - r_{fd,t}\right) = \alpha_{it} + \beta_{it}\left(r_{md,t} - r_{fd,t}\right) + \varepsilon_{id,t} \tag{3}$$

Idiosyncratic risk is the risk specific to the firm, i.e., the residual risk that cannot be explained by movements in market returns. Hence, we calculate idiosyncratic risk as the monthly variance of the residuals (i.e., the sum of squared errors) from estimating the market model above. Following Ferreira and Laux (2007) and Luo and Bhattacharya (2009), we compute a relative measure of idiosyncratic risk, i.e., for each month t, we divide idiosyncratic volatility by total volatility, which is represented by 1 – R^2 (R^2 being the coefficient of determination). Performing a logistic transformation of 1 – R^2, we end up with the following:

$$v_{it} = ln\left(\frac{1 - R_{it}^2}{R_{it}^2}\right) \tag{4}$$

In addition to estimating risk measures according to the market model (1-factor model), we calculate idiosyncratic risk and systematic risk using the 3-factor model developed by Fama and French (1993):

$$\left(r_{id,t} - r_{fd,t}\right) = \alpha_{it} + \beta_{it}\left(r_{md,t} - r_{fd,t}\right) + s_{it}SMB_{d,t} + h_{it}HML_{d,t} + \varepsilon_{id,t} \tag{5}$$

3.3. Empirical framework

For the purpose of this paper, we employ two empirical approaches to examine the extent to which corporate social performance (CSP) affects financial risk. The first exercise applies robust causality tests to revisit the evidence in the existing literature (Benlemlih & Girerd-Potin, 2017; Chollet & Sandwidi, 2018). This exercise allows testing for *H1* and *H3* which state that there is no systematic causality between CSP and financial risk. Causality is, however, a stronger form of association than dependence. In other words, if causality is established (either one way or both ways), then dependency is valid. Furthermore, the presence of a causal link implies the endogenous nature of the association between financial risk and CSP (Ioannou & Serafeim, 2015). Under the absence of causality, endogeneity may not be an issue. It may, however, imply the existence of a dependency form of statistical association. The second exercise aims to examine whether CSP is at all related to firm's risk, either idiosyncratic risk (*H2*) or systematic risk (*H4*). We test for the presence of a statistically significant relationship between CSP and risk by applying panel data regression framework.

3.3.1. Causality test

We begin our econometric analysis by testing our research hypotheses *H1* and *H3* for the presence of any potential causal relationship using the concept of causality as proposed by Granger (1969) and used in several previous CSR studies (Benlemlih & Girerd-Potin, 2017; Bird, Hall, Momentè, & Reggiani, 2007; Bouslah et al.,2013; Nelling & Webb, 2009; Scholtens, 2008).

The concept of Granger causality tests whether the dynamics of a variable is better explained by its own past behaviour and the past of other variable(s) than by its own past values alone. This implies that the test of whether a variable – *CSP* in our case – Granger causes variable *Risk* rests on the joint significance of the coefficients of lagged values of *CSP* when included to predict the dynamics of *Risk*. Moreover, the concept allows three possibilities of causality: *(i)* no causality, *(ii)* one-way causality and *(iii)* feedback or two-way causality. Our aim in this paper is to assess all three possibilities, which requires using a Vector Autoregressive model (VAR). The test is performed on the following general *VAR*(*p*) model:

$$Risk_t = \beta_0 + \sum_{j=1}^{p} \beta_{Risk,j} Risk_{t-j} + \sum_{j=1}^{p} \beta_{CSP,j} CSP_{t-j} + u_{Risk,t} \tag{6A}$$

$$CSP_t = \gamma_0 + \sum_{j=1}^{p} \gamma_{Risk,j} Risk_{t-j} + \sum_{j=1}^{p} \gamma_{CSP,j} CSP_{t-j} + u_{CSP,t} \tag{6B}$$

where $Risk_t$, CSP_t, $u_{Risk,\ t}$ and $u_{CSP,\ t}$ are n-dimensional vectors, and p is the optimal lag length. The null hypotheses being tested are as follows, respectively:

$H_{0,\ 6A}$: *CSP_t does not Granger causes $Risk_t$* and $H_{0,\ 6B}$: *$Risk_t$ does not Granger causes CSP_t.*

against the alternative hypotheses:

$H_{A,\ 6A}$: *CSP_t Granger causes $Risk_t$* and $H_{A,\ 6B}$: *$Risk_t$ Granger causes CSP_t*

Under the null hypotheses, we apply the Wald test of joint significance, which tests the following restrictions under $H_{0,\ 6A}$: $\beta_{CSP,\ j} = 0$ and $H_{0,\ 6B}$: $\gamma_{Risk,\ j} = 0$ for $j = 1, 2, \ldots, p$.

The above restrictions can directly be tested as long as the data are stationary. Recent literature, however, proposed extensions and modified versions of Granger causality tests that account for non-stationary time series or the case of mixed statistical properties including random walk or process with ARCH properties. In this context, we employ robust tests of causality due to Toda and Yamamoto (1995). These tests account for the possibility of the presence of a unit root in the data. Furthermore, we also perform the modified Toda-Yamamoto test proposed by Hacker and Hatemi-J (2006), which performs well for small samples and error terms with ARCH structures. Results presented in the paper assume no unit roots in the data (i.e., or the case of an integrated process of order zero, I(0)). We also allow for the cases of I(1), mixed I(1) and the presence ARCH effect in the errors in robustness analysis.[4] Furthermore, unlike the common practice in standard literature, the causality tests are performed assuming unknown lag length. Following Hacker and Hatemi-J (2012), we determine the optimal order of lag length endogenously using the information criterion proposed by Hatemi-J (2003), which performs well on both stable and unstable VAR models.[5]

3.3.2. *Panel linear regression*

The second part of the analysis is to examine the dependency of financial risk measures on CSP (*H2* and *H4*). For this, we employ panel data methods to model the extent to which this relationship exists. Since the data we use in this paper are two-dimensional (i.e., variables vary across both time and individual firms), panel data methods are suitable to empirically assess the nature and strength of the relationship between our financial and social constructs. The literature, however, does not follow a common modelling strategy when handling similar data. Broadly speaking, three variations of models are implemented, including Pooled, Fixed Effect and Random Effects models.

The former is rarely seen in the literature as it assumes that all individuals in the data are the same. In other words, all individual firms are treated as homogenous entities that are subject to the same individual and time effects. For example, Ferreira and Laux (2007) estimate a variation of pooled cross-sectional time-series regression using monthly data. Although the authors relax the assumption of poolability by accounting for firms' individual characteristics, the qualitative findings remain the same as those obtained by the pooled panel model. This, however, does not lead to a generalisation that suggests pooling panel data or allowing for some degree of heterogeneity across individual entities lead to the same conclusions. In some cases, pooling the data is a restrictive form that implicitly ignores the unobserved – or indeed unmeasured – individual characteristics of firms, which give a rise to heterogeneity. Failing to account for this heterogeneity in the data will result in bias in estimation. Consequently, it is of great importance to formally test for the validity of pooling the data and assume common effects across section and time.

Thus, we extend the analysis by accounting for heterogeneity using two widely used models: Fixed Effects (FE) and Random Effects (RE) models. The FE model is widely used to account for heterogeneity (Oikonomou et al., 2012; Salama et al., 2011) by allowing each individual in the data to have its own intercept. This allows to account for unit fixed effects that arise from the differences across sections (or indeed the factors that differ across sections but are time independent), while assuming the same slopes for all individuals. The FE can also have time fixed effects, which capture the characteristics – in particular the unobserved ones – that are common to all units but vary across time.

In the context of our paper, the general model is formally expressed as follows:

$$Risk_{it} = \alpha + \beta_{CSR}CSP_{it} + X_{it}^{'}\beta + u_{it} \quad i = 1, \ldots, N; \mathrm{t} = 1, \ldots, T \tag{7}$$

with i denoting firms and t denoting time. α and β_{CSR} are scalars, with the latter being the true effect of *CSP* on *Risk*, β is $K \times 1$ and X_{it} is the *ith* observation on K control variables. While much of the work utilise a one-way error component model to describe the disturbances, u_{it}, we utilise a two-way error component model, with:

$$u_{it} = \mu_i + \lambda_t + v_{it} \tag{8}$$

where μ_i captures the unobservable individual time-invariant effect, λ_t represents the unobservable individual-invariant time effect and v_{it} is the remainder of the random disturbance term. Under the presence of the fixed effects, both μ_i and λ_t are assumed to be fixed parameters, while the remainder disturbance term v_{it} is assumed to be independent of the set of explanatory variables, CSP_{it} and X_{it}, for all i and t and $v_{it} \sim IID(0, \sigma_v^{\,2})$. Substituting (8) into (7) allows expressing the fixed effects explicitly in the model:

$$Risk_{it} = \alpha + \beta_{CSR}CSP_{it} + X_{it}^{'}\beta + \mu_i + \lambda_t + v_{it} \tag{9}$$

The model in (9) is estimated using FE estimator, which is based on an easy transformation of the data that consists of de-meaning the data (i.e., subtracting from each observation of each variable the average of all observations of that variable). Then, ordinary least squares, OLS, is implemented on these demeaned data to obtain the desired estimates. Furthermore, the FE model is a valid choice over pooling the data as long as the presence of the fixed effect hypothesis is not rejected. In this context, we test the null hypothesis of the joint significance of the fixed effects – both individual and time effects – using an *F*-test. Formally, we test the validity of model (9) against pooling the data by imposing the restrictions under the null hypothesis:

$H_0 : \mu_i = 0$ and $\lambda_t = 0$ for $i = 1, \ldots, N-1$; $\mathrm{t} = 1, \ldots, T-1$

The FE model is also an appropriate choice if the individual effects (and indeed the time effects) represent omitted variables, which are likely to be correlated with other regressors (Judson & Owen, 1999). Furthermore, if the data contain all firms of interest, and thus, will not likely be a random draw from much bigger population of firms, then the FE model is more appropriate (Baltagi, 2005; Judson & Owen, 1999). This, however, may not be satisfied in the case of our data and firms examined in this empirical work may well represent a random draw of a population. This led us to also examine the presence of random effects. In addition, the transformation implemented to estimate the FE model removes all time-invariant explanatory variables within an individual firm, which leads to failing to estimate the marginal effects of these variables.

The second way of allowing for different individual and time effects is utilising the RE model, which is designed to overcome the drawbacks of the FE model. The RE model is similar to FE in the way it accounts for different individual and time effects. The RE model, however, interprets these effects as randomly drawn from the set of all possible effects. Thus, the difference between the two models lies with the way the two-way error component in Eq. (8) is defined. While the error component under the FE model follows the structure defined by (9), the error component under the RE model assumes that $\mu_i \sim IID(0, \sigma_\mu^{\,2})$, $\lambda_t \sim IID(0, \sigma_\lambda^{\,2})$ and $v_{it} \sim IID(0, \sigma_v^{\,2})$ independent of each other. Furthermore, the set of explanatory variables is also assumed to be independent of μ_i, λ_t and v_{it} for all i and t. Although the RE model appears to produce a more efficient estimator of the panel data models than the FE model, the RE model may suffer from biases due to the fact that the individual effects – and their intercepts – are explicitly part of the error term, which may lead to correlation between set of explanatory variables and the error term. Thus, the RE model should only be used when the error component is uncorrelated with the set of explanatory variables. This latter can be tested using the Hausman test (Hausman, 1978), which suggests to use the RE model under the null, while the FE model under the alternative.

In summary, we estimate all three models: pooled panel model (using Pooled OLS), FE model and RE model. We first test for the poolability if the null of pooling the data is rejected, we then apply the Hausman test to assess the nature of the effect. The structure of the panel data at hand

[4] This does not produce conclusions that are qualitatively different from the case of stationary time series.

[5] Granger causality test is applied on CSP–Risk pairs of each firm separately.

is of the long-narrow nature. This implies the sample size, *T*, is larger than the number of firms, *N*. This type of panel data often suffers from serial correlation. Thus, we estimate pooled OLS model correcting for serial correlation and heteroscedasticity; the FE model is estimated using within estimator with AR(1) disturbances; while the RE model is estimated using Generalised Least Square (GLS) with AR(1) disturbances. Finally, we report Baltagi and Wu (1999) LBI test for serial correlation.

4. Data collection

4.1. Dependent variables

The original sample from Covalence covers 124 large UK companies from January 2002 to July 2018. For each company, ESG data is collected throughout the month and the final score *CSP* is calculated at the end of the month as the average across the different ESG categories:

$$CSP = (\text{Transversal} + ((\text{Governance} + \text{Economic} + \text{Environmental} + \text{Labour Practices and Decent Work} + \text{Human Rights} + \text{Society} + \text{Product Responsibility})/7))/2 \quad (10)$$

The final score includes a transversal performance which can be strongly influenced by one or a few widely-shared issues, initiatives or controversies that are found across categories and criteria; for example, a major accident with human, economic and environmental consequences, or a corporate initiative aiming at improving labour conditions, supporting local communities and stimulating economic development. The way the final score is calculated favours companies showing a diversified performance, i.e., in order to get a good CSP (closer to 100), a company must demonstrate solid credentials across all, or most dimensions. The data is unbalanced, i.e., not all 124 companies have an ESG score over the entire sample period (about ¼ of them start in 2002).

In order to compute systematic risk and idiosyncratic risk, stock returns and market returns were collected on a daily basis from 31/12/1999 (2 years before the start of our sample) until 31/07/2018. The FTSE All Share is used as proxy for the market portfolio. For each stock in our sample, total return index was collected as it represents the change in price with dividends reinvested. The risk-free rate is proxied by the 1-month UK T-bill yield. SMB was calculated as the difference in daily returns between the FTSE Small Cap and the FTSE 100; HML is the difference in daily returns between the MSCI UK Value and the MSCI UK Growth; all downloaded from Bloomberg. Once all financial data was matched with ESG data from Covalence, we end up with a total of 19,832 firm-months over 111 UK firms. However, in some cases missing values have led to smaller sample size. Therefore, for different control variables we end up with different number of observations.

Table 3 Panel A reports key descriptive statistics for our measures of financial risk: mean, standard deviation (SD), minimum (Min), maximum (Max) and number of observations (T). Total risk and systematic risk seem to be within reasonably short range – e.g., market beta ranges from −0.27 to +2.53 in the one-factor model, and from −0.91 to +2.96 in the three-factor model. Idiosyncratic risk has a wider range with wider length, with a standard deviation of 0.97 (0.83) for the one-factor (three-factor) model respectively. This is consistent with idiosyncratic risk being a source of volatility due to firm-specific characteristics. Table 3 Panel B reports descriptive statistics for our CSP and control variables. The mean of CSP is about 54, suggesting that corporate social performance is above average for all firms (ranging from 15 to 87) with a standard deviation of 0.12.

4.2. Control variables

In our panel data analysis, we control for firm characteristics that have been found to significantly impact the financial risk of individual firms. *PTBV* is the ratio of stock price to book value per share and is reported to impact the risk of the firm (Lewellen, 1999; Oikonomou et al., 2012). *Leverage* is the long-term debt divided by common equity and is used as a proxy for capital structure. A higher leverage means higher risk as a result of lower cash flows due to interest payments on existing borrowings (Benlemlih & Girerd-Potin, 2017). *Size* is calculated by taking the natural logarithm of market value and has been extensively used as a key control variable (Andersen & Dejoy, 2011; Jo & Na, 2012). Larger firms tend to be less risky than smaller companies (Oikonomou et al., 2012), and may have more funds available to invest in social and environmental projects (Margolis, Elfenbein, & Walsh, 2009). The age of the firm has been found to impact its risk (Ferreira & Laux, 2007; Sun & Cui, 2014). *Age* is measured by taking the natural logarithm of the number of months since incorporation as in Luo and Bhattacharya (2009). CF/*P* is measured by taking the inverse of price to cash flow ratio, following the same approach as Hou, Karolyi, and Kho (2011). The authors suggest that CF/P ratio is linked to covariance risk model. *ROE* measures the profitability of the firm for shareholders and is calculated by dividing net profit by shareholders' equity. A trade-off exists between profitability and risk, which is directly linked to shareholders' confidence (Benlemlih & Girerd-Potin, 2017; Ferreira & Laux, 2007). *Earnings before Interest and Tax (EBIT)* measures the firm's profit, including revenues and all expenses, apart from interest and taxation; therefore, it is directly linked to how a firm manages its operating activities and earnings (e.g. Dhaliwal et al., 2011; Prior, Surroca, Tribó, & A., 2008). *Dividend Dummy (DD)* equals 1 if a firm pays dividends and 0 otherwise. According to Luo and Bhattacharya (2009), dividend payments affect the way shareholders value a firm; i.e., higher dividend payout will attract more investors.

Our control variables also include industry and year dummies. On one side, different industries may have different approaches to corporate social responsibility, be subject to different levels of regulation, or be considered more or less environmentally friendly (Ferreira & Laux, 2007; Margolis et al., 2009). On the other side, it is important to control for time effects in order to capture any economic changes in accordance with previous studies (e.g. Benlemlih & Girerd-Potin, 2017; Chang et al., 2014). All data was collected from Datastream and available either monthly (PTBV, Size, Age) or annually (Leverage, CF/P, ROE, EBIT).

Descriptive statistics for our control variables can be found in Table 3 Panel B. Firms in our sample have an average *PTBV* of 9.13; mean *leverage* of 155.6% and mean *ROE* of 27.9%. The average firm value slowly increased over the years from a market capitalisation of about £8 billion in 2002 to a market value around £15 billion in 2018. The majority of firms did pay out dividends over our sample period, with an average *DD* equal to 0.91.

5. Empirical results

5.1. Granger causality

Table 4 shows the causality between CSP and different types of risks. Overall, there is very weak evidence of causality. We find that there is no causality reported (either way) between all types of risk and CSP in the majority of cases, that is 75%–85% of the time. Interestingly, these results are in contrast with previous findings (Benlemlih & Girerd-Potin, 2017; Chollet & Sandwidi, 2018). The absence of causality is more important (up to 85%) for systematic risk than for idiosyncratic risk (up to 78%), which is consistent with the idea that firm-specific risk matters

Table 3
(Panel A): Descriptive statistics for our measures of risk.

Variable (%)		Mean	SD	Min	Max	Observations	
Total Risk	Overall	2.092813	0.984727	0.7372	8.6855	*NT*	19,832
	Between		0.509323	1.151308	3.591742	*N*	111
	Within		0.861091	0.20699	7.692191	T-*bar*	179
1-factor Sys. Risk	Overall	99.4685	35.1612	−26.8191	253.4572	*NT*	19,832
	Between		27.56574	54.22623	188.8237	*N*	111
	Within		23.85114	−15.466	223.2059	T-*bar*	179
1-factor Idio. Risk	Overall	77.60176	96.98619	−152.739	1614.454	*NT*	19,832
	Between		59.80858	−43.9528	342.2252	*N*	111
	Within		76.16906	−193.82	1349.831	T-*bar*	179
3-factor Sys. Risk	Overall	109.6595	40.99497	−90.9469	296.2896	*NT*	19,832
	Between		31.27809	47.24965	205.766	*N*	111
	Within		27.34571	−43.4134	267.5178	T-*bar*	179
3-factor Idio. Risk	Overall	59.48131	82.97696	−161.855	558.4777	*NT*	19,832
	Between		51.90709	−66.0912	235.0105	*N*	111
	Within		64.66109	−148.234	386.1849	T-*bar*	179

NT: the overall sample size where *N* is the number of firms and *T-bar* is the average sample size of each firm.

(Panel B): Descriptive statistics for CSP and control variables

Variable		Mean	SD	Min	Max	Observations	
CSP	Overall	54.39444	11.84028	14.76855	87.49196	*NT*	19,832
	Between		8.929476	27.61583	78.45951	*N*	111
	Within		8.387748	18.65589	88.05663	*T-bar*	179
PTBV	Overall	9.132	124.321	0.02	6500.3	*NT*	19,832
	Between		44.502	0.815	468.849	*N*	111
	Within		115.235	−459.667	6040.583	*T-bar*	179
Leverage	Overall	155.553	470.693	0	10,080	*NT*	19,104
	Between		273.504	0	1629.081	*N*	111
	Within		405.056	−1314.848	8890.079	*T-bar*	172
Size	Overall	8.519	1.287	1.089	11.94	*NT*	19,832
	Between		1.135	5.983	11.557	*N*	111
	Within		0.566	3.288	10.937	*T-bar*	179
AGE	Overall	6.04	1.077	0	8.703	*NT*	19,373
	Between		1.061	3.292	8.686	*N*	111
	Within		0.333	1.734	7.022	*T-bar*	175
CF/P	Overall	10.156	76.366	−2516.88	767.05	*NT*	19,128
	Between		18.556	−159.85	57.914	*N*	111
	Within		73.908	−2346.874	937.056	*T-bar*	172
ROE	Overall	27.878	192.85	−143.56	7206.45	*NT*	18,920
	Between		66.815	−25.53	613.587	*N*	111
	Within		182.038	−671.369	6620.741	*T-bar*	170
EBIT	Overall	1,158,717	2,855,669	−32,800,000	30,700,000	*NT*	18,951
	Between		2,111,830	−595,253.3	12,000,000	*N*	110
	Within		1,960,172	−34,100,000	26,100,000	*T-bar*	172
DD	Overall	0.91	0.286	0	1	*NT*	19,832
	Between		0.217	0	1	*N*	111
	Within		0.196	−0.083	1.823	*T-bar*	179

NT: the overall sample size where *N* is the number of firms and *T-bar* is the average sample size of each firm.

Table 4
Results for Granger causality test.

	Total risk	1-factor systematic risk	3-factor systematic risk	1-factor idiosyncratic risk	3-factor idiosyncratic risk
No Causality	84 (75%)	95 (85%)	92 (82%)	85 (77%)	87 (78%)
CSP → Risk	14 (13%)	4 (4%)	3 (3%)	13 (11%)	11 (10%)
Risk → CSP	10 (9%)	8 (7%)	12 (11%)	8 (7%)	10 (9%)
Risk ↔ CSP	3 (3%)	4 (4%)	4 (4%)	5 (5%)	3 (3%)
	111	111	111	111	111

The values reported represent the number of firms for which the Granger causality tests returned no causality, unidirectional causality and bidirectional causality, respectively.

Table 5
Panel estimates.

	TR	1FSR	3FSR	1FIR	3FIR	TR	1FSR	3FSR	1FIR	3FIR
	Baseline Model					**Extended Model**				
POLS Model										
CSP	-.00972***	-.11986***	-.33115***	-1.23592***	-1.2069***	-.0015***	-.16535***	-.10943***	-.05758	-.16133***
PTBV						.76246***	9.47616***	-12.57734***	11.34754***	4.95961***
Leverage						.01439	.20825	-.20295	.21967	2.0804**
SIZE						-.1246***	5.3311***	-4.26456***	-33.79778***	-29.25982***
AGE						.04611***	4.73486***	5.86854***	-6.3159***	-5.98827***
CF/P						.11013***	.80938	-4.76045*	12.047***	13.26795***
ROE						-.14627***	-8.54775***	-8.73064***	3.94866***	4.34425***
EBIT						.00014***	-.00634***	-.00396***	.02206***	.00578***
DD						-.97913***	-24.32448***	-27.83518***	-39.51209***	-30.06552***
C	3.49493***	109.06453***	129.97435***	195.80276***	161.69492***	4.69264***	66.08013***	151.78024***	480.3465***	407.63618***
Obs.	19832	19832	19832	19832	19832	18273	18273	18273	18273	18273
R-sq.	0.50	0.10	0.07	0.26	0.29	0.63	0.18	0.15	0.43	0.47
F	546.19***	77.68***	72.22***	439.67***	460.10***	293.71***	117.76***	96.99***	487.27***	597.78***
FE Model										
CSP	.00116*	-.02358	-.02998	-.2344***	-.22277***	.00037	-.02479	-.03261	-.31537***	-.30433***
PTBV						.07744***	1.66148***	2.83029***	.54972	-3.83178**
Leverage						-.01003	-.19554	-.127	-.47898	-.46749
SIZE						-.11767***	.51574*	-1.32347***	.78991	-1.16927
AGE						.39243***	4.71956***	6.91789***	17.11746***	14.8306***
CF/P						.01981	-.44001	-.01617	1.61178	2.66873
ROE						.04834***	.4512	.21103	-1.44141	-1.23048
EBIT						.00006***	-.00016	-.00033	.00349**	.00123
DD						-.15249***	-1.67595***	-.11916	.63002	.94941
C	1.90047***	115.48193***	121.64442***	75.64927***	59.58751***	.81366***	80.62041***	89.83851***	-24.15284***	-9.48283***
Obs.	19721	19721	19721	19721	19721	18163	18163	18163	18163	18163
R-sq.	0.34	0.03	0.005	0.12	0.15	0.12	0.02	0.03	0.001	0.02
F/ Wald	95.39	1.58	1.58	15.16	21.36	96.49	2.69	2.35	8.64	13.15
F-FE	11.81***	2.83***	3.25***	5.15***	7.45***	14.00***	4.10***	4.20***	6.85***	9.39***
LBI	0.14	0.06	0.07	0.11	0.12	0.17	0.06	0.07	0.12	0.13

	TR	1FSR	3FSR	1FIR	3FIR	TR	1FSR	3FSR	1FIR	3FIR
	Baseline Model					**Extended Model**				
RE GLS Model										
CSP	-.00203***	-.02848	-.04036	-.39376***	-.37302***	-.00159**	-.02958	-.03992	-.42051***	-.41065***
PTBV						.08276***	1.69784***	2.87892***	.8924	-3.53105**
Leverage						-.00985	-.14264	-.07455	-.61454	-.54225
SIZE						-.13844***	.97418***	-1.20026***	-3.52758***	-4.63237***
AGE						-.04713***	3.23871***	2.79406**	-8.85735***	-8.54506***
CF/P						.01923	-.4984	-.07758	2.01967	3.00452
ROE						.03056*	.19061	-.1809	-1.61839	-1.58281
EBIT						.00006***	-.00019	-.00043	.00336**	.00113
DD						-.16599***	-1.8167***	-.39947	-.29692	.0987
C	2.96082***	126.96199***	134.47811***	140.66401***	111.47754***	4.49478***	101.87942***	129.10996***	222.39089***	201.52232***
Obs.	19832	19832	19832	19832	19832	18273	18273	18273	18273	18273
R-sq.	0.30	0.04	0.04	0.16	0.16	0.37	0.09	0.08	0.19	0.22
F/ Wald	1740.47***	43.69***	40.42**	343.65***	469.93***	2514.11***	103.6***	69.66***	401.31***	611.22***
LBI	0.14	0.06	0.07	0.11	0.12	0.17	0.06	0.07	0.12	0.13
H	NA	355.8***	58.8***	NA	630.8***	NA	168.0***	NA	215.4***	201.0***

This table presents the coefficients estimated from Eq. (9) using alternatively Pooled OLS, Fixed Effects and Random Effects. TR: Total Risk, 1FSR: One-factor model Systematic Risk, 3FSR: Three-factor model Systematic Risk, 1FIR: One-factor model Idiosyncratic Risk and 3FIR: Three-factor model Idiosyncratic Risk. Standard errors are robust to heteroskedasticity and serial correlation. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. F: the overall significance test statistic. F-FE: the poolability test (the null states that all fixed effects are jointly insignificant). H: the Hausman statistic (the null states the model follows RE). NA: the model failed to meet the asymptotic assumptions of the Hausman test. It returns a negative statistic (it can also be interpreted as failure to reject the null hypothesis). LBI: Baltagi and Wu (1999) test statistic (the null states that there is no serial correlation in the model). Time and Industry Dummies are included. For presentation purposes, some of the control variables are scaled as follows: PTBV, Leverage, CF/P and ROE are scaled by 1000, EBIT is scaled by 10,000. For each dependent variable, we have highlighted in grey the most suitable model estimation.

more than systematic risk in how companies manage their ESG efforts. For firms that do exhibit a causal relationship, there is very little evidence of a virtuous circle, as less than 5% of firms display a two-way causality. The Granger test for the remaining firms indicates a one-way causality, split equally between CSP ➔ risk and risk ➔ CSP in the case of the three-factor idiosyncratic risk.[6]

Our evidence strongly suggests that there is no causal relationship between CSP and financial risk. The lack of causality shows that CSP and risk are not driven by the dynamics of one another. In other words, a shock on either CSP or financial risk does not necessarily predict nor explain the shock on the other. Furthermore, the no causality conclusion implies there is no endogeneity. Our findings are unique as we have used monthly CSP data to perform the test, whereas previous published results (e.g. Benlemlih & Girerd-Potin, 2017; Chollet & Sandwidi, 2018) were based on annual data. This represents a milestone in the corporate finance literature as we refute the existence of a lagged relationship between CSP and firm risk (and for that matter, between CSP and firm performance). The two concepts do not lead one another and a model assuming a lead/lag relationship is thus misspecified.

5.2. Panel regression results

To test further the relationship between risk and CSP, we estimate three models: Pooled OLS (POLS), Fixed Effects (FE) and Random Effects (RE). For each we consider two specifications: baseline model and extended model. The baseline model refers to the simple panel regression where our measure of risk is regressed only on CSP. The extended version includes the set of control variables. Each column in Table 5 represents a different measure of risk as dependent variable: total risk (TR), one-factor systematic risk (1FSR), three-factor systematic risk (3FSR), one-factor idiosyncratic risk (1FIR) and three-factor idiosyncratic risk (3FIR). All estimated models report robust standard errors and allow for both time and industry dummies. In general, qualitative implications of the relationship between CSP and different types of risks are consistent across all model specifications, i.e., CSP is found to be negatively related to risk. However, the coefficient estimates and

[6] The test of Granger causality is conducted under two settings: assuming CSP and financial risk (i) to be stationary processes and (ii) to be integrated of order 1 processes. Wald statistics are calculated for each pair being tested. The critical values are simulated. The rejection of the null hypothesis is based on all levels of significance (1%, 5% and 10% levels). Detailed results are available upon request.

significance levels differ between POLS and FE/RE models so it is important to assess the suitability of each model. The poolability test (reported as F-FE under the FE Model) rejects the null hypothesis of pooling firms into one homogenous panel. In other words, the panel data suffers from heterogeneity and therefore individual specific effects – both time variant and invariant – need to be accounted for.

FE and RE models report very similar results for both systematic and idiosyncratic risk. On one side, the effect of CSP on systematic risk (1FSR and 3FSR) is found to be negative and statistically insignificant, consistent with *H4*. On the other side, the effect of CSP on firm-specific risk is negative and statistically significant at the 1% level for 1FIR and 3FIR. This is consistent with *H2* and the existence of a contemporaneous relationship between CSP and firm-specific risk. The Hausman test (denoted *H*) indicates that FE model is more appropriate than RE for most risk measures, namely 1FSR, 1FIR and 3FIR (in the extended version). According to the FE estimates, an increase in CSP by 1 point reduces systematic risk (1FSR) by around 2.5%; although the estimated effect is not statistically significant. Furthermore, a 1-unit increase in CSP is accompanied by a sharp fall in idiosyncratic risk by about 30% (both 1FIR and 3FIR) and statistically significant. It is worth noting that, according to the Hausman test, FE model is not appropriate for total risk (TR). Total risk is better explained using RE model, which reports a small but significant 0.2% fall in TR for every 1-point increase in CSP (under both baseline and extended specifications).

The LBI statistics is below the standard normal critical value at all levels of significance (e.g., 1.96 at 5% level). This indicates failing to reject the null of no serial correlation in all cases. F/ Wald statistics show that all specifications are jointly significant. In terms of control variables, some variables have more impact than others. For instance, *Age* is significantly and positively related to systematic risk and idiosyncratic risk (Luo & Bhattacharya, 2009). On the contrary, *Leverage* and CF/*P* do not seem to have a significant impact on risk.

To summarize, we find strong support for our hypotheses. On one side, idiosyncratic risk is strongly and negatively related to CSP, so that better corporate social performance is associated with lower firm-specific risk by as much as 30%. This result is consistent with previous studies showing a negative contemporaneous relationship between CSP and idiosyncratic risk (Benlemlih et al., 2018; Benlemlih & Girerd-Potin, 2017; Mishra & Modi, 2013; Sassen et al., 2016). On the other side, we do not find any significant relationship between CSP and systematic risk. Previous evidence here is mixed, and we support the idea that systematic risk is not important relative to firm-specific risk when companies manage their ESG efforts (Benlemlih et al., 2018; Sassen et al., 2016).

5.3. Robustness tests

Given that the originality and key contribution of the paper is the use of monthly ESG data, we test here whether our findings (i.e., the estimated effects of CSP on risk presented in Table 5) are driven by the monthly variations in CSP, or due to the unique structure by which the CSP measure is constructed (i.e., ESG score).[7] For this purpose, we construct an annual measure of CSP that updates on a given month each year. This value remains the same for the next eleven months. This implies, instead of observing CSP every month, we allow for it to remain constant for twelve months following the reported update on the given month. For example, if we suppose that the ESG score updates every December, then CSP_{Dec} would be the annual measure of CSP that occurs in December and for the next eleven months.

Constructing this measure this way has a number of empirical implications. On one side, if previous findings remain the same when using the annual measure of CSP (e.g., there is a negative and significant relationship between CSP and idiosyncratic risk), this implies that CSP as measured by ESG has a unique construct that makes it different from other annual CSP measures. It also implies that monthly variations are too small and negligible to cause any meaningful impact on monthly risk. On the other side, if findings change and lead to results that are different from those presented in Table 5, then ESG monthly variations are meaningful to explain monthly risk.

We estimate Eq. (9) using an annualised measure of CSP that updates at a given month in a year. In this context, the model is estimated using two alternative annual measures that update in *(i)* December (CSP_{Dec}) and *(ii)* January (CSP_{Jan}). Appendix 1 reports estimation output using CSP_{Dec}.[8] Under Pooled OLS, the effect of CSP_{Dec} on risk is similar to what is reported in Table 5. The Pooled OLS model is, however, rejected by the Poolability tests. Thus, firms are not homogeneous, and they shouldn't be pooled into one homogeneous block of panels. When accounting for heterogeneity (using both FE and RE), the findings suggest the absence of any statistically significant role of CSP in explaining monthly risk. In particular, the relationship between CSP and idiosyncratic risk is insignificantly different from zero, both economically and statistically. Since each firm's annual CSP is separated from one another, CSP observations are constant annually where one single value of CSP each year is matched against 12 monthly risk values. This is as if regressing a variable on a constant annually leading to a severe lack of variations. In addition, this will cause multicollinearity due to the presence of a constant (fixed effects and random effects) leading to incorrect signs and larger standard errors. As such, the statistical significance may not be achieved. In summary, the robustness check exercise suggests that higher frequency CSP data – or the monthly variations – are indeed relevant to inform monthly risk, and that research based on annual CSP measures is missing important information present in higher frequency data.

6. Conclusion

Using a unique dataset of monthly ESG scores, our paper makes a significant contribution to the literature investigating the link between corporate social performance (CSP) and financial risk. Where previous studies usually assume that causality runs from CSP to risk (presumably because of lack of higher frequency data), we formally test the direction of the relationship using robust Granger causality. Similar tests performed in the past using annual data have produced inconsistent results (Benlemlih & Girerd-Potin, 2017; Chollet & Sandwidi, 2018), hence the need to reconcile the evidence with the theory on corporate social responsibility (CSR). As a matter of fact, and contrary to previous evidence, our results strongly emphasize the lack of causality (either way) between CSP and financial risk, and this is true for all measures of market risk (total, systematic and idiosyncratic risk). In other words, a shock on either CSP or risk does not necessarily predict nor explain the shock on the other. This finding is in opposition with the mainstream theory of CSR – namely the stakeholder or good management theory. Indeed, the theory suggests that companies should engage in ESG activities (e.g., on carbon footprint, waste management and product safety) in order to reduce uncertainty (to minimise the likelihood of a lawsuit, a product recall, a strike, etc.), and as a consequence, decrease the firm's risk. In this paper we find that better CSP does not actually lead to lower risk. Beyond the theory, our result also has implications for past, present and future empirical research in the area, as it is wrong to model the CSP-risk relationship with an arbitrary one-period lag (whether monthly or annual). Empirical studies should use monthly data whenever possible and at least test for statistical causality in the first instance. Our recommendations are not limited to the CSP-risk literature, but also apply to research about the CSP-performance link.

[7] We thank an anonymous referee for proposing this robustness check, which offers better insights on the role of the frequency of the data in explaining our findings.

[8] Results using CSP_{Jan} reach similar conclusions and are available upon request.

Since the absence of causality does not equate to an absence of association, we also test for dependency between CSP and risk. We distinguish between systematic and idiosyncratic risk as their relationship to CSP is based on distinct theoretical arguments. Using various panel data estimation methods (POLS, FE and RE models), we find strong evidence of a significant and negative relationship between CSP and idiosyncratic risk. In other words, companies that perform better in terms of CSP also enjoy lower firm-specific risk. We emphasize the existence of a contemporaneous (rather than lagged) relationship. The absence of causality between the two implies that one doesn't lead the other, but instead they go hand in hand to assure the long-term success of the firm. In that vein, Benlemlih et al. (2018) argue that ESG disclosures can be seen as part of the overall business risk reduction strategy of a firm. Consistent with our hypothesis, we do not find any statistical dependency between CSP and systematic risk. The impact of CSP on systematic risk is negative but statistically insignificant. Overall, we argue that there is still a case for companies to engage in ESG activities although CSR should not be considered as a driver for lower risk.

This is the first paper to use monthly ESG data in the CSR literature, hence our results represent a milestone where extant evidence is widely mixed. Hopefully it is the first of many. We can only recommend future studies to use monthly CSP data to investigate the many intricacies of the CSP-risk (and CSP-performance) relationship. For instance, future research should look into the existence of other factors that help shape the relationship between social performance, financial performance and firm risk, consistent with the moderating or intermediary variables hypothesis (Waddock & Graves, 1997). Also, it will be useful to investigate the CSP-risk relationship through the various components of CSP (e.g., diversity, environment, governance), as both the direction of causality and the sign of the relationship tend to differ across the different CSP dimensions (Bouslah et al., 2013).

Appendix 1. Panel estimates using December ESG

	TR	1FSR	3FSR	1FIR	3FIR	TR	1FSR	3FSR	1FIR	3FIR
		Baseline Model					Extended Model			
					POLS Model					
CSP_{Dec}	-.00902***	-.10703***	-.32414***	-1.17614***	-1.17014***	-.00045	-.15013***	-.08875***	.04411	-.08077**
PTBV						.75488***	8.84664***	-13.18916***	11.73016***	5.22832***
Leverage						.01357	.10718	-.32827	.41687	2.01006**
SIZE						-.14148***	4.69303***	-4.90038***	-34.03921***	-29.634***
AGE						.05316***	5.0592***	6.24234***	-6.2493***	-5.88601***
CF/P						.11596***	.62515	-4.99667*	13.02822***	14.38772***
ROE						-.14482***	-8.56122***	-8.56311***	3.69346**	4.31652***
EBIT						.00018***	-.00495***	-.00282**	.02214***	.00598***
DD						-1.00044***	-25.02176***	-28.91962***	-40.31575***	-30.51106***
C	3.54914***	112.04725***	134.82207***	169.67656***	137.76532***	4.80592***	72.97969***	158.83709***	449.52719***	380.34006***
Obs.	17493	17493	17493	17493	17493	17493	17493	17493	17493	17493
R-squared	0.51	0.08	0.06	0.25	0.29	0.64	0.16	0.15	0.42	0.47
F	489.36	53.97	51.26	354.73	388.93	524.95	100.69	91.49	438.41	558.12
					FE Model					
CSP_{Dec}	.00186***	.00833	.00484	.07082	-.00605	.00121**	.00713	.00448	-.00192	-.08063
PTBV						.08123***	1.67279***	2.86109***	.63794	-3.73861**
Leverage						-.00918	-.1865	-.12519	-.55968	-.57793
SIZE						-.12252***	.22332	-1.91703***	.95561	-.98526
AGE						.40673***	4.83009***	6.96193***	16.01427***	14.7227***
CF/P						.02254	-.40118	.04543	1.60769	2.66253
ROE						.04786***	.45258	.23015	-1.44577	-1.20407
EBIT						.00006***	-.00013	-.00028	.00334**	.00113
DD						-.16954***	-1.68851***	-.14349	.62451	.93036
C	1.74853***	113.22944***	118.66414***	74.21241***	62.03421***	.62828***	80.88897***	92.281***	-22.66891***	-9.1203***
Obs.	17383	17383	17383	17383	17383	17383	17383	17383	17383	17383
R-squared	0.34	0.02	0.002	0.15	0.17	0.13	0.02	0.04	0.001	0.02
F/ Wald	92.72	1.84	1.36	8.47	13.63	105.30	2.50	2.60	8.46	13.35
F-FE	13.62***	3.50***	4.11***	4.21***	6.50***	15.65***	4.21***	4.25***	6.71***	9.43***
LBI	0.15	0.05	0.06	0.09	0.11	0.18	0.06	0.07	0.12	0.13
					RE GLS Model					
CSP_{Dec}	-.00043	.00583	-.00267	-.02278	-.09572	.00002	.00472	-.00076	-.05657	-.13779**
PTBV						.08675***	1.70841***	2.90308***	.9715	-3.46282**
Leverage						-.00895	-.12968	-.05313	-.65443	-.61389
SIZE						-.15352***	.78926***	-1.7462***	-3.58486***	-4.4335***
AGE						-.03801**	2.63653**	1.71912	-4.28717	-4.42166**
CF/P						.02144	-.47924	-.03346	2.05736	3.02914
ROE						.03115*	.18087	-.20058	-1.5383	-1.50325
EBIT						.00006***	-.00013	-.00035	.00325**	.00099
DD						-.17577***	-1.77154***	-.35277	-.93357	-.425
C	2.88605***	128.9244***	136.32277***	107.89215***	84.75297***	4.49162***	108.6286***	141.23424***	165.94387***	151.20093***
Obs.	17493	17493	17493	17493	17493	17493	17493	17493	17493	17493
R-squared	0.31	0.04	0.04	0.10	0.12	0.39	0.07	0.08	0.18	0.23
F/ Wald	1604.03***	47.26**	34.67*	202.40***	308.94***	2672.10***	86.61***	68.56***	292.30***	458.67***
LBI	0.15	0.05	0.06	0.09	0.11	0.18	0.06	0.07	0.12	0.13
H	NA	93.13***	NA	28.54**	NA	2072.44***	127.39***	NA	722.62***	337.72***

This table presents the coefficients estimated from Eq. (7) using alternatively Pooled OLS, Fixed Effects and Random Effects. TR: Total Risk, 1FSR: One-factor model Systematic Risk, 3FSR: Three-factor model Systematic Risk, 1FIR: One-factor model Idiosyncratic Risk and 3FIR: Three-factor model Idiosyncratic Risk. Standard errors are robust to heteroskedasticity and serial correlation. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. F: the overall significance test statistic. F-FE: the poolability test (the null states that all fixed effects are jointly insignificant). H: the Hausman statistic (the null states the model follows RE). NA: the model failed to meet the asymptotic assumptions of the Hausman test. It returns a negative statistic (it can also be interpreted as failure to reject the null hypothesis). LBI: Baltagi and Wu (1999) test statistic (the null states that there is no serial correlation in the model). Time and Industry Dummies are included. For presentation purposes, some of the control variables are scaled as follows: PTBV, Leverage, CF/P and ROE are scaled by 1000, EBIT is scaled by 10,000. For each dependent variable, we have highlighted in grey the most suitable model estimation. CSP is captured by CSP_{Dec}, which is measured by the value observed in December of the previous year

References

Aguilera, R. V., Rupp, D. E., Williams, C. A., & Ganapathi, J. (2007). Putting the S back in corporate social responsibility: A multilevel theory of social change in organizations. *Academy of Management Review, 32*(3), 836–863.

Albuquerque, R., Koskinen, Y., & Zhang, C. (2018). Corporate social responsibility and firm risk: Theory and empirical evidence. *Management Science, 65*(10), 4451–4469.

Alexandridis, G., Antypas, N., & Travlos, N. (2017). Value creation from M&as: New evidence. *Journal of Corporate Finance, 45*, 632–650.

Amel-Zadeh, A., & Serafeim, G. (2018). Why and how investors use ESG information: Evidence from a global survey. *Financial Analysts Journal, 74*, 87–103.

Andersen, M. L., & Dejoy, J. S. (2011). Corporate social and financial performance: The role of size, industry, risk, R&D and advertising expenses as control variables. *Business and Society Review, 116*, 237–256.

Baltagi, B. (2005). *Econometric analysis of panel data* (Third edition ed.). John Wiley & Sons.

Baltagi, B. H., & Wu, P. X. (1999). Unequally spaced panel data regressions with AR(1) disturbances. *Econometric Theory, 15*, 814–823.
Barnea, A., & Rubin, A. (2010). Corporate social responsibility as a conflict between shareholders. *Journal of Business Ethics, 97*, 71–86.
Becchetti, L., Ciciretti, R., & Hasan, I. (2015). Corporate social responsibility, stakeholder risk, and idiosyncratic volatility. *Journal of Corporate Finance, 35*, 297–309.
Benlemlih, M., & Girerd-Potin, I. (2017). Corporate social responsibility and firm financial risk reduction: On the moderating role of the legal environment. *Journal of Business Finance & Accounting, 44*, 1137–1166.
Benlemlih, M., Shaukat, A., Qiu, Y., & Trojanowski, G. (2018). Environmental and social disclosures and firm risk. *Journal of Business Ethics, 152*, 613–626.
Bird, R., Hall, A. D., Momentè, F., & Reggiani, F. (2007). What corporate social responsibility activities are valued by the market? *Journal of Business Ethics, 76*(2), 189–206.
Bouslah, K., Kryzanowski, L., & M'Zali, B. (2013). The impact of the dimensions of social performance on firm risk. *Journal of Banking & Finance, 37*, 1258–1273.
Bouslah, K., Kryzanowski, L., & M'Zali, B. (2018). Social performance and firm risk: Impact of the financial crisis. *Journal of Business Ethics, 149*, 643–669.
Boutin-Dufresne, F., & Savaria, P. (2004). Corporate social responsibility and financial risk. *The Journal of Investing, 13*, 57–66.
Brown, T. J., & Dacin, P. A. (1997). The company and the product: Corporate associations and consumer product responses. *Journal of Marketing, 61*(1), 68–84.
Carter, C. R. (2000). Ethical issues in international buyer–supplier relationships: A dyadic examination. *Journal of Operations Management, 18*(2), 191–208.
Chahine, S., Fang, Y., Hasan, I., & Mazboudi, M. (2019). Entrenchment through corporate social responsibility: Evidence from CEO network centrality. *International Review of Financial Analysis, 66*. in print.
Chang, K., Kim, I., & Li, Y. (2014). The heterogeneous impact of corporate social responsibility activities that target different stakeholders. *Journal of Business Ethics, 125*, 211–234.
Chatterji, A., & Levine, D. (2006). Breaking down the wall of codes: Evaluating non-financial performance measurement. *California Management Review, 48*, 29–51.
Chava, S. (2014). Environmental externalities and cost of capital. *Management Science, 60*(9), 2223–2247.
Cheng, B., Ioannou, I., & Serafeim, G. (2014). Corporate social responsibility and access to finance. *Strategic Management Journal, 35*, 1–23.
Cho, S. Y., Lee, C., & Pfeiffer, R. J., Jr. (2013). Corporate social responsibility performance and information asymmetry. *Journal of Accounting and Public Policy, 32*, 71–83.
Chollet, P., & Sandwidi, B. W. (2018). CSR engagement and financial risk: A virtuous circle? International evidence. *Global Finance Journal, 38*, 65–81.
Curran, M. M., & Moran, D. (2007). Impact of the FTSE4Good index on firm price: An event study. *Journal of Environmental Management, 82*, 529–537.
Dhaliwal, D. S., Li, O. Z., Tsang, A., & Yang, Y. G. (2011). Voluntary nonfinancial disclosure and the cost of equity capital: The initiation of corporate social responsibility reporting. *The Accounting Review, 86*, 59–100.
Donaldson, T., & Preston, L. E. (1995). The stakeholder theory of the corporation: Concepts, evidence, and implications. *Academy of Management Review, 20*, 65–91.
El Ghoul, S., Guedhami, O., Kwok, C. C., & Mishra, D. R. (2011). Does corporate social responsibility affect the cost of capital? *Journal of Banking & Finance, 35*(9), 2388–2406.
Fama, E. F., & French, K. R. (1993). Common risk factors in the returns on stocks and bonds. *Journal of Financial Economics, 33*, 3–56.
Farag, H., Meng, Q., & Mallin, C. (2015). The social, environmental and ethical performance of Chinese companies: Evidence from the Shanghai stock exchange. *International Review of Financial Analysis, 42*, 53–63.
Fatemi, A., Fooladi, I. J., & Wheeler, D. (2009). The relative valuation of socially responsible firms: An exploratory study. In *Finance for a better world* (pp. 140–167). Springer.
Ferreira, M. A., & Laux, P. A. (2007). Corporate governance, idiosyncratic risk, and information flow. *The Journal of Finance, 62*, 951–989.
Fornell, C., Mithas, S., Morgeson, F. V., III, & Krishnan, M. S. (2006). Customer satisfaction and stock prices: High returns, low risk. *Journal of Marketing, 70*, 3–14.
Freeman, R. E. (1984). *Stakeholder management: A strategic approach*. New York: Pitman.
Godfrey, P. C. (2005). The relationship between corporate philanthropy and shareholder wealth: A risk management perspective. *Academy of Management Review, 30*(4), 777–798.
Granger, C. W. J. (1969). Investigating causal relations by econometric models and cross-spectral methods. *Econometrica: Journal of the Econometric Society, 37*(3), 424–438.
Hacker, R. S., & Hatemi-J, A. (2006). Tests for causality between integrated variables using asymptotic and bootstrap distributions: Theory and application. *Applied Economics, 38*, 1489–1500.
Hacker, S., & Hatemi-J, A. (2012). A bootstrap test for causality with endogenous lag length choice: Theory and application in finance. *Journal of Economic Studies, 39*, 144–160.
Harjoto, M., & Laksmana, I. (2018). The impact of corporate social responsibility on risk taking and firm value. *Journal of Business Ethics, 151*, 353–373.
Harrison, J. S., & Wicks, A. C. (2013). Stakeholder theory, value, and firm performance. *Business Ethics Quarterly, 23*, 97–124.
Hatemi-J, A. (2003). A new method to choose optimal lag order in stable and unstable VAR models. *Applied Economics Letters, 10*, 135–137.
Hausman, J. A. (1978). Specification tests in econometrics. *Econometrica: Journal of the Econometric Society, 46*(6), 1251–1271.
Hou, K., Karolyi, G. A., & Kho, B. (2011). What factors drive global stock returns? *Review of Financial Studies, 24*, 2527–2574.
Hsu, F. J., & Chen, Y. (2015). Is a firm's financial risk associated with corporate social responsibility? *Management Decision, 53*, 2175–2199.
Huang, K., Sim, N., & Zhao, H. (2020). Corporate social responsibility, corporate financial performance and the confounding effects of economic fluctuations: A meta-analysis. *International Review of Financial Analysis, 70*. in print.
Humphrey, J. E., Lee, D. D., & Shen, Y. (2012). Does it cost to be sustainable? *Journal of Corporate Finance, 18*, 626–639.
Ioannou, I., & Serafeim, G. (2015). The impact of corporate social responsibility on investment recommendations: Analysts' perceptions and shifting institutional logics. *Strategic Management Journal, 36*, 1053–1081.
Jo, H., & Na, H. (2012). Does CSR reduce firm risk? Evidence from controversial industry sectors. *Journal of Business Ethics, 110*, 441–456.
Judson, R. A., & Owen, A. L. (1999). Estimating dynamic panel data models: A guide for macroeconomists. *Economics Letters, 65*, 9–15.
Kim, J. W. (2010). Assessing the long-term financial performance of ethical companies. *Journal of Targeting, Measurement and Analysis for Marketing, 18*, 199–208.
Krasnikov, A., Mishra, S., & Orozco, D. (2009). Evaluating the financial impact of branding using trademarks: A framework and empirical evidence. *Journal of Marketing, 73*(6), 154–166.
Lee, D. D., & Faff, R. W. (2009). Corporate sustainability performance and idiosyncratic risk: A global perspective. *Financial Review, 44*(2), 213–237.
Lewellen, J. (1999). The time-series relations among expected return, risk, and book-to-market. *Journal of Financial Economics, 54*, 5–43.
Lin, Y.-E., Li, Y.-W., Cheng, T. Y., & Lam, K. (2021). Corporate social responsibility and investment efficiency: Does business strategy matter? *International Review of Financial Analysis, 73*. in print.
Lins, K. V., Servaes, H., & Tamayo, A. (2017). Social capital, trust, and firm performance: The value of corporate social responsibility during the financial crisis. *Journal of Finance, 72*(4), 1785–1824.
Luo, X., & Bhattacharya, C. B. (2009). The debate over doing good: Corporate social performance, strategic marketing levers, and firm-idiosyncratic risk. *Journal of Marketing, 73*, 198–213.
Margolis, J. D., Elfenbein, H. A., & Walsh, J. P. (2009). *Does it pay to be good… and does it matter? A meta-analysis of the relationship between corporate social and financial performance*. SSRN paper series. https://doi.org/10.2139/ssrn.1866371.
McWilliams, A., & Siegel, D. (2001). Corporate social responsibility: A theory of the firm perspective. *Academy of Management Review, 26*, 117–127.
Mishra, S., & Modi, S. B. (2013). Positive and negative corporate social responsibility, financial leverage, and idiosyncratic risk. *Journal of Business Ethics, 117*, 431–448.
Modi, S. B., & Mishra, S. (2011). What drives financial performance–resource efficiency or resource slack?: Evidence from US based manufacturing firms from 1991 to 2006. *Journal of Operations Management, 29*(3), 254–273.
Nelling, E., & Webb, E. (2009). Corporate social responsibility and financial performance: The "virtuous circle" revisited. *Review of Quantitative Finance and Accounting, 32*, 197–209.
O'Hara, M. (2003). Presidential address: Liquidity and price discovery. *Journal of Finance, 58*(4), 1335–1354.
Oikonomou, I., Brooks, C., & Pavelin, S. (2012). The impact of corporate social performance on financial risk and utility: A longitudinal analysis. *Financial Management, 41*, 483–515.
Orlitzky, M. (2013). Corporate social responsibility, noise, and stock market volatility. *Academy of Management Perspectives, 27*, 238–254.
Orlitzky, M., & Benjamin, J. D. (2001). Corporate social performance and firm risk: A meta-analytic review. *Business & Society, 40*, 369–396.
Pastor, L., & Veronesi, P. (2003). Stock valuation and learning about profitability. *Journal of Finance, 58*, 1749–1789.
Pastor, L., & Veronesi, P. (2009). Learning in financial markets. *Annual Review of Financial Economics, 1*, 361–381.
Preston, L. E., & O'Bannon, D. P. (1997). The corporate social-financial performance relationship: A typology and analysis. *Business & Society, 36*, 419–429.
Prior, D., Surroca, J., Tribó, J., & A.. (2008). Are socially responsible managers really ethical? Exploring the relationship between earnings management and corporate social responsibility. *Corporate Governance: An International Review, 16*, 160–177.
Rajgopal, S., & Venkatachalam, M. (2011). Financial reporting quality and idiosyncratic return volatility. *Journal of Accounting and Economics, 51*, 1–20.
Salama, A., Anderson, K., & Toms, J. S. (2011). Does community and environmental responsibility affect firm risk? Evidence from UK panel data 1994–2006. *Business Ethics: A European Review, 20*, 192–204.

Sassen, R., Hinze, A., & Hardeck, I. (2016). Impact of ESG factors on firm risk in Europe. *Journal of Business Economics, 86*, 867–904.
Scholtens, B. (2008). A note on the interaction between corporate social responsibility and financial performance. *Ecological Economics, 68*, 46–55.
Sen, S., & Bhattacharya, C. B. (2001). Does doing good always lead to doing better? Consumer reactions to corporate social responsibility. *Journal of Marketing Research, 38*(2), 225–243.
Sharfman, M. P., & Fernando, C. S. (2008). Environmental risk management and the cost of capital. *Strategic Management Journal, 29*(6), 569–592.
Sun, W., & Cui, K. (2014). Linking corporate social responsibility to firm default risk. *European Management Journal, 32*, 275–287.
Toda, H. Y., & Yamamoto, T. (1995). Statistical inference in vector autoregressions with possibly integrated processes. *Journal of Econometrics, 66*, 225–250.
Ullmann, A. (1985). Data in search of a theory: A critical examination of the relationship among social performance, social disclosure, and economic performance. *Academy of Management Review, 10*, 540–577.
Waddock, S. A., & Graves, S. B. (1997). The corporate social performance–financial performance link. *Strategic Management Journal, 18*, 303–319.
Wang, Y., & Berens, G. (2015). The impact of four types of corporate social performance on reputation and financial performance. *Journal of Business Ethics, 131*, 337–359.