The effects of CSR on Risk Dynamics and Risk Predictability: A Value-At-Risk Perspective

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Abstract

This paper empirically examines the relationship between Corporate Social Responsibility (CSR) and financial risk by measuring the Value-at-Risk (VaR) of a sample of 1091 international stocks during the period 2007-2012. CSR data are extracted from the Vigeo social ratings while the VaR of individual stock returns is calculated using GARCH time series models to account for volatility over time. This approach not only allows investigating the relationship between CSR and the risk level of stock returns as in prior studies, but also enables measuring the impact of CSR on the risk dynamic of stock returns and risk predictability. In terms of the estimated risk characteristics, we conclude that good 'Corporate Governance' scores reduce the downside risk level (measured by VaR), dampen the effect of negative returns on volatility by reducing the leverage effect (for the 'Human Resources' and 'Community Involvement' dimensions) and by softening the volatility movements (for the 'Human Rights at workplaces' and 'Community Involvement' dimensions). In terms of risk predictability, we find a clear relationship between the 'Human Resources' dimension and the statistical quality of the prediction of stock return risk (measured by VaR) for short sales.

Keywords: Corporate Social Responsibility (CSR), GARCH, Predictability Risk, Times Series Models, Value-at-Risk (VaR).

JEL Classifications: A13, G11, G32

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Introduction

Numerous studies investigate the relationship between Corporate Social Responsibility (CSR) and company risk at both the theoretical and empirical level. Theoretically, due to better balancing the interests of the various stakeholders (Mishra and Modi, 2013), greater reputation (Godfrey et al., 2005) and less information asymmetry (Lahrech, 2011), companies with higher CSR standards should be less risky and more resilient in times of crisis. However, as the risk measures (total risk, systematic risk and idiosyncratic risk), methodologies (for instance, measures of the various dimensions of social responsibility) and samples are heterogeneous, extant empirical studies do not provide clear evidence of these claims. Nonetheless, such studies suggest a slightly negative relationship between CSR and financial risk measured as total risk (Jo and Na, 2012; Kim, 2010), idiosyncratic risk (Boutin-Dufresne and Savaria, 2004; Lee and Faff, 2009; Luo and Bhattacharya, 2009; Mishra and Modi, 2013; Bouslah et al., 2013) and systematic risk (Jo and Na, 2012; Luo and Bhattacharya, 2009; Kim, 2010).

Due to regulatory constraints (Basel 2-3) and equity optimization in banks, portfolio and risk managers use specific risk measures (namely, Value-at-Risk and Conditional Value-at-Risk measuring downside risk) but the effect of CSR on these measures has to date only been partially investigated (Benlemlih and Girerd-Potin, 2014). Moreover, the question of how CSR can improve the predictability of these measures remains unanswered. Contrary to prior studies on the relationship between CSR and company risk, empirical studies in financial risk management take into account the fact that risk is not constant in time. Moreover, they tend to account for several stylized facts (volatility clustering and leverage effect). Technically, risk measures are often predicted using an econometric times series model in the GARCH family, which enables investigating the effect of CSR on the time series properties of stock return volatility.

In the present paper, we not only investigate the relationship between social rating and market risk level but also the risk dynamics and the risk predictability to assert whether the social rating can be used as an additional indicator of risk. We measure market risk levels by Value-at-Risk (VaR) while the risk dynamics are given by the parameters of a GARCH model. We then measure market risk predictability by observing how well standard parametric VaR modelling predicts extreme returns. In terms of the estimated risk characteristics, we conclude that good 'Corporate Governance' scores reduce the downside risk level (measured by VaR), dampen the effect of negative returns on volatility by lessening the leverage effect (for the 'Human Resources' and 'Community Involvement' dimensions) and by softening the volatility movements (for the 'Human Rights at workplaces' and 'Community Involvement' dimensions). In terms of risk predictability, we find a clear relationship between the 'Human Resources' dimension and the statistical quality of the prediction of stock return risk (measured by VaR) for short sales.

These results have considerable theoretical and managerial implications. From a theoretical viewpoint, to the authors' knowledge, this paper is one of the first to investigate the CSR-risk relationship measured by VaR while also measuring the impact of CSR on the risk dynamics of stock returns and risk predictability using a large international sample and sophisticated econometric models. From a managerial viewpoint, this research provides portfolio managers with the possibility of considering good CSR practices (by dimensions) to enhance the quality of their prediction of VaR accuracy, reduce the 'risk-VaR' of their portfolios and the effect of negative returns on volatility while improving their capacity to soften the volatility movements of their portfolios.

The remainder of the paper is structured as follows. We first provide the theoretical foundations of the relationship between CSR and company risk and review the empirical evidence of this relationship (sections 2 and 3). We then introduce our sample and methods (section 4), present our empirical results (section 5) and end with our conclusions.

Theoretical Foundations of CSR and Company Risk

Some arguments developed in literature explain the relationship between social performance and financial risk (for a review, see Benlemlih and Girerd-Potin, 2014).

CSR commitment may have a positive impact on the relationship with stockholders and more generally with stakeholders. Stakeholder theory (Freeman, 1984; Cornell and Shapiro, 1987; Mishra and Modi, 2013) suggests that managers should balance the interests of shareholders, employees, customers and the community to ensure the organization's survival. Indeed, achieving the organization's objectives may depend on the interests of different stakeholders. CSR reduces the risk of losing the support of one or more stakeholders.

Moreover, by increasing social performance and meeting stakeholder expectations, companies preserve and develop their reputation. Reputation is an important intangible asset impacting firm value and producing potential tangible benefits (Barney, 1991; Fombrun, 1996; Little and Little, 2000; Godfrey et al., 2005). The impact of reputation on financial performance is mainly due to insulation from negative financial performance. Participating in some types of CSR activities leads to a form of goodwill or moral capital (Godfrey et al., 2005, 2009) that protect many of the firm's relationship-based intangible assets, providing shareholders with insurance-like protection and contributing to shareholder wealth. Firms will thus benefit from the lesser likelihood of legal actions resulting in financial penalties, more lenient regulatory controls, higher employee loyalty and stronger customer trust. The authors add that CSR activities can ease the negative measures of stakeholders in case of a negative event. This leads to avoiding punitive measures that could otherwise result in decisions that have a negative effect on stakeholder interests. According to Fombrun et al. (2000) "reputational capital safeguards the existing assets of the firm, serving as a buffer against losses".

High quality relationships with stakeholders have a positive effect on risk management by reducing uncertainty in the market place, creating controls that minimize or eliminate disruption, loss or damage to business operations, and reduce the impact of an undesirable event on the business (Kytle and Ruggie, 2005). More specifically, CSR adoption and compliance with environmental and social issues improve the firm's ability to control and reduce environmental and other risks such as damage to brand image, reputation and trust, consumer boycotts, high exposures to fines, penalties and punitive damages.

High social performance may also decrease the cost of capital especially in the presence of investors concerned about the social commitments of firms. Sharfman and Fernando (2008) and Hong and Kacperczyk (2009) affirm that socially responsible investors tend to exclude firms with low CSR levels from their portfolios since they consider socially irresponsible firms more risky. Less information asymmetry and high information quality in business decisions also have the effect of reducing the cost of capital (Lahrech, 2011).

Finally, environmental, social and governance (ESG) performance may in fact affect the risk profile of firms by adding a non-sustainability risk component in addition to market risk, size, book-to-market and other systemic risks documented theoretically and empirically (Manescu, 2011). Under this assumption, the expected returns of low-ESG firms are higher primarily due to carrying a premium for the non-sustainability risk. The ESG rating of a company could indicate its exposure to a non-sustainability risk factor. This risk factor may include environmental risk but also product and commercial-practice risks or those associated with workplace quality of life, litigation risk, investor trust and other intangible advantages (Boutin-Dufresne and Savaria, 2004; Becchetti and Ciciretti, 2006; Derwall and Verwijmeren, 2007).

Increased awareness of sustainability risk is thus expected to lead to a higher non-sustainability premium.

Empirical Evidence of CSR and Company Risk

This section presents a literature review of the impact of CSR on various measures of risk: total risk, systematic risk (rewarded by the market) and idiosyncratic risk (not rewarded by the market). We isolate the few studies on downside risk as these constitute the measures used in this paper.

Total, idiosyncratic and systematic risk

Some empirical studies examine the relationship between CSR and financial risk through components of total risk (measured by variance or standard deviation of stock returns), systematic risk (or market risk) or specific risk (or idiosyncratic risk).

Using a meta-analysis, Orlitzky and Benjamin (2001) reconsider various empirical studies addressing the link between social performance and financial risk in the US between 1978 and 1995. Their results support the existence of a negative relationship between these two variables. More recently, Jo and Na (2012) and Kim (2010) studied the relationship between CSR and firm total risk using KLD data in the American market. Jo and Na (2012) conclude that firm total risk is negatively related to CSR engagement. The reasons why empirical literature yields few significant relations between Socially Responsible Investment (SRI) and expected returns are noted and may be due to the aggregation of different dimensions that have contrasting effects (Scholtens and Zhou, 2008). This therefore requires investigating different dimensions of social responsibility. Kim's (2010) results illustrate this point: composite CSR measures show a positive effect while some individual components of CSR measured with the business ethics score show a negative effect on total firm risk.

In terms of idiosyncratic risk, the results of empirical studies do not provide clear evidence on the negative effect of CSR. Most studies find a negative relationship between CSR and firm idiosyncratic risk (Boutin-Dufresne and Savaria, 2004; Lee and Faff, 2009; Luo and Bhattacharya, 2009; Mishra and Modi, 2013; Bouslah et al., 2013), yet Humphrey et al. (2012) and Kim (2010) find no evidence. Finally, Bouslah et al. (2013) focus on individual components of social performance and find that idiosyncratic risk is negatively related to employee relations and human rights, while other CSR components do not affect financial risk. This study supports the notion that not all CSR dimensions are relevant in evaluating a company's risk.

CSR engagement also has an effect on systematic risk. Studies on the US markets (Jo and Na, 2012; Luo and Bhattacharya, 2009; Kim, 2010) find that corporate social performance is negatively related to systematic risk. However, Oikonomou et al. (2012) show that individual KLD[1] strength components are negatively but insignificantly related to systematic risk while three out of five individual social concerns (community, employment and environment) have a positive and significant effect. Salama et al. (2011), focusing on environmental responsibility using a sample of UK firms, find that the environmental performance of these firms is inversely related to systematic risk.

From a general viewpoint, extant literature suggests there is a slight negative relationship between CSR and the different measures of financial risk (stock volatility, idiosyncratic risk and systematic risk).

Downside risk

Few studies analyse the impact of CSR ratings on downside risk measures. Nofsinger and Varma (2014) show that SRI funds perform better during bear markets as their attributes dampen downside risk. Oikonomou et al. (2012) show no significant effect of CSR on financial risk when using the Bawa and Lindenberg beta downside risk measure, while their Harlow and

Rao beta results analysis shows a positive relationship between downside risk and some individual components of social irresponsibility (community concerns, employee relation concerns and environmental performance concerns). Benlemlih and Girerd-Potin (2014) use 'Value-at-Risk' (VaR) and 'Conditional VaR' (CVaR) measures of downside risk and find that portfolios with high social responsibility scores are less risky than portfolios with low social responsibility scores.

Sample and Methodology

Sample

The daily returns obtained from Datastream from 1 January 2000 until 31 December 2012 for all common shares with a Vigeo social rating[2] resulted in a sample of 1839 companies. The following filters were then applied:

- Datastream stocks with available prices
- Less than 5% missing data for each stock per year
- Stock with at least five consecutive years of data (a requirement for Value-at-Risk estimates).

The final sample consisted of 1091 eligible companies. Vigeo provides CSR scores for six dimensions for each company ('Environment', 'Corporate Governance', 'Human Rights at workplaces', 'Human Resources', 'Business Behaviour' and 'Community Involvement'). However, the average scores differ for each dimension. To deal with this problem, we transform the scores into one given dimension per company taking into account the average score of this dimension. Thus, each dimension score is transformed into a dummy variable taking the value of 1 if the corresponding score for a given company is above its specific dimension average and 0 otherwise. Indeed, due to the intrinsic differences in CSR practices across dimensions, it would seem more relevant to classify firms in terms of their best/worst behaviours than in absolute terms. This allows disentangling high or low-ranking companies across the dimensions. We then transform each continuous score into dummies variables. Table 1 provides the summary statistics for each of the original scores.

Table 1 – Summary statistics

Vigeo scores	Min	Max	Med	Mean	Std
HR	0	80	29	30.816	17.163
ENV	0	84.5	33	32.530	17.747
BB	4	82	42	41.377	12.998
CG	5	91	51	51.526	14.744
CIN	0	94	40	40.581	18.579
HRTS	4	91	41	41.965	13.923
MV	4.808	13.034	8.943	8.970	1.3179
DEBT (%)	3.689	20.513	14.804	14.785	2.134

This table summarizes the six Vigeo scores (Environment (ENV), Corporate Governance (CG), Human Rights at workplaces (HRTS), Human Resources (HR), Business Behaviour (BB) and Community Involvement (CIN). MV and Debt refer respectively to the 'log of market capitalization' and the 'ratio of debt over total assets'.

Value-At-Risk Methodology

We use the Value-at-Risk framework to assess stock market risk. In recent years, the tremendous growth in trading activity and the widely publicized trading losses of well-known financial institutions (for a brief history of these events, see Jorion, 2000) have led financial regulators and supervisory authorities to favour quantitative techniques that appraise the possible losses that these institutions may incur. Value-at-Risk has become one of the most widely used techniques as it provides a simple answer to the following question: with a given probability (say α), what is my predicted financial loss over a given time horizon? The answer is the VaR at level α, which gives an amount in the currency of the traded assets (in dollar terms for example) and is thus easily understandable. VaR has a simple statistical definition: the VaR at level α for a sample of returns is defined as the corresponding empirical quantile at α%. The quantile definition implies that with probability 1 -α the returns will be larger than the VaR. In other words, with probability 1 -α, the losses will be smaller than the dollar amount given by the VaR. From an empirical point of view, computing the VaR for a collection of returns thus requires computing the empirical quantile at level α of the distribution of the returns of the portfolio.

Formally, the conditional VaR (for a long position) can be defined as:

$$\Pr\left[r_t < -VaR_{t|t-1}(\alpha)\right] = \alpha\,, \qquad \forall\, t\ \in \mathbb{Z} \qquad (1)$$

In the present paper, we adopt an out-of-sample methodology to compute VaR, which entails an iterative procedure where forecasts are made as in 'real' conditions, meaning that the estimation part that calibrates the model does not include observations of the forecast period but is updated daily in the same way practitioners do. The estimation part is based on a minimum of four years of data regularly updated with the most recent days. This out-of-sample methodology is coupled with an update of the econometrical model every 50 trading days. Calibrated (to the data) models are used to predict one-day ahead the future mean and variance process allowing the authors to compute *ex-ante* the one-day ahead VaR (long and short positions).

The procedure can be summarized as follow:

(1) Starting with an initial sample of four years of data, for each series we calibrate the model and predict the following day's (t+1) conditional mean and variance process.

(2) Moving to one day ahead, we observe the realized value and compare this with the predicted value and store the result. We then add this day in the estimation sample and predict the following day's mean and variance values.

(3) We repeat the second step until we reach the end of the sample and update the model calibration (parameters are estimated via maximum likelihood estimation) every 50 days.

(4) We observe the number of violations for both the long and short positions and deduce the theoretical annual VaR based on the conditional mean and variance process. We then derive statistical significance for the quality of the VaR estimation. These results and the VaR parameters are stored annually per stock and used later on in the panel data analysis.

In addition to the standard long VaR computation, we also consider the short VaR. The long side of the daily VaR is defined as the VaR level for traders with long positions in the relevant stocks, which is the 'usual' VaR where traders incur losses when negative returns are observed. Correspondingly, the short side of the daily VaR is the VaR level for traders with short positions, i,e,, traders incurring losses when stock prices increase. The model's goodness at predicting long VaR thus relates to its ability to model large negative returns, while its performance regarding the short side of VaR is based on its ability to take into account large positive returns.

For the normal GARCH model, the VaR for long and short positions is given by:

$$\text{Long VaR:} \quad u_t + N_{\alpha,}\, \sigma_t \qquad (2)$$

$$\text{Short VaR:} \quad u_t - N_{1-\alpha,}\, \sigma_t \qquad (3)$$

where N_α ($N_{1-\alpha}\sigma_t$) is the left (right) quantile at α% for the normal and u_t and σ_t are respectively the conditional mean and conditional variance at time *t*.

Modelling the stock returns process

As presented in the previous section, the necessary elements to compute VaR are the volatility and mean of the returns process. We consider a collection of daily log returns (in %), $y_t = 100[log(p_t) - log(p_{t-1})]$ where $t = 1, \ldots T$ and p_t is the stock price at time *t*. We rely on the ARMA-GJR model (Glosten et al., 1993) to forecast the mean and variance process, The 'ARMA' part forecasts the conditional mean process (μ) while the 'GJR' part forecasts the conditional variance process (σ_t). The ARMA orders (*p*,*q*) are determined by minimizing the Akaike information criterion with *p*,*q*=0:1 (four combinations). Accordingly, the conditional mean process equation is:

$$\emptyset(L)y_t = u + \theta(B)\varepsilon_t \qquad (4)$$

where $\emptyset(L)$, $\theta(B)$ are polynomials in the lag operator of order p, q respectively, with all their roots lying outside the unit circle, and L is the lag operator.

To model the conditional variance process, we use the GJR Model (which allows modelling asymmetric volatility clustering). The conditional variance process is defined as:

$$\sigma_t^2 = w + \sum_{i=1}^{q}(\alpha_i^{GJR}\varepsilon_{t-i}^2 + \gamma_i^{GJR}\, S_{t-i}^{-}\varepsilon_{t-i}^2) + \sum_{j=1}^{p}(\beta_i^{GJR}\sigma_{t-j}^2) \quad (5)$$

where S_{t-i}^{-} is a dummy variable that takes t value 1 when ε_t is negative and 0 otherwise. This permits the effect of a shock ε_t^2 on the conditional variance σ_t^2 to differ when the shock on returns is positive or negative. This asymmetric effect in financial series is widely documented: volatility increases by a greater amount following negative shocks and is often associated with the 'leverage effect' whereby a firm's debt-to-equity ratio increases when equity values decline, and equity holders perceive the firm's future income streams as more risky (Black, 1976; Christie, 1982).

Evaluation of the quality of the VaR estimation

Our aim is to evaluate to which extent the VaR methodology accurately predicts extreme returns and whether this accuracy is linked to social ratings. We thus focus on so-called 'VaR violations'. A violation occurs when the returns are lower (higher) than VaR for the long position (short position). The expected number of violations depends on the confidence level, Let $I_t(\alpha)$ denote the exception variable associated with the ex-post observation of an α% VaR exception at time *t* for a long position case, $I_t(\alpha)$ is then defined as:

$$I_t(\alpha) = \begin{cases} 1 & if\ r_t < -VaR(\alpha)_{t|t-1} \\ & 0\ else \end{cases} \quad (6)$$

VaR forecasts are valid if and only if the violation process $I_t(\alpha)$ satisfies the Unconditional Coverage Property and the Independence Property (Christoffersen, 1998). We rely on the most distinguished Dynamic Quantile Test of Engle and Manganelli (2004) to jointly test whether these two conditions are satisfied, i.e., that the frequency of exceptions is consistent with the expected number of violations (Unconditional Coverage Property) and that violations are independently distributed (Independence Property). The Dynamic Quantile is based on a simple linear regression that links the violations to the lagged Hit. In our case, we include 5 lagged Hit variables (for technical details, see Dumitrescu et al., 2012). Formally, this test defines the Hit variable as follows (long position VaR):

$$Hit_t(\alpha) = I_t(\alpha) - \alpha \qquad (7)$$

The Hit variable takes values $1 - \alpha$ every time $r_t < -VaR$ and $-\alpha$ otherwise. We verify the Unconditional Coverage Property by testing whether the expected Hit value is equal to zero while the independence property is verified by observing the correlation of Hit sequence using a regression framework on its lag values. If the intercept and all coefficients are null then the Independence property is fulfilled. Engle and Manganelli (2004) show that, under the null hypothesis of adequate modelling, the Dynamic Quantile Statistic (see equation below) follows a Chi-Square distribution. The test statistic is given by:

$$DQ = \frac{\beta' X' X \beta}{\alpha(1-\alpha)} \sim \chi^2(k) \qquad (8)$$

where β is a vector composed of the regression coefficients, X is the explanatory variable matrix and k depends of the number of explanatory variables.

In the following, we present our two econometric panel data models. We use a static panel data model to assess the link between CSR and market risk characteristics, and a logistic panel model to evaluate the relation between CSR and market risk predictability.

Impact of CSR scores on market risk characteristics

Since the computation part is performed daily for individuals stocks while storing the results at the annual frequency, we obtain cross-sectional time series data. To unveil the relationship between market risk and CSR rating, we employ an (unbalanced) panel data model.

The static single equation model is given by:

$$y_{i,t} = X'_{i,t}\gamma + \delta_t + \eta_i + v_{i,t} \qquad (9)$$

where i denotes individuals and t denotes time, η_i and δ_t are respectively individual effects and time specific effects, $X_{i,t}$ is a vector of observations on k explanatory variables, γ is a k vector of unknown coefficients, η_i is assumed random and independent of $X_{i,t}$ and $v_{i,t}$. We include as explanatory variables the six Vigeo scores as well as two control variables (Market Capitalization, Debt Ratio) and country and year dummy variables to control for country and year specific effects. Since Vigeo scores cover large domains (Business, Environment and so forth), it appears reasonable to assume that the omitted variables are few and have small effects. We estimate the random effect panel model with the feasible GLS estimation method (Swamy and Arora, 1972). This method replaces the explanatory variables and the dependent variable by deviations from weighted time means. The weights are computed based on a parameter (λ) that depends on the relative size of the (estimated) variance of η_i relative to the variance of $v_{i,t}$ and is formally defined as:

$$\lambda = 1 - \left[\frac{\sigma_v^2}{\sigma_v^2 + T\sigma_\eta^2}\right]^{0,5} \qquad (10)$$

This transformation aims to eliminate serial correlation in the errors. This estimation method is flexible in the sense that it approximates in its limiting behaviour a fixed effect model when $\lambda = 1$or a Pooled OLS ($\lambda = 0$), σ_v^2 and σ_η^2 are derived from residuals obtained after running both 'within' and 'between' panel data models (for details, see Baltagi, 2005).

We consider the following dependent variables to evaluate the relationship between CSR and market risk:

- The empirical Value-at-Risk values
- The three parameters of the conditional variance: the asymmetric parameter of the GJR Model (the so-called 'leverage effect' parameter) and ARCH and GARCH parameters (respectively γ_i^{GJR} α_i^{GJR} and β_i^{GJR} of equation (2)).

To summarize, the equations model is formally stated as:

$$\mathrm{Y_{it,}} = \beta_1 * \mathrm{HR_{i,t}} + \beta_2 * \mathrm{ENV_{i,t}} + \beta_3 * \mathrm{BB_{i,t}} + \beta_4 * \mathrm{CG_{i,t}} + \beta_5 \mathrm{CIN_{i,t}} + \beta_6 * \mathrm{HRTS_{i,t}} + \beta_7 * \mathrm{MV_{i,t}} + \beta_8 * \mathrm{DEBT_{i,t}} + \mathrm{Year_t} + \mathrm{Countries_i} + \eta_i + v_{i,t}$$

$$i = 1{:}\,1091, N \quad t = 2007{:}\,2012 \qquad (11)$$

where $\mathrm{Year_t}$ and $\mathrm{Countries_i}$ are respectively time and country dummy variables, β_1 to β_6 are coefficients of the Vigeo scores dummy variables and β_7 and β_8 are control variable coefficients. The dependent variable Y successively takes the following five variables: the empirical Value at Risk for 1) Long and 2) Short position, 3) the Leverage coefficient β_i^{GJR}, 4) the ARCH β_i^{GJR} coefficient and 5) the GARCH parameters β_i^{GJR} of the conditional variance process.

Impact of CSR scores on market risk predictability

As previously stated, we use the DQT test to assess VaR accuracy as a proxy of market risk predictability. We therefore observe two scenarios: 1) either the DQT test accepts the null hypothesis of adequate VaR prediction, or 2) the VaR prediction fails and the model does not capture the return dynamics. We classify as successful whenever the null hypothesis of the DQT test of adequate modelling is accepted at a 5% confidence level. Thus, for each firm and each year, we obtain a time-series of a binary variable indicating success or failure regarding the VaR prediction. To evaluate the relationship between CSR and this VaR accuracy, we use a random-effects logistic regression. The dependent variable can take only two states: 0 for failure in predicting VaR or 1 for success in predicting VaR. The logistic model is therefore suitable. Formally the model is defined as:

$$\mathrm{P}(y_{i,t} \neq 0 \middle| X'_{i,t}) = X'_{i,t}\gamma + v_i$$

$$i = 1{:}\,1091 \; t = 2007{:}\,2012 \qquad (12)$$

where we assume a normal distribution $N(0, \sigma_v^2)$ for the random effects v_i, and $P(z) = \{1 + \exp(-z)\}^{-1}$. $X_{i,t}$ is a vector of observations on the explanatory variables and γ is a vector of unknown coefficients. The same explanatory variables as in the static panel case are included.

Empirical Results

CSR Scores and market risk predictability

The Panel data logistic regressions for the 'short' VaR are reported in Table 2 (the results regarding the long position VaR are not reported as none of the CSR Vigeo scores had a significant effect).

Three variables at the 0.1 level of confidence have a significant effect on the probability that the VaR methodology adequately predicts extreme variations for 'short' positions. Firm size (Market Capitalization) and HR scores show a significant positive coefficient of respectively 0.17(0.04) and 0.22(0.13). This indicates that the probability of a correct VaR prediction for a highly ranked company in terms of HR is 1.28 (e^0.2204=1.24) times greater than for low ranked companies. The positive and significant effect of the market capitalization variables also indicates that VaR accuracy increases with firm size. As expected, the debt ratio has a significant and negative coefficient indicating the higher the firm is financed by debt the worse the accuracy of the VaR prediction. Finally, to note is that good 'Corporate Governance' has an almost significant (p=0.106) positive effect on the quality of the VaR prediction and good 'Human Rights at workplaces' protection has an almost significant (p=0.104) negative effect on this quality.

Table 2 – Panel data logistic regressions results

Vigeo Scores	Coef.	Std. Err.	z	P>z
HR	0.220	0.133	1.66	0.096
ENV	0.0569	0.135	0.42	0.673
BB	0.080	0.127	0.63	0.527
CG	0.172	0.107	1.61	0.106
CIN	-0.155	0.124	-1.25	0.212
HRTS	-0.211	0.129	-1.63	0.104
MV	0.178	0.045	3.94	0.000
DEBT	-2.27e-09	7.35e-10	-3.09	0.002
Cst	-0.283	0.381	-0.74	0.457

Dependent variables: Dynamic Quantile Test: 1 if success, 0 if failure. Explanatory Variables: Human Resources (HR), Environment (ENV), Corporate Governance (CG), Community Involvement (CIN), Business Behaviour (BB), Human Rights at workplaces (HRTS), Market Capitalization (MV), Debt over total asset (DEBT).

CSR scores and market risk characteristics

Table 3 presents the results of the effect of the CSR scores on the VaR of long and short positions and on the parameters of the GJR GARCH model.

Table 3 – Panel data results - feasible generalized least squares

Vigeo Scores	Negative VaR	Positive VaR	GJR Parameters	ARCH Parameter	GARCH Parameter
HR	0.047 (0.067)	0.001 (0.066)	**-0.345* (0.204)**	-0.010 (0.140)	0.036 (0.352)
ENV	-0.012 (0.071)	0.011 (0.070)	0.332 (0.222)	-0.155 (0.154)	0.351 (0.378)
BB	0.063 (0.064)	-0.070(0.063)	-0.089 (0.196)	0.091 (0.135)	-0.150 (0.336)
CG	0.041 (0.062)	**-0.114* (0.062)**	**-0.419** (0.191)**	-0.095 (0.131)	**0.808** (0.328)**
CIN	-0.054 (0.061)	0.075 (0.060)	**-0.309* (0.185)**	-0.199 (0.127)	**0.597* (0.319)**
HRTS	-0.083 (0.064)	0.058 (0.063)	-0.036 (0.197)	**-0.308** (0.136)**	0.468 (0.339)
MV	**0.282*** (0.039)**	**-0.364*** (0.040)**	**0.604*** (0.153)**	-0.075 (0.119)	0.308 (0.233)
DEBT	**-0.000*** (0.000)**	**0.000*** (0.000)**	**0.000*** (0.000)**	0.000 (0.000)	-0.000 (0.000)
R2	0.608	0.570	0.167	0.237	0.105

Explanatory Variables :Human Resources (HR) , Environment: (ENV), Corporate Governance (CG),Community Involvement (CIN),Business Behaviour (BB), Human Rights (HRTS), Market Capitalization (MV), Debt over Total assets (DEBT). The year and group coefficients are not reported for more clarity. Standard errors are reported in parentheses. Negative VAR and Positive VAR are the value at risk level for long and short position.

Empirical value at risk - market risk

In terms of the Empirical Value at Risk, the 'Corporate Governance' (CG) score has a negative and significant coefficient on the level of positive VaR, reducing the value of positive extreme returns (CG coefficient: -0.114*(0.062)). The other Vigeo rates do not have an effect on the empirical VaR. This finding indicates that good ‘Corporate Governance’ practices tend to reduce market risk (reducing extreme variations). Market Capitalization tends to reduce market risk since it lowers positive VaR and increases negative VaR. Conversely, and as expected, the debt ratio increases market risk since it is positively related to extreme variation (increasing positive VaR and lowering negative VaR).

Asymmetric parameter

Regarding the asymmetric parameter of the GJR Model, we observe a negative and significant relation between this leverage effect and the ‘Human Resources’ (-0.345*(0.204)), ‘Corporate Governance’ (-0.419**(0.191)) and ‘Community Involvement’ scores (-0.309*(0.185)). This finding indicates that for highly ranked companies volatility increases less following negative shocks than for lower ranked companies. In other words, they have a lower asymmetric effect, which is a good signal of market risk. As predicted by theory, good CSR practices dampened the effect of negative returns on volatility.

GARCH parameter

Finally, regarding the conditional variance process, we observe that the ‘Corporate Governance’ (0.808** (0.328)) and the ‘Community Involvement’ (0.597*(0.319)) variables both have a positive and significant effect on the GARCH parameters, indicating higher persistence in the variance. Volatility is therefore more stable. Correspondingly, we observe a negative and significant coefficient for the HRTS variables (-0.308**(0.136)) indicating that highly ranked companies in terms of ‘Human Rights at workplaces’ have a variance process that is less affected by shocks than low ranked companies.

Discussion and Conclusion

This paper examines the relationship between CSR and financial risk (measured by VaR) in an international context. The originality of this paper is in simultaneously proposing a measure of risk (Value-at-Risk) with a measure of the impact of CSR on the risk dynamics of stock returns and risk predictability.

While extant 'CSR-Risk' related literature focuses on the measure of this relationship, it has thus far been silent on the effect of CSR on risk predictability and risk dynamics. Indeed, although knowledge on the relation between risk level and CSR is certainly valuable, risk managers tend to take this risk into account with tools such as VaR models. Therefore, in addition to measuring the level of risk, evaluating the relation between CSR and risk model characteristics and accuracy would also seem relevant.

We first find a relationship between the 'Human Resources' dimension (measured by Vigeo) and the statistical quality of the prediction of stock return risk (measured by VaR) for short sales. This reinforces the argument that social considerations allow more accurately anticipating and managing the social risk of a company and thus the financial risk through what Kurtz (2002) termed the 'information effect' (better control of environmental and social risks lead to better anticipating financial risk).

As a main contribution, we also find that 'Corporate Governance' appears to be the more relevant CSR dimension in relation to company risk as it has a clear significant and positive effect on the risk level and risk characteristics of companies. More specifically, this CSR dimension reduces the downside risk level (measured by VaR), dampens the effect of negative returns on volatility and softens volatility movements. These results thus confirm the importance of implementing corporate governance that reflects stockholder (and stakeholder) rights and expectations, controlling for risk and finally ensuring financial performance (Brown and Caylor, 2004; Core et al., 2006; Gompers et al., 2003; Hillman and Keim, 2001; Smith, 1996). Our results also confirm the influence wielded by shareholder activism and the interest this generates among investors (Core et al., 2006; Gompers et al., 2003). Furthermore, our results may also be supported by the fact that "bad governance can impose substantial ongoing costs on shareholders" and thus increase the company's risk (Core et al., 2006),

We find also that the 'Community Involvement' dimension (as the 'Human Resources' dimension) lessens the leverage effect by reducing the impact of negative returns on volatility with better absorption of volatility shocks (as the 'Human Rights at workplaces' dimension). Concerning the 'Community Involvement' dimension, our results are in line with Oikonomou et al.'s (2012) conclusions obtained through the KLD ratings and on idiosyncratic and downside risk (although in this case, there is a slight difference between the 'positive' relationship observed between risk and community concerns and our 'negative' link between risk and community good practices). Our results confirm that involvement of, and interest in, stakeholders through community reduces the company's risk. As Boutin-Dufresne and Savaria state (2004: p.60),

"… moreover, by its development in local communities through charity, for instance, the firm develops a better understanding of its market while at the same forging a sustainable relationship with its local stakeholders, thus possibly avoiding a commercial boycott in the future".

Concerning the 'Human Rights at workplaces' dimension (better absorption of volatility shocks), our results are in line with the results of Bouslah et al. (2013) on the systematic risk of companies and reinforced by Boutin-Dufresne and Savaria (2004: p.60) for whom, "the risks associated with the quality of life in the workplace at local and international levels are the loss of profitability resulting from, e.g., strikes, legal actions related to work safety, or sweat shop issues".

The theoretical and managerial implications of this research are multiple. From a theoretical viewpoint, our study confirms the results observed (negative relationship between CSR scores and risk) between CSR and total, specific and idiosyncratic risks, starting to bridge the gap in the sphere of 'CSR-downside risk' using the VaR approach. Our methodology based on the study of risk dynamics and predictability enables going beyond the single 'CSR-risk' measure to understand how CSR dimensions can absorb volatility shocks or dampen the impact of negative returns while considering the quality of the VaR prediction. From a managerial perspective, portfolio managers are encouraged to consider the CSR dimensions that could positively act on their risk management processes and predictability.

However, in terms of robustness, this study requires further evidence, Indeed, the issue of the influence of CSR on company risk remains central and decisive to answer issues about profitability or performance (and not the inverse), As MacGuire et al. (1988: p.868) state,

"… rather than looking for increased profitability from socially responsible actions, managers and those interested in the financial impact of social responsibility might look toward reduced risk. Since high risk must be balanced by high returns, firms with low social responsibility should earn high returns to justify the increased risk".

Better risk management always entails more profitability in the long term, yet the inverse is not always true. The lack of conclusions in this sphere and especially in risk management through downside risk requires future research to encourage and nourish this debate, testing other data, markets and periods, to provide practitioners with the ability to consider CSR practices in their risk management processes,

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Appendix 1

Vigeo Social Ratings

The Vigeo frame of reference has 38 generic criteria divided into 6 distinct domains:

1. Human Resources: constant improvement of professional and labour relations as well as working conditions.

2. Environment: protection, safeguarding, prevention of attacks on the environment, implementation of an adequate managerial strategy, ecodesign, protection of biodiversity and reasonable control of environmental impacts on the overall lifecycle of products and services.

3. Corporate Governance: efficiency and integrity, insuring the independence and effectiveness of the Board of Directors, effectiveness and efficiency of audit and control systems and particularly social responsibility risks, respect of shareholder rights and especially minorities, transparency and moderation in executive remuneration.

4. Community Involvement: effectiveness, managerial integration of commitment, contribution to economic and social development of the territories of establishment and their human communities, concrete commitment in favour of controlling the societal effects of products and services, transparent and participative contribution to causes of general interest.

5. Business Behaviour: taking into account clients' rights and interests, integrating social and environmental standards both in the selection of suppliers and in the overall supplying chain, efficient prevention of corruption and respect of competition laws.

6. Human Rights at Workplaces: respect of trade union freedom and promoting collective negotiation, non-discrimination and equality, eradication of banned working practices (child and forced labour), preventing inhumane or humiliating treatments such as sexual harassment, protecting private life and personal data.

More precise definitions of these criteria are available on the Vigeo website: http://www.vigeo.fr/.

ENDNOTES

[1] Kinder, Lydenberg, Domini Research & Analytics (today owned by MSCI ESG Research).
[2] Vigeo is the leading European social rating agency that measures the performances of companies in six social responsibility domains: Environment (ENV), Corporate Governance (CG), Human Rights at workplaces (HRTS), Human Resources (HR), Business Behavior (BB) and Community Involvement (CIN). Each of these domains has a rating from 0 for the least socially responsible firms to 100 for the most responsible firms. The different criteria evaluated by Vigeo to establish the social ratings are explained in Appendix 1. A merger between Vigeo and EIRIS (English social rating agency) was approved in October 2015 to form the Vigeo-EIRIS group.