How bad is your company? Measuring corporate wrongdoing beyond the magic of ESG metrics

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Abstract

Most earlier attempts to measure corporate wrongdoing rely on data and indexes sold by Environmental, Social and Governance (ESG) data providers. Developed for investors and market players, ESG data have been widely used in the academia, but so far very little research has been conducted to assess and overcome their limitations. In this paper, we take a first step into this direction and propose to use an M-quantile regression approach to develop an index of corporate wrongdoing, understood as firms' involvement in controversies over universal human rights. We apply our proposed methodology to a novel and unique hand-collected dataset of 380 large publicly-listed firms from both advanced and emerging economies, covering the period 2003-2012. We discuss the importance of these indexes for managers and practitioners.

Keywords: Corporate wrongdoing; Business and human rights; M-quantile regression; Index; ESG data.

THE SALIENCE OF MEASURING CORPORATE WRONGDOING

In early 2018, the Cambridge Analytica-Facebook scandal was high in the news after allegations that millions of the social network's users may have had their personal information harvested without their knowledge. This is just one of latest of a relatively long list of cases of corporate wrongdoing, where companies enact corrupt or illegal conducts causing noxious impacts on society, or violating some fundamental rights of certain constituencies. Volkswagen's violation in 2015 of the US Clean Air Act is another such case and the recent history of capitalism is punctuated by similar events – some of which have had catastrophic impacts on people's livelihood like the 1984 Union Carbide Limited's (now part of Dow Chemicals) major accident in Bhopal, India. Because of these events, corporate wrongdoing, which we define here as transgressions of international soft law instruments, like the International Bill of Human Rights (Nieri & Giuliani, 2018), became a topic of scholarly interest for both economists and management scholars already in the 1960-70s (e.g. Staw & Szwajkowski, 1975) and has recently gained momentum (Fiaschi, Giuliani, & Nieri, 2017; Palmer, Greenwood, & Smith-Crowe, 2016, among others).

Despite its salience, research and scholarly attention on measurement issues on corporate wrongdoing and related constructs such as corporate misconduct, deviant organizational practices or corporate social irresponsibility (CSIR) (for a review, see Nieri & Giuliani, 2018), has been so far scant (Greve, Palmer, & Pozner, 2010; Palmer, 2012). We fill this gap by proposing a new methodology to compute a firm-level index of corporate wrongdoing. Previous empirical studies have either used very narrow or issue-specific measures of corporate wrongdoing, which focus on only one dysfunctional dimension of the organization – such as the amount of toxic emissions (e.g. Chatterji & Toffel, 2010); bribing (see Martin, Cullen, & Johnson, 2007); financial fraud (see Shi, Connelly, & Sanders, 2016); wage arrears (e.g. Earle, Spicer, & Sabirianova Peter, 2010); or products recall due to safety issue for costumers (e.g. Zavyalova, Pfarrer, Reger, & Shapiro, 2012)

– or they have measured corporate wrongdoing using the scores developed by Environmental, Social and Governance (ESG) data providers, like MSCI KLD (formerly Kinder, Lydenberg, Domini Research and Analytics, and now known as MSCI ESG ratings) ‘concerns’ data (among many others, Keig, Brouthers, & Marshall, 2015; Muller & Kraussl, 2011; Strike, Gao, & Bansal, 2006), Sustainalytics scores (see Surroca, Tribo, & Zahra, 2013; Walker, Zhang, & Yu, 2016), or RepRisk ratings (e.g. Kölbel, Busch, & Jancso, 2017).

Given the growing relevance that investors and practitioners attach to the unsustainable conduct of companies (Flammer, 2013; Muller & Kraussl, 2011), ESG data providers compile these scores for industrial or financial use as they are useful to orient managers’ investments or collaborations decisions. However, although these ESG scores have been generally well received, there are numerous caveats and concerns around their elaboration and validity (Chatterji, Durand, Levine, & Touboul, 2016; De Felice, 2015).

To address these concerns, we claim that it is about time to start moving beyond existing measures of corporate wrongdoing, as a better measurement of this phenomenon is also likely to lead to improve the understanding of its causes and consequences. More specifically, the relevance of this issue is both practical and theoretical. From a practical perspective, evidence of corporate wrongdoing can give a sense of the magnitude of the phenomenon and allows managers, CEOs as well as regulators to work more effectively in preventing harmful events. Most of the earlier managerial rhetoric has been that of promoting sustainable practices by ‘doing good’ through corporate social responsibility (CSR) initiatives in the form of donations, community support or general endorsement of principle based-initiatives or industry-specific codes of conducts (Gilbert, Rasche, & Waddock, 2011). In contrast, far less emphasis has been put on the need to avoid ‘doing bad’, which is a challenging issue especially for companies whose operations stretch beyond national borders to institutionally weak countries (Donaldson, 1996). According to this, we reject the idea that a firm's failure to respect a negative duty (i.e. doing harm) can be compensated by a positive duty or action in favour of the affected or other constituencies (i.e. by being more socially responsible through the explicit adoption of CSR policies).

Having metrics about the extent to which companies enact wrongful conducts at home or abroad, would improve accountability and could put considerable pressure on the elaboration of doing-no harm strategies. Theoretically, improving measurement of this very important construct would allow to further understand the circumstances under which wrongdoing is more likely to manifest, along with studying its outcomes for firms and society at large. Consequently, it is necessary to discuss more in depth issues about the measurement of this phenomenon.

A CRITICAL REVIEW OF ESG METRICS

ESG data providers' measurements have become 'the de facto research standard' (Waddock, 2003) of the academic research aiming to study the positive and negative impact exerted by business operations on social and environmental issues. Although ESG data have been used mainly to measure firms' adoption of CSR policies or corporate social performance (CSP), which refers to the whole social and environmental conduct firms have undertaken, considering both their positive and negative impact (for more details about CSP, see Wood 2010), they have been increasingly used also to measure firm's involvement in wrongful business conducts (De Felice, 2015). Also, they have assumed a growing practical relevance for managers and investors who increasingly rely on these ratings to make strategic and investment decisions. In spite of being widely employed in academic research, these indexes have been rarely subject to external validation, while some recent studies have found poor consistence among the different indexes (see Chatterji et al., 2016). While a consistency test for corporate wrongdoing indexes is beyond the scope of this paper, we note that the convergence of these measures requires that the ESG data providers use (i) comparable or homogeneous corporate wrongdoing raw data and (ii) similar methodologies to derive indexes.

Unfortunately, these requirements are seldom met, which casts doubts on the meaningfulness of such validations. Rather, it seems that one more fruitful avenue of research is that of developing a new index that attempts to overcome the limitations of existing corporate wrongdoing raw data and indexes.

In this section, we carry out a critical assessment of the most widely used ESG data for measuring corporate wrongdoing along two dimensions. First, the characteristics and quality of the 'raw data', namely the basic information and material used to inform the construction of the corporate wrongdoing index – e.g. what type of information is used, whether and how it is subject to codification, how many issues are covered etc. Second, how the raw data have been used to construct corporate wrongdoing indexes.

Raw data on corporate wrongdoing

Regarding the characteristics of the raw data used by ESG data providers, we believe they suffer from at least one of the following main limitations:

- *Temporal inconsistency and lack of details of the concerns or controversies:* ESG scores do not always allow to identify when the wrongful business conduct has taken place (i.e. in which year(s)). One of the problems is that some of these scores are given on the basis of the year in which the alleged wrongful conduct has been discovered or sanctioned (i.e. via a fine, or a judicial process, etc.), which may differ from the year in which the wrongful conduct did actually take place. For instance, in the case of MSCI KLD, the controversy concerning 'Health and Safety concerns' is phrased as: 'the company recently has either *paid substantial fines or civil penalties* for wilful violations of employee health and safety standards, or *has been otherwise involved* in major health and safety controversies', which does not allow to disambiguate the year of occurrence of the wrongful event, from the year in which it was actually fined or sanctioned. This problem arises with reference to numerous other items. Only Sustainalytics' controversy reports provide more in-depth qualitative information on the controversies which means they can be used as raw data for identifying the wrongful conducts firms may be involved in, provided that their content is analysed and further validated.

- *Ad hoc and poorly transparent scoring of corporate involvement in wrongful business conduct.* Most ESG raw data is codified using proprietary methodologies, which often require the use of ad hoc loadings and weighting exercises, which depend on a wide array of dimensions also defined arbitrarily by the data providers. For instance, Sustainalytics offers a battery of 'controversy' indicators that are measured on a 0 to 100 scale, depending on the impact that the controversy is deemed to generate on both the impacted constituencies and the company's own operations, given by Sustainalytics' analysts and the way in which the analysts melt together all these criteria and come up with a number is not entirely transparent. MSCI KLD is more straightforward because it uses a dichotomous coding for each concern on a 'yes' or 'no' basis. This comes however at the cost of treating all concerns and all firms involved in at least one controversy as being equally serious.

Given these limitations, we propose that corporate wrongdoing's raw data, should seek to have two properties: (i) guardantee temporal consistency, which means that instances of wrongful business conduct should be codified according to the year(s) in which they allegedly occurred, rather than in the year(s) in which they were sanctioned or reported - unless these years coincide; (ii) corporate wrongdoing raw data should be subject to the least possible number of alterations via arbitrary and poorly transparent manipulations, as this may run the risk of artificially modifying the quality of the variables used to develop indexes of corporate wrongdoing.

Indexes on corporate wrongdoing

The scores attributed to each of the concerns or controversies' items can be used as an input to develop firm-level corporate wrongdoing indexes. Generally, the indexes developed in earlier research and practice can be classified as formative indexes. Formative measurement is relevant for dealing with corporate constructs, and formative indexes are conceived as 'explanatory combinations of indicators that are determined by a combination of variables' (Diamantopoulos & Winklhofer, 2001). Such constructs are measured by a latent variable that is a function of multiple variables, which reflect dimensions that are expected to contribute to the formation of the latent variable (i.e. the relevant organizational construct). In the case of corporate wrongdoing, these dimensions are captured by the different areas where firms may enact a wrongful conduct, spanning different operational areas or functions; involving different types of stakeholders (employees, indigenous communities, communities in general, clients, etc.) and, consequently, generating different types of impacts on the affected constituencies (violation of workers' rights, right to life, right to health, right to land, etc.) Therefore, unlike other types of indexes, these dimensions need not to be internally consistent – because some firms may do harm to certain stakeholders, but not to others – but all these dimensions need to be accounted for as omitting one of them, means omitting part of the construct.

ESG data providers sometimes elaborate their own indexes for managers, investors and practitioners at large (as in the case of Sustainalytics). In other cases, it is academic scholars who develop their indexes using ESG raw data – for instance, in the case of MSCI KLD data – by standardizing the sum of scores of the 'concerns' items (Keig et al., 2015; Muller & Kraussl, 2011; Strike et al., 2006, among many others). However, given the weaknesses of the raw data, and the sometimes arbitrary procedures with which these indexes are formed either by the ESG data providers or by scholars themselves, it has been hard to discern the validity of existing formative indexes.

A NEW APPROACH: MEASURING CORPORATE WRONGDOING THROUGH AN M-QUANTILE APPROACH

We suggest that an index of corporate wrongdoing should possess a set of characteristics. First, its elaboration should be transparent and replicable; second, it should be provided with a measure of reliability; and third it should, depeding on its intended use, be robust to a firm's (i) exposure to media scrutiny; (ii) scale and (iii) industry characteristics. The reason for focusing on media attention is that companies are differently exposed to the press and NGOs' scrutiny so that some firms' wrongdoing may be reported more frequently simply because they are more on the spotlight, not because they are more harmful than other firms. Existing measures of corporate wrongdoing tend to neglect this aspect, so that formative indexes summing up scores based on the number of concerns or controversies fail to account for the different firms' exposure to the media and the NGOs reporting work. Note that the different likelihood of firms to being reported as wrongdoers may well have a firm-specific motivation, as in the case of firms that happen to be more on the spotlight of the press, as well as being tied to the context where firms operate, because different countries and their governments may vary in the extent to which they allow the business sector to be scrutinized and held accountable for its wrongful conduct. Hence, both dimensions need to be taken into account as otherwise inter-firm comparisons across space would be invalid.

Additionally, existing indexes are often not scale-neutral, while accounting for the scale of firms' operation may be important because bigger firms may have more chances to be involved in wrongful conduct simply because of their size, not because they are necessarily more evil than smaller firms (Strike et al., 2006). Finally, because some sectors are by their very nature more bound to generate harmful impacts than others (see Giuliani & Macchi, 2014), indexes that consider this dimension can be important as well. Finally, similarly to the existing ESG scores, an index of corporate wrongdoing should assume values in a limited range, ideally in the [0,1] interval as to allow comparisons across firms and time for a given universe or sample of firms.

An M-quantile regression approach

In order to turn the raw data into a firm-level index of firms' involvement in wrongful business conduct addressing the limits of earlier indexes, we propose to use a M-quantile regression approach. M-quantile regression provides a 'quantile-like' generalization of regression (Breckling & Chambers, 1988). While the standard M-quantile regression requires continuous dependent variables, it becomes a challenge when we count on discrete dependent variables – as in our case, where the raw data for the calculation of the corporate wrongdoing index is y_{jt}, measured as the number of alleged wrongful event firm j is involved in at period t. Each event captures a different type of wrongful conduct in which the firm is involved in each year (e.g. if at time t, the firm is found abusing labor rights in one of its plants, and in the same year, there is evidence of it violating indigenous communities right to land, the corporate wrongdoing value for this particular firm at time t would be two). Each single event is counted yearly as one, whether it occurs in one particular year only, or extends across more than a year (e.g. a firm poisoning the environment and violating the right to health of local residents over several years). In this case, we count this multi-year event as one for each year in which it occurs. To account for the characteristics of the corporate wrongdoing variable, we assume that the response variable follows a Poisson distribution using the logarithm as link function. In particular, Tzavidis, Ranalli, Salvati, Dreassi, & Chambers (2015) propose the log-linear specification for count data:

$$MQ_y(\tau|\mathbf{x}_{jt};\psi) = k_{jt}\exp(\mathbf{x}_{jt}^T\boldsymbol{\beta}_\tau), \qquad (1)$$

where k_{jt} is an offset term, $\mathbf{x}_{jt}$ is the vector of covariates for firm j, $j = 1, \dots, n$, at time t, $t = 1, \dots, T$, $\boldsymbol{\beta}_\tau$ is the vector $p \times 1$ of regression coefficients and ψ is the appropriate influence function. To estimating $\boldsymbol{\beta}_\tau$, Tzavidis et al. (2015) consider extensions of the robust version of the estimating equations for GLMs by Cantoni and Ronchetti (2001) to the M-quantile case (for more details see Appendix 1). For each firm an M-quantile coefficient τ_{jt} is defined such that $y_{jt} = MQ_y(\tau|\mathbf{x}_{jt};\psi)$ and it takes values between 0 and 1; τ_{jt} indicates the quantile of the distribution of y_{jt} each firm is estimated to belong to, conditioned to the firm-level variables included in the M-quantile regression, which in our case, based on our earlier considerations include: (i) firms' media exposure and NGOs scrutiny, (ii) firms' scale, and (iii) firms' industry (hereinafter 'conditional variables'). In the limiting case where only the intercept is included in the regression, τ_{jt} indicates the quantile of the *observed* distribution of wrongful events a firm belongs to; for example, a value of τ_{jt}=0.9 for a firm indicates that the firm belongs to top 10% of the distribution of the reported controversies. We estimate a τ_{jt} for each firm and in each year included in our panel data, and consider both the whole time series of the corporate wrongdoing index, and its time average for each firm (the latter taken as an average behavior of the firm in the period): $\tau_j = \sum_{t=1}^{T} \tau_{jt}/T$.

In a bid to clarify our approach, we provide an illustrative simplified example. We denote by x the firms' conditional variables. A standard linear regression model can provide an estimate of the *expected* wrongful conduct of the firm conditioned to its conditional variables, i.e. $\hat{y} = E[y|x]$. In other words, $\hat{y}$ summarizes the *average wrongful business conduct* of y given x. Figure 1 reports the simplest case where it is considered only one firm's characteristics x, which positively affects the firms' involvement in wrongful conduct in a linear fashion. The bold line in the figure corresponds to the linear regression of y on x, i.e. in term of quantile regression to the $\tau = 0.5$-th quantile. We also report some of the estimated quantiles for each level of x (in particular $\tau \in \{0.1, 0.25, 0.5, 0.75, 0.9\}$). In each quantile we observe the same relationship between y and x (the slope of dashed lines are the same) but a different intercept. Firm A in the figure is involved in a lower number of wrongful conduct than firm B, but given x_A and x_B, the estimated quantile regression indicates that firm A belongs to $\tau = 0.9$-th quantile (i.e. to the 90% percentile of distribution of the wrongful behaviour), while firm B belongs to $\tau = 0.25$-th quantile. Therefore, the value of the corporate wrongdoing index for firm A will be 0.9 and equal to 0.25 for firm B. Hence, although firm B has a higher number of reported wrongful events than firm A, *conditioned* to firms' characteristics x, firm B turns out to have a lower value of the corporate wrongdoing index.

[Figure 1 about here]

The proposed M-quantile regression approach provides a corporate wrongdoing index that ranges from 0 to 1, respectively indicating the lower and upper boundaries of the wrongful business conduct. This means that (in relative terms) firms approaching an index of 1 are more wrongful than others at any given point in time.

This methodology provides a direct measure of reliability by calculating the confidence interval of the estimated corporate wrongdoing index. In particular, taken y_A in Figure 1 as the estimated index of firm A, its reliability is given by the confidence band (at a given significant statistical level) of this estimated value (for more details see Appendix 2).

Empirical Application: The raw data

To investigate the proposed issue we conceptualized corporate wrongdoing as firms' involvement in human rights infringements and we have developed a novel dataset (called BHR-FULL-2003-2012 dataset) that includes and codifies evidence on business-related human rights (BHRs) controversies involving a sample of 380 publicly listed firms, ranked by Forbes Global 2000 (2012 Edition), selected for being the largest public companies in their respective countries, and observed from 2003 to 2012. The dataset has global coverage including 245 firms from emerging economies (i.e. Brazil, China, India, Malaysia, Mexico, Russia, South Africa and Thailand) and 135 firms from advanced economies (i.e. U.S., Europe, Japan and South Korea). Both samples have been selected using a stratified sampling with equal allocation. The allocation is done by industry in the case of advanced country firms and by country of origin in the case of emerging country firms.

In line with previous studies (e.g. Fiaschi et al., 2017; Ruggie, 2008), we define BHRs controversies referring to the 1948 Universal Declaration of Human Rights and subsequent covenants and treaties. The focus on universal human rights as form of wrongful business conduct is justified by the global scope of the dataset, which set the need to identify a global institutional framework for what could be considered 'wrongful', thus leaving very little leeway for ad hoc interpretations of wrongful conduct (Wettstein, Giuliani, Santangelo, & Stahl, 2019). Moreover, it is all-encompassing and does therefore not focus on only one set of very narrow issues (Giuliani, Macchi, & Fiaschi, 2013). It covers a very wide spectrum of controversies, spanning from civil and political rights to socio-economic and cultural rights. It thus covers issues such as labor rights (e.g. child labor, labor discrimination, union busting, among others), violations of local indigenous communities' rights to land and to life, violations of right to health of communities or consumers, women's rights, children's rights, among others.

For each company in our dataset we have retrieved the BHRs controversies raw data primarily through the Business and Human Rights Resource Centre (BHRRC), which is widely used by international law scholars (Ruggie, 2008, among others). We used this information source to search for alleged BHRs controversies connected to the firms in our sample. This search included news and reports providing evidence of 'events' of negative human rights impacts. This data collection was started in 2011 and it has been updated and amended systematically through six years, and has been based on a scan and analysis of over 7,000 documents retrieved through the BHRRC. We have cross-checked BHRRC information through numerous sources, including

Sustainalytics controversy reports (for the subsample of emerging country firms) and KLD (for a subsample of U.S. firms) and by searching for secondary information directly to the source of the raw data, where available. We codified the information on individual BHRs controversies into our dataset as to ensure that our raw data have little risk of suffering from problems of temporal inconsistency and we do not have altered the records with ad hoc manipulations. We also cross checked our codification process via two external coders. Between 2003 and 2012 our dataset includes 1,078 controversies over 102 counties and 3,473 firm-year events. In bulding our dataset, we do not include events where the abuse manifestly is unrelated to firm-level decision making, nor events causing damages to the natural environment or animals, unless the evidence proves there to be a connection of the latter with some form of human rights abuse.

Following the M-quantile approach proposed above, as benchmark for the other types of corporate wrongdoing indexes, we calculate an index, denoted by *unconditioned index of corporate wrongdoing* (hereinafter *Uncond-CWi*), conditioning the number of BHRs controversies in which a firm is involved in each year only to a constant and *time dummies*. In addition, we propose three other indexes which differ for the conditional variables used for controlling the firms-level characteristics that may effect their involvement in BHRs controversies, in particular:

• *Firm's media exposure-conditioned corporate wrongdoing index* (*cMedia-CWi*): Media exposure variables should take into account that firms are not equally monitored by press organizations and NGOs. This index is suitable for analysts who are interested in a corporate wrongdoing index that is robust to the different firm-level exposures to the media and other means of communication. We measure media exposure following standard practice and using the: (i) information retrieved from Lexis Nexis (News section) and computed as the log of the ratio between the number of news items/articles mentioning firm j at time t, and the total number of articles mentioning any of our sample firms at time t (*Firm's Media Exposure*), in order to have a measure of the probability for firm *j* to be observed by the media, compared to the other firms in our sample (as in Fiaschi et al., 2017; Marquis & Qian, 2014); (ii) level of 'voice and accountability' of the firm's home country (based on the Worldwide Governance 'Voice and Accountability' Indicator) (*Home Country V&A*) (see Marano, Tashman, & Kostova, 2017), and (iii) the 'voice and accountability' of the host countries where the firm has foreign direct investments (FDI)) (*Host Countries V&A*), which have been retrieved from FDIMarkets, Zephyr and SDC Platinum (e.g. Keig et al., 2015; Surroca et al., 2013).

• *Firm's media exposure and scale-conditioned corporate wrongdoing index* (*cMediaScale-CWi*): besides the exposure to the media, we propose to condition the index to a 'scale effect', which is useful if one is interested in comparing the wrongful conduct of a company without being influenced by the scale of their operations. Following prior art (e.g. Fiaschi et al., 2017; Strike et al., 2006), we measure scale here considering (i) *Firm's Size*, which is proxied by the log of the number of employees in each year (Datastream), and (ii) *Firm's Internationalization*, measured as the number of different countries in which firm *j* is present with its FDI (in the form of greenfield, brownfield, majority, or full stake M&A) up to time t.

• *Firm's media, scale and industry-conditioned corporate wrongdoing index* (*cMediaScaleIndustry-CWi*), where we further condition our index to industry specificities. There are different ways in which industry specificity can be accounted for. In this paper, we use industry dummies by grouping firms according to the extent to which a given industry is more or less likely involved in wrongful events (see Giuliani & Macchi, 2014): the reference group (*Industry dummy I*) includes firms in the extractive (oil, mining and steel), tobacco, energy and water industries, the second group (*Industry dummy II*) includes retail, banking, insurance, optical, footwear and textile, chemicals and pharmaceuticals, and the third group (*Industry dummy III*) includes cosmetics, pulp and paper, aerospace, automotive, tires, heavy industry, telecommunications (TLC), food and beverages, electricity, electronics, computer services and software, real estate, tourism, health care, advertising, appliance.[1]

Empirical Application: The indexes

Table 1 (a) presents the descriptive statistics for our variables and the correlation matrix which reveals no multicollinearity issue. Table 1 (b) presents the results of the M-quantile regressions, where we generally find our conditional variables to be statististically significant (*Firm's Media Exposure* has a concave effect). We include in the regression model a dummy variable (*Dummy adv. countries*) to check whether there is a statistically significant difference between firms from advanced and emerging countries. Since its magnitude is in general very small, the pooling of firms from the set of two countries seems to be not problematic. The pseudo-R^2 (the values of a local relative measure of goodness-of-fit of the M-quantile regression model with respect to the null model at a specific τ), obtained extending the work by Bianchi, Fabrizi, Salvati, & Tzavidis (2018), at different τ show that all the conditional M-quantiles are equally successful in reduction variability, and this result allows us to obtain accurate estimates of the corporate wrongdoing indexes.

[Table 1 about here]

By estimating the M-quantile regression, we obtain an index of corporate wrongdoing for each firm in each of the observed years, i.e. we build an unbalanced panel of corporate wrongdoing indexes for the 380 firms in our sample covering the period 2003-2012. Taking the average firm-level value of the yearly corporate wrongdoing index for the observed period, in Figure 2 we compare the *UNCOND-CWi* with *cMedia-CWi* (Figure 2(a)), *cMediaScale-CWi* (Figure 2(b)), and *cMediaScaleIndustry-CWi* (Figure 2(c)).

[1] The use of logarithmic transformations for some of our variables is justified by their different metric compared to that of the other variables considered (Wooldridge, 2015).

[Figure 2 about here]

Observations below the diagonal correspond to firms whose conditioned index is higher than their unconditioned one, while the reverse holds for observations above the diagonal. The more we increase the number of conditional variables, the higher the difference is. Since all the conditional variables have a significant impact on the indexes (see Table 1(b)), this result was expected. Therefore, these figures show that there is a significant difference between the unconditional and conditional values of the corporate wrongdoing indexes.

Indexes reliability

To assess the reliablity of the indexes we apply a block bootstrap procedure (Chambers, Salvati, & Tzavidis, 2016; see Appendix 2). We focus here on *cMediaScaleIndustry-CWi* and report in Figure 3 the value of the average index for the period of observation (2003-2012) and for all firms in our sample, ranked in increasing order according to their index value. The 95% confidence band is a measure of its reliability, because it shows the range of variability of the index for each firm in the period considered, and helps assessing the differences potentially existing across firms based on their index values. We find that firm-level index values lower than 0.2 are not statistically different from 0 at the 5% significance level. This implies that all firms with a *cMediaScaleIndustry-CWi* lower than 0.2 should be equally considered among the least wrongful firms in the sample. On the contrary, a value of the index above 0.8 is not statistically different from 1 at the 5% significance level, which implies that these firms should be equally considered among the most wrongful firms in the sample. Values of the index between 0.2 and 0.8 indicate different degrees of involvement in wrongful conducts, demonstrating a certain variability in the extent to which our sample of firms engage in corporate wrongdoing.

[Figure 3 about here]

Indexes dynamics

Through Markov transition matrices we can analyse the dynamics of the indexes over time. In this exercise we split our observations into three groups: 'the innocents', i.e. a first range corresponding to the group of least wrongful firms (i.e their index is in the range [0,0.2)); the 'evils', i.e. a group including the most wrongful firms (i.e. their index is in the range [0.8,1]) and the 'undecided' – i.e. a third group of average wrongful firms whose index is in the range [0.2,0.8)). Table 2 presents the Markov transition matrices with one-year lag for the three types of conditioned indexes, i.e. the probabilities of moving from one of the three groups among those defined above (reported in the first column 'innocents', 'undecided' and 'evil' and the raws). All three Markov matrices display a very high persistence at the extremes, that is, among the 'innocents' (90% is persistent) and the 'evils' (above 70% is persistent). In contrast the 'undecided' display higher inter-group mobility (ranging approximately from 10 to 30 per cent). To illustrate these patterns, Figure 4 shows the time trend of the *cMediaScaleIndustry-CWi* index for three firms covered in our sample. According to our records, Wal-Mart Stores Inc. turns out to fall among the 'evil' firms for its persistent track record of involvement in several BHRs controversies, while Ineos is among the 'innocents' and Shell Oil among the 'undecided' for its more pronounced fluctuations over the observed period.[2]

[Table 2 about here]

[Figure 4 about here]

Further development of the raw data and the indexes

In our empirical application, we considered all BHRs controversies as being equally serious and thus coded them all as 1. However, our methodology is very flexible and our raw data allow for different operationalizations of our indexes. One further development would be that of weighting the wrongful events on the basis of their salience, that is, on the extent to which they are at risk of

[2] More details about these companies' controversies are available upon request by the authors.

generating the most severe negative impacts on human rights, as defined by the UN Guiding Principles on Business and Human Rights (Ruggie, 2011). Alternatively, wrongful events could be classified according to the *derogable* or *non derogable* nature of the human rights abuse, following an international law perspective where abuses of non derogable rights include all wrongful conducts leading to or implying arbitrary deprivation of life, torture, slavery, child labour and forced labour, while abuses of derogable human rights would include less severe events such as e.g. discrimination at work; violations of the right to health, union busting, among many others (see Giuliani et al., 2013 for a discussion on this distinction). In principle therefore, we could weight these events differently, or measure separate indexes for different types of abuses, and we could also consider the firms' different degrees of involvement in the controversies, depending on whether they are directly attributable to a firm's operations or indirectly attributed to it through complicity with third-party actors such as clients, suppliers or even governments. Finally, while our focus here is on human rights, our methodological approach could be extended to incorporate other wrongful events, including damages to the natural environment, to animals, evidence of tax evasion and bribery, and possibly also account for the action taken by firms to minimize such harmful impacts (on this see e.g., the Corporate Human Rights Benchmark by the BHRRC).

IMPLICATIONS FOR PRACTICE

The growing evidence about firms' involvement in wrongful business conduct, as reflected by the infringement of universally defined human rights, is increasing the exposure of companies to BHR-related risks (Nersessian, 2018). In parallel, this is calling for more accountability and for better measurement of the harmful impacts companies generate on the society and the environment in the form of human rights controversies. While the scholarly debate about how to measure these bad impacts is still incipient (see Chatterji et al., 2016; De Felice, 2015), we provide a replicable and transparent methodology which we apply to a novel hand-collected longitudinal dataset. For the purpose of this work, we have refrained from listing companies by name according to how wrongful they appear to be, but it is apparent that this kind of information can be used to rank companies and inform managers and CEOs about their harmful impacts. Notably, our index could be superior to existing CSP metrics, because it signals companies that do harm, irrespective of how much good they do through their meritorious CSR-related projects and initiatives. Ultimately, the power of our proposed metrics would be that of prompting wrongful companies to shift their CSR focus from doing good, to doing no harm, and to take more seriously the prevention, avoidance and mitigation of their direct or indirect harmful impacts on humanity and the environment.

In so doing, however, we need not be naïve about the practical implications of our indexes, because the eradication of a human rights harm may have unintended consequences on the enjoyment of other rights. Detractors of the universal human rights approach, for instance, would argue that, in some contexts, the elimination of any form of child labour may severely undermine the economic right to subsistence of many families, while the reduction of pulluting emissions from a plant may come with a downsizing of production activities and employment, thus also causing negative consequences on people's right to work. Discussing these trade offs is beyond the scope of this article. However, we maintain here that the unintended consequences of the eradication of one kind human rights abuse are not a good enough motivation for allowing the perpetration of the abuse. Rather, we maintain that these negative consequences should be addressed and remedied to the extent possible. For this reason, we think that improving their measurement is key to spot these potential trade-offs and take action to ensure that they are mitigated or addressed.

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TABLES

Table 1(a). Descriptive statistics and correlation matrix

	Min	Max	Mean	S.d.	1	2	3	4	5	6	7	8
1.BHRs controversies	0.00	21.00	0.67	1.70								
2.Firm's media exposure	0.00	1.74	0.05	0.15	0.28							
3.Home country V&A	-1.68	1.81	0.22	1.07	0.20	0.04						
4.Host countries V&A	0.00	5.03	2.67	1.72	0.17	0.13	0.36					
5.Firm's size	0.33	23.68	10.34	1.53	0.32	0.26	0.20	0.38				
6.Firm's internationalization	0.00	74.00	7.72	10.69	0.34	0.31	0.43	0.42	0.49			
7.Industry dummy I	0.00	1.00	0.20	0.40	0.11	0.10	-0.10	-0.01	-0.03	-0.04		
8.Industry dummy II	0.00	1.00	0.30	0.46	0.03	-0.05	0.04	0.04	-0.02	0.01	.0.32	
9.Industry dummy III	0.00	1.00	0.49	0.50	-0.10	-0.03	0.02	0.01	0.07	0.04	-0.49	-0.64

Table 1(b). Results of M-Quantile regression model

	$\tau =$ 0.10		$\tau =$ 0.25		$\tau =$ 0.50		$\tau =$ 0.75		$\tau =$ 0.90	
	Estimate	*p-value*	*Estimate*	*p-value*	*Estimate*	*p-value*	*Estimate*	*p-value*	*Estimate*	*p-value*
Intercept	-7.34	0.00	-5.80	0.00	-4.75	0.00	-3.86	0.00	-3.31	0.00
Firm's media exposure	8.73	0.00	7.02	0.00	5.35	0.00	4.00	0.00	3.16	0.00
Firm's media exposure^2	-5.67	0.00	-4.91	0.00	-3.98	0.00	-3.02	0.00	-2.38	0.00
Home country V&A	0.65	0.01	0.44	0.00	0.40	0.00	0.31	0.00	0.23	0.00
Host countries V&A	0.29	0.01	0.25	0.00	0.16	0.00	0.08	0.00	0.04	0.03
Firm's size	0.20	0.00	0.23	0.00	0.29	0.00	0.32	0.00	0.34	0.00
Firm's internationalization	0.86	0.10	0.88	0.01	0.69	0.00	0.74	0.00	0.86	0.00
Industry dummy II	-0.40	0.06	-0.70	0.00	-0.78	0.00	-0.67	0.00	-0.47	0.00
Industry dummy III	-1.00	0.00	-1.16	0.00	-1.14	0.00	-0.98	0.00	-0.83	0.00
Dummy adv. Countries	0.83	0.04	0.76	0.00	0.49	0.00	0.28	0.00	0.15	0.04
pseudo-R^2	0.27		0.46		0.46		0.42		0.40	

Table 2. Markov transition matrix with one-year lag

	cMedia-CWI			cMediaScale-CWi			cMediaScaleIndustry-CWi		
	Innocent	**Undecided**	**Evil**	**Innocent**	**Undecided**	**Evil**	**Innocent**	**Undecided**	**Evil**
Innocent [0-0.20)	0.92	0.04	0.04	0.92	0.05	0.04	0.91	0.05	0.04
Undecided [0.20-0.80)	0.27	0.58	0.15	0.26	0.60	0.14	0.19	0.71	0.10
Evil [0.80-1]	0.13	0.12	0.75	0.12	0.13	0.75	0.11	0.17	0.72

FIGURES

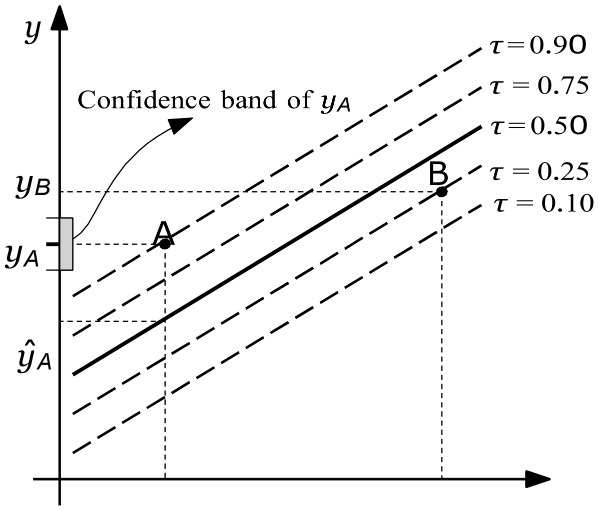

Figure 1. Illustrative example of a corporate wrongdoing index estimated by an M-quantile regression.

Note: This example considers only one conditional variable x. Source:Authors' own elaboration.

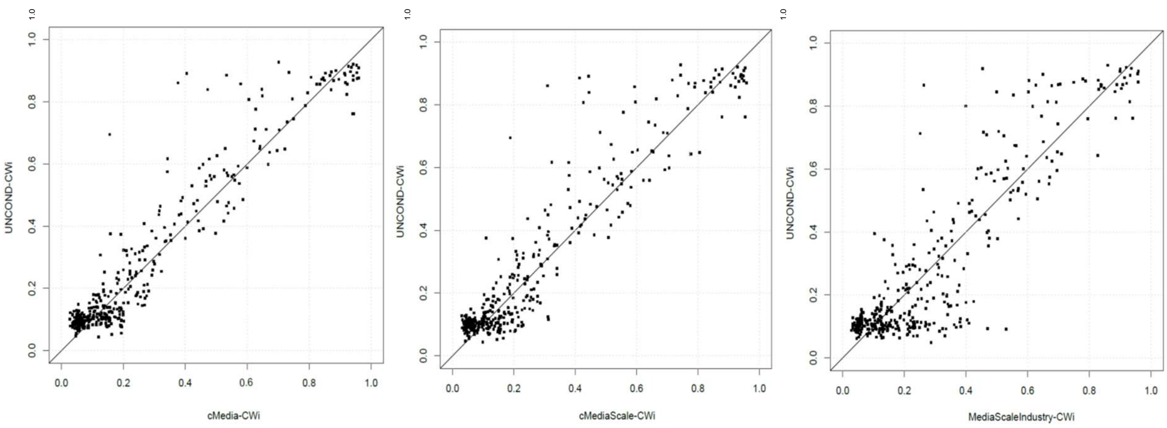

Figure 2. Comparison between the unconditioned index and the three conditioned indexes.

Note that Figure 2(a) compares the unconditioned index (UNCOND-CWi) with the media exposure-conditioned index (cMedia-CWi); Figure 2(b) compares the unconditioned index (UNCOND-CWi) with the media exposure and scale-conditioned index (cMediaScale-CWi); Figure 2(c) compares the unconditioned index (UNCOND-CWi) with the Media exposure, scale and industry-conditioned index (cMediaScaleIndustry-CWi).

Source:Authors' own elaborations.

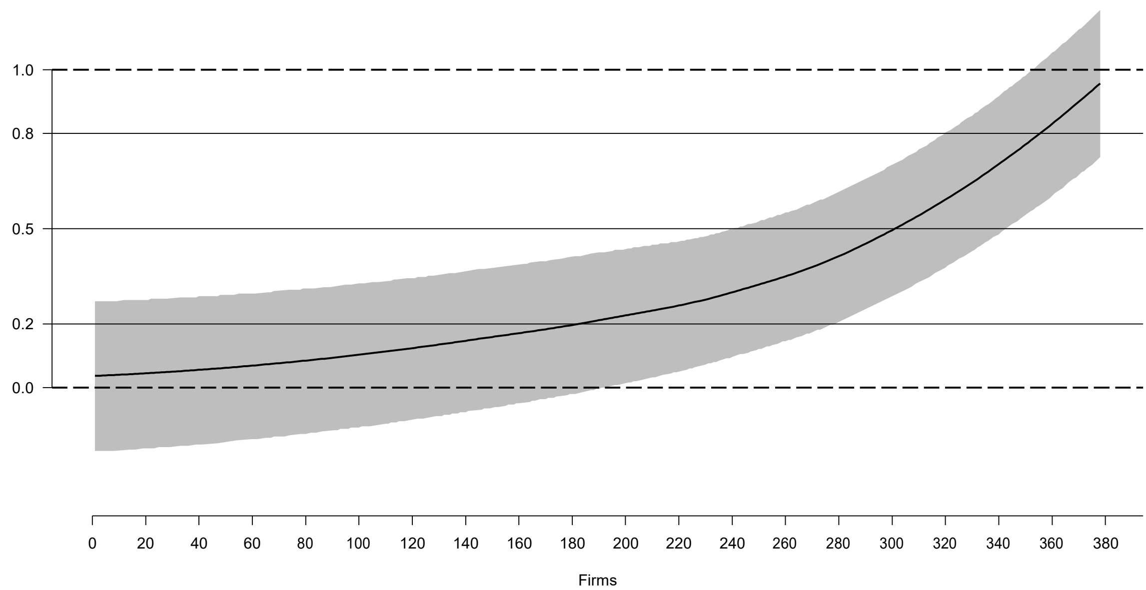

Figure 3. Estimated media-scale and industry conditioned corporate wrongdoing index (*cMediaScaleIndustry-CWi)* and its 95% confidence band.

Source: Authors' own elaboration

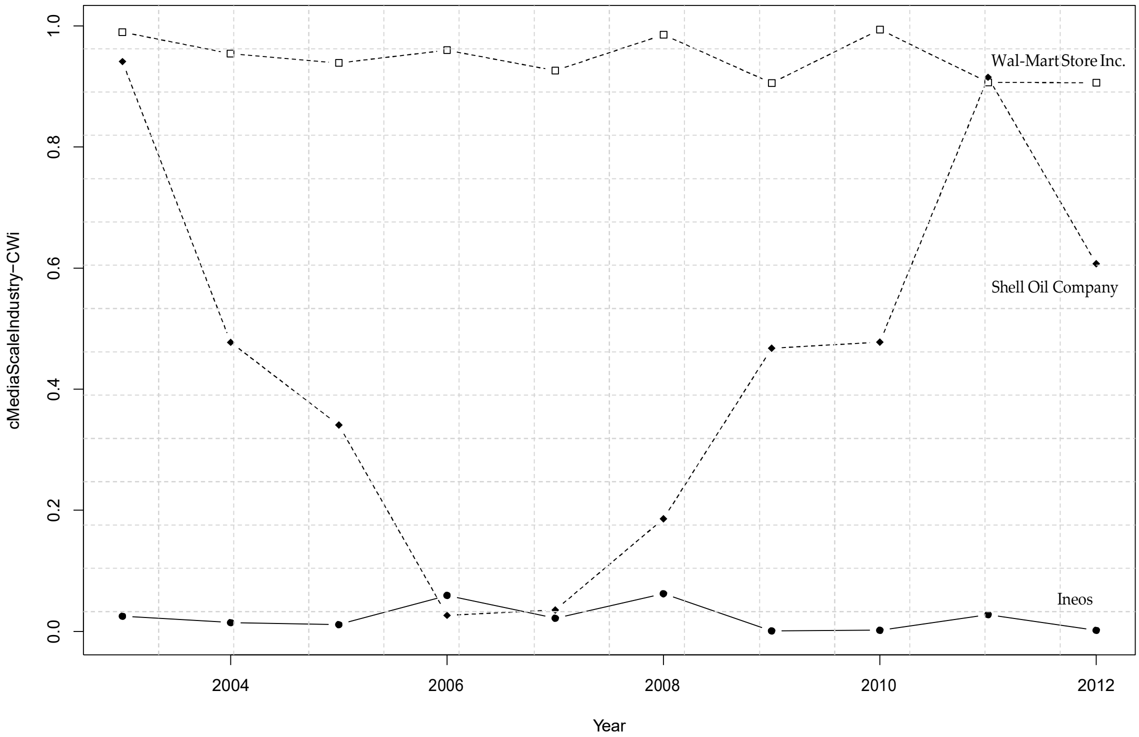

Figure 4. Example of the media-scale and industry conditioned corporate wrongdoing index (*cMediaScaleIndustry-CWi*) time trend for three firms in our sample.

Source: Authors' own elaboration.

APPENDICES

1. M-quantile regression

M-quantile regression provides a 'quantile-like' generalization of regression based on influence functions (Breckling & Chambers, 1988). The use of M-quantile regression with discrete outcomes is challenging, since in this case there is no agreed definition of an M-quantile regression function (Tzavidis et al., 2015). A popular approach for modeling the mean of a discrete outcome as a function of predictors is through the use of generalized linear models (GLMs), by assuming that the response variable follows a Poisson distribution and using the logarithm as link function. Because the theory developed in this section can be applied more generally and not only to the case study of this paper, we drop subscript t from our notation. In the same way that in M-quantile regression has been imposed in the linear specification the continuous case, Tzavidis et al. (2015) propose the log-linear specification for count data. That is,

$$MQ_y(\tau|\mathbf{x}_j;\psi) = t_j \exp(\mathbf{x}_j^T \boldsymbol{\beta}_\tau), \tag{2}$$

where t_j is an offset term, $\mathbf{x}_j$ is the vector of covariates for firm j, $j = 1, \dots, n$, $\boldsymbol{\beta}_\tau$ is the vector $p \times 1$ of regression coefficients and ψ function is introduced to control deviation in y-space. For estimating $\boldsymbol{\beta}_\tau$, Tzavidis et al. (2015) consider extensions of the robust version of the estimating equations for GLMs by Cantoni and Ronchetti (2001) to the M-quantile case.

For M-quantile regression the estimating equations can be written as:

$$\Psi(\boldsymbol{\beta}_\tau) := \frac{1}{n}\sum_{j=1}^{n} \{\psi_q(r_{j\tau}) w(\mathbf{x}_j) \frac{1}{\sigma(MQ_y(q|\mathbf{x}_j;\psi))} MQ_y'(\tau|\mathbf{x}_j;\psi) - a(\boldsymbol{\beta}_\tau)\} = \mathbf{0}, \tag{3}$$

where $r_{j\tau} = \sigma(MQ_y(\tau|\mathbf{x}_j;\psi))^{-1}(y_j - MQ_y(\tau|\mathbf{x}_j;\psi))$, $\sigma\left(MQ_y(\tau|\mathbf{x}_j;\psi)\right) = MQ_y(\tau|\mathbf{x}_j;\psi)^{1/2}$, $MQ_y'(\tau|\mathbf{x}_j;\psi) = MQ_y(\tau|\mathbf{x}_j;\psi)\mathbf{x}_j^T$ and $a(\boldsymbol{\beta}_\tau)$ is a correction term ensures the Fisher consistency of the estimator (Tzavidis et al., 2015). The weights $w(\cdot)$ are used to down-weight the leverage points.

When $w(\mathbf{x}_j) = 1, j = 1, \dots, n$ a Huber quasi-likelihood estimator is obtained. An alternative simple choice for $w(\mathbf{x}_j)$ suggested by robust estimation in linear models is $w(\mathbf{x}_j) = \sqrt{1 - h_j}$ where $h_j = \mathbf{x}_j^T (\sum_{j=1}^{n} \mathbf{x}_j \mathbf{x}_j^T)^{-1} \mathbf{x}_j$, i.e. the jth diagonal element of the hat matrix. The solution to the estimating equations (3) can be obtained numerically by using a Fisher scoring procedure. R routines for fitting M-quantile regression for count data are available from Tzavidis et al. (2015). In the continuous y case, the M-quantile coefficient for observation j is simply defined as the unique solution τ_j to the equation $y_j = \widehat{MQ}_y(\tau_j | \mathbf{x}_j; \psi)$. However, for count data the equation $y_j = \widehat{MQ}_y(\tau_j | \mathbf{x}_j; \psi)$ does not have a solution when $y_j = 0$. To overcome this problem we use the definition by Tzavidis et al. (2015):

$$\widehat{MQ}_y(\tau_j | \mathbf{x}_j; \psi) = \begin{cases} \min\{1 - \varepsilon, \frac{1}{\exp(\mathbf{x}_j^T \widehat{\boldsymbol{\beta}}_{0.5})}\} & y_j = 0 \\ y_j & y_j = 1, 2, \dots \end{cases} \tag{4}$$

where $\varepsilon > 0$ is a small positive constant. For a detailed discussion see Tzavidis et al. (2015) and Chambers et al. (2016). The results of equation (4) gives the corporate wrongdoing index for each firm at any period.

2. M-quantile block-bootstrap procedure

The steps of the bootstrap procedure for computing the variability of M-quantile coefficients τ_j are summarized below:

1. Fit (1) and for each firm compute the pseudo-random effect $\hat{u}_j^{MQ}$ by computing the $E(\mathbf{x}_{jt}^T(\boldsymbol{\beta}_{\tau_j} - \boldsymbol{\beta}_{0.5}))$ for each firm. It is convenient to re-scale the elements $\hat{\mathbf{u}}^{MQ}$ so that they have mean exactly equal to zero.
2. Construct the vector $\hat{\mathbf{u}}^{MQ*} = \{\hat{u}_1^{MQ*}, \dots, \hat{u}_n^{MQ*}\}^T$, whose elements are obtained by extracting a simple random sample with replacement of size n from the set $\{\hat{u}_1^{MQ}, \dots, \hat{u}_n^{MQ}\}^T$.
3. Generate a bootstrap population U^* of size $n \times T$, by generating values from a Poisson distribution with $\mu_{jt}^* = \exp\{\mathbf{x}_{jt}^T\widehat{\boldsymbol{\beta}}_{0.5} + \hat{u}_j^{MQ*}\}, j = 1, \dots, n; t = 1, \dots, T$.
4. Fit the model (1) on the bth bootstrap population $U^{*(b)}$ and compute the bootstrap M-quantile coefficient for firm j, τ_j^*.
5. Repeat steps 2-4 B times.
6. Denoting by $\tau_j^{*(b)}$ the M-quantile coefficients for firm j in the b-th bootstrap replication and by τ_j the corresponding value computed on the original data, a bootstrap estimator of MSE is $MSE\ (\tau_j) = B^{-1} \sum_{b=1}^{B} (\tau_j^{*(b)} - \tau_j)^2$.

REPLY TO REVIEWER'S COMMENTS

Thank you for your interest in our article. Below you find our reactions to your critical comments. We hope our revisions are satisfactory.

Comment #1

There seem to be two extremes with respect to the current measures of corporate wrongdoing. On one hand is the MSCI KLD measure that does a dichotomous coding of wrongdoing, thereby treating all kinds of wrongdoings as equally serious. This we know is not true. Certain wrongdoings cause much greater harm than others. On the other end of the spectrum is the ESG measure provided by Sustainlytics, which although codes wrongdoings by their seriousness, doesn't use a transparent process to evaluate the validity of this coding procedure. The authors' claim that their measure is a good middle ground between these two extremes. However, the authors' measure also seems to be treating all wrongdoings equally when they are coding each wrongdoing event within a year as 1. I might be wrong in my interpretation of the authors' procedures, but if this is the case, then the authors need to provide greater clarity on how they are evaluating the severity of different types of corporate wrongdoings.

Reply: Thank you for picking up this point. We were not sufficiently clear about this very important issue. Let us clarify that, although in our empirical exercise we dichotomize the data so that, in effects, we treat each wrongdoing as 1, our raw data allow for a different treatment of the data. For instance, based on our methodology, we could develop different indexes for different categories of wrongful conducts, depending e.g. on their salience or on how irreversibly they are infringing on the fundamental rights of others, or on the basis of the degree of involvement of firms in the alleged wrongful conduct. Similarly, we can calculate an index where wrongdoing is weighted differently depending on these dimensions. We did not perform these additional analyses because of space, but we have now added a section 'Further development of the raw data and the indexes' (p. 17-18) where we explain these issues in some details.

Comment #2

The empirical application of the authors' proposed measure used human rights violations data from BHRRC to rate firms on their wrongdoing. I agree that firms that violate human rights are engaging in wrongdoing. However, there are also many cases in the ethics literature where corporations putting a stop on a certain human rights violation created a greater negative impact on the lives of people. For example, when MNCs adopted strict regulations on child labor in developing countries, children in certain developing countries were exposed to greater risks such as drugs, losing the opportunity for education, and reduced family income that ultimately harmed the kids. The point is that using a Western lens to evaluate corporate wrongdoing may not always be appropriate or even the most ethical thing to do. I understand that no measure of corporate wrongdoing can effectively address all the idiosyncrasies of societal conditions. However, this needs to be acknowledged as a limitation of the measure.

Reply: This is a fundamental issue concerning the debate on universal human rights, which, in the interest of space, we could not discuss in the paper as we would have liked, but this point is well taken. Let us clarify that, in taking universal human rights to operationalize the concept of wrongdoing, we do align with extant 'business and human rights' research (see Baumann-Pauly & Nolan, 2016; Bernaz, 2016; Mares, 2011; Ruggie, 2008; 2011; Wettstein, 2009, among others), *which tends not to see human rights as a purely 'Western' concept. Human rights are rather seen as universal, as the UN Declaration of Human Rights and subsequent covenants (especially those adopted in 1966) have been ratified by most countries in the world. The 'Zero Draft' currently under discussion at the UN level to make companies legally liable for their infringements of universal human rights has been forcefully promoted by Ecuador, South Africa and other developing countries,[1] with several Western countries (including the US) remaining relatively peripheral in pushing this agenda. This said, we do agree that the eradication of one form of human rights violation (say child labour) can affect the enjoyment of other rights negatively (e.g. undermine the economic rights of the child's family). Yet, the unintended consequences of the eradication of human rights abuses are not a good motivation for allowing the perpetration of the abuse. Rather, these negative consequences should be addressed and remedied to the extent possible. For instance, in the case of child labour, the government should ensure that children are guaranteed access to education, as the literature shows that this is the only way in which eventually their country can grow and combat their poverty. This said, we have acknowledged this point in the conclusive section of the paper (p. 19)*

Comment #3
It was unclear to me if the authors used the human rights violations data just as a way to illustrate how their formula for corporate wrongdoing could be used, or if they believe the human rights violations are the primary means of evaluating corporate wrongdoing. If it is the former, then I would recommend that the authors devote a few paragraphs how their measure could capture corporate wrongdoing that negatively impacts the environment and animals. If it is the latter, then the authors' measure has serious lacunae, because there is no reason why corporations engaging in animal rights violations should not be considered corporate wrongdoings, because they still violate the fundamental premise of "do no harm."

Reply: Thanks for this comment. We think that in the context of international companies and multiple countries, the UN Declaration of Human Rights represents a good international benchmark. But we do agree at the same time that it does not cover the whole spectrum of wrongful actions. For instance, damages to animals, or the natural environment are not accounted for unless these damages also affect human rights (e.g. as in the case of a degradation of the natural environment that undermines some fishing communities right to work or to a decent livelihood). We have now clarified this in the revised version of the paper both in the data section (see p.13) and in the limitations (p.19).

Comment #4
I appreciate that their measure incorporates important control variables such as firm size, industry characteristics, and exposure to media and NGO scrutiny. However, I did not understand the basis of computing some of these variables. For example, why is Firm's Media Exposure calculated using log of the ratio between the number of news items mentioning the particular firm and the total number of articles mentioning any of the firms in the sample? What is the basis of this calculation? Why is a logarithmic ratio more appropriate for such a measure than any other form of ratio?

[1] https://www.business-humanrights.org/en/binding-treaty last access January 9 2019

Reply: Due to space limitations, we could not duly justify the operationalization of our variables. However, the operationalization is largely based on standard practice, for instance the use of log calculations is standard in econometric analyses when the metric of the variables considered in the analysis is different, as suggested e.g. by Wooldridge, 2015. We now acknowledge that these variables can be measured in different ways and refer to the relevant literature to justify their use in this paper (p.13-15).

Comment #5
Although the authors control for the extent of media exposure, it seems that the primary way they calculate wrongdoings is based on the number of times a corporation's wrongdoing is reported in the media. Using the media as the data source can be very problematic because many ethical violations are not even considered wrongdoings in certain cultures. For example, in the cultures where meat eating is considered acceptable, media houses may rarely ever report on the companies in the meat industry despite their basic business model being based on the violation of animal rights. Relying on media reporting to calculate corporate wrongdoings also means that the authors' measure is going to be susceptible to variations in media fads and trends.

Reply: Regarding this point, the issue is twofold. On the one hand, there is a 'natural' bias in the data (i.e. as with any other ESG source, we can include in the dataset only events that have been discovered by the media, NGOs and other watchdog organizations). However, we account for this by controlling for the reporting activity exerted by those organizations over the firms' operations. Thus, unlikely other ESG metrics, we do account for the different exposure of firms to the media, which is one of the ways in which the news about the wrongful conduct get broadcasted. On the other hand, we do control for the fact that firms may have operations in different countries where, as you rightly point out, governments or other organizations may have different propensity or interest in reporting the wrongful conduct. To account for this, and unlike other ESG metrics, we condition our index also to the institutional qualities of the firm's home country as well as that of the host countries where the firm has its own operation through its foreign direct investments (considering the Voice and Accountability index of the Worldwide Governance Indicators). We therefore consider that our cMedia-CWi index is specifically meant to account for these concerns. We are sorry it was not so clear in the earlier version, we have now clarified this point in the text (p.8).

Comment #6
One can argue that the killing of animals as an unavoidable harm that we have to engage in for our own survival, and in that case, we need to evaluate the steps that the companies in the meat industry take to "minimize harm." After all, "minimizing unavoidable harm" is a direct corollary of the "do no harm" principle. Similar kind of arguments could also be made with respect to the environmental damage caused by corporations. In the context of the current article, this means that we might have to ask if the measure of corporate wrongdoing should incorporate a component that offsets the scores of wrongdoing for a company when they take appropriate measures to minimize harm.

Reply: This is an interesting suggestion which could be incorporated into further developments of our indexes. We have now included this possibility in the new section on further developments (p.18).

Comment #7

Overall, I liked the article, and think that it makes a valuable contribution to the literature. I agree that a measure of corporate wrongdoing has a lot of practical significance. I would recommend that the authors be given an opportunity to revise their paper where they provide greater clarity on their measure of corporate wrongdoing. Given that the authors are proposing a new measure, I think that they should also clearly enumerate the weaknesses/limitations of their approach.

Thank you for your comments and the opportunity to revise our paper.

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