Bank HUMAN RIGHTS Index: Methodology

Preamble

We develop a Bank HUMAN RIGHTS Index (hereinafter "index") to measure the harmful impact on human rights of banks and financial institutions (hereafter "banks"). We consider that this index should have the following characteristics. First, its elaboration should be transparent and replicable; second, it should ensure a measure of reliability; and third, depending on its intended use, it should be robust to bank characteristics that might affect the probability of being associated with a human rights abuse.

We define human rights according to the 1948 Universal Declaration of Human Rights, and subsequent covenants and treaties and, more specifically, in defining the responsibility of banks to respect human rights, we refer to the UN Guiding Principles on Business and Human Rights. Our focus covers a wide spectrum of abuses, from civil and political rights abuses to socio-economic and cultural rights misuses. Thus, it includes labour rights (e.g., child labour, labour discrimination, union busting, among others), violations of local indigenous communities' rights to land and to life, violations of the right to health of communities or consumers, women's rights, children's rights, etc.

Disclaimer: our ranking is based on evidence of alleged human rights abuses based on publicly available information.

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Sample

For the Banking on Human Rights project we developed a novel dataset that includes and codifies evidence on bank-related human rights abuses, for a sample of 178 banks from 27 countries and 5 continents, observed over the period 2000 to 2015. This global dataset includes 122 banks from so called 'advanced' economies (high income countries such as Canada, Europe, the US) and 56 banks from a set of 'emerging' economies (i.e., Brazil, China, India, Malaysia, Mexico, Russia, South Africa and Thailand). The emerging economy banks were selected by means of stratified sampling with equal allocation, from the Forbes 2000 ranking (2012 edition). The advanced economy banks were retrieved from Orbis Bureau van Dijk using a propensity-score matching method that takes account of the bank's profits to total assets ratio, the bank's profits to sales ratio, the bank's market value and the bank's total assets.

Data Sources

For each bank in our sample, we retrieved information on their involvement in human rights abuses mostly from Business and Human Rights Resource Centre (BHRRC) portal, but also several other sources. The BHRRC portal was used to search for information on alleged human rights abuses connected to the banks in our sample. The materials searched include news and reports providing evidence of negative human rights impacts 'events'. We codified information on individual human rights abuses in our dataset as to ensure our raw data have maximum temporal consistency and that records have not been altered by ad hoc manipulations.

Methodology

We follow the methodology in Fiaschi, Giuliani, Nieri and Salvati (2020) and use an M-quantile regression approach to measure the extent to which the banks in our sample are likely to be involved in human rights abuses. M-quantile regression provides a 'quantile-like' generalization of regression (Breckling and Chambers 1988). The standard M-quantile regression requires continuous dependent variables and becomes more complex if, as in our case, we rely on discrete dependent variables. The the raw data

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used to calculate the index is y_{jt}, measured as the number of alleged human rights abuses bank j is involved in in period t. Each event represents a different type of human rights abuse, in which the bank is involved in each year, based on our search. In each year, each individual event is counted as 1, regardless of whether it was confined that that particular year or extends across more than one year. We would count multi-year event as 1 for each of the years in which it occurred. To account for the characteristics of the human rights abuse variable, we assume that the response variable follows a Poisson distribution, using the logarithm as a link function. Tzavidis, Ranalli, Salvati, Dreassi and Chambers (2015) propose the following log-linear specification for count data:

$$MQ_y(\tau|x_{jt};\psi) = k_{jt}exp(x_{jt}^T\beta_\tau), \tag{1}$$

where k_{jt} is an offset term, x_{jt} is the vector of the covariates for bank j, $j = 1,\dots,n$, at time t, $t = 1,\dots,T$, β_τ is the vector $p\times 1$ of the regression coefficients and ψ is the appropriate influence function. To estimate β_τ, Tzavidis et al. (2015) consider extensions of the robust version of the estimating equations for GLMs, proposed by Cantoni and Ronchetti (2001), to the M-quantile case. For the M-quantile regression the estimation equations can be written as:

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

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

If $w(x_j) = 1, j = 1,\dots,n$ a Huber quasi-likelihood estimator is obtained. An alternative simple choice for $w\left(x_j\right)$, suggested by robust estimation in linear models, is $w(x_j) = \sqrt{1-h_j}$ where $h_j = x_j^T(\sum_{j=1}^{n}x_jx_j^T)^{-1}x_j$, that is, the jth diagonal element of the hat matrix. The solution to the estimation equation (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). For each bank, an M-quantile coefficient τ_{jt} is defined, such that $y_{jt} = MQ_y(\tau|x_{jt};\psi)$ and takes values between 0 and 1; τ_{jt} indicates the quantile of the

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distribution of y_{jt} to which it is estimated that each bank belongs, conditioned on a set of variables (see below "Conditioning variables") included in the M-quantile regression. In the continuous y case, the M-quantile coefficient for observation j is simply defined as the unique solution τ_j to the equation $y_j = \hat{MQ}_y(\tau_j|x_j;\psi)$. However, for count data, if $y_j = 0$, the equation $y_j = \hat{MQ}_y(\tau_j|x_j;\psi)$ has no solution. To overcome this problem, we use the definition in Tzavidis et al. (2015):

$$\hat{MQ}_y(\tau_j|x_j;\psi) = \{min\{1-\varepsilon, \frac{1}{exp(x_j^T\hat{\beta}_{0.5})}\} \; y_j = 0 \; y_j \; y_j = 1, 2, \ldots \tag{4}$$

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) give the index for each bank in any period.

Conditioning variables

We condition the index on media exposure and time dummies. Based on extant research, media exposure is used to account for each bank's press coverage, based on the assumption that banks that attract more media attention are more closely monitored and their abuses are more likely to be reported. We measure media exposure using: (i) information retrieved from Lexis Nexis (News section) and computed as the log of the number of news items/articles mentioning bank j at time t; (ii) the level of 'Voice and Accountability' of the bank's home country (based on the Worldwide Governance 'Voice and Accountability' Indicators); and (iii) the 'Voice and Accountability' of countries in which the bank has foreign direct investments, retrieved from FDIMarkets, Zephyr and SDC Platinum. We also include time dummies in the estimations to account for time trends in reporting abuses.

In the limiting case where only the intercept is included in the regression, τ_{jt} indicates the quantile of the *observed* distribution of human rights abuses to which the bank belongs; for example, a value of τ_{jt} =0.9 indicates that the bank belongs to the top 10% of the distribution of the reported abuses. We estimate a τ_{jt} for each bank and each year included in our panel data, and consider both the whole time series of the index, and its time average for each bank (this latter based on the average behaviour of the bank in

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the period): $\tau_j = \sum_{t=1}^{T} \tau_{jt}/T$.

To clarify our approach, we provide a simplified illustrative example. We use x to denote the bank's conditional variables. A standard linear regression model can provide an estimate of the *expected* human rights abuses of the bank conditioned on its conditional variables, that is, $\hat{y} = E[y|x]$. In other words, $\hat{y}$ summarizes the *average human rights conduct* of y given x. Figure 1 reports the simplest case, which considers the characteristics x, of just one bank, which positively affect the bank's involvement in human rights abuses in a linear fashion. The bold line in Figure 1 corresponds to the linear regression of y on x, that is, 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 slopes of the dashed lines are the same), but a different intercept. Bank A in Figure 1 is involved in fewer human rights abuses than bank B, but given x_A and x_B, the estimated quantile regression indicates that bank A belongs to the $\tau = 0.9$ -th quantile (i.e., to the 90th percentile of distribution of human rights abuses), while bank B belongs to $\tau = 0.25$ -th quantile. Therefore, the value of the index is 0.9 for bank A 9 and 0.25 for bank B. Hence, although bank B has a higher number of reported human rights abuses than bank A, *conditioned* on bank characteristics x, bank B has a lower index value.

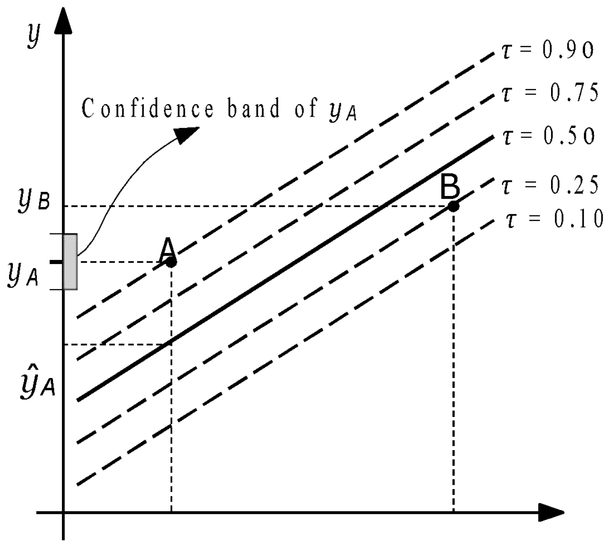

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Figure 1. Illustrative example of a human rights abuses index estimated by M-quantile regression

The proposed M-quantile regression approach provides an index that ranges between 0 and 1, which we have rescaled on a 0-100 basis, indicating the respective lower and upper bounds of human rights conduct. This means that (in relative terms) banks approaching an index value of $1$00 display a more alleged abusive conduct than other banks, at any point in time.

By using a bootstrap procedure to calculate the confidence interval of the index, this methodology provides a direct measure of reliability. For instance, if we take y_A in Figure 1 as the estimated index of bank A, its reliability is given by the confidence band (at a given significant statistical level) of this estimated value. The steps in the bootstrap procedure used to compute the variability of the M-quantile coefficients $\tau_{j,}$ are summarized below:

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

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More information about the project is available at www.bankingonhumanrights.org.

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