# Redefining the Degree of Industry Greenness Using Input-Output Tables

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**Abstract**

Climate risk is a novel exposure that may rock the financial stability world-wide. For this reason the world standards-setter in banking regulation the Basel Committee on Banking Supervision suggested to consider pricing in the climate risk and adopt its relevant regulation. It listed input-output tables as one of the key tools to measure the climate riskiness of a borrower. Such an estimate may form the basis for the subsidy funding to greener industries following the example of the Bank of Japan. The novelty of this work is the use of a new data source on climate risk ratings for the Fortune 2000 companies. Those are the environmental risk scores (E part of the ESG score) developed by the Sustainalytics.com and publicly disclosed on the finance.yahoo.com website. We are the first to amalgamate it with the world input-output database (WIOD) for 2000-2014. The major finding of ours is that the greenness of industries is materially perturbated when considering WIOD-based full climate risk estimate as an equivalent to the Leontief full production costs. Our results are solicited by the Central Banks to accurately design the specialized lending facilities to truly green industries.

# 1 Introduction

The climate change risk, or climate risk, is massively discussed throughout the globe. Bolton et al. (2020); Pereira da Silva (2020) even named it "Green swan" in parallel to the Taleb (2010)'s black swan event of 2007-09 world financial crisis. Global warming is called to be one of its detrimental consequences as argued by Westerhold et al. (2020); Kotlikoff et al. (2021).

The international and local authorities attempt to prevent or at least to slow down the pace of climate change and global warming. They promote more climate-friendly ("green") industries and support climate-improving ("green") projects as opposed to so-called "brown" ones. This might be done either by preferential capital treatment from the perspective of bank regulation as recommended by BCBS (2021b) and approved by People's Bank of China (2021), or by interest rate subsidies as adopted by BoJ (2021).

All of the described measures rely on the definition of industry "greenness". The immediate approach is to look at the developed ESG ratings and particularly those of E-ratings (environmental ones). For instance, the website finance.yahoo.com has the section "Sustainability" where every ordinary private investor may become aware to what extent the asset of one's interest is "green". The producers of beverages will be seen twice "browner", than the broadcasting and cable enterprises. The reader may find the respective mean climate risk estimates of 3,63 and 8,18 (see lines 8 and 38 from the column $Absolute/Mean(M)$ in Table 1). Here is a natural implication. Suppose, a private investor shares the view that "greener" companies should be supported more actively, than "browner" enterprises. Then such investor is more likely to invest into the beverage producers' assets.

However, the climate risk estimates for the two industries in our example might be called marginal ones. They reflect the climate change impact only from the perspective of an enterprise taken alone. Same time to produce a unit by such an enterprise the products of very many other enterprises are required. Those companies earlier in the production chain might be quite different in terms of climate impact, than the end enterprise being the object of climate risk evaluation. For instance, the end producer might be quite "green". Nevertheless, it may consume many interim outputs from very "brown" industries. Then a unit of a "green" enterprise *de facto* produces lots of climate risks by claiming demand on "brown" industries' products. Thus, we need to have full climate risk estimates, not limited to the marginal ones.

We wish to exploit the novel climate risk ratings data. First, by controlling for the regional specifics we may obtain the marginal climate risk per each of 43 world industries. As a result, we have industry rankings by the degree of greenness. Second, by applying the input-output tables to the novel dataset we compute the full climate risk per industry. We also transform the absolute scores into relative industry rankings. Overall, our research objective is to investigate how the industry rankings are impacted by transiting from the marginal to the full climate risk estimates.

Our findings deliver important information for decision-making at both private and government levels. We are able to cluster industries world-wide into five distinct clusters. Two of them attract most of our attention.

First, there is a dozen of enterprises with the full climate risk rankings being more than 10 places above their rankings by marginal climate risk estimates. Such industries produce much more climate risk than expected from the perspective of the readily available climate risk ratings. The absolute full climate risk for them is up to five times larger, than the marginal ones. They are "browner", than were thought to be.

Second, as might be expected, there is a second cohort that is at least ten ranks below in terms of greenness, than expected. Such industries are "greener" than expected from the readily-available marginal data. Here the full climate risk estimate is at most twice as high as the marginal one.

To explain the route to our findings, we start from the brief literature review in section 2. The

two data sources from finance.yahoo.com and world input-output tables (WIOD) are described in section 3. We present the methodology in section 4. The key results on industry rankings are discussed in section 5. Section 6 concludes.

# 2 Literature Review

William D. Nordhaus is considered to be the leader in climate change modeling and in evaluating its economic consequences. Simplistically, due to the introduction of DICE model he gained the Nobel Prize in economics, see Nordhaus (2018). Kotlikoff et al. (2021) refer to his book Nordhaus (1979) as the first milestone in the research progress, while Nordhaus himself counts the development since the working paper Nordhaus (1975).

Climate risk exposure is the foundation to developing the relevant financial regulation, see BCBS (2021b). To evaluate such an exposure the world standards-setter in the area of banking regulation lists several approaches in BCBS (2021a) including the following ones:

- general equilibrium modeling (CGE, DSGE) like is done in Kotlikoff et al. (2021).
- agent-based modeling. One of recent examples can be found in Makarov et al. (2020);
- use of input-output tables. For instance, Votinov et al. (2021) evaluates the carbon tax imposition implications for the selected countries.

We wish to focus this paper on the third item from the above list. The input-output tables were largely developed by Wassily Leontief, President of the American Economic Association. He got the Nobel Prize in economics, see Leontief (1973). More important is that in our consideration he should have the honour of being proclaimed the pioneer of the climate risk study launch. Even formally he coined such an issue during his Nobel Prize lecture when discussing the presence of the abatement industry to combat pollution in the world economy. In our expectation, it was exactly Wassily Leontief presentation from 1973 that inspired William Nordhaus to embark on this topic two years later in 1975.

Since then the use of input-output (IO) tables has received wide proliferation. To list several results, Munksgaard et al. (2005) used life-cycle applications of IO tables when combined with other data. We would follow his idea as are going to combine IO data with the novel dataset. We will cover it in more detail in section 3. Makarov and Sokolova (2014); Shirov and Kolpakov (2017) used it to measure carbon intensity of exports and benchmark countries to each other. Different to Shirov and Kolpakov (2017) we focus on industry rankings (see Table 1), rather than the country ones (though we also present those in Table 2).

The climate risk was also investigated from the non-IO tables' perspective. A large discussion as a part of ESG ratings is available in Boubaker et al. (2019). Nielsen et al. (2021) argue that carbon tax agreement might not be that efficient as do not bind that much. In their logic, only countries with low emissions, do sign in. There occurs a sort of a natural positive self-selection (as opposed to the negative selection in insurance industry). However, Kotlikoff et al. (2021) stress the importance to agree on carbon tax agreements today in 2022 to benefit 200 years later. Moreover, Kotlikoff et al. (2021) argue that countries located closer to the North Pole are to gain from global warming. That is why, today they should pay carbon tax. However, authors omit the possibility of designing a stabilization fund within a particular country to fund its prospective expense for the unearned benefits due to more moderate global warming than expected. Such a national finance vehicle creates no external credit risk for a given country with particular importance when we consider 200Y horizon.

We are not going to debate on the need of carbon tax agreements and on the optimal tax rates. Nevertheless, even such discussions are based on the degree of enterprise or, more generally,

industry greenness. To evaluate one, authorities promote disclosures. For instance, for the listed companies in the UK by Financial Conduct Authority (2021) or for the Central Banks by Network for Greening the Financial System (2021). However, we should process the disclosed data with due consideration and not be obsessed by the transparency, i.e., by the mere fact of disclosure. For instance, Degryse et al. (2021) fall into such a trap by calling an industry a green one if it only reports on climate risks. Thus, emission-intensive oil & gas producers occur green by their classification, and not brown. We avoid such a flaw.

# 3 Data

We depart from the two types of data sources:

- Environmental Risk Scores; and
- World Input-Output Database (WIOD).

First, the Environmental Risk Scores, or climate risk estimates, are produced by the Sustainalytics (2021) and publicly reported at the finance.yahoo.com website. It includes the company exposure to various climate risk events. The data has two advantages and a shortcoming. Its limitation is the absence of publicly available historical track record. However, its strong points are the free-of-charge availability and the comparability of absolute risk score in-between companies from non-adjacent sectors like banking and agriculture.

We start with the Fortune 2000 list of the world largest companies. For each of them we parse the recent climate risk scores. We use regression analysis to disentangle industry specifics from the country ones. Overall, we have climate risks for only half of a sample (around a thousand of companies). Bloomberg provides us with 72 industries and 52 countries assignments for the chosen companies.

At a glance, downloading data from finance.yahoo.com on climate risk seems an ease task when we have Bloomberg tickers for the Fortune 2000 companies. Unfortunately, the automated ticker transformation is applicable to roughly a half of the sample. As for the rest, we undertake manual search and matching. For instance, Bloomberg has a single 'SS' country identification for China, while Yahoo differentiates 'SS' for the Shanghai stock exchange and 'SZ' for the Shenzhen one.

To give a flavor of the climate risk magnitude we present the mean climate (environmental) risk scores in the column $Absolute/Mean(M)$ in Table 1. For instance, Advertising industry (row No. 18) has the lowest mean climate risk estimate of 0,06. On the contrary, Electric Equipment (row No. 21) has the largest one of 13,58. The overview of the entire company-level climate risk estimates is available in Figure 1.

Second, the WIOD is an annual registry of production technology snapshots per countries and industries (Timmer et al., 2015). There are two WIOD releases of the database. We use the most recent one[1] applicable from 2000 to 2014 data. We use the last available 2014 WIOD tables. The data is classified within 56 industries of 43 countries and the rest of the world (ROW).

To join our two dataset we merge countries to the WIOD list, while make an industry aggregation to end up with 43 common ones. There are cases when multiple industries from Bloomberg are merged to a single WIOD industry, and vice versa when multiple WIOD industries form a single Bloomberg industry. The classifiers might be provided upon request.

[1] WIOD 2016 Release, see `https://www.rug.nl/ggdc/valuechain/wiod/wiod-2016-release`

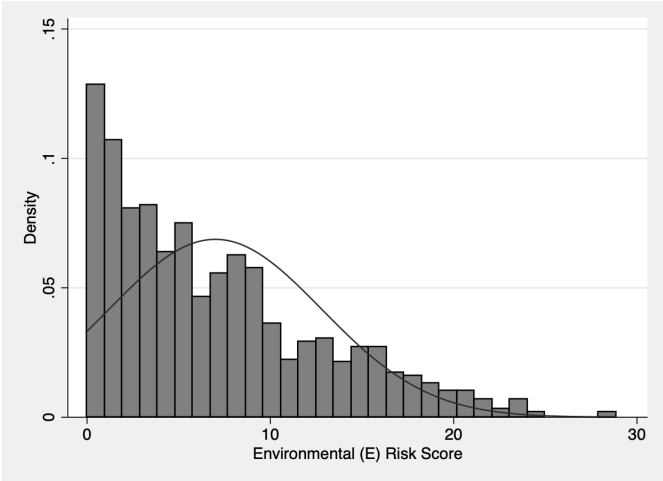


Figure 1: The Assigned Climate (E) Risk Scores Are Concentrated in the Low Range Values.

# 4 Methodology

To evaluate full climate risk per world industry we proceed in three steps:

- Poisson regression to obtain the marginal climate risk estimates per industry;
- Input-Output (IO) model to consider network effect (the production chain) and transit from the marginal climate risk estimates to the full ones;
- Transform the cardinal (absolute) full climate risk estimates to ordinal (relative) ones, i.e., to ranks.

## 4.1 Poisson Regression

The raw data from finance.yahoo.com has the climate risk values per companies. This means that taking average values per industries might be biased as they reflect both industry and regional specifics. That is why we regress the company individual climate risk scores over the country and industry dummies.

The initial application of the ordinary least squares (OLS) specification from Eq. (1) has a principal shortcoming. The climate risk predictions from OLS model for some countries and industries take negative values.

$$Y_k = \beta_0 + \sum_{c=1}^{C} \beta_c \cdot D_c + \sum_{i=1}^{I} \gamma_i \cdot D_i + \epsilon_k, \tag{1}$$

where $Y_k$ is the climate risk estimate per company $k$ from finance.yahoo.com; $c$ is the indicator of a country ($D_c$ is the corresponding dummy variable if the company belongs to the country $c$); $i$ is the indicator of the particular industry to which the company is assigned to ($D_i$ is respective dummy flag); $\epsilon_k$ is the residual error (noise) component.

Negative climate risk values are non-interpretable. They also do not exist in the raw dataset. We need to predict the dependent variable $Y$ that is bounded from below and potentially not limited from the right. This is a canonical setting of the Poisson regression model from Eq. (2) and Eq. (3), see (Green, 2018, p. 885), Stata (2022).

$$Prob(Y_k = y_i|\mathbf{x}_i) = \frac{e^{-\lambda_i} \cdot \lambda_i^{y_i}}{y_i!}, \tag{2}$$

where $ln(\lambda_i) = x_i' \cdot \beta$.

$$Y_k = e^{\beta_0 + \sum_{c=1}^{C} \beta_c \cdot D_c + \sum_{i=1}^{I} \gamma_i \cdot D_i + \epsilon_k}. \tag{3}$$

Thus, having disentangled the country and industry specifics, we proceed with industry-marginal climate risk contributions in the form of $exp(\gamma_i)$ per industry and $exp(\beta_c)$ per country. Such estimates for industries are available in the column *Absolute/Regression* in Tables 1, 2, respectively.

As a result, we have an industry-country matrix. The value at the intersection of row $i$ and column $c$ equals to $\hat{Y_{ic}} = \exp(\hat{\beta}_0 + \hat{\beta}_c \cdot D_c + \hat{\gamma}_i \cdot D_i)$, where the hat symbol stands for the prediction (forecast) for $Y_{ic}$ and otherwise - for the coefficient estimates from the Poisson model in Eq. (3). We call these estimates the marginal climate risk ones and feed the matrix into the input-output model.

## 4.2 Input-Output Model

We use input-output (IO) model to account for the network effects and compute full climate risk per industries world-wide. Let us introduce key notations below:

- $1, \ldots, N$ – the producers' set (as for WIOD a producer is a country-sector combination);
- $y_i$ – the total output value of the i-th producer ($i \in 1, \ldots, N$);
- $x_{ij}$ – the cost of goods or services of the i-th producer purchased by the j-th producer (this is the element of the WIOD input-output table);
- $F_i$ – end consumption of the producer $i$;
- $r_i$ – initial (marginal) climate risk estimate for the producer $i$ (it does not account for the network effects of the production chain structure).

We treat $r_i$ as an absolute measure of the climate risk per unit of production (simplistically, the larger the value is, the higher CO2 emissions are produced by the enterprises in the industry).

Let $\mathbf{A} = \{a_{ij}\}_{i,j=1,\ldots,N}$ be the Leontief (1973) matrix of technological coefficients, i.e, $a_{ij} = \frac{x_{ij}}{y_j}$. Then we can describe the entire production process as follows:

$$\mathbf{y} = (\mathbf{I} - \mathbf{A})^{-1}\mathbf{F}, \tag{4}$$

where $\mathbf{F} = (F_1, \ldots, F_N)'$, $\mathbf{y} = (y_1, \ldots, y_N)'$, $\mathbf{I}$ – is the identity matrix with ones on the principal diagonal and zeros everywhere else.

For notation simplicity we introduce $\mathbf{L} = (\mathbf{I} - \mathbf{A})^{-1}$. Matrix $\mathbf{L}$ is called the Leontieff inverse matrix. The column $i$ of the matrix shows that we require $(L_{1i}, \ldots, L_{ii}, \ldots, L_{Ni})'$ output of other industries to produce a unit of industry $i$ output. We should distinguish the interpretation based on the inputs used. When we process the current year prices, the end consumption is measured in current year USD. When we consider the baseline year prices, the output is respectively measured in constant prices. WIOD provides data both in current and previous year prices. Thus, it is possible to recalculate the production costs in constant 2000-year prices. However, for now we focus on the current year prices.

Getting back to the evaluation of the full climate risk cost, we may denote that the additional climate risk would be generated in the amount of $(L_{1i}r_1, \ldots, L_{Ni}r_N)$. Hence, we may derive the final output by industries $\mathbf{R}$ as follows:

$$\mathbf{R} = \mathbf{L}'\mathbf{r}, \tag{5}$$

where $(\cdot)'$ denotes the transpose operation.

For discussion purposes we wish to cite Elliott et al. (2014). The authors employ network analysis from input-output tables to identify the financial asset ultimate ownership. They exclude cyclical ownership as a sort of double treatment for producer $i$ and require imposing $c_{ii} = 0$. Authors suggest considering the end ownership (in parallel to finished goods consumption) in the following form to arrive at the total ownership $\mathbf{v} = (v_1, \ldots, v_N)$:

$$\mathbf{v} = \hat{\mathbf{C}}(\mathbf{I} - \mathbf{C})^{-1}\mathbf{p}, \tag{6}$$

where $\mathbf{C} = \{c_{ij}\}_{i,j=1,\ldots,N}$ is the matrix of firms' shares in other companies, $0 \leq c_{ij} \leq 1$, $\forall i \neq j$ and $c_{ii} = 0$. $\hat{\mathbf{C}} = \mathrm{diag}(\hat{c}_1, \ldots, \hat{c}_N)$, where $\hat{c}_i = 1 - \sum_j c_{ji}$, $\mathbf{p} = (p_1, \ldots, p_N)$ the values of the firms' primary assets.

Such a methodology may also have sense in the framework of the climate risk estimation. In particular, instead of distribution of the firms value through the network we may distribute the responsibility of the sectors in creation of climate risks of the other ones. However, there are two arguments which limit the utilisation of the model described in our study. First, as noted above, the estimate of initial (marginal) climate risks used in the study are better to interpret as the value per unit produced, not the total climate risk of the sector (the correct substitute for the firms' primary assets value). Second, in our research the requirement of $c_{ii} = 0$ is not applicable as it does not enable to differentiate two cases: when an industry does not consume any output of its own and when it does consume. That is why we proceed with the approach in Eq. (5).

## 4.3 Rankings

When defining our research objective, we departed from the BoJ (2021) case when the "green" projects are funded with a lower interest rate. We recall that mere information disclosure of climate risk impact as considered by Degryse et al. (2021) yields counter-intuitive results. That is why to undergo with the BoJ-alike stimulus projects we need to differentiate truly "green" industries from the truly "brown" ones. This means that we wish to order all the industries by the degree of their greenness. We have three climate risk estimates (they are available in columns $Relative(Rank)$ in Tables 1, 2:

- $Mean(M)$ - mean from the raw data;
- $Regression$ - predictions from the Poisson model;
- $IO$ - IO-based forecasts.

We wish to transform these estimates to ranks. Mean values are readily available from the website. Any retail investor perceives the corresponding rank by looking at those. Running regression and applying IO tables is not straight-forward to be processed mentally from the website figures. However, the Poisson regression does not account for the network effects. That is why we compare ranks from the mean values from the website and from the IO forecasts. We report the results in column $Rank/IO - M$ in Tables 1, 2. When the difference is positive, the industry/country of interest is "browner", than we thought from the website raw figures. On the opposite, when the difference is negative, the industry/country is "greener" than expected.

# 5 Findings

The full climate risk score is on average two-three times higher than the marginal one (13,0-15,0 vs. 6,0). There are distinct clusters of industries and countries in terms of full-versus-marginal climate risk assessment. We added horizontal lines to distinguish such clusters in Table 1 for industries and Table 2 for countries.

For instance, recall the illustrative industries from the Introduction: Beverages and Broadcasting & Cable (see rows No. 8 and 38 in Table 1). Looking at the marginal climate risk estimates we expected the former industry to be "greener" than the second one. The respective scores are 3,6 vs. 8,2. However, when considering the corresponding production technologies encapsulated in IO tables we arrive at the full climate risk scores for Beverages of 15,3 and that for the Broadcasting & Cable of 13,5. To produce a monetary unit of output, Broadcasting generates less climate risk, than Beverages. Thus, the Broadcasting industry is truly "greener" and should be favoured more, than the Beverages one. For instance, we may apply the loan interest rate reduction to Broadcasting, and not to Beverages. If we ignored the IO network effects and relied on the marginal estimates from the website, we would incentivize the "browner" sector.

We also find that the products of the East European countries like Slovakia, Latvia, Bulgaria are "browner" than expected, while their West European peers including Sweden, Norway, France are "greener" than expected. When designing credit stimulus to truly "greener" countries, we should favour those in rows No. 32–44, while limit lending to those in rows No. 1–16.

# 6 Conclusion and Discussion

The Basel Committee recommended the use of input-output tables as one of the reliable sources to identify climate risk exposure, see BCBS (2021a). The knowledge of such exposure enables the authorities to design stimulus measures for "green" industries and projects.

Several authors including Makarov and Sokolova (2014); Shirov and Kolpakov (2017); Votinov et al. (2021) attempted to use IO tables to evaluate the carbon intensity of the exported goods. However, they based their study on the amounts of carbon dioxide emissions. Carbon emissions are an important, but not a single driver for the overall climate risk that an enterprise produces.

That is why we are the first to exploit the novel dataset of the publicly available climate (environmental) risk scores. We delineate the country and industry specifics using the Poisson regression to obtain pure marginal climate risk estimates per country and industry. We aggregate marginal estimates to the full ones considering network effects captured by the IO tables.

We demonstrate that the full climate risk exceeds the marginal one by two-three times. This finding is an expected one as follows from the essence of IO methodology developed by Leontief (1973).

A novel finding is the identified material change in industry rankings when network effects are considered. "Green" industries by marginal climate risk estimates occur "brown" ones when full climate risk estimates are derived. This implies that lending by marginal climate risk criteria might have perverse consequences, or a "cobra effect". The effect got its name from the Siebert (2002) book. Author reminds of the English occupation of India. When Englishmen wished to get rid of cobras, they offered remuneration for every killed cobra. As a response, locals started breeding cobra to kill them and earn money. Ultimately, the cobra population rose four to five times in India because of an adopted economic measure intended to reduce the number of snakes.

That is why our findings have important applications for the economic policies of the Central Banks like that of BoJ (2021). When designing any stimulus measures or preferential treatment for the "green" industries and projects, authorities should rely on the full climate risk estimates, rather than being limited by the marginal ones. Our paper offers benchmarks for the relative comparison of industries and countries to be used as a first proxy when designing such measures.

Table 1: Climate Risk Estimates by Industries World-Wide.

| # | industry name | Absolute Mean (M) | Absolute Regression | Absolute IO | Relative (Rank) Mean (M) | Relative (Rank) Regression | Relative (Rank) IO | Rank IO-M |
|---|---|---|---|---|---|---|---|---|
| 1 | Heavy Equipment | 7,05 | 1,43 | 21,07 | 11 | 11 | 34 | 23 |
| 2 | Specialized Chemicals | 2,41 | 0,49 | 17,00 | 10 | 10 | 30 | 20 |
| 3 | Electric Utilities | 1,08 | 0,22 | 13,73 | 4 | 4 | 21 | 17 |
| 4 | Apparel/Accessories | 1,59 | 0,35 | 14,67 | 6 | 6 | 23 | 17 |
| 5 | Diversified Chemicals | 3,52 | 0,71 | 16,92 | 12 | 14 | 29 | 17 |
| 6 | Computer & Electronics Retail | 4,36 | 0,86 | 20,15 | 19 | 18 | 33 | 14 |
| 7 | Conglomerates | 2,18 | 0,48 | 14,3 | 9 | 9 | 22 | 13 |
| 8 | Beverages | 3,63 | 0,69 | 15,3 | 14 | 12 | 27 | 13 |
| 9 | Containers & Packaging | 3,70 | 0,70 | 16,47 | 15 | 13 | 28 | 13 |
| 10 | Aluminium | 6,96 | 1,24 | 25,18 | 28 | 26 | 41 | 13 |
| 11 | Paper & Paper Products | 3,58 | 0,75 | 14,85 | 13 | 17 | 25 | 12 |
| 12 | Auto & Truck Parts | 5,40 | 0,97 | 17,77 | 21 | 19 | 32 | 11 |
| 13 | Furniture & Fixtures | 6,08 | 1,10 | 17,11 | 23 | 24 | 31 | 8 |
| 14 | Railroads | 0,46 | 0,10 | 8,91 | 3 | 3 | 7 | 4 |
| 15 | Auto & Truck Manufactures | 7,22 | 1,35 | 21,83 | 31 | 29 | 35 | 4 |
| 16 | Recreational Products Auto | 0,07 | 0,01 | 5,79 | 2 | 1 | 3 | 1 |
| 17 | Other Transportation | 6,25 | 1,34 | 15,05 | 25 | 27 | 26 | 1 |
| 18 | Advertising | 0,06 | 0,01 | 4,49 | 1 | 2 | 1 | 0 |
| 19 | Airlines | 9,84 | 1,99 | 22,82 | 38 | 39 | 38 | 0 |
| 20 | Natural Gas Utilities | 13,15 | 2,43 | 31,07 | 42 | 41 | 42 | 0 |
| 21 | Electrical Equipment | 13,58 | 2,71 | 32,38 | 43 | 43 | 43 | 0 |
| 22 | Construction Materials | 9,67 | 1,96 | 22,45 | 37 | 38 | 36 | -1 |
| 23 | Pharmaceuticals | 11,4 | 2,41 | 23,46 | 40 | 40 | 39 | -1 |
| 24 | Diversified Metals & Mining | 12,9 | 2,63 | 23,68 | 41 | 42 | 40 | -1 |
| 25 | Business & Personal Services | 1,92 | 0,37 | 6,69 | 7 | 7 | 5 | -2 |
| 26 | Printing & Publishing | 1,50 | 0,31 | 5,11 | 5 | 5 | 2 | -3 |
| 27 | Biotechs | 6,79 | 1,34 | 14,82 | 27 | 28 | 24 | -3 |
| 28 | Business Products & Supplies | 1,99 | 0,43 | 6,39 | 8 | 8 | 4 | -4 |
| 29 | Hotels & Motels | 3,88 | 0,75 | 10,52 | 17 | 16 | 13 | -4 |
| 30 | Enviromental & Waste | 5,39 | 1,01 | 11,69 | 20 | 21 | 16 | -4 |
| 31 | Diversified Utilities | 16,2 | 2,86 | 22,66 | 44 | 44 | 37 | -7 |
| 32 | Casinos & Gaming | 3,78 | 0,74 | 9,21 | 16 | 15 | 8 | -8 |
| 33 | Air Courier | 6,22 | 1,23 | 11,51 | 24 | 25 | 15 | -9 |
| 34 | Aerospace & Defense | 6,69 | 1,45 | 11,86 | 26 | 33 | 17 | -9 |
| 35 | Drug Retail | 5,63 | 1,07 | 10,10 | 22 | 23 | 11 | -11 |
| 36 | Financial | 4,17 | 1,00 | 8,54 | 18 | 20 | 6 | -12 |
| 37 | Internet & Catalog Retail | 7,51 | 1,47 | 12,84 | 32 | 34 | 19 | -13 |
| 38 | Broadcasting & Cable | 8,18 | 1,62 | 13,51 | 36 | 37 | 20 | -16 |
| 39 | Department Stores | 6,97 | 1,35 | 10,41 | 29 | 30 | 12 | -17 |
| 40 | Software & Programming | 7,99 | 1,57 | 12,73 | 35 | 36 | 18 | -17 |
| 41 | Home Improvement Retail | 7,52 | 1,41 | 11,18 | 33 | 31 | 14 | -19 |
| 42 | Trading companies | 7,10 | 1,03 | 9,99 | 30 | 22 | 10 | -20 |
| 43 | Real Estate | 7,89 | 1,47 | 9,81 | 34 | 35 | 9 | -25 |

*Note: Mean (M) are mean Environmental risk estimates by industries based on company data from finance.yahoo.com (not cleaned from the country effects); Regression is the $EXP(COEF)$, where $COEF$ is the Poisson regression coefficient for the respective industry dummy when additionally controlled for the country dummy (netted from the country effects); IO stands for the full climate risk load derived from the input-output tables where marginal industry risks are those from the Poisson regression (cleaned from the country-specific effects and accounting for the production chains).*

Table 2: Climate Risk Estimates by Countries.

| # | country name | Absolute | | | Relative (Rank) | | | Rank |
|---|---|---|---|---|---|---|---|---|
| | | Mean (M) | Regression | IO | Mean (M) | Regression | IO | IO-M |
| 1 | Slovakia | 0 | 1.3 | 16.96 | 1 | 25 | 37 | 36 |
| 2 | Latvia | 0 | 1.3 | 16.73 | 1 | 25 | 35 | 34 |
| 3 | Bulgaria | 0 | 1.3 | 16.6 | 1 | 25 | 34 | 33 |
| 4 | Estonia | 0 | 1.3 | 15.45 | 1 | 25 | 30 | 29 |
| 5 | Romania | 0 | 1.3 | 15.38 | 1 | 25 | 29 | 28 |
| 6 | Slovenia | 0 | 1.3 | 14.71 | 1 | 25 | 28 | 27 |
| 7 | Lithuania | 0 | 1.3 | 14.61 | 1 | 25 | 27 | 26 |
| 8 | Luxembourg | 3.93 | 1.45 | 15.77 | 7 | 29 | 32 | 25 |
| 9 | Croatia | 0 | 1.3 | 13.87 | 1 | 25 | 25 | 24 |
| 10 | Hungary | 0 | 1 | 13.41 | 1 | 19 | 22 | 21 |
| 11 | Greece | 0 | 1 | 10.86 | 1 | 19 | 18 | 17 |
| 12 | Taiwan | 7.98 | 1.22 | 17.34 | 21 | 22 | 38 | 17 |
| 13 | China | 9.21 | 1.36 | 23.83 | 26 | 27 | 43 | 17 |
| 14 | South Korea | 8.86 | 1.25 | 17.35 | 24 | 23 | 39 | 15 |
| 15 | Indonesia | 11.61 | 2.54 | 29.78 | 29 | 32 | 44 | 15 |
| 16 | Rest of the world | 7.51 | 1 | 15.68 | 19 | 19 | 31 | 12 |
| 17 | Russia | 16.16 | 1.45 | 18.16 | 32 | 29 | 41 | 9 |
| 18 | Poland | 22.22 | 1.67 | 19.24 | 34 | 31 | 42 | 8 |
| 19 | Czech Republic | 18.32 | 1.32 | 17.35 | 33 | 26 | 40 | 7 |
| 20 | Brazil | 11.75 | 1.65 | 16.84 | 30 | 30 | 36 | 6 |
| 21 | Malta | 3.48 | 0.45 | 9 | 4 | 2 | 9 | 5 |
| 22 | India | 10.83 | 1.37 | 16.45 | 28 | 28 | 33 | 5 |
| 23 | Japan | 6.85 | 1.03 | 12.93 | 16 | 20 | 20 | 4 |
| 24 | Denmark | 3.32 | 0.47 | 7.7 | 3 | 4 | 6 | 3 |
| 25 | Australia | 7.93 | 1 | 13.41 | 20 | 19 | 23 | 3 |
| 26 | Cyprus | 0 | 0.49 | 7.18 | 1 | 5 | 3 | 2 |
| 27 | Belgium | 4.2 | 0.65 | 9.2 | 8 | 9 | 10 | 2 |
| 28 | Germany | 6.62 | 0.9 | 10.8 | 15 | 16 | 17 | 2 |
| 29 | Ireland | 4.51 | 0.78 | 9.37 | 10 | 12 | 11 | 1 |
| 30 | Switzerland | 5.2 | 0.83 | 9.82 | 12 | 13 | 13 | 1 |
| 31 | USA | 6.4 | 0.94 | 10.21 | 14 | 18 | 15 | 1 |
| 32 | Turkey | 2.39 | 0.24 | 4.9 | 2 | 1 | 1 | -1 |
| 33 | United Kingdom | 4.22 | 0.74 | 8.99 | 9 | 11 | 8 | -1 |
| 34 | Sweden | 5.25 | 0.83 | 9.55 | 13 | 14 | 12 | -1 |
| 35 | Norway | 9.95 | 1.26 | 14.18 | 27 | 24 | 26 | -1 |
| 36 | France | 3.83 | 0.64 | 7.3 | 6 | 8 | 4 | -2 |
| 37 | Netherlands | 6.95 | 0.89 | 10.59 | 18 | 15 | 16 | -2 |
| 38 | Canada | 8.25 | 1.16 | 13.34 | 23 | 21 | 21 | -2 |
| 39 | Spain | 3.48 | 0.45 | 6.38 | 5 | 3 | 2 | -3 |
| 40 | Finland | 6.95 | 0.73 | 10.03 | 17 | 10 | 14 | -3 |
| 41 | Italy | 4.9 | 0.57 | 7.75 | 11 | 6 | 7 | -4 |
| 42 | Austria | 8.9 | 0.92 | 11.18 | 25 | 17 | 19 | -6 |
| 43 | Mexico | 13.2 | 1.36 | 13.74 | 31 | 27 | 24 | -7 |
| 44 | Portugal | 8.02 | 0.58 | 7.63 | 22 | 7 | 5 | -17 |

*Note: please, refer to descriptions for Table 1.*

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