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Measuring climate-credit risk relationship using world input-output tables[☆]

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Abstract

The Basel Committee recommended the use of input-output tables to properly measure climate risks. However, the majority of previous studies only limits the use of input-output tables to carbon emissions and this is not applied in climate risk ratings. The existing climate (E) risk ratings (scores) was modified or transformed from Sustainalytics to the full climate risk scores using input-output tables. Positive relationship between credit risks and the full climate risk estimates at the industry level was identified, and this justifies the interest rate discount granted to firms in the green industries. Thus, for the purpose of lending the full degree of greenness derived from input-output tables should be considered, not substituting this by the easily observable and publicly available marginal climate risk ratings like those provided by Sustainalytics.

Keywords: climate risk, input-output tables, WIOD, Poisson regression, ESG.
JEL classification: C4, C5, Q54.

1. Introduction

Climate risk and climate change risk play an important role on the global agenda specifically after the year 2018 when the respective Nobel Prize in economics was awarded (Nordhaus, 2018). This triggered enhanced research in the area. (Boubaker et al., 2019) collected up-to-date research covering climate risk as an E (environmental risk) component for the ESG acronym.

Moreover, the broader debates of climate risk led to the introduction of the "green swan" special term see Bolton et al. (2020), Pereira da Silva (2020), Brunnermeier (2022). It expands the concept of "black swan" coined by

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Taleb (2010). The consequences of climate change will most likely be devastating, although it is impossible to properly preview and manage and/or hedge against it henceforth.

Nevertheless, the Basel Committee initiated discussions on how to create a financial "cushion" against the climate-change-related financial risk implications (BCBS, 2021b). The first step is to evaluate the scale of the risk. Therefore the Basel Committee described the current modern climate risk measurement beforehand (BCBS, 2021a).

Though climate change is globally discussed, putting it right now on central banks' agendas and adjusting banking regulations with respect to it might be a premature step. For instance, there was a U.S. Federal Reserve nominee who actively promoted the stance, argued that it should be the central bank (i.e., the Federal Reserve Board (FRB) in the U.S.) that has to take responsibility for the issue (Siegel et al., 2022). The rationale of undertaking such a mandate was suggested by Brunetti at al. (2021), raising concerns over the challenges that climate risk poses to financial stability. However, these views over the central bank's (FRB) principal role in pushing the climate change agenda might have forced the nominee to resign from the contest for the FRB chairmanship (Horsley, 2022).

The key point from the above discussion is that climate change may pose a challenge to the financial system, but whether it should fall to the central bank to handle it is a contentious issue. So the central banks need to probe the topic more deeply themselves, as well as motivate stakeholders to raise their financial literacy with respect to climate risk.

In line with this, the Bank of Russia actively promotes such an agenda by organizing conferences where people are able to share their views as well as gain insights from those colleagues who are strongly involved in the subject. For instance, during the summer 2022, a conference was administered by the Bank of Russia together with the New Economic School.[1] The respective review is available in Ivanova et al. (2022).

Overall, the Bank of Russia collects all the relevant information about sustainable development in general and climate risk in particular at its website.[2]

By promoting the climate change discussion forums, the Bank of Russia stresses on how important the issue is to the Russian economy. Such a priority as part of ESG domain is coined in the Bank of Russia prospective monetary policy measures (Bank of Russia, 2022, p. 164).

The Bank of Russia's activity within climate risk measurement and management may well illustrate how broad the subject area is. This paper seeks to answer a particular research question relevant to finance, risks, and the financial stability managed by central banks. Specifically, it is to evidently determine if there is any climate-credit risk relationship. Thus, it investigates whether "greener" (more climate-friendly) projects and companies are worth a credit

[1] Conference materials: http://www.cbr.ru/about_br/activity/perekhod-k-nizkouglerodnoy-ekonomike-izderzhki-i-riski-dlya-finansovogo-sektora/ (in Russian).
In autumn 2022, the Bank of Russia organized a one-week autumn school for students together with the HSE Higher School of Business. More information about the event is available at: https://www.hse.ru/bkbr/news/782583582.html (in Russian).

[2] http://www.cbr.ru/eng/develop/ur/

risk discount (i.e., should receive loans at lower rates or not) benchmarked to their “brown” peers.

The limitation of this study is that previous relationships may not demonstrate the likely effects after the green transition, i.e., when green energy and green production come to be preferred over “brown” rivals.

Available climate risk ratings and well-known credit ratings were used in this study. The limitation is that each climate risk rating as well as credit rating might have its specificities, and this may cause different paths and dependence signs. However, in our opinion, it is particularly important to study alternative data sources or study alternatives to conventional methodologies to ascertain whether the earlier findings, conclusions and statements are reliable. For instance, if the various studies are able to demonstrate that the climate-credit risk has a positive relationship, then green projects and companies should be favored over “brown” ones when pricing debt obligations. However, if these studies arrive at contradicting findings, this may signal that it is irrational to differentiate the green projects and companies from the “brown” ones based exclusively on the risks they pose to the climate.

This study contributes to the literature in terms of methodology as well as content. Methodologically, three building blocks that were previously treated separately were combined. Available climate risk ratings from Sustainalytics, and not the widespread carbon (CO_2) emissions was used in this study. By using input-ouput tables climate risk was fully studied. Full climate risk against the default probability was benchmarked. This helps to arrive at a conclusion that there is a positive climate-credit risk relationship at the industry level.

However, it is important to indicate that the findings herein do not mean that it is sufficient to consider neither firms with the highest climate risk ratings nor the most creditworthy company as the “greenest.” To make such a statement, one needs to transform the marginal risk into the full estimate. And this is neither a straightforward, nor a simple arithmetic exercise that can be easily processed by a single person.[3]

2. Literature review

There are three major streams of literature that interconnect the discussion of the relationship between full climate and credit risks. The first one focuses on climate risk of financial implications. The second discusses green finance and credit risk. The third is devoted to the use of input-output tables. However, none of these works dealt with the three issues simultaneously (Table 1). Thus, this study attempts to bridge the existing gap.

Wassily Leontief should be considered the pioneer of climate risk debate as in his Nobel Lecture (Leontief, 1973) he had already introduced the abatement industry that was aimed at combating pollution. For more studies on Professor Leontief’s contributions and input-output model extension in Russian economic literature read works such Ershov and Kim (2004), Kim (2006), and Granberg (2006).

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[3] Refer to Appendix A to see which industry should be considered a “greener” one, and which one — a “browner” one judging by the full climate risk score.

Table 1
Comparing relevant literature by key criteria.

#	Paper	Input-output	Climate risk: CO_2 emissions	Climate risk: Other ratings, incl. Sustainalytics	World trade	Credit risk (bonds)	Green finance (equity)
1	Kotlikoff et al. (2021)	–	+	–	–	–	–
2	Degryse et al. (2021)	–	+	–	–	+	–
3	UN PRI (2017 (p. 29)	–	+	–	–	+	+
4	Capasso et al. (2020)	–	+	–	–	+	+
5	Rudebusch (2021)	–	+	–	–	+	+
6	Janosik and Verbraken (2021)	–	+	–	–	+	+
7	Danilova et al. (2022)	–	+	–	–	+	+
8	Penikas (2022)	–	–	+	–	+	–
9	Porfiriyev (2016)	–	+	+	–	+	–
10	Bogacheva and Smorodinov (2016)	–	+	+	–	+	–
11	Rubtsov and Annenskaya (2019)	–	+	+	–	+	–
12	Danilov (2021)	–	+	+	–	+	–
13	Bolton and Kacperczyk (2021)	–	+	+	–	–	+
14	Kant (2021)	–	–	+	–	+	–
15	Lioui and Tarelli (2022)	–	+	+	–	–	+
16	Vymyatnina and Chernykh (2022)	–	–	+	–	+	+
17	Leontief (1973)	+	+	–	+	–	–
18	Timmer et al. (2015)	+	–	–	–	–	–
19	Nordhaus (2018)	–	+	–	–	–	–
20	Makarov et al. (2020)	–	+	–	–	–	–
21	Munksgaard et al. (2005)	+	+	–	+	–	–
22	Shirov and Kolpakov (2017)	+	+	–	+	–	–
23	Votinov et al. (2021)	+	+	–	+	–	–
24	Makarov and Sokolova (2014)	+	+	–	+	–	–
25	BCBS (2021a)	+	+	+	–	+	+
26	Current paper	+	–	+	–	+	+

Source: Compiled by the authors.

However, most scholars credit Professor Nordhaus for his works in the field of climate risk research, which earned him the Nobel Prize in economics (Nordhaus, 2018; Kotlikoff et al., 2021) extend the Nordhaus dynamic stochastic general equilibrium (DSGE) model and make a 200-year prediction. It is argued that China is the most urgently sought negotiating partner when it comes to limiting the rise in global temperature. Makarov et al. (2020) use an alternative modeling tool called an agent-based model (ABM) to predict environmental changes from human activity. However, these studies do not make conclusions on the implications for loan pricing, or for the financial regulation of climate-related risks.

The second stream of literature focuses on green finance as a tool to fund climate-friendly or climate-improving projects like in Porfiriyev (2016), Rubtsov and Annenskaya (2019), Danilov (2021). To achieve of this paper, the implication of climate risk for financial strategies and regulation was equally studied. Several studies conclude that green assets are favored by investors. They either receive an equity return premium or have smaller credit risks, see Capasso et al. (2020), Degryse et al. (2021), Vymyatnina and Chernykh (2022). Their arguments are, however, objected to by Penikas (2022) and Ivanova et al. (2022). For instance, using the same initial input dataset Capasso et al. (2020) argue that the climate-credit risk relationship is positive, while Penikas (2022), on the other hand, found a negative relationship.

However, all these papers are limited to studying the so-called marginal climate risks. These are the risk values directly observed or derived from existing climate (E) ratings. The limitation of such an approach is the mistreatment of formally green industries that nevertheless consume certain "brown" inputs. From the full climate risk perspective such industries are by no means green, although it is difficult to compute full climate risk. If such data was present the authors could have redone or extended their research and most probably adjusted their concluding statements and recommendations.

The third stream of research focuses on the use of input-output tables (IOTs). The Basel Committee sees IOTs as a possible way to derive full climate risk (BCBS, 2021a, p. 50), together with the ABMs as used by Makarov et al. (2020). However, the majority of studies use the IOTs for assessing trade flows and the corresponding carbon emissions like in Munksgaard et al. (2005), Makarov and Sokolova (2014), Shirov and Kolpakov (2017), Votinov et al. (2021). The limitation of the findings therein is that the use of climate risk ratings and the full climate risk estimates are omitted. In addition, the findings are not applied to financial risk and its regulation.

This paper merges the various approaches from the three literature streams mentioned above. First, the marginal climate risk estimates from the climate risk ratings were used, which as far as this paper is concerned are more comprehensive than the mere CO_2 emissions. Second, the paper transits from these marginal climate risk estimates to the full ones by using IOTs. Third, the relationship between the derived full climate risk measures and the creditworthiness measure was tracked, i.e., the probability of default (PD). Thus, we can make recommendations on the loan pricing and climate-risk-related financial regulation.

3. Data

Two different datasets were used: the climate and credit risk data and IOTs. The climate and credit risk data were retrieved from Yahoo Finance[4] and Bloomberg. Every company that has its stock listed at any of the global exchanges has a Sustainability section at the website. Most of the companies have the ESG scores therein produced by Sustainalytics (2021). There are total ESG scores and the components. The climate (E — environmental) risk component was of utmost importance to this study.

Data from Forbes Global 2000,[5] which comprises of the world's largest companies (actual to January 2022). There are 72 industries and 52 countries in the dataset by Bloomberg classification. The industry and country flags were as-

[4] https://finance.yahoo.com/
[5] https://www.forbes.com/lists/global2000/

signed by Bloomberg data provider, and this was used to extract the credit ratings. The US companies are overrepresented in the sample, while industry breakdown is more even (see Freq_PD and Freq_E in Appendices A and B).

Half of the companies have the E risk scores. For each, the credit ratings were collected and the historical default rate was assigned as the probability of default (PD) proxy to each of them. See Penikas (2022, pp. 33–35) for more details on the PD assignment procedure.

The data focus might be seen as a non-representative of a particular company or industry. However, two advantages of such an approach must be taken into account. First, the larger the company, the higher the probability of it having a climate risk rating. Second, psychologically, people tend to processing information from a reduced-dimensional information. That explains why people prefer indexes to sets of inputs. The financial sector performance is conventionally studied by the dynamics of the stock indexes. Those are often either the simple or weighted sums or the averages of the stock quotes of the largest companies. The example is the Moscow Exchange (MOEX) index. It includes 50 stocks (MOEX, 2022, p. 11, par. 3.3.1). That is why it is a conventional approach in finance to focus on the largest companies. As climate risk is on the global agenda, it is natural to consider the world's largest companies, e.g., the Global 2000 list, as we did.

Fig. 1 offers the data demonstration at the initial company level. The PD values in logarithms are close to the Gaussian distribution (see panel B). It means that

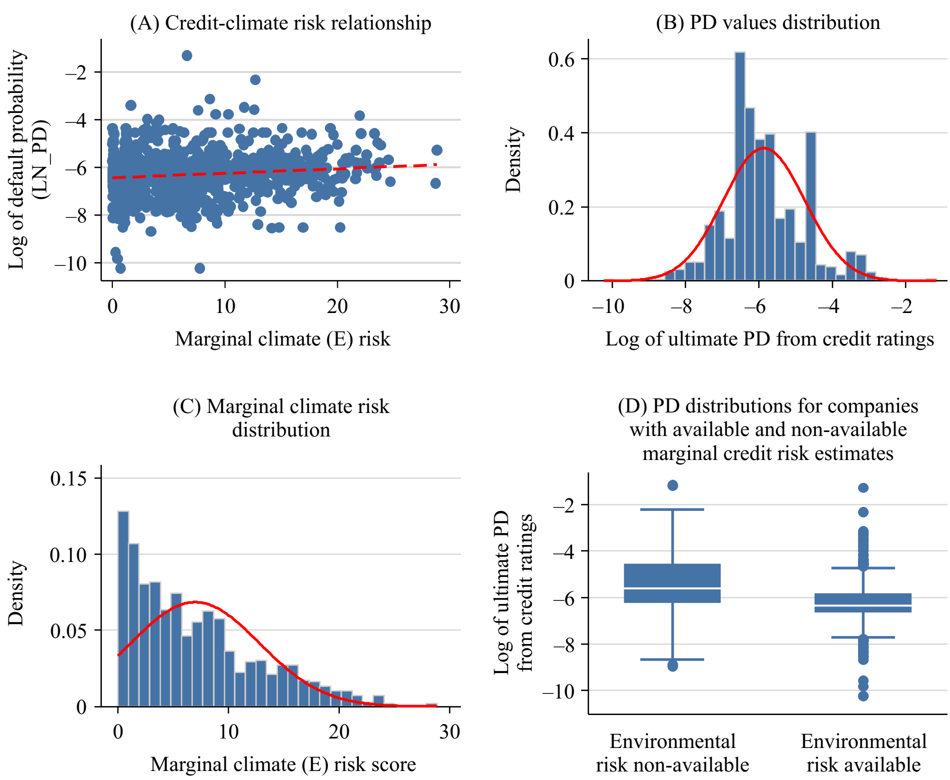

Fig. 1. Company-level data.

Source: Compiled by the authors using data from Sustainalytics (2021).

there is an equal number of low and high credit risk companies with respect to the population mean. The marginal climate (E) risk scores are concentrated at the lower segment of the axis (see panel C). It means there are more green companies in the sample than “brown” ones. Moreover, the mean default probabilities (PDs) are lower for the companies where the climate (E) risk scores are available (see panel D). However, the dispersion of PD values is comparable for those companies that have climate risk values, and those that do not have them.

The straight-forward credit-climate risk relationship is not stated. The respective trend line is almost horizontal (see panel A at Fig. 1). However, this is a marginal-credit-risk perspective. Objective of this paper is to define whether the relationship changes when the full climate risk estimates are used in IOTs approach.

For that purpose the World Input-Output Database (WIOD) from Timmer et al. (2015) was employed. See Makarov and Sokolova (2014), Leonidov and Serebryannikova (2019), Votinov et al. (2021) for more research using this dataset.

The recent version of WIOD tables which covers 2000–2014 was processed. The last 2014 release, which consists of 56 industries and 43 countries according to WIOD classification, was used.

The climate risk data stands for 2022, while IOTs — only for 2014. However, there is no time to wait another 8 years when the IOTs of 2022 could be utilized for benchmarking against 2022 climate risk data. Thus, the “second best” option available was employed.

To proceed in a unified format, the industry and country classifiers from the climate (Bloomberg) risk part of the dataset and that from the WIOD ones were merged. For the countries, some of the Bloomberg countries were grouped to arrive at the WIOD classification.

While for the industries, the procedure was longer as two groupings were made. A group of Bloomberg industries could correspond to a single WIOD classification. Moreover, this could take place in the opposite direction. Consider Table 2 as an example. The WIOD code “r05” (C10–C12) comprises three Bloomberg industries: beverages (10), food processing (36), tobacco (69). Inversely, the single Bloomberg industry of “Furniture and fixtures” (38) contains two WIOD industries: “manufacture of wood and wood products […]

Table 2
Example of industry classifications alignment.

WIOD			Bloomberg	
Code	ISIC_Rev_4	WIOD_industry_name	ind_code	ind_name
r05	C10-C12	Manufacture of food products, beverages and tobacco products	10 36 69	Beverages Food processing Tobacco
r07	C16	Manufacture of wood and of products of wood and cork, except furniture; manufacture of articles of straw and plaiting materials	38	Furniture and fixtures
r22	C31_C32	Manufacture of furniture; other manufacturing		

Source: Compiled by the authors.

except furniture" (r07, C16; an equivalent to "Fixtures"), "manufacture of furniture" (r22, C31–C32).

4. Methodology

To evaluate the sign of the relationship between the credit risk and the full climate risk we need to proceed in three steps:

1. Derive the marginal climate risk per industries and countries;
2. Obtain the full climate risk;
3. Benchmark the full climate risk to the credit risk.

To derive the marginal climate risk, a Poisson regression with the company-level climate (E) risk scores as the dependent variable and the country and industry dummies as the independent ones was run. The Poisson regression is preferred to the classical ordinary least squares (OLS) one as we need the output variable of the climate risk to be non-negative (this requirement is violated when proceeding with OLS).

We include the intercept when running the regression. We run full sample estimation with no validation at the testing set as explained by Diebolt (2015). The statistically insignificant coefficients are treated as zeros. Then we compute a country-industry matrix to arrive at the marginal climate risk estimates $\mathbf{r} = \{r_1, \ldots, r_N\}'$ for industries in particular countries.

Then we transit from the marginal risk estimates to the full ones. To do so, the input-output-based cost computation introduced by Wassily Leontief was used.

The production structure of the economy is characterized by the production function. More precisely, by the technological coefficients $a_{ij} = x_{ij}/y_j$. The coefficient a_{ij} shows how much the monetary contribution of i-th factor x_{ij} is to the total monetary cost of the j-th good output y_j. Given the interrelationship of industries we may derive a Leontief matrix of these technological coefficients $\mathbf{A} = \{a_{ij}\}_{i,j = 1,\ldots,N}$. The matrix $\mathbf{L} = (\mathbf{I} - \mathbf{A})^{-1}$ is referred to as the Leontief inverse matrix.

Let $\mathbf{F} = \{F_1, \ldots, F_N\}'$ be a vector of end consumption by producers, and apostrophe denotes the transpose operation. Hence the total production cost can be derived as follows:

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

where $\mathbf{y} = \{y_1, \ldots, y_N\}'$ is a vector of total output.

To apply the input-output cost computation methodology to climate risk we introduce the full risk $\mathbf{R} = \{R_1, \ldots, R_N\}'$. The underlying logic fully replicates the Leontief technological cost approach. If the industry consumes some factors including from itself, and the marginal (own) climate risk assessment of each industry is $\mathbf{r}$. Then the total climate risk per industry has to trace back the entire production chain, by weighting the inputs proportionate to their technological contribution $\mathbf{A}$. Thus, the full climate risk is obtained as follows:

$$\mathbf{R} = \mathbf{L}'\mathbf{r}. \tag{2}$$

Finally we aggregate the full climate risk estimates at the level of industries and countries separately to benchmark those against the credit risk aggregates per countries and industries. We present the charts, as well as baseline linear regressions with the mean of PD logarithms by country or by industry being the dependent variable and the full climate risk as the independent one.

For the robustness check we recall the stylized fact about our dataset. The marginal climate risk estimates are available only for half of the observations; see panel D at Fig. 1. Therefore we compute the mean of PD logarithms at the country and industry levels only for those observations that have the marginal climate risk data (during the main course we use the mean of PD logarithm for all the observations by industry and by country). We use non-conventional marks for the statistical significance of 10%, 20%, 30% to differentiate our results and report the levels at which the results might be statistically significant.

The country and industry data is presented in Appendices A and B. It can be considered as the country and industry relative ranking between themselves on the ground of the full climate risk data. For comparison, the mean values of the marginal climate risk were added to provide a reader with the feeling of scale as to how much the full climate risk changed when transiting from the marginal one, but expressed in the same units of measurement as the marginal one.

5. Empirical findings

The marginal climate risk data for Greece and Hungary were unavailable, although there are five companies from these countries with PD available. Nevertheless, the full climate risk is available for for the countries mentioned above as they form part of the global division of labor and have non-zero technological coefficients in WIOD set. Hence, the countries were included in our main findings, but they were excluded from the robustness check. As a result, the number of country observations changes from 35 in Table 3 to 33 in Table 4.

Our research objective was to trace the relationship between the credit risk and the full climate risk. The findings are presented in four charts in Fig. 2. Horizontally, the panels A and B refer to the dataset collapsed (aggregated) by country; the panels C and D stand for by-industry aggregation. Vertically, panels A and C report the relationship of PD and the marginal climate risk; while for vivid difference panels B and D do the same for the full climate risk derived from IOTs.

Table 3 provides a more formal measurement of the relationship through the OLS regression with intercept. The angle coefficients are insignificant at the conventional significance levels up to 10%. In part, this is the result of processing a statistically small sample (below 50 observations). However, it is not important to augment the set by running a Monte-Carlo, bootstrap or jackknife resampling. Such resampling just creates an illusion of statistical significance yielding no difference in substance as explained by Demidenko (2016).

Transiting to the full climate risk makes to meaningful difference at the country level, compare panel B to A in Fig. 2. The relationship is still negative, see "…_cty" in Table 3. So the "browner" the company is in terms of either marginal, or full climate risk, the more creditworthy it is.

Past credit data was used, which do not consider the green transition. Therefor if a simulation scenario analysis was performed when consumers shift to greener

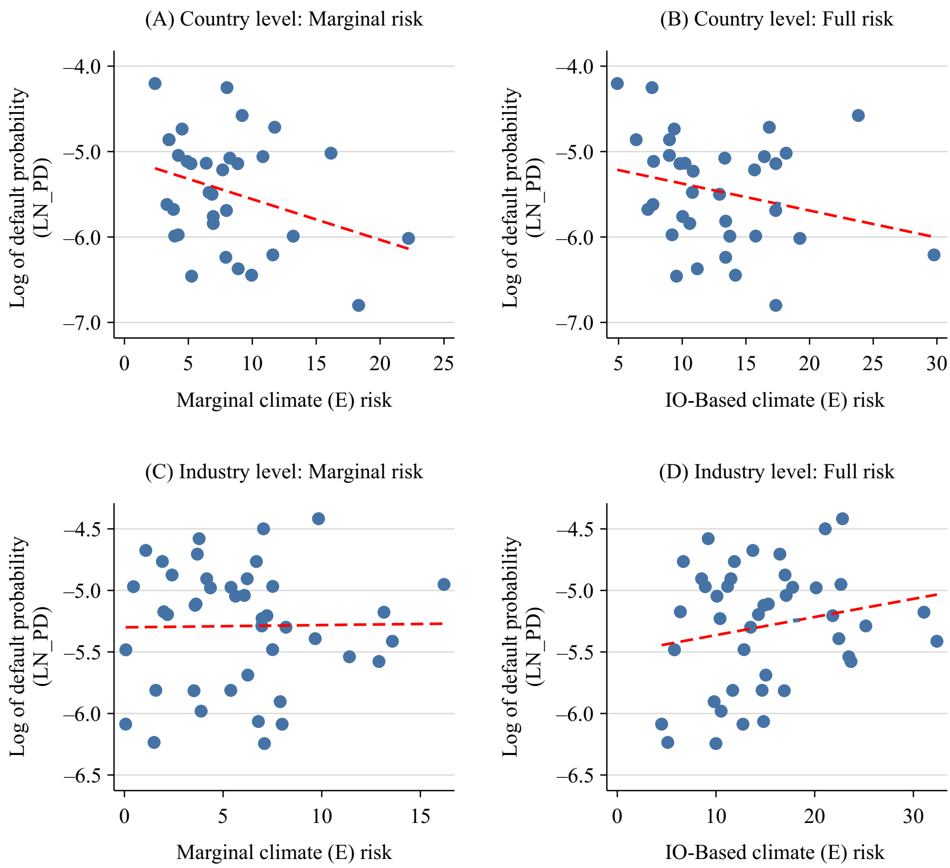

Fig. 2. Credit-climate risk relationship at the country and industry levels.

Source: Compiled by the authors.

Table 3

Regression output at the country and industry levels.

Variable	M_cty	M_ind	F_cty	F_ind
Environm	-0.048^{***}	0.002		
IOfull			-0.032^{**}	0.015^{*}
_cons	-5.082^{***}	-5.300^{***}	-5.058^{***}	-5.511^{***}
R^2	10.40	0.00	6.40	4.00
Adjusted R^2	7.50	–2.40	3.50	1.60
N	33	43	35	43

Note: M—marginal climate risk; F—full climate risk; ind—aggregation by industry; cty—aggregation by country; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Source: Authors' calculations.

energy and to more climate-friendly goods and services, which might have resulted in a positive relationship between credit and climate risks.

At the industry level we notice a shift from the horizontal trend in panel C of Fig. 2 to the positively sloping one at panel D there-in. This means that credit-climate risk relationship is important at the industry level unlike the country-level.

To sum up, we find that industry-wide there is a positive relationship of credit risk and the full climate one, despite the fact that past historical data was analyzed.

6. Robustness check

The previous section dealt with the credit risk estimated across the entire set of companies within a country or an industry. However, there is a downward bias in the mean PD values for companies that were assigned with the marginal climate risk by Sustainalytics, recall panel D at Fig. 1. Such a bias may affect the relationship of credit-climate risks.

To ensure confidence level of the findings herein, we limit the PD estimates to the companies with the non-empty marginal climate risk data only. The robustness check results are available in Fig. 3 and Table 4.

Then an angle change was observed — though statistically insignificant — at the country level also, compare panel B to A at Fig. 3. Positive relationship between credit risk and the full climate risk is more relevant at the industry level, see panel D at Fig. 3. Precisely, the positive relationship, in fact,

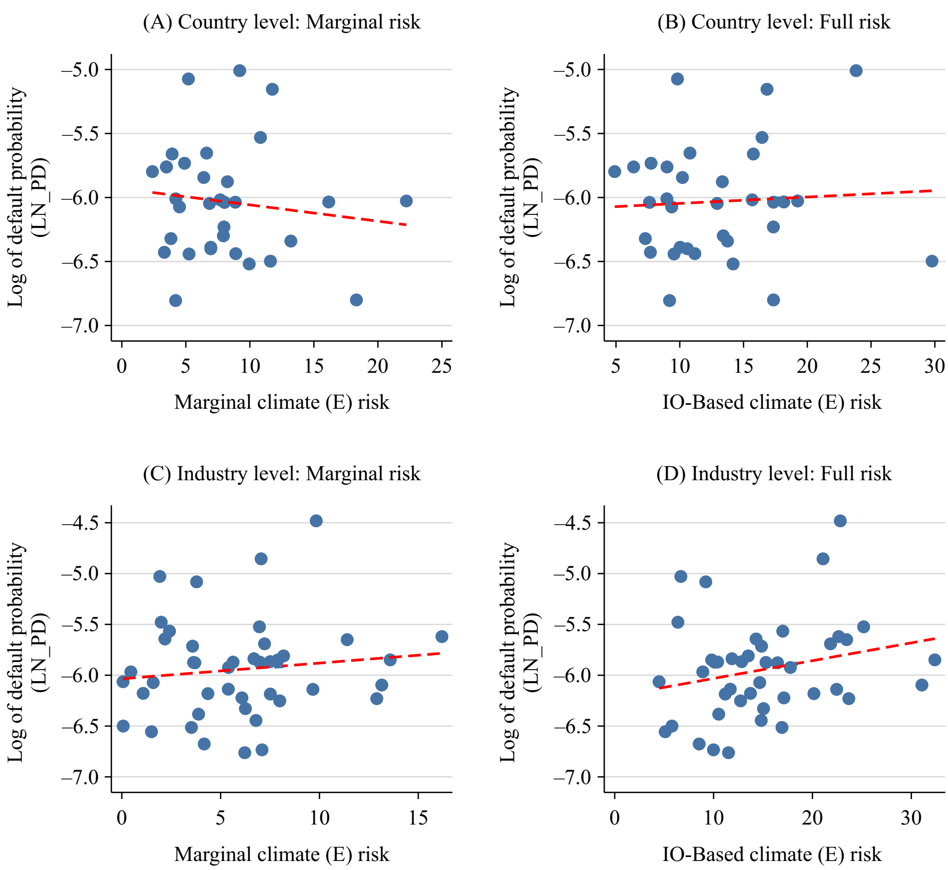

Fig. 3. Robustness check: Climate-credit risk relationship for data with non-empty climate (E) risk scores.

Source: Compiled by the authors.

Table 4
Robustness check: Regression for data with non-empty climate risk scores.

Variable	M_cty	M_ind	F_cty	F_ind
Environm	–0.013	0.002		
IOfull			0.005	0.015*
_cons	–5.930***	–5.300***	–6.096***	–5.511***
R^2	1.70	0.00	0.40	4.00
Adjusted R^2	–1.50	–2.40	–2.90	1.60
N	33	43	33	43

Note: M — marginal climate risk; F — full climate risk; ind — aggregation by industry; cty — aggregation by country; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.
Source: Authors' calculations.

became more significant than it is observed in panel C (before it was almost horizontal).

Thus, it must be noted that despite the use of past performance data that does not account for the prospect of the green transition, a positive credit-climate risk relationship at the industry level was revealed. The use of input-output tables and the study of full climate risk measure help arrive at this conclusion.

7. Discussion and conclusion

Previous studies argued for the positive climate-credit relationship presence (see Capasso et al., 2020; Vymyatnina and Chernykh, 2022). The researchers used the marginal climate risk estimates therein. Alternative studies using the marginal climate risk data concluded that the relationship is negative (see Penikas, 2022). Such a negative relationship might be the consequence of not considering the structural change in the economy due to the green transition.

Previous studies used the marginal climate risk data which as far as this paper is concerned does not help to arrive at reliable conclusions. It is an obvious fact that can quickly be found the research studies. However, the marginal climate risk may produce a biased perception of an industry. To achieve reliable result, the Basel Committee recommended using IOTs. However, the input-output tables approach is applied to carbon emissions in most studies but its use is neglected in the marginal climate ratings.

Despite the use of past data for this study, it was revealed that a positive relationship exists between credit risks and the full climate risks at the industry level.

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Appendix A. Industry data

#	Industry	Freq_PD	PD_all, %	PD_E, %	Freq_E	E_mean	E_IO_full
1	Advertising	7	0.23	0.23	5	0.06	4.49
2	Aerospace & defense	37	0.85	0.29	17	6.69	11.86
3	Air courier	25	0.74	0.12	10	6.22	11.51
4	Airlines	27	1.21	1.13	8	9.84	22.82
5	Aluminium	19	0.50	0.40	10	6.96	25.18
6	Apparel/accessories	39	0.30	0.23	26	1.59	14.67
7	Auto & truck manufactures	34	0.55	0.34	24	7.22	21.83
8	Auto & truck parts	43	0.69	0.27	20	5.40	17.77
9	Beverages	120	0.60	0.28	51	3.63	15.30
10	Biotechs	32	0.23	0.16	16	6.79	14.82
11	Broadcasting & cable	74	0.50	0.30	43	8.18	13.51
12	Business & personal services	31	0.85	0.65	13	1.92	6.69
13	Business products & supplies	61	0.57	0.42	36	1.99	6.39
14	Casinos & gaming	123	1.03	0.62	59	3.78	9.21
15	Computer & electronics retail	180	0.69	0.21	88	4.36	20.15
16	Conglomerates	6	0.55	0.35	3	2.18	14.30
17	Construction materials	74	0.46	0.22	36	9.67	22.45
18	Containers & packaging	14	0.91	0.28	9	3.70	16.47
19	Department stores	128	0.54	0.28	70	6.97	10.41
20	Diversified chemicals	12	0.30	0.15	7	3.52	16.92
21	Diversified metals & mining	42	0.38	0.20	23	12.90	23.68
22	Diversified utilities	66	0.71	0.36	20	16.20	22.66
23	Drug retail	140	0.64	0.28	63	5.63	10.10
24	Electric utilities	6	0.93	0.21	2	1.08	13.73
25	Electrical equipment	138	0.45	0.29	67	13.58	32.38
26	Environmental & waste	41	0.30	0.22	24	5.39	11.69
27	Furniture & fixtures	42	0.65	0.20	16	6.08	17.11
28	Heavy equipment	49	1.11	0.78	18	7.05	21.07
29	Home improvement retail	35	0.70	0.21	16	7.52	11.18
30	Hotels & motels	14	0.25	0.17	11	3.88	10.52
31	Internet & catalog retail	37	0.42	0.28	25	7.51	12.84
32	Natural gas utilities	166	0.56	0.23	83	13.15	31.07
33	Other transportation	31	0.34	0.18	20	6.25	15.05
34	Paper & paper products	32	0.60	0.33	16	3.58	14.85
35	Pharmaceuticals	11	0.39	0.35	6	11.40	23.46
36	Printing & publishing	3	0.20	0.14	2	1.50	5.11
37	Railroads	16	0.69	0.26	8	0.46	8.91
38	Real estate	18	0.27	0.29	15	7.89	9.81
39	Recreational products auto	4	0.42	0.15	1	0.07	5.79
40	Software & programming	37	0.23	0.19	21	7.99	12.73
41	Specialized chemicals	35	0.76	0.38	13	2.41	17.00
42	Trading companies	10	0.19	0.12	6	7.10	9.99
43	Financial	7	0.74	0.13	3	4.17	8.54

Note: Freq_PD is the number of companies that have the default probability (PD) per a particular *industry* (there are 2066 companies in total for PD data PD_all is the PD average over all the companies for a given *industry*; PD_E is the PD average over the companies with non-empty climate (E) risk scores for a given *industry*; Freq_E is the number of company observations that do have the climate (E) risk publicly disclosed by Sustainalytics for a given *industry* (there are 1030 such companies in total, i.e., around one half of those that do have the PD); E_mean is the company-average climate (E) risk for a given *industry*; E_IO_full is the full climate risk estimate for a given *industry* using the input-output (IO) tables.
Source: Authors' calculations.

Appendix B. Country data

#	Country	Freq_PD	PD_all, %	PD_E, %	Freq_E	E_mean	E_IO_full
1	Australia	36	0.20	0.18	23	7.93	13.41
2	Austria	5	0.17	0.16	4	8.90	11.18
3	Belgium	8	0.25	0.11	4	4.20	9.20
4	Brazil	30	0.90	0.58	12	11.75	16.84
5	Canada	61	0.62	0.28	33	8.25	13.34
6	China	291	1.03	0.67	66	9.21	23.83
7	Czech Republic	1	0.11	0.11	1	18.32	17.35
8	Denmark	13	0.36	0.16	10	3.32	7.70
9	Finland	10	0.32	0.17	4	6.95	10.03
10	France	71	0.34	0.18	36	3.83	7.30
11	Germany	63	0.42	0.35	43	6.62	10.80
12	Greece	4	0.54		n/a	n/a	10.86
13	Hungary	1	0.30		n/a	n/a	13.41
14	India	43	0.64	0.40	24	10.83	16.45
15	Indonesia	5	0.20	0.15	3	11.61	29.78
16	Ireland	15	0.88	0.23	7	4.51	9.37
17	Italy	19	0.60	0.32	7	4.90	7.75
18	Japan	200	0.41	0.24	137	6.85	12.93
19	Luxembourg	9	0.25	0.35	2	3.93	15.77
20	Mexico	18	0.25	0.18	9	13.20	13.74
21	Netherlands	24	0.29	0.17	9	6.95	10.59
22	Norway	9	0.16	0.15	6	9.95	14.18
23	Poland	6	0.24	0.24	4	22.22	19.24
24	Portugal	5	1.42	0.24	1	8.02	7.63
25	Russia	56	0.66	0.24	8	16.16	18.16
26	South Korea	60	0.59	0.24	28	8.86	17.35
27	Spain	24	0.77	0.31	9	3.48	6.38
28	Sweden	24	0.16	0.16	18	5.25	9.55
29	Switzerland	42	0.58	0.63	23	5.20	9.82
30	Taiwan	39	0.34	0.20	15	7.98	17.34
31	Turkey	9	1.49	0.30	1	2.39	4.90
32	United Kingdom	99	0.64	0.25	32	4.22	8.99
33	USA	662	0.59	0.29	418	6.40	10.21
34	Rest of the world	104	0.54	0.24	33	7.51	15.68

Note: Freq_PD is the number of companies that have the default probability (PD) per a particular *country* (there are 2066 companies in total for PD data); PD_all is the PD average over all the companies for a given *country*; PD_E is the PD average over the companies with non-empty climate (E) risk scores for a given *country*; Freq_E is the number of company observations that do have the climate (E) risk publicly disclosed by Sustainalytics for a given *country* (there are 1030 such companies in total, i.e., around one half of those that do have the PD); E_mean is the company-average climate (E) risk for a given *country*; E_IO_full is the full climate risk estimate for a given *country* using the input-output (IO) tables; n/a — not available.
Source: Authors' calculations.