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The Interrelationship of Credit and Climate Risks

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The Interrelationship of Credit and Climate Risks

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Abstract

The focus of our study is the environmental (E) risk score. For this paper, we have collected a unique database of public ESG ratings for the world largest companies in the *Fortune* Global 2000 list. The credit risk estimates are derived from publicly available credit ratings. The probability of default (PD) levels result from the use of historical default data. We control for the specifics of industries and sectors. The availability of E-risk data for half of the sample implies the need to apply the Heckman selection model. We show cases when the climate-credit risk relationship is robustly positive for a particular industry and region: in such cases, loan subsidies are indeed advisable to finance large green projects and green corporations (e.g. the 2021 Bank of Japan program – though it was tailored for SMEs). Otherwise – in the predominant number of cases – such a loan rate reduction may foster the accumulation of credit risks and pose a threat to financial stability. We contribute to the literature by showing that the revealed positive climate-credit risks dependence is not ubiquitous – which is argued by (Capasso, Gianfrate, & Spinelli, 2020).

Key words: green company, brown company, Sustainalytics, carbon dioxide emissions, Heckman.

JEL Codes: C24, E52, H23, O44.

1. Introduction

The climate change agenda attracts increasingly more attention each year after the 2015 Paris Agreement. Two terms were introduced to the subject area: green and brown industries. Green industries are those that contribute to the negative climate change impact to the lowest extent, while brown ones contribute most detrimentally. Concurrently, the notion of greenness is applied to investment projects and bonds. The tools to fund positive (or improving) contributions to climate change are deemed green ones. These may be projects intended to limit carbon dioxide (CO2) emissions, among others.

Climate change is said to represent an immense challenge to mankind, and global warming is viewed as one of its detrimental consequences. Carbon dioxide emitted by industrial enterprises is considered to be a major contributor to global warming. The international community is implementing a package of measures intended to slow down the pace of global warming.

First, to control, to the maximum extent possible, climate change, it is necessary to become knowledgeable about the climate change contribution of a particular enterprise. That is why efforts are being made to promote information disclosures on the amounts of pollution and carbon dioxide emissions. For instance, this disclosure is now a standard requirement for listed companies introduced by the UK regulator in 2021 (FCA 2021). An equivalent recommendation for central banks was developed by the task force of the Network for Greening the Financial System (NGFS 2021).

Second, since climate change risks are considered material, financial products should price them in. The 'green swan' term was even introduced in (Bolton, Després, Pereira da Silva, Samama, & Svartzman, 2020) and in (Pereira da Silva, 2020) – as a measure to consider when evaluating the stability of enterprises as borrowers and banks as lenders to such borrowers. As a result, the Basel Committee, the world's standards-setter in banking regulation, issued relevant guidelines for regulators (BCBS 2021). The People's Bank of China has recently become one of those advocating their adoption (PBC 2021). Furthermore, there are proposals in the US that the scope of such regulation be extended to cover, beyond the largest banks, even small credit unions (Baumann, 2021).

Third, in addition to climate-related risk regulation, banks may be incentivized to lend to green projects and green industries. For instance, such a stimulus program was launched by the Bank of Japan in September 2021 (BoJ 2021). For all the relevance of the measure, regulators should be cautious when introducing such stimulus measures. Let us recall the preferential treatment of small and medium enterprise (SME) loans in the Internal-Ratings Based (IRB) approach of Basel II accord (BCBS 2006). The intent was to promote the growth of SMEs. However, it turned out in practice that the SME segment was the least creditworthy compared to conventional corporate borrowers. As a result, the relaxed capital requirements resulted, expectedly and intendedly, in the wider supply of loans but also, unexpectedly and unintendedly, in more defaults.

The shift to green energy has faced a number of impediments in 2022. For instance, Till Requate of the Department of Economics at Kiel University (Germany), a member of the Commission of Experts for Research and Innovation of the German Government, speaking at the 2022 International Symposium on Environment and Energy Finance Issues (ISEFI-2022), drew attention to the following fact. Postponing the introduction of carbon policy, as Portugal has decided this year, to prevent energy costs from rising may bring a perverse impact. The shift away from Russian oil and gas because of the EU sanctions and a later introduction of the carbon tax will likely extend the use of much browner resources such as coal. Thereafter, the increased exposure to coal would make it even harder to switch to greener sources. That is why the question of green transition is of particular importance today.

Our objective is to explain and confirm the rationale for subsidized interest rate schemes, in the manner of the one launched by the Bank of Japan, and to show when they pay off and when they do not. Publicly available data on climate (environmental) risks enable us to trace the relationship of credit and climate risks – the focus of multiple recent studies. We control for company size as well as industrial and regional specifics of companies. We find out that the economic stimulus initiative of the Bank of Japan, although overall justified, might fail in the case of oil-exporting countries.

We are conscious of limitations to this statement. The Bank of Japan's program is tailored for SME projects, while we study large firms. SMEs are a priori viewed as riskier borrowers than large corporations. Hence they might be more likely to demonstrate a positive climate-credit risk dependency. In this context we should mention the paper by (Capasso, Gianfrate, & Spinelli, 2020), the focus of which was also large companies. Contrary to their findings, we find that the largest global companies are marked by a negative climate-credit risk relationship. Such a controversy in the findings supports the argument that climate ratings might vary widely in their methodology. We may find a positive climate-credit relationship based on one rating and start promoting lending to green projects and companies. However, other climate ratings may bring about a negative climate-credit relationship (as is the case in this paper) and warn against green lending. In the latter (our) case regulators should rather be preoccupied with developing appropriate tools to combat the negative outcome in case of large credit losses related to unfinished or unproductive green projects and companies. Given this sensitivity of outcomes to input data on climate ratings, a policy-maker should at least become less enthusiastic about embracing green finance. Unsurprisingly, any statements about the pros and cons of green projects and industries would be more vigorously challenged.

The reader may deem the principal finding of the paper as trivial and expected. Historical data show that browner (e.g. energy) companies, which regularly paid out their debts and never defaulted, seem much more creditworthy than their greener peers. In other words, one might say that the interrelationship of climate and credit risks is negative. Nevertheless, we suggest it is worth considering this comment from a different angle.

The author fully agrees that from a certain viewpoint a negative climate-credit risk interrelationship could have been expected. This paper also relies on historical data about company creditworthiness. In retrospect, browner companies are more solid than their greener competitors. An alternative approach might be an analysis of climate change scenarios with an evaluation of brown and green companies' creditworthiness after the climate has changed or consumers have shifted to green energy sources. In this analysis, the sign of the climate-credit risk relationship might become inverted, e.g. turn positive. Having said that, (Capasso, Gianfrate, & Spinelli, 2020) do not employ potential climate scenarios but rely in their findings on historical stock price volatility. That is why it comes as no surprise that they should have also obtained a negative sign for the climate-credit risk relationship based on their historical data,. When commenting on Table 4 later on, we will explain in more detail the methodology that led (Capasso, Gianfrate, & Spinelli, 2020) to obtain the positive sign. For this reason, we suggest that this paper be viewed as a correct starting point, rather than the one by (Capasso, Gianfrate, & Spinelli, 2020).

Separately, the negative interrelationship of climate and credit risks seems to form the basis for the concept of transition (transitional) risks. These risks were mentioned in two reports, one by a European regulator and one by the UN (ESRB, 2016), (UN PRI, 2017, p. 29). Should most of consumers switch to green energy sources, their producers would have sufficient cash to pay for existing debts and land new loans, while brown energy producers would face revenue shortages to a point of default. Therefore, it is reasonable to expect that the climate-credit risk relationship is negative up to a point of full transition to green energy, and positive once this transition has occurred.

The predicted change in the sign of the credit-climate risk relationship faces two challenges: one from the use on non-ferrous metals and another from the transition process itself. Aluminium market developments vividly illustrate the first challenge. On the one hand, it is extensively used for the production of green energy products such as solar panels. On the other hand, aluminium has one of the largest carbon footprints. This controversy was named 'Aluminium's Climate Paradox' (Goldman Sachs, 2021). The paradox involves a hypothesis that the all-out green transition will come with expansion in brown production facilities, and the expansion will probably be disproportionately larger than that in the green economy. This means that the rise in green energy demand may even make brown borrowers more creditworthy from the standpoint of capital markets and lending banks. Thence, the negative climate-credit risk relationship might hold even after the mass green transition takes place.

The second challenge relates to the transition process. Neither relaxed capital requirements for green companies and projects (in the form of reduced risk weights to calculate the capital adequacy ratio) nor preferential interest rates on their loans might be sufficient to trigger structural changes in the economy. A carbon tax or an intra-country emissions exchange might help in the rollout of this transition. In this context, it is useful to monitor the 'Sakhalin experiment' and evaluate its impact (Interfax, 2022): the experiment provides for the payment of one thousand rubles per ton of carbon dioxide emissions in excess of the pre-set quota.

Let us formalize the research hypotheses as the following questions:

1) When using an appropriate regression specification with the climate risk being the dependent variable and credit risk the independent one, is the estimated coefficient preceding the credit risk proxy positive or negative? (We do not aim to study the causality.) If it is statistically negative, then we conclude that the climate-credit risk relationship is inverted (negative).

2) Is there data censoring? In other words, are climate risk ratings assigned in a non-random mode? If so, does adjusting for such censoring produces material changes to our findings? Does it invert the sign of the climate-credit relationship?

3) When defining our contribution to the literature, based on the findings from the above points, should we agree with (Capasso, Gianfrate, & Spinelli, 2020) that there is a positive relationship between credit and climate risks? From a policy implication perspective, should we agree with the Bank of Japan's approach that green projects (companies) deserve the right to subsidized loans?

To answer the aforesaid questions, we organize the paper in the following way. We start with a literature review in Section 2. We describe the available data and describe the methodology in Section 3 (granular statistical data are available in Annex A). Our findings follow in Section 4, with granular regression estimates shown in Annex B. Section 5 concludes and presents answers to the aforesaid questions.

2. Literature Review

The climate (environmental) risk gained particular attention and became part of the ESG acronym. A review of substantial progress in this area is presented in the book by (Boubaker, Cumming and Nguyen 2019).

While it is not our intention to challenge the basic parameters of the climate change agenda, it is important to admit that this domain still involves a high degree of uncertainty.

(Kotlikoff, Kubler, Polbin, & Scheidegger, 2021) make a 200-year ahead prediction and forecast the global temperature to rise by 3.6 degrees Celsius. At the same time, the joint efforts and the introduction of carbon tax in the amount of $27-100 per ton of carbon emissions may limit the global warming growth only to 2.6 degrees Celsius by 2200. The rise in temperature operated by (Kotlikoff, Kubler, Polbin, & Scheidegger, 2021) is in line with the NASA statement (NASA, 2022) according to which today's global temperature is the highest for the last two thousand years, and with a forecast by (Westerhold, et al., 2020) who also predict an upward trend in global temperatures. That said, the NASA forecast (NASA, 2022) is built on global temperature records for only the last 120 years. A concurrent report (Legner, 2022) makes the case that one to two thousand years ago global temperature was somewhat 4 degrees Celsius above today's level. The researcher's data are aligned with a 66 million-year track presented by (Westerhold, et al., 2020), who argues that global temperature had declined by around 16 degrees Celsius in this time span.

Anna Creti of Paris Dauphine University at the 2022 International Symposium on Environment and Energy Finance Issues (ISEFI-2022) brought examples of intergenerational transfers that are actually thought of when researchers propose any redistributions for N-years ahead. In this context, let us recall Professor John Nash, the 1994 Nobel Prize winner in economics, and the distinction between Pareto optimality and the Nash equilibrium. The proposed 200-year ahead redistribution is a sort of a desirable Pareto optimum, but it is not a robust equilibrium point. Given the average tenure of political leaders (4-7 years per election), it is highly likely that society will move from the desirable Pareto optimum to the undesirable but stable Nash equilibrium.

Due to the uncertainty over the impact of climate change on temperature and the economy as described above, we are not producing our estimates of either of these impacts. Instead, we will rely on external publicly available estimates for the climate risk to define its relationship to the credit risk.

The impact of the climate risk on the credit risk was raised as a discussion point at the UN level back in 2017 (UN PRI, 2017, p. 29). It is argued that a late and abrupt transit to green technologies will render carbon-intensive and particularly debt-laden projects less creditworthy. This statement is more about the transition risks than the long-term effects of climate change risks.

(Rudebusch, 2021) and (Janosik & Verbraken, 2021) agree that accounting for the climate risk should increase credit risk estimates, i.e. probability of default (PD) predictions. Their logic comes from the principle of adding this factor to PD models which have never before accounted for the climate risk. However, they do not run a marginal analysis to detect which marginal change in PD is due to a marginal change in the climate risk. We are closing this gap.

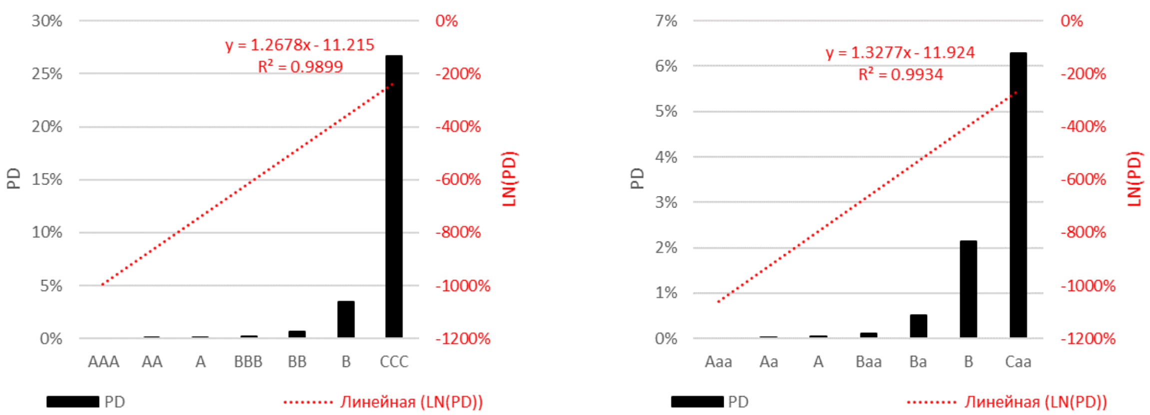
To do so, we need relevant data. We have made progress compared to (Degryse, Goncharenko, Theunisz, & Vadasz, 2021). They use the mere fact of information disclosure as a proxy for the climate risk. They omit the intensity of the disclosed impact and classify carbon-intensive but transparent companies as green ones. We have made a point of avoiding such a misjudgment by relying on public estimates of the environmental risk that are not limited to the mere presence of climate risk information disclosures.

The closest work to ours is that by (Capasso, Gianfrate, & Spinelli, 2020). The researchers find that the 'corporate default risk is positively associated with carbon footprint', i.e., the larger the climate risk, the larger the credit risk. However, our preliminary finding is the opposite: the larger the climate risk, the smaller the credit risk (we do not argue about the particular direction of causal inference – we seek to asess the relationship). We will discuss causes for such material discrepancy in Table 4.

3. Data and Methodology

To assess the interrelationship of credit and climate risks, we collect publicly available registries of these two risks. We start from the Fortune 2000 list of the world largest companies. The list of the variables used, their descriptive statistics and the correlation matrix is available in Annex A (Table 5-Table 9).

First, we retrieve information on credit risk estimates. We extract credit ratings assigned by the Big Three credit rating agencies from Bloomberg files: Standard & Poor's (S&P, SP), Moody's, and Fitch. To make data comparable, we move away from ordinal (relative) risk measurement in terms of credit rating grades to probability of default (PD) estimates. We proceed from the historical default rates for the seven high-level credit grades from the credit rating agencies' reports, both public (Moody's, 2018), (S&P Global Ratings, 2019) and non-public (FitchRatings, 2021).



(a) Standard&Poor's (b) Moody's

Figure 1. PD Extrapolation by Credit Ratings Using the Historical Default Rates by Credit Grades

We transform the default rate estimates into the logarithmic scale as it is the baseline principle for designing the Master Scale credit rating. This enables us to linearly extrapolate the PD estimates in logarithms from high-level grades to sub-notches. The evaluation logic is illustrated in Figure 1. If the company has multiple credit ratings, we compute the mean PD.

Table 1. PD Estimates by the Bloomberg Composite Index

			Mean PD by Bloomberg Composite Rating Grade, pp						# obs.	
#	Blmb_ COMP	Freq.	S&P	Moody's	Fitch	Mean	Bloom.	Final	ols7	H6
1	#N/A	10	0.43	0.43	0.39	0.38		0.38	0	0
2	IG1	553	0.15	0.16	0.12	0.15	0.15	0.15	406	541
3	IG2	106	0.21	0.24	0.17	0.24	0.24	0.24	77	105
4	IG3	119	0.23	0.22	0.18	0.21	0.21	0.21	82	116

			Mean PD by Bloomberg Composite Rating Grade, pp						# obs.	
#	Blmb_ COMP	Freq.	S&P	Moody's	Fitch	Mean	Bloom.	Final	ols7	H6
5	IG4	118	0.30	0.26	0.23	0.28	0.28	0.28	71	117
6	IG5	113	0.26	0.24	0.19	0.24	0.24	0.24	65	110
7	IG6	139	0.42	0.44	0.24	0.42	0.42	0.42	81	139
8	IG7	129	0.30	0.32	0.20	0.30	0.30	0.30	55	122
9	IG8	126	0.40	0.38	0.27	0.36	0.36	0.36	52	116
10	IG9	130	0.60	0.83	1.57	1.06	1.06	1.06	38	116
11	IG10	98	0.71	0.70	0.33	0.61	0.61	0.61	27	83
12	HY1	94	1.01	1.24	0.49	1.04	1.04	1.04	28	80
13	HY2	103	1.04	1.50	0.64	1.04	1.04	1.04	20	76
14	HY3	82	1.22	1.17	0.52	1.03	1.03	1.03	11	55
15	HY4	42	4.78	2.39	8.99	3.66	3.66	3.66	4	25
16	HY5	17	3.23	2.51	1.51	2.70	2.70	2.70	1	13
17	HY6	18	3.76	8.80	1.25	6.01	6.01	6.01	2	11
18	DS1	14	2.68	2.52		3.04	3.04	3.04	0	8
19	DS2	8	2.98	2.93	3.52	2.76	2.76	2.76	0	6
20	DS3	5					3.04	3.04	0	1
21	DS4	2					3.04	3.04	0	1
22	**Total**	**2030**	**0.48**	**0.50**	**0.44**	**0.51**	**0.60**	**0.60**	**1020**	**1841**

Note: IG – investment grade; HY – high yield; DS – distressed; # obs – presents the number of observations by grade that entered the respective model specification: ols7 for OLS and H6 for Heckman. For details on the Bloomberg Composite Credit Rating refer to (Zhang, 2015, p. 9).

Half of the companies do not have any of Big Three credit risk ratings. Nevertheless, all of them have a Bloomberg Composite Credit Risk Rating (see column 1 in Table 1). To assign a PD level to those with the Bloomberg credit rating only, we estimate the mean PD (see the column 'Mean' in Table 1) for Big Three rating agencies by Bloomberg credit rating grades at each company level.

Let us illustrate the procedure using an example with randomly selected companies in Table 2. The first company, Hakuhodo DY Holdings, has no Big Three ratings; the second one, WPP, has a Standard & Poor's (SP) rating; the third one, AirBus, has all the three. As for the third company, the mean PD is the average of the three values; as for the second company, it equals to the only available PD by Standard&Poor's.

Table 2. Example of PD Computation for Available Data

1	Company	1) Hakuhodo DY Holdings	2) WPP	3) AirBus
2	Ticker_Blmb	2433 JP Equity	WPPGF US Equity	EADSY US Equity
3	Ticker_Yahoo	2433.T	WPPGF	AIR.DE
4	SP		BBB	A
5	Moodys			A2
6	Fitch		WD	BBB+
7	Blmb_COMP	IG3	IG3	IG6
8	PD_SP		0.0021	0.0006
9	PD_M			0.0005

1	Company	1) Hakuhodo DY Holdings	2) WPP	3) AirBus
10	PD_F			0.0012
11	PD_mean		0.0021	0.0008
12	PD_BL	0.0021	0.0021	0.0042
13	PD_fin	0.0021	0.0021	0.0008

Note: WD – withdrawn; SP – Standard & Poor's, M – Moody's, F - Fitch.

As we can see from row 4, the column "Bloom." in Table 1, the PD average for all companies having ratings from at least one of the Big Three agencies and having the IG3 rating by Bloomberg equals 0.21%. That is why the applicable PD for the first company with no Big Three ratings but with the IG3 Bloomberg rating is 0.21%. The third company has the IG6 Bloomberg rating. The pooled mean for it equals to 0.42% (see row 7, column "Bloom." in Table 1). However, we have individual Big Three ratings for the third company. That is why for the purpose of our study we use its own mean of 0.08% (see row 13 in Table 2). We could have directly used historical default rates for Bloomberg credit rating grades, but these data are not accessible to us.

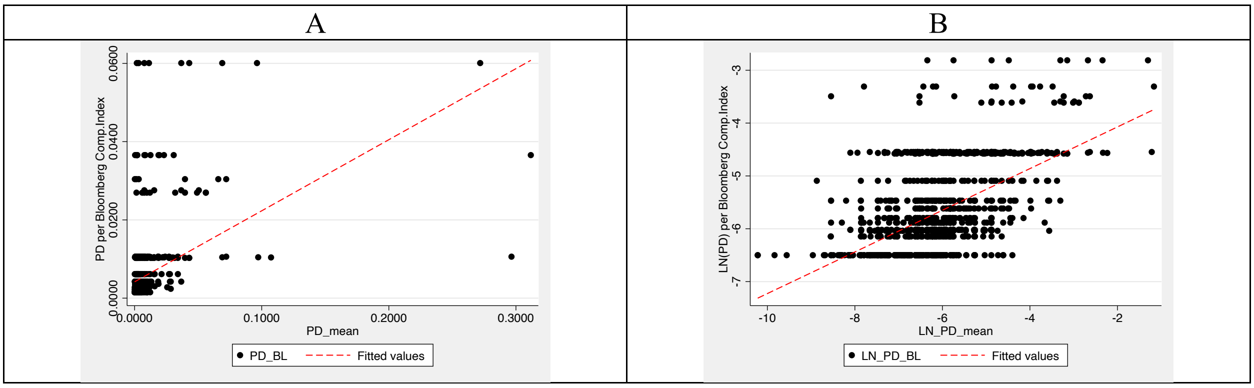


Figure 2. Credit Risk Estimates by International Rating Agencies (PD_mean) are aligned with the Bloomberg Composite

Overall, we can see that – by construction – the assigned Bloomberg PD values are aligned with individual Big Three PD proxies, as shown in Figure 2. The correlation in PD levels is 43% (see panel A on Figure 2), and in logarithms of PD is 54% (see panel B in Figure 2). On average, we also confirm the stylized fact that the larger a company in terms of total assets, the lower its PD, see Figure 3.

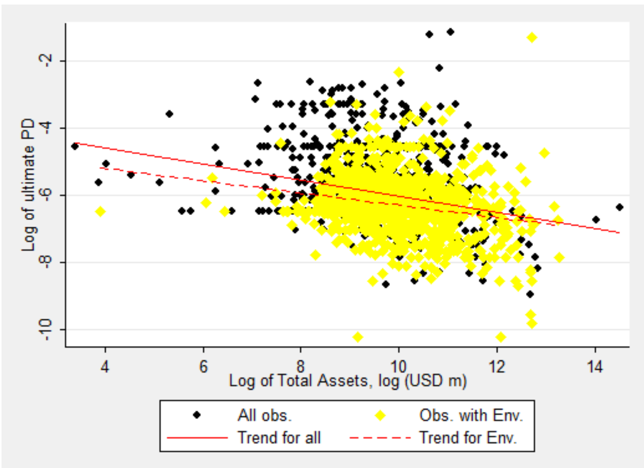


Figure 3. Larger Companies Tend to Be Assessed as More Creditworthy

Second, we use the data on climate (environmental) risk estimates. It is publicly available on the website finance.yahoo.com. The special 'Sustainability' section has respective information per listed company (though not for any company). The climate risk estimate as of the latest available date is provided by the company (Sustainalytics, 2021). It accounts for various events that might trigger the realization of the climate risk. Yet, it is not a measure of the systemic risk and should not be mistaken for it. More importantly, the available climate (environmental) risk score is comparable between industries, as the developers argue. This is quite useful for us as the PD is also an indicator comparable for companies of different industries as well as those within one industry.

Using the Sustainalytics climate (environmental, E) risk score, we may define green companies as those that have the lowest score, and brown ones as those that have the highest score. Let us highlight the advantages of the Sustainalytics rating. The rating does not measure the intensity of climate risk-related disclosure, but focuses on the overall sensitivity to the climate risk. Though Sustainalytics (similar to the Big Three) does not disclose the granular rating methodology (e.g. factor weights), the Sustainalytics climate risk rating is not about the transition risk, but about a comprehensive assessment of the company's exposure to the climate change risk.

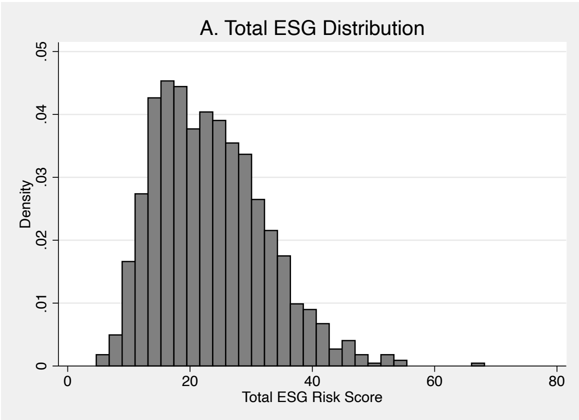


Figure 4. Total ESG score is distributed in the 5-55 range out of 100 points (potential maximum value)

The available data are not limited to the climate risk. They yield estimates for all the three ESG dimensions, as well as for the total ESG risk score (Figure 4). For information purposes, we demonstrate the dependence patterns of the risk scores by dimension in Figure 5.

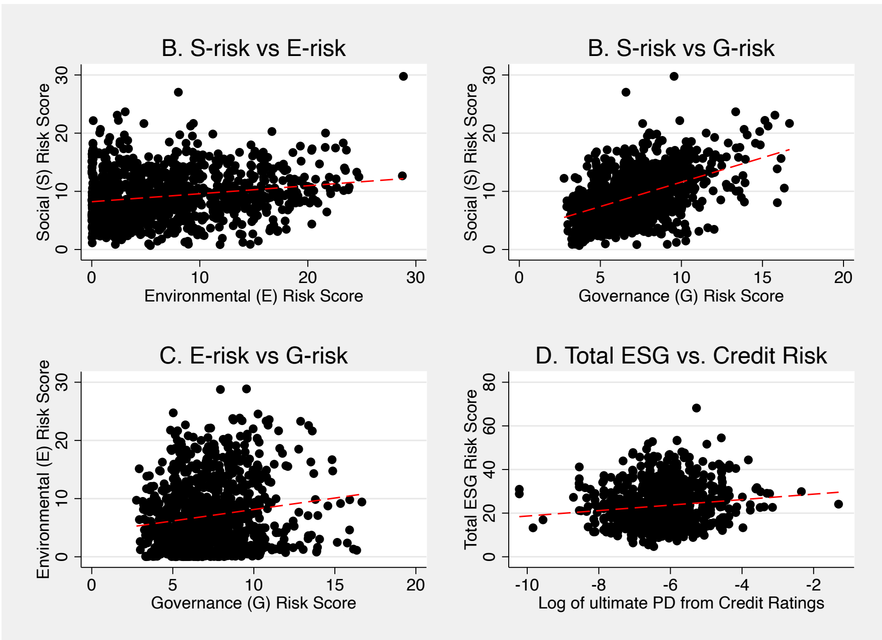


Figure 5. Three ESG Risk Dimensions Are Relatively Highly Co-Dependent, While the Total ESG Score is On Average Positively Related to the Credit Risk Estimates

The publicly available data from Sustainalytics have a specific feature. Though all the companies are on the Fortune 2000 list of the world largest companies, only half of them were assigned climate risk estimates by Sustainalytics. More precisely, companies with lower PD levels tend to be more often assigned with the climate risk score, as shown in Figure 6. These noticeable specifics in data are censoring. Censored observations lack the values of the dependent variable (the climate risk score in our case). In order to use the climate risk score as the dependent variable, we have to address the problem that half observations are missing. Based on the way the data are handled, it is advisable to use the Heckman selection model since the data censoring may not be random in nature.

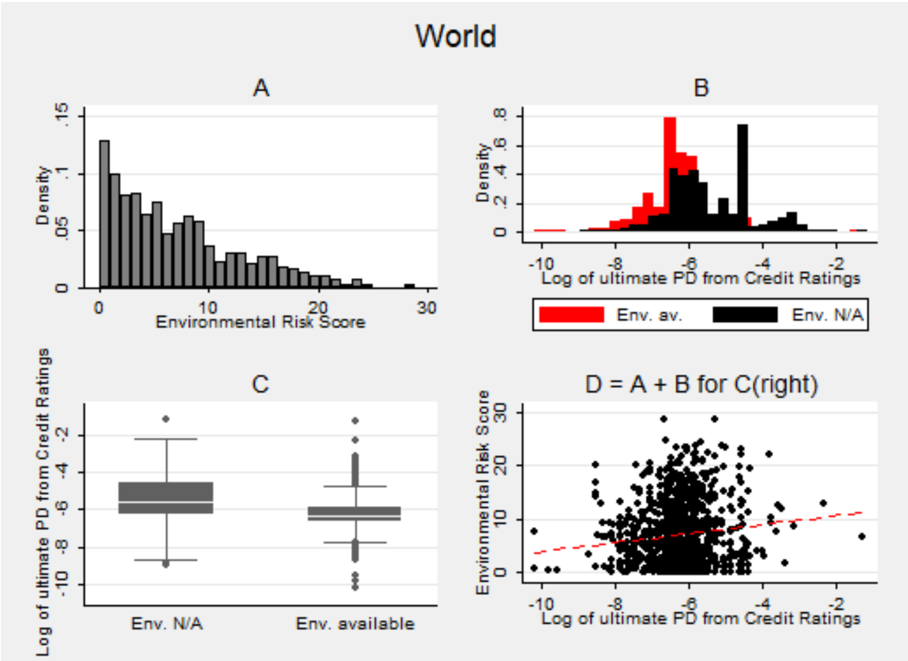


Figure 6. Half of the World-Largest Companies Have Environmental Risk Assessment Out of Those Considered from the Fortune 2000 List, for which the Environmental Risk Is More Concentrated in the Range of Low Values

Our first observation is that the total ESG score and the climate risk score are positively related to the credit risk estimates, see sections D in Figure 5 and Figure 6. We should remember that this is the dependence on the average value that does not control for industrial and regional specifics. Moreover, the respective pairwise correlation is too low (+13%, see Table 9). Thus, we should not be misled and confirm the message about the positive climate-credit risk relationship.

To properly investigate the interrelationship of climate and credit risks, we run the following ordinarily least squares (OLS) regression, in the manner of (Horny, Manganelli, & Mojon, 2018), to decompose the credit spreads of sovereign eurobonds.

$$E - Risk_{isr} = \beta_0 + \theta_1 \cdot LN(TA_{isr}) + \beta_1 \cdot LN(PD_{isr}) + \sum_{s=1}^{S} \beta_{1+s} \cdot D_s + \sum_{r=1}^{R} \beta_{1+S+r} \cdot D_r + \sum_{s=1}^{S} \beta_{1+S+R+s} \cdot D_s \cdot LN(PD_{isr}) + \sum_{r=1}^{R} \beta_{1+2S+R+r} \cdot D_r \cdot LN(PD_{isr}) + \varepsilon_{isr}$$

where we use the following denotations: i – company (I=2030), s – sector (S=14), r – region (R=11); $E - Risk_{isr}$ is the climate risk score by Sustainalytics, downloaded in mid-January 2022; $LN(TA_{isr})$ – the company size (the log of total assets); D_k is the dummy variable that takes the value of one if it corresponds to the k-th attribute (sector or region). We add interactions with the log of PD and the dummy indicators to differentiate angles (the sign of climate-credit risk relationship) by region ($D_r \cdot LN(PD_{isr})$) and sector ($D_s \cdot LN(PD_{isr})$).

However, the above OLS specification does not account for the detected non-random data censoring, but the Heckman model does. The Heckman selection model was articulated in the papers (Heckman, 1976), (Heckman, 1979). The basic principle in the Heckman model is adjusting the estimated coefficients when there is non-random data censoring, that is, more precisely, when the absence of registered data for the dependent variable might be driven by some factors. The textbook example is tracing for the wage determinants (the so-called Mincer equation, (Heckman, Lochner, & Todd, 2006), (Belzil, 2008)). There are conventional drivers such as tenure and age. However, the wage is not observed (registered) for the unemployed. It does not mean that the unemployed do not 'deserve' a particular level of remuneration if they were employed. Making no adjustment for the skills and features of the unemployed may bias the true coefficient estimates. In our case, we notice that the climate risk score is more often assigned to more creditworthy companies (those with lower PD levels).

To run the Heckman procedure, two equations need to be estimated. The first equation below is called the main (major, principal, response) one (H_resp). It essentially reproduces the aforementioned conventional OLS regression specification:

$$E - Risk_{isr} = \beta_0 + \beta_1 \cdot LN(PD_{isr}) + \sum_{s=1}^{S} \beta_{1+s} \cdot D_s + \sum_{r=1}^{R} \beta_{1+S+r} \cdot D_r + \sum_{s=1}^{S} \beta_{1+S+R+s} \cdot D_s \cdot LN(PD_{isr}) + \sum_{r=1}^{R} \beta_{1+2S+R+r} \cdot D_r \cdot LN(PD_{isr}) + \varepsilon_{isr}$$

The first equation is augmented by a second (minor, auxiliary, selection) one (H_select). We feed the dependent variable of the climate risk ($E - Risk_{isr}$) with missing values into the Heckman model (for comparison, the OLS specification accepted only fully present values for the dependent variable). The algorithm by itself creates an auxiliary dummy (indicator) variable ($I\{E - Risk_{isr} <>.\}$) that takes the value of one when the dependent variable is observed (registered). Otherwise, it takes the value of zero. The second (selection) equation is formalized and presented below:

$$I\{E - Risk_{isr} <>.\} = N\left(\beta_0 + \boldsymbol{\theta_1} \cdot \boldsymbol{LN(TA_{isr})} + \beta_1 \cdot LN(PD_{isr}) + \sum_{s=1}^{S} \beta_{1+s} \cdot D_s + \sum_{r=1}^{R} \beta_{1+S+r} \cdot D_r + \sum_{s=1}^{S} \beta_{1+S+R+s} \cdot D_s \cdot LN(PD_{isr}) + \sum_{r=1}^{R} \beta_{1+2S+R+r} \cdot D_r \cdot LN(PD_{isr}) + u_{ijt}\right)$$

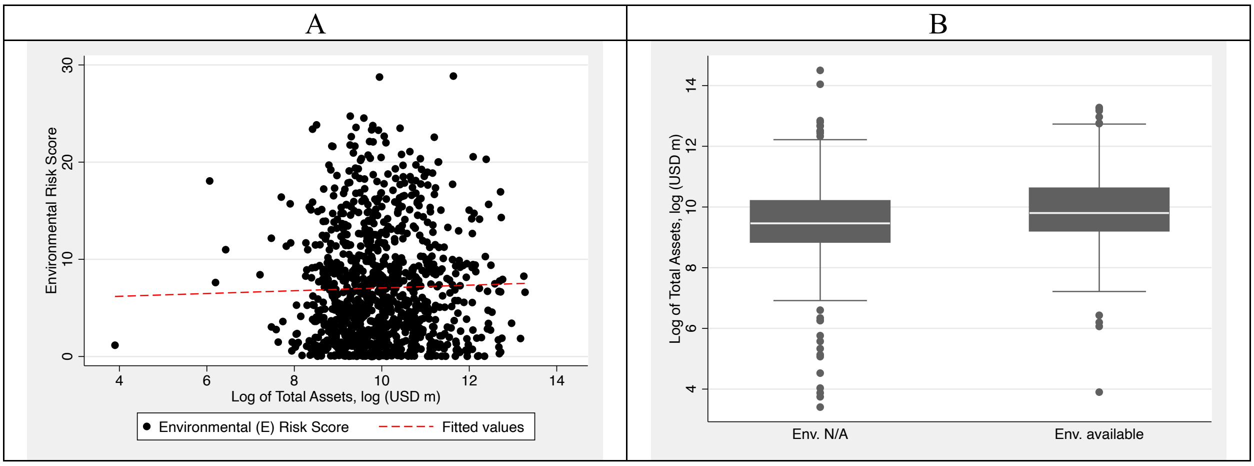


Figure 7. The company size (log of total assets, LN_TA) is essentially not associated with environmental risk scores, while the presence of climate risk estimates tends to cover larger companies

The difference between the response (principal) equation and the selection (auxiliary) one in our case is the presence of company size $LN(TA_{isr})$ in the selection equation and its absence in the principal one. The reason for this is that company size is essentially not associated with the value of the climate risk score (see panel A in Figure 7), but it does relate to the fact that such a score is assigned (see panel B in Figure 7). The respective correlations equal to +3% and +19% (see Table 9).

The principal novelty of the Heckman model is the link between the two equations. If censoring (data absence) is non-random, then there should be a relation between the error components of the two equations, i.e. between ε_{isr} and u_{ijt}. Heckman used the correlation to model the relation pattern between the errors. An auxiliary test is needed to check the error independence. The zero hypothesis of the test is the correlation equaling zero – which means there is no dependence. If so, then an OLS model is sufficient. In the case of the correlation statistically different from zero, the Heckman model should be preferred to the OLS.

We estimate the model using a full sample following the justification by the author of the Diebolt-Mariano test in (Diebolt 2015). His key argument is that strategically one can always select the best model and obtain the highest pseudo-predictability by decomposing the data into training and testing (validation) subsamples. The researcher insists that the Bayesian updating principles essentially also rely on full sample estimates. That is why we proceed with no breakdown into training and testing subsets of the raw data.

Endogeneity is not an issue in our analysis by construction. First, international credit rating agencies do not consider the climate risk in their credit ratings; there are separate products for climate ratings. For instance, one of the Big Three agencies launched a commercial product called "Climate Credit Analytics" (S&P Global, 2021). It is separate from the conventional credit ratings used in the present study. That is why the major argument against endogeneity is its absence by data construction. Second, Sustainalytics is too small a company to be considered by the Fortune 2000 giants. Companies' CEOs do not view climate risk scores as part of their financial KPIs. Such score should rather reflect a company's operational profile. However, there might be a certain relation in loan pricing. Importantly, we are interested neither in the impact analysis nor in detecting the causal relationship, i.e. understanding how the climate risk impacts PD (notwithstanding that we mentioned (Rudebusch, 2021) and (Janosik & Verbraken, 2021) who argue that PD estimates tend to rise with the climate risk factored in). Our objective is to trace the relation path (and not the causal relationship) that we may consider in loan pricing and, more specifically, when and if we design a loan subsidy program for green industries or projects.

We would like to stress the way climate risk occurrences should be handled from the methodological perspective. The need for them to be considered over a longer-term horizon is evident, yet credit risk occurrences tend to be short-term in nature. Credit risks can be directly assigned to a particular company, while climate risks are not linked to particular companies. That is why at the current stage of our research we cannot account for the differences in horizons over which climate and credit risk materialize.

4. Empirical Findings

We consider ols7 to be the best specification of the ordinary least squares ones. It has the largest R-squared of 84%. It is neither too large to deem it a spurious regression nor too small to be concerned about the omitted variables. For comparison, regressing the climate risk score through the logarithms of total assets and PD yields R-squared of around 1% (this is the ols1 specification that we do not include in Table 10 due to its low informativeness, though it can be provided upon request). We prefer ols7 to ols6 as the former one has only statistically significant variables. Such an adequate R-squared value together with the statistical significance of coefficients suggests we can consider and further interpret the coefficients' values, moving beyond their mere sign.

The reader may wonder whether the uneven distribution of observations by region (Table 8) or sector (Table 7) might bias the coefficient estimates. For instance, there are slightly more than 40 observations from India and around 600 from the United States. To ensure the absence of bias, we refer to the statistical adequateness of the estimated specifications. Moreover, the sufficiently large number of degrees of freedom (above 900 for OLS and above 1,700 for Heckman) provides us with the guarantee that the estimates are not prone to cliff effects, i.e. to material changes to output when the input data is perturbed (negligibly augmented or reduced).

For our data, we reject the null hypothesis of error independence between the two Heckman equations (see rho +78% and corresponding p-value (p_c) of 0% for the H6 specification in Table 11). This means that data censoring takes place, i.e., the missing values of the dependent variable are not random in nature. The more creditworthy and larger companies are more likely to be assigned with a climate risk score by Sustainalytics. Thus, the Heckman specification should be preferred to OLS.

We choose the H6 Heckman model specification as the best one since it has the most statistically significant correlation of error components. The constant (intercept) was excluded both in H5 and H6, but H5 still had an insignificant correlation value. The statistical significance of correlation in H6 is driven only by the inclusion of statistically significant independent variables. Therefore, we obtain the additional evidence that including all the possible determinants into a regression model is not always advisable.

The sample intersection for the OLS and Heckman models is shown in Table 3. The entire set comprises 2,030 observations. Climate risk estimates are present for 1,020 observations. We have this set in the ols7 specification. However, 17 observations of this number lack data on total assets. That is why when applying the Heckman model with the logarithm of total assets in the selection equation, we use 1,020 - 17 = 1,003 observations with climate risk data. We add another 838 censored observations that lack climate risk data but that have values for total assets. Thus, the Heckman model (H6) is based on 1,003 + 838 = 1,841 observations.

Table 3. Comparing the Number of Observations in OLS and Heckman

		Rest of data	OLS set (ols7)	
		0	1	Total
Rest of data	**0**	172	17	**189**
Heckman set (H6)	**1**	838	1003	**1841**
	Total	**1010**	**1020**	**2030**

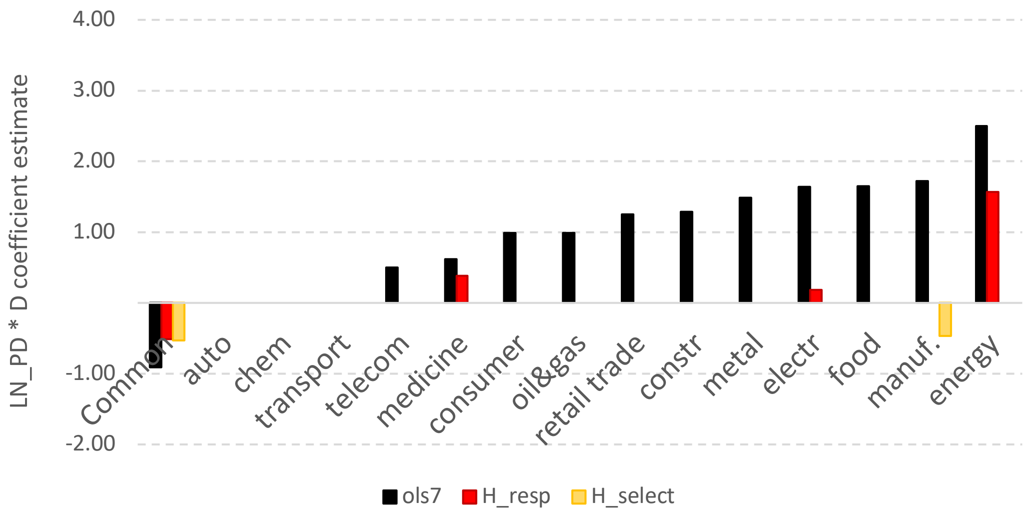


Figure 8. Credit-Climate Risk Relationship is Positive for Energy Sector, While in General It Is Negative, All Else Being Equal

Note: Here the best model for OLS is ols7 from Table 10, and for Heckman (H_resp, H_select) is H6 from Table 11.

We aggregate our regression estimates in Figure 8 and Figure 9. As for the Heckman model, we present the coefficients from both the response (H_resp) and selection (H_select) equations of the H6 specification. Figure 8 shows the results by sector, and Figure 9 by region. The granular estimates are available in Annex B (see Table 10 for OLS and Table 11 for Heckman). We demonstrate the coefficients preceding the products of LN(PD) and sectoral and regional dummies. The statistically insignificant values are presented as zeros.

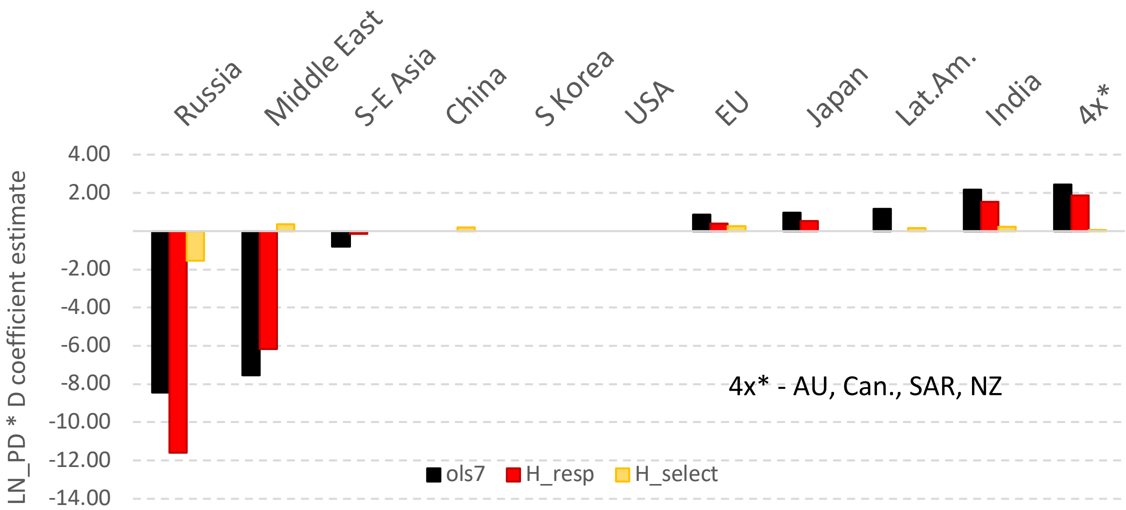


Figure 9. Oil-Exporting Countries Exhibit a Negative Relationship of Credit and Climate Risks, While It Is Positive for India, South Africa, New Zealand, Australia, and Canada (the latter four are grouped and jointly indicated as 4x)*

Note: The best model for OLS here is ols7 in Table 10, and for Heckman (H_resp, H_select) is H6 in Table 11.

Even the OLS model yields a negative climate and credit risk relationship, all else being equal (see 'Common' in Figure 8). Applying the Heckman model enables us to break down the overall OLS impact into two mostly equal parts (coefficient estimates). The first half of the negative relationship comes from the Heckman selection equation, i.e. the fact that the companies with lower PD levels are assigned climate risk scores. The second half originates from the Heckman response equation. Moreover, once the Heckman model is applied, most of industrial specifics disappears. The only material positive climate-credit relationship remains in the energy sector, all else being equal.

As for the countries, three distinct patterns can be seen in Figure 9. First, there are countries with no particular impact on the climate-credit risk relationship. Those are the USA, China, South Korea and some South-East Asian countries. Second, there are countries with a more positive add-on to the climate-credit risk co-dependence. Those are the European Union, Japan, Latin America, India, Australia, Canada, South African Republic, and New Zealand. Third, there is a cluster of oil-exporting countries (including Russia) that have a significant negative contribution to the climate-credit risk relationship.

To make quantitative interpretations of the obtained coefficients, we should recall that they relate to the logarithm of the independent variable (PD), while the dependent is in levels (without a logarithm). Therefore, the coefficient estimate relates to the relative, not absolute, change in the PD level. Let us take the coefficient -6 for Middle East Asian countries from Figure 9 as an example. Let us consider two hypothetical companies located in this region with PD levels of 10% and 11.5%. The absolute difference in-between is 1.5 pp. The relative difference against the former is 15%. Then the latter company with the PD of 11.5% should have the climate risk score lower than the former by 15% * -6 ~ -0.84 units (the approximation sign is used since the change is precisely computed via logarithm transformation that yields differences with the direct product of the two values). If the former company with the PD of 10% had the climate risk score of 10 units, we may expect the climate risk score for the second company to equal 10.00 – 0.84 = 9.16.

When one wishes to arrive at the joint (cumulative, aggregate) estimate of the climate-credit relationship for a sector in a chosen country, one should sum up all the applicable coefficient estimates. Let us consider, for instance, the construction sector in Japan. Based on the Heckman response equation at the H6 model (Table 11), we find the (principal) coefficient preceding the PD logarithm of -0.5. The coefficient for the sector-specific interaction with the PD logarithm (PD_S3) is +0.2. The coefficient for the country-specific interaction (PD_R4) is around +0.5. Thus, the sum equals -0.5 + 0.2 + 0.5 = +0.2. This implies that the sign of the climate-credit risk relationship for building societies (construction companies) in Japan should be considered positive. If we assume that the Bank of Japan loan subsidy program covers this sector (although we remember that it targeted only SMEs), then the program should pay off. The cost of lending to greener construction companies in Japan can decrease as the associated credit risks are lower due to the revealed positive climate-credit relationship for this sector.

For comparison, we cannot state the same about construction companies in China. The applicable country-specific coefficient (PD_R1) is zero. Thus, the resultant sum is -0.5 + 0.2 + 0 = -0.3. It appears that subsidized loans to greener construction companies in China will only undermine financial stability. Here we may consider the notorious case of Evergrande (The Economist, 2021). In climate risk terms, it is greener than an average Chinese construction company. The respective environmental risk scores for the company and the sector are 6.65 and 7.45. However, it has the largest PD of 27% according to Moody’s at the moment of data download. Thus, we can see that the climate risk for Evergrande is below average, while the credit risk is much above average. Hence, this observation fits in the negative climate-credit risk relationship coming from the computed -0.3 total coefficient value.

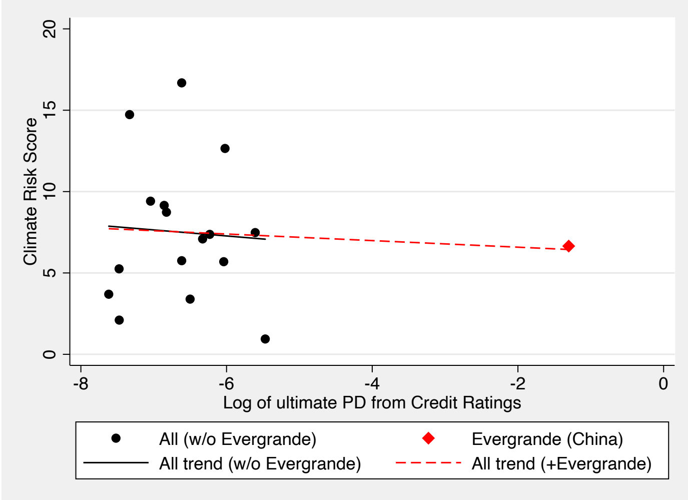


Figure 10. Climate Risk (vertical axis) and Credit Risk (horizontal axis) Snapshot of the Chinese Construction Sector

Note: w/o – without.

Although one may view Evergrande as an outlier given its excessive PD value, it perfectly fits in the trend for Chinese construction companies in Figure 10 (compare the almost overlapping solid black and dashed red linear fit lines, excluding and including, respectively, Evergrande). For this reason, we may consider Evergrande to be a kind of indirect confirmation of our findings.

Consequently, we arrive at the finding that using historical data the climate-credit risk relationship has the negative sign, despite that (Capasso, Gianfrate, & Spinelli, 2020) claim it is positive. We remember that using potential scenarios assuming climate change or changes in the use of green energy might invert the findings and give the positive sign to the climate-credit relationship. However, neither we nor (Capasso, Gianfrate, & Spinelli, 2020) use future scenarios: both of us use historical data but come to the opposite conclusions. Let us sum up the sources of differences in Table 4.

Table 4. Differences in Findings Come from Using Unobserved (Non-Verifiable) Data in the Alternative Studies

No.	**Parameter for comparison**	**(Capasso, Gianfrate, & Spinelli, 2020)**	**Current Paper**
1	Climate risk proxy	CO2 emissions	Climate (environmental) risk scores by Sustainalytics.com
2	Aware of Sustainalytics data	Yes, but do not use it	Yes, use it directly
3	Accounting for climate data censoring	No	Yes
4	Credit risk proxy	PD estimates from an iterative structural model	PD from the world leading credit rating agencies
5	Climate-credit risk relationship (finding/conclusion)	Positive	Negative

First, we would like to stress once again that it was our intention to rely on the figures and values that are universally available (such as climate risk scores from Sustainalytics.com) and actually used in decision-making. For instance, credit ratings form the basis of capital adequacy requirements worldwide after the introduction of the Basel II Accord in 2004. In contrast, the authors of (Capasso, Gianfrate, & Spinelli, 2020) prefer their own estimates that may be reproduced at best but which are not part of standard practice at either banks or regulators.

Second, (Capasso, Gianfrate, & Spinelli, 2020) use carbon dioxide emissions as the indicator of the climate risk, though they recognize sustainalitics.com as the alternative data source. However, they limit themselves to citing a paper by (Busch, Johnson, & Pioch, 2020) with a message that the data from sustainalytics.com correlates to that of CO2 emissions, but CO2 emissions should be preferred.

There are several shortcomings in such a cross-reference. The authors of (Capasso, Gianfrate, & Spinelli, 2020) do not explicitly run a benchmarking of the climate risk estimates at least in terms of relative ranking. It is true that CO2 emissions and climate risk estimates may correlate to a low degree. For instance, such was the message with respect to ESG ratings and CO2 data in (Brunnermeier, 2022, p. min 25). However, ESG does not only stand for the climate risk: it also has social and governance dimensions (which do correlate but not materially, as we show in Figure 5). That is why it is only natural that ESG is a poor proxy for the climate risk, and we should use only its E component. Moreover, a recent study by (Dreyfus, Xu, Shindell, Zaelke, & Ramanathan, 2022) shows that accounting for CO2 is not at all enough. It captures at best half of the contribution to climate change, while other gases, such as methane and ozone, contribute another half. That is why limiting a study to CO2 delivers a non-representative picture – the one at best captures half of substantial contributions). This is why the climate risk definition itself is the first cause for deviation, as long as one operates non-representative data on carbon emissions.

Third, (Capasso, Gianfrate, & Spinelli, 2020) disregard data censoring, which is also likely as regards CO2 emissions. To account for the arising bias, the Heckman model is required but not used in (Capasso, Gianfrate, & Spinelli, 2020). This is the gap we intend to close in this work.

Forth, the authors of (Capasso, Gianfrate, & Spinelli, 2020) proceed from a structural model of credit risk introduced in (Merton, 1974). The idea is to define the probability of default (PD) by the likelihood that the value of corporate assets slips below the value of its liabilities. However, the authors do not explicitly compare their PD estimates to those implied from the Big Three ratings. This leads to the emergence of the second cause for discrepancy – the authors' own credit risk estimates.

Fifth, we can see that the authors of (Capasso, Gianfrate, & Spinelli, 2020) use semi-representative climate risk data and benchmark them against their own credit risk estimates. Unsurprisingly, their results demonstrate the reversion of the entire climate-credit risk dependence path. Thus, our principal contribution is the demonstration of the negative relationship of climate-credit risks, as well as the case for the inappropriate approach and the incorrect general findings of (Capasso, Gianfrate, & Spinelli, 2020). To be fair, we should admit that in several cases – as shown for Japan's energy sector – such a positive climate-credit risk relationship may still take place.

5. Conclusion and Discussion

Using Sustainalytics climate risk ratings data and international credit ratings data, we have shown that there are three groups of countries that are marked by a positive, negative or neutral contribution to the climate-credit risk relationship. At the industry level, only the energy sector is characterized by a positive add-on. Such a positive mark-up means that higher climate risks are associated with higher credit risk estimates, all else being equal. This implies that there is indeed a rationale for loans to greener energy sector companies at lower interest rates, all else being equal.

In a similar vein, there is a strong rationale for the Bank of Japan's loan subsidies to greener projects. Due to the revealed positive specifics of Japan as a country, it is reasonable to subsidy greener projects in Japan. However, when the estimated climate-credit risk relationship for a region and/or sector is negative, such a preferential treatment of greener projects implies credit risk accumulation for the lending institutions.

As a reminder, let us mention some potential limitations to our rationale. The Bank of Japan focused on SME projects, not on large corporates. That is why the climate-credit risk relationship might be positive for SMEs due to the higher credit risk of SMEs. Unfortunately, the potential dataset on SMEs is not available to cross-validate this hypothesis. Moreover, we have only credit risk realizations, whereas climate risk realizations are not explicitly linked to a particular company.

To formally summarize our findings, we provide answers to the initial questions:

1) We find the negative sign for the (principal) coefficient preceding the credit risk proxy, i.e. the logarithm of default probability (LN_PD). This holds true when we control for industrial and sectoral specifics. This means that we introduce sector and industry dummies, as well as their interactions with the logarithm of default probability. The coefficients preceding such interactions vary in sign. Thus, we reveal the sectors and regions that positively or negatively contribute to the overall negative climate-credit risk relationship. To trace the impact for a particular sector in a given region, we should sum up all the coefficients preceding the applicable dummies and the principal coefficient. We find that there is no sector that outweighs the negative regional impact of oil-exporting regions. For them the climate-credit risk relationship is the most negative in scale. As the principal coefficient is negative, we conclude that the climate-credit risk relationship is negative, all else being equal.

2) We find that there is data censoring. Only half of the two thousand world largest companies have climate risk ratings, of which 40% is concentrated in the best investment grade (IG1) in the Bloomberg classification. Moreover, we have statistical evidence showing that such censoring takes place. When applying the Heckman model, the correlation of error components from the two model equations equals 78%. This is why we prefer the Heckman model over the ordinary least squares (OLS) specification. When applying the Heckman model (i.e. when accounting for data censoring), we find that the positive industry-level climate-credit risk relationship established through OLS disappears almost completely. The only sector to retain it is energy. The scale of the negative principal coefficient does not offset the positive coefficient for energy. However, the specifics of oil-exporting countries do outweigh even the positive impact for the energy sector, invariably resulting in a negative climate-credit relationship for such countries.

3) We find the principal coefficient for the climate-credit risk relationship to be negative. Adjustments for data censoring essentially brought the positive effect at the industry level to zero. Accordingly, we make the case for the negative climate-credit risk relationship for major companies. That is why we conclude that the findings by (Capasso, Gianfrate, & Spinelli, 2020) on the positive climate-credit risk relationship should be treated skeptically. The relationship sign strongly depends on the ratings used and on the modeling methodology. Occasionally, the relationship may indeed turn positive, but policy-makers should not assume that the sign is positive in all cases. In what we show, it is quite often negative.

4) As a policy implication, we agree in principle with the Bank of Japan's approach to subsidizing domestic green projects. In the case of Japan, we indeed observe a positive country contribution to the climate-credit relationship. Moreover, this contribution is comparable in scale to the principal coefficient estimate. Therefore, the overall relationship

for Japan is likely to be positive. We bear in mind the limitation: we study major companies, whereas the Bank of Japan is focused on SMEs. However, the second best approach available for us supports the Japanese regulator's approach (while the first best one would be studying the relevant SME dataset if it exists). However, subsidizing green lending in other countries may result in a rise in the credit risk, as was the case of SME lending under the Basel II IRB approach.

In addition to the above-discussed econometric evidence, our findings are supported by observed facts. In the first instance, the reason for the lower credit risk of browner companies and projects is quite natural. Mostly often, a browner company is the one that is quite well established in the market. In contrast to green projects and companies, brown businesses enjoy steady cash flows. In fact, they pay dividends (their dividends per share ratios are strong), while some green companies (e.g. in the IT sector) have only high earnings per share (EPS) and may have paid no dividend at all since their establishment, for all the high quality of their services. This is the expected limitation to a research effort that relies solely on past data. Potential scenarios of the future would likely bring us the positive sign of the climate-credit risk relationship.

That is why reduced loan rates for green companies are feasible only with a systematic consumption shift from brown to only green goods and services. Unless this is the case, our findings might provide a policy-maker with the first proxy estimates to detect regions and sectors where the reduction is justified (when the cumulative effect is positive, as is the case of construction in Japan) as well as to identify cases where a premium is warranted (when the effect is negative, as is the case of construction in China).

ANNEX A. Input Data

Table 5. List of considered variables

#	Variable	Definition	Units	Source
1	Total_ESG	Total ESG score	points	Sustainalytics
2	Environm	Environmental (climate) risk score	points	Sustainalytics
3	Social	Social risk score	points	Sustainalytics
4	Govern	Governance risk score	points	Sustainalytics
5	ERS	Dummy flag for the presence of climate risk score	0 / 1	Author
6	LN_Env	Log of environmental (climate) risk score	LN(points)	Author
7	Ind_id	Ordinal number of industry	counter	Author
8	Cty_id	Ordinal number of country	counter	Author
9	Sect_id	Ordinal number of sector (several industries)	counter	Author
10	Reg_id	Ordinal number of region (several countries)	counter	Author
11	PD_SP	Default probability (PD) from Standard & Poor's	proportion	(S&P Global Ratings, 2019)
12	PD_M	Default probability (PD) from Moody's	proportion	(Moody's, 2018)
13	PD_F	Default probability (PD) from Fitch Ratings	proportion	(FitchRatings, 2021)
14	PD_mean	Mean PD among the available PDs (No. 11-13)	proportion	Author
15	PD_BL	PD according to Bloomberg Composite Rating	proportion	Bloomberg
16	PD_fin	Ultimate PD (either mean of rating agencies' ones or the one from Bloomberg Composite)	proportion	Author
17	LN_PD	Log of ultimate PD	LN(pp.)	Author
18	TA2020	Total assets as of end 2020	USD m	Bloomberg
19	LN_TA	Log of total assets	LN(USD m)	Author

Table 6. Descriptive Statistics

#	Variable	Obs	Mean	Std. Dev.	Min	Max
1	Total_ESG	1043	23.33	8.95	4.67	68.15
2	Environm	1020	7.06	5.81	0.01	28.85
3	Social	1021	9.17	4.18	0.68	29.76
4	Govern	1021	7.08	2.26	2.76	16.67
5	ERS	2030	0.51	0.50	0.00	1.00
6	LN_Env	1020	1.36	1.46	-4.61	3.36
7	Ind_id	2030	29.82	18.81	1.00	70.00
8	Cty_id	2030	33.67	18.81	2.00	53.00
9	Sect_id	2030	7.58	3.95	1.00	14.00
10	Reg_id	2030	6.22	4.13	1.00	11.00
11	PD_SP	1079	0.00	0.01	0.00	0.34
12	PD_M	997	0.01	0.01	0.00	0.27
13	PD_F	600	0.00	0.03	0.00	0.49
14	PD_mean	1240	0.01	0.02	0.00	0.31
15	PD_BL	2016	0.01	0.01	0.00	0.06
16	PD_fin	2020	0.01	0.01	0.00	0.31
17	LN_PD	2020	-5.86	1.12	-10.22	-1.17
18	TA2020	2009	31 792	72 978	0	1 985 617
19	LN_TA	1842	9.74	1.15	3.41	14.50

Table 7. Data Breakdown by Sector

Sec_id	Freq.	mean(Environm)	mean(PD_fin)
1	84	5.87	0.59%
2	103	12.53	0.40%
3	223	5.86	0.93%
4	227	3.56	0.44%
5	152	13.47	0.36%
6	105	9.88	0.35%
7	72	5.44	0.37%
8	179	7.40	0.61%
9	128	1.84	0.47%
10	129	14.86	0.77%
11	152	15.96	0.82%
12	196	4.26	0.66%
13	189	2.55	0.65%
14	91	6.21	0.69%
Total	2030	7.06	0.60%

Note: 1. auto; 2. chem; 3. constr; 4. electr; 5. energy; 6. food; 7. consumer; 8. manuf.; 9. medicine; 10. metal; 11. oil&gas; 12. retail trade; 13. telecom; 14. Transport.

Table 8. Data Breakdown by Regions.

Reg_id	Freq.	mean(Environm)	mean(PD_fin)
1	287	9.21	1.03%
2	436	5.56	0.48%
3	43	10.83	0.64%
4	197	6.85	0.41%
5	29	5.04	0.67%
6	62	11.93	0.78%
7	58	16.16	0.67%
8	60	8.86	0.59%
9	92	8.38	0.40%
10	112	8.09	0.45%
11	654	6.49	0.59%
Total	2030	7.06	0.60%

Note: 1. China; 2. EU; 3. India; 4. Japan; 5. Middle East; 6. Lat.Am.; 7. Russia; 8. S Korea; 9. S-E Asia; 10. AU, Can., New Z., SAR; 11. USA.

Table 9. Correlation Matrix of the Variables under Consideration

#	Variable	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19
1	Total_ESG	+1.00																		
2	Environm	+.79	+1.00																	
3	Social	+.72	+.20	+1.00																
4	Govern	+.60	+.19	+.47	+1.00															
5	ERS	.	.	.	.	+1.00														
6	LN_Env	+.59	+.78	+.10	+.14	.	+1.00													
7	Ind_id	-.03	+.09	-.15	-.09	+.01	+.06	+1.00												
8	Cty_id	-.13	-.10	-.02	-.21	+.10	-.13	-.04	+1.00											
9	Sect_id	-.00	-.09	+.19	-.13	-.04	-.16	-.11	+.07	+1.00										
10	Reg_id	-.04	-.01	+.04	-.21	+.17	-.05	-.01	+.66	+.09	+1.00									
11	PD_SP	+.11	+.08	+.10	-.00	-.18	+.06	+.01	-.01	+.07	+.00	+1.00								
12	PD_M	+.03	+.00	+.03	+.02	-.19	+.01	+.02	-.03	+.02	-.04	+.74	+1.00							
13	PD_F	+.15	+.17	+.13	+.02	-.11	+.08	+.03	-.09	-.05	-.07	+.97	+.65	+1.00						
14	PD_mean	+.05	+.03	+.04	+.03	-.15	+.03	+.02	-.05	+.01	-.05	+.99	+.86	+.98	+1.00					
15	PD_BL	+.16	+.15	+.11	+.09	-.30	+.12	+.01	-.01	+.10	-.01	+.47	+.51	+.23	+.43	+1.00				
16	PD_fin	+.05	+.03	+.04	+.03	-.20	+.04	+.02	-.04	+.03	-.04	+.99	+.86	+.98	+1.00	+.58	+1.00			
17	LN_PD	+.13	+.13	+.07	+.02	-.39	+.07	-.04	-.02	+.10	-.01	+.57	+.62	+.39	+.56	+.62	+.61	+1.00		
18	TA2020	+.10	-.01	+.15	+.17	+.06	-.01	-.02	-.03	-.04	-.05	-.06	-.00	-.02	-.00	-.03	-.01	-.19	+1.00	
19	LN_TA	+.11	+.03	+.13	+.14	+.19	+.01	+.02	-.05	-.03	-.04	-.10	-.07	+.01	-.04	-.07	-.03	-.25	+.60	1

ANNEX B. Regression Estimates

Table 10. OLS Model Estimates with Region and Sector Dummies

Variable	ols2	ols3	ols4	ols5	ols6	ols7
LN_PD	0.739***	0,097	0,097	0,097	-0.830***	-0.913***
LN_TA	0,019	0,018	0,018	0,018	0,076	
S1	-0,473	-2,857	-2.857***	-2,857	2.007*	
S2	6.755***	18.038***	18.038***	18.038**	23.022**	6.885***
S3	-0,163	4,437	4.437**	4,437	9.235*	8.188**
S4	-2.388***	2,61	2,61	2,61	8.146***	8.084***
S5	7.501***	19.259***	19.259***	19.259**	24.087***	23.595***
S6	3.793***	9.672*	9.672***	9,672	14.665***	14.383***
S7	-0,349	0,363	0,363	0,363	6.174***	6.074***
S8	1.823***	8.774*	8.774***	8,774	13.805***	12.892***
S9	-3.855***	-2,579	-2,579	-2,579	3,025	
S10	8.154***	12.640**	12.640***	12.640*	17.673***	17.277***
S11	9.871***	11.201**	11.201***	11.201**	16.533***	16.187***
S12	-1.823***	0,235	0,235	0,235	5.836**	6.135***
S13	-3.301***	-2,964	-2.964*	-2,964	2,425	
R1	2.048***	-0,594	-0,594	-0,594	0,489	2.119***
R2	-1.327***	1,396	1,396	1.396***	2.384***	4.091***
R3	1,158	11.347*	11,347	11.347***	11.751***	14.189***
R4	0,588	2,789	2,789	2.789**	4.523***	6.847***
R5	0,054	-53.295**	-53.295***	-53.295***	-52.947***	-49.497***
R6	2.097***	6,192	6,192	6.192***	7.806***	9.021***
R7	1,177	-51,668	-51.668***	-51.668***	-52.605***	-49.767***
R8	1.611**	1,701	1,701	1,701	2.414**	1.589***
R9	1.164*	-7,253	-7,253	-7.253***	-5.882***	-3.895*
R10	-0,12	12.712**	12.712**	12.712***	13.925***	15.234***
PD_S1		-0,395	-0.395***	-0,395	0,383	
PD_S2		1.809*	1.809***	1,809	2,603	
PD_S3		0,734	0.734***	0,734	1.501*	1.291**
PD_S4		0,8	0.800***	0,8	1.681***	1.637***
PD_S5		1.851**	1.851***	1,851	2.626**	2.498**
PD_S6		0,928	0.928**	0,928	1.725***	1.646***
PD_S7		0,125	0,125	0,125	1.042***	0.991***
PD_S8		1,088	1.088***	1,088	1.893***	1.718***
PD_S9		0,222	0,222	0,222	1.116**	0.614***
PD_S10		0,777	0.777***	0,777	1.577*	1.483*
PD_S11		0,235	0,235	0,235	1.088***	0.991**
PD_S12		0,338	0,338	0,338	1.233***	1.250***
PD_S13		0,071	0,071	0,071	0.930***	0.499***
PD_R1		-0,42	-0,42	-0,42	-0,243	
PD_R2		0,429	0,429	0.429***	0.581***	0.855***
PD_R3		1,716	1,716	1.716***	1.773***	2.173***
PD_R4		0,351	0,351	0.351**	0.616***	0.974***

Variable	ols2	ols3	ols4	ols5	ols6	ols7
PD_R5		-8.137**	-8.137***	-8.137***	-8.081***	-7.531***
PD_R6		0,728	0,728	0.728**	0.976**	1.170***
PD_R7		-8,76	-8.760***	-8.760***	-8.921***	-8.459***
PD_R8		0,009	0,009	0,009	0,125	
PD_R9		-1,341	-1,341	-1.341***	-1.134***	-0.807**
PD_R10		2.045**	2.045**	2.045***	2.235***	2.446***
_cons	10.325***	6.399*	6.399**	6,399		
Error clust.	No	No	By Sectors	By Regions	By Regions	By Regions
Region D.	Yes	Yes	Yes	Yes	Yes	Stat.Sign.Only
Sector D.	Yes	Yes	Yes	Yes	Yes	Stat.Sign.Only
N	1003	1003	1003	1003	1003	1020
R^2	60,2%	61,6%	61,6%	61,6%	84,4%	84,3%
R^2_adj	59,2%	59,7%	59,7%	59,7%	83,6%	83,7%

Note: S stands for a sector-specific dummy (D) with 1. auto; 2. chem; 3. constr; 4. electr; 5. energy; 6. food; 7. consumer; 8. manuf.; 9. medicine; 10. metal; 11. oil&gas; 12. retail trade; 13. telecom; 14. Transport.
R stands for a regional dummy (D) with 1. China; 2. EU; 3. India; 4. Japan; 5. Middle East; 6. Lat.Am.; 7. Russia; 8. S Korea; 9. S-E Asia; 10. AU, Can., New Z., SAR; 11. USA.
N – number of observations. We are aware of the R-square critique from (Shalizi, 2015). However, we report it from the conventions' perspective. We adopt conventional statistical significance notations for *** 1% level, ** 5%, * 10%.

Table 11. Heckman Model Specification Estimates

Variable	H1	H2	H3	H4	H5	H6
H_resp (main, major, principal, response equation)						
LN_PD	1.034***	0.655***	0,054	0,029	-0.925***	-0.499***
S1		-0.464	-2.865	-2.938	1.511	
S2		6.741***	17.996***	17.882***	22.366***	7.891***
S3		-0.154	4.425	4.273	8.665**	
S4		-2.404***	2.589	2.707	7.953***	
S5		7.519***	19.258**	19.364**	24.067***	18.012***
S6		3.780***	9.715	9.705	14.456***	5.150***
S7		-0.389	0.362	0.429	5.928***	
S8		1.817**	8.705	8.491	12.879***	3.272***
S9		-3.867***	-2.557	-2.507	2.778	
S10		8.141***	12.604**	12.614**	17.386***	9.107***
S11		9.882***	11.087***	11.219***	16.249***	10.917***
S12		-1.831**	0.174	0.217	5.471***	
S13		-3.305***	-3.023	-2.897	2.254*	
R1		1.815***	-0.916	-0.848	-0.04	
R2		-1.441***	1.200***	1.393***	2.342***	
R3		1.093***	11.342***	11.518***	12.216***	9.881***
R4		0.570***	2.771***	2.771***	4.429***	4.086***
R5		-0.413	-53.504***	-53.046***	-52.143***	-45.513***
R6		1.966***	5.977***	6.039***	7.414***	0.776***
R7		0.909**	-50.784***	-52.256***	-52.790***	-63.938***

Variable	H1	H2	H3	H4	H5	H6
R8		1.525***	1.522	1.471	1.867**	1.285***
R9		1.024***	-7.284***	-7.107***	-5.556***	
R10		-0.206	12.553***	12.618***	13.652***	10.837***
PD_S1			-0,401	-0,414	0,291	
PD_S2			1.804*	1.784*	2.500*	
PD_S3			0,735	0,711	1.415**	
PD_S4			0,798	0,816	1.656***	0.188***
PD_S5			1,853	1,871	2.627**	1.515*
PD_S6			0,936	0,934	1.695***	
PD_S7			0,126	0,136	1.008***	
PD_S8			1,079	1,044	1.749***	
PD_S9			0,225	0,232	1.074**	0.381***
PD_S10			0,777	0,78	1.550**	
PD_S11			0,222	0,245	1.055***	
PD_S12			0,331	0,338	1.182***	
PD_S13			0,063	0,084	0.907***	
PD_R1			-0.449*	-0.430*	-0,267	
PD_R2			0.410***	0.444***	0.607***	0.380***
PD_R3			1.723***	1.754***	1.870***	1.523***
PD_R4			0.350***	0.351***	0.608***	0.493**
PD_R5			-8.126***	-8.043***	-7.848***	-6.079***
PD_R6			0.707***	0.721***	0.952***	
PD_R7			-8.587***	-8.833***	-8.902***	-10.494***
PD_R8			-0,011	-0,019	0,053	
PD_R9			-1.331***	-1.299***	-1.041***	-0.151***
PD_R10			2.028***	2.040***	2.214***	1.823***
_cons	14.052***	9.877***	6.248*	6.071*		
H_select (minor, auxiliary, selection equation)						
LN_PD	-0.476***	-0.481***	-0.476***	-0.610***	-0.634***	-0.519***
LN_TA	0.141***	0.161***	0.184***	0.195***	0.195***	0.136***
R1		-1.340***	-1.326***	0.273	0.303	
R2		-0.698***	-0.695***	1.369***	1.388***	0.911***
R3		-0.397***	-0.374***	1.078***	1.107***	0.995***
R4		-0.177***	-0.212***	-0.306	-0.272	
R5		-2.434***	-2.417***	0.426	0.465	
R6		-0.616***	-0.563***	0.778**	0.817**	0.260*
R7		-1.436***	-1.286***	-9.476***	-9.444***	-8.956***
R8		-0.613***	-0.638***	-0.883*	-0.850*	-0.396***
R9		-0.750***	-0.766***	-0.205	-0.172	
R10		-0.478***	-0.387***	0.633***	0.662***	
S1			0.171	-0.913	-0.801	
S2			0.035	-1.61	-1.504	
S3			-0.237	-1.508	-1.377	
S4			0.03	0.995	1.12	
S5			-0.296	0.195	0.314	

Variable	H1	H2	H3	H4	H5	H6
S6			-0.003	-0.673	-0.566	
S7			0.256	0.511	0.607	
S8			-0.07	-3.085***	-2.978***	-3.103***
S9			0.124	-0.15	-0.007	
S10			-0.223	-0.235	-0.121	
S11			-0.397*	0.307	0.419	
S12			-0.117	0.236	0.363	
S13			-0.076	0.788	0.915	
PD_S1				-0,19	-0,171	
PD_S2				-0,278	-0,26	
PD_S3				-0,212	-0,19	
PD_S4				0,162	0,183	
PD_S5				0,079	0,098	
PD_S6				-0,111	-0,092	
PD_S7				0,033	0,049	
PD_S8				-0.505***	-0.486***	-0.513***
PD_S9				-0,046	-0,021	
PD_S10				0,002	0,021	
PD_S11				0,12	0,139	
PD_S12				0,057	0,08	
PD_S13				0,143	0,166	
PD_R1				0.271***	0.276***	0.199***
PD_R2				0.347***	0.350***	0.242***
PD_R3				0.247***	0.252***	0.211***
PD_R4				-0,016	-0,01	
PD_R5				0.439***	0.445***	0.351***
PD_R6				0.234***	0.241***	0.118***
PD_R7				-1.399***	-1.393***	-1.301***
PD_R8				-0,058	-0,053	
PD_R9				0,093	0,098	
PD_R10				0.170***	0.175***	0.059***
_cons	-4.074***	-3.754***	-3.863***	-4.759***	-4.895***	-3.876***
Statistics						
Error clust.	No	By Region	By Region	By Region	By Region	By Region
Region D.	No	Yes	Yes	Yes	Yes	Stat.Sign.Only
Sector D.	No	Yes	Yes	Yes	Yes	Stat.Sign.Only
N	1841	1841	1841	1841	1841	1841
N_cens	838	838	838	838	838	838
athrho	-0.133	0.087	0.056	0.072	0.146	1.033***
lnsigma	1.757***	1.301***	1.282***	1.283***	1.288***	1.487***
ll	-4,20E+03	-3,70E+03	-3,60E+03	-3,60E+03	-3,60E+03	-3,70E+03
rho, %	-13.2	8.7	5.6	7.2	14.5	77.5
p_c, %	38.5	57.3	44.6	25.1	16.9	0

Note: S stands for a sector-specific dummy (D) with 1. auto; 2. chem; 3. constr; 4. electr; 5. energy; 6. food; 7. consumer; 8. manuf.; 9. medicine; 10. metal; 11. oil&gas; 12. retail trade; 13. telecom; 14. Transport.

R stands for a regional dummy (D) with 1. China; 2. EU; 3. India; 4. Japan; 5. Middle East; 6. Lat.Am.; 7. Russia; 8. S Korea; 9. S-E Asia; 10. AU, Can., New Z., SAR; 11. USA.
N – number of observations; N_cens – number of censored observations; athrho – the hyperbolic tangent of rho, i.e., athrho = 1/2 * ln((1+rho) / (1-rho)). If athrho is significant, the Heckman model should be preferred to running two separate regressions (response and select); lnsigma is the standard error of the response equation. If it is significant, it is a second proof of the Heckman model's domination over two separate equations; athrho and lnsigma are standardized Stata outputs for the Heckman model. For Stata it is easier to optimize athrho and lnsigma rather than rho directly.
ll – the value of the likelihood function; rho – the estimate of the correlation coefficient for the two errors (in the response and selection equations); p_c – the p-value for the null hypothesis testing of rho being equal to zero (when p_c exceeds a chosen confidence level, we conclude that the null hypothesis is not rejected). We adopt conventional statistical significance notations for *** 1% level, ** 5%, * 10%.

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