Planet Tracker

NDEs and Credit Ratings

THE IMPACT OF THE 2007-2008 GLOBAL FINANCIAL CRISIS ON THE CREDIT RATINGS OF NATURE DEPENDENT EXPORTERS

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CONTENTS

EXECUTIVE SUMMARY

Why read this paper?

Credit ratings are forward-looking assessments by a credit rating agency regarding the ability and willingness of an entity such as a government or corporation to meet its financial obligations in full and within the established due dates. A credit rating also signifies the likelihood a debtor will default. The financial crisis of 2007–2008 affected the ability and willingness of different sovereigns to meet such obligations differently. This paper shows how the nature dependency of countries, as defined by Planet Tracker's categories of High and Low Nature Dependent Exporters (HNDEs and LNDEs), are useful in partially explaining this difference. We show a link between countries' dependence on natural resources and credit ratings, a metric which is a key input in many investment decisions. This correlation could be useful to the financial community for assessing nature- or climate-related financial sovereign risks.

What we did in NDE2022

This paper is a follow-up to the Planet Tracker report Nature Dependent Exporters: What Do They Have in Common? (NDE2022), which explored the relationship between the share of a nation's directly nature-dependent exports – as defined in that report – and several other national characteristics. It provided an introduction to the factors potentially impacting a society's exposure to export-side environmental risks.

What we are examining in NDE2023

Here we explore the relationship between NDE categories, sovereign credit ratings, and resilience to global economic shocks at the national level. We use the 2007–2008 global financial crisis as our global economic shock reference. We contrast credit ratings outcomes between the groups of countries whose exports are highly dependent on nature versus those with low nature dependency before and after this period of economic shock. We further subdivide these groups to reflect both renewable and non-renewable export shares. Renewable products include those from agriculture, forestry and seafood; while non-renewables comprise oil & gas, minerals, and metals and ores.

EXPLORING the relationship between **NDE** categories, sovereign **credit ratings** and **RESILIENCE** to **global economic shocks** at the national level.

Main Conclusions: Exporters of Renewables

- **Renewable HNDEs have worse credit ratings on average**, although there are some notable exceptions, including New Zealand and Iceland.
- **Prior to the financial crisis, both renewable HNDEs and LNDEs experienced a gradual decline in their credit ratings. After the financial crisis, renewable HNDE credit ratings remained nearly stable.** Meanwhile, **renewable LNDEs continued to demonstrate a downward correction**. The net effect is that relative to LNDEs, the position of **renewable HNDEs improved post-crisis at a rate of one credit grade every 6 years**. If this trend were to continue, average credit ratings between the two groups would converge about a decade from now.
- **Economies with a lower gross domestic product (GDP) in the renewable HNDE group continue to show a trend towards downgraded credit ratings** relative to renewable HNDEs with a higher GDP. This suggests credit ratings issuers consider them more vulnerable in their ability to respond to future shocks.

Main Conclusions: Exporters of Non-Renewables

- We find **the credit scores of non-renewable HNDEs show a relative worsening over time**. We calculated the rate of this divergence and found **the position of non-renewable HNDEs drops at a rate of one full letter credit rating every 4.2 years relative to non-renewable LNDEs**. These groups had roughly similar ratings on average immediately following the financial crisis, but their ratings have since continued to diverge. This implies that these nations struggle to obtain climate-related financing, whether to fund economic transitions or recovery from global events related to climate change, going forward.
- **Non-renewable HNDE credit ratings continue to worsen in relative terms, but the effect is greatest among non-renewable HNDEs with a lower GDP**. Again, credit ratings issuers may view these nations as having less capacity to adapt to or overcome future shocks.

Other Conclusions

- We don't see a particularly large downward correction in credit scores directly before, during, or after the financial crisis for most nations.
- There are outliers that retain their credit ratings throughout the period of analysis; e.g., Germany, Sweden and Switzerland.
- **Sovereigns rated prior to 2000 often have higher credit ratings in both renewable and non-renewable groups**, compared to those that have received a credit rating for less than 20 years. The later additions to S&P credit ratings tend to be economies that are more specialised in either renewable or non-renewable exports and they are often nations with comparatively lower GDP.
- We can also observe that **the majority of nations rated after 2000, particularly renewable HNDEs or non-renewable LNDEs, fall firmly in the speculative grade rating group**.

INTRODUCTION

In this paper, we are following up to our work in the Planet Tracker report [Nature Dependent Exporters: What Do They Have in Common?](i) (September 2022) herein referred to as the NDE2022 report. There, we defined direct nature dependence as follows: the economic reliance on exports which are sold in a state similar to the state they are found in nature. In other words, relatively unprocessed exports are more nature dependent.

We explored the relationship between the share of a nation's directly nature-dependent and several national characteristics. We then grouped the characteristics into the categories of population-resource dynamics, social stability, domestic income, land tenure, financial access, and long-term influences such as the rate of patent applications and climate change resilience composite scores. NDE2022 was exploratory in nature, meaning that it introduced readers to the factors potentially impacting a society's exposure to export-side environmental risks. We refer to that work for background reading.

In this study, we have chosen to dive into a particular topic from NDE2022 more rigorously. Fitting with Planet Tracker's mission to align capital markets with planetary boundaries, we explore the relationship between Nature Dependent Exporter (NDE) categories, sovereign credits ratings as assessed by S&P Global, and national-scale resilience to global economic shocks. For S&P credit rating definitions – see Table 1.

Table 1: Summary of the Opinions reflected by S&P ratings. Source: S&P Global 2022.[ii]

Investment Grade	
AAA	Extremely strong capacity to meet financial commitments. Highest rating.
AA	Very strong capacity to meet financial commitments.
A	Strong capacity to meet financial commitments, but somewhat susceptible to adverse economic conditions and changes in circumstances.
BBB	Adequate capacity to meet financial commitments, but more subject to adverse economic conditions.
BBB–	Considered lowest investment grade by market participants.
Speculative Grade	
BB+	Considered highest speculative grade by market participants.
BB	Less vulnerable in the near-term but faces major ongoing uncertainties to adverse business, financial and economic conditions.
B	More vulnerable to adverse business, financial and economic conditions but currently has the capacity to meet financial commitments.
CCC	Currently vulnerable and dependent on favourable business, financial and economic conditions to meet financial commitments.
CC	Highly vulnerable; default has not yet occured, but is expected to be a virtual certainty.
C	Currently highly vulnerable to non-payment and ultimate recovery is expected to be lower than that of higher rated obligations.
D	Payment default on a financial commitment or breach of an imputed promise; alsoused when a bankruptcy petition has been filed or similar action taken.

Note: Ratings from 'AAA' to 'CCC' may be modified by the addition of a plus (+) or minus (–) sign to show relative standing within the major rating categories.

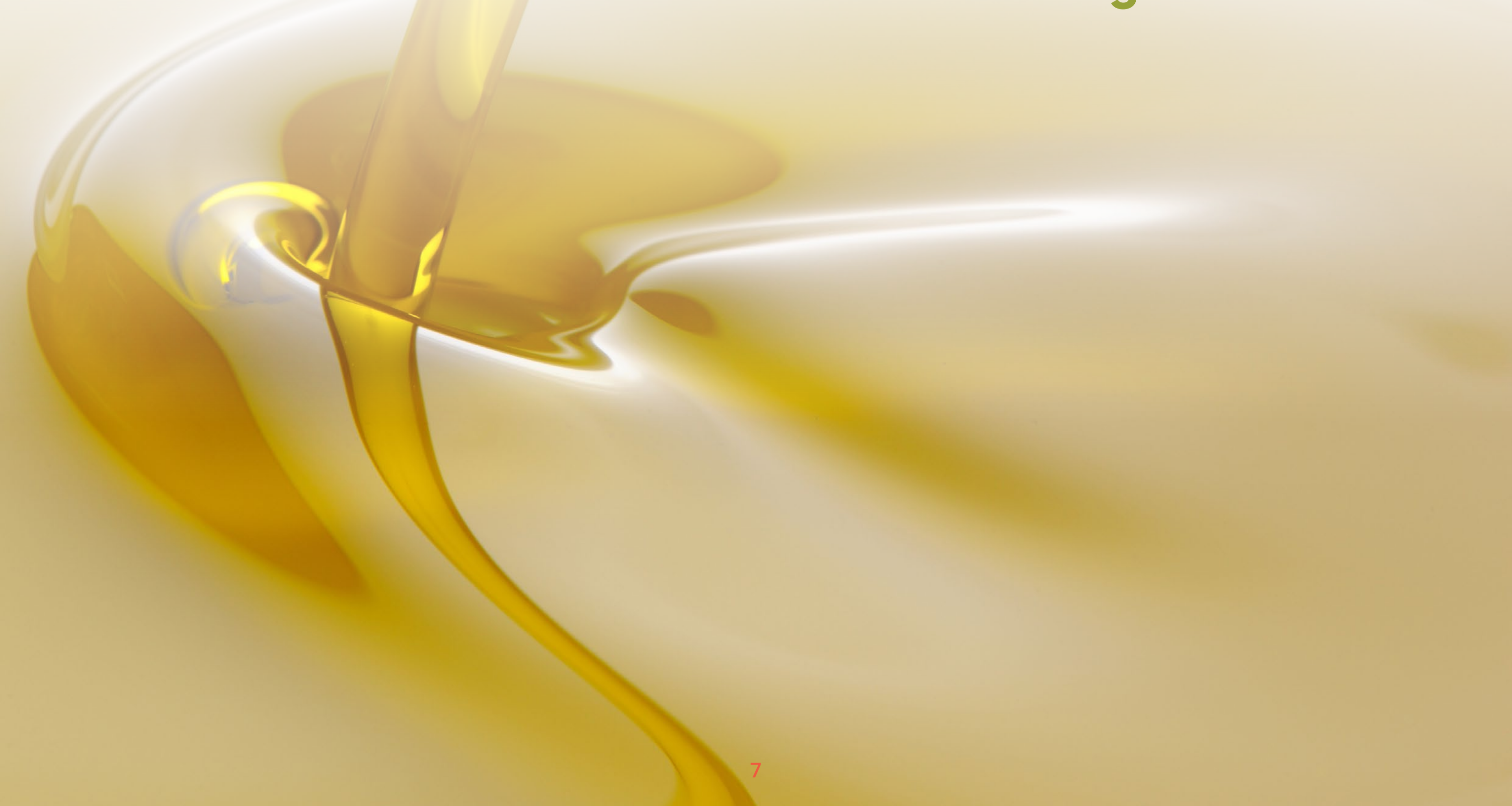
We contrast credit ratings outcomes between the groups of countries whose exports are highly dependent on nature (HNDEs) versus those with low nature dependency (LNDEs). Using the global distribution of countries with export shares that are directly nature dependent, we classify HNDEs as the countries in the top third and LNDEs as those in the bottom third.

Credit ratings are forward-looking assessments by a credit rating agency regarding the ability and willingness of an entity such as a government or corporation to meet its financial obligations in full and within the established due dates. A credit rating also signifies the likelihood a debtor will default.

The financial crisis of 2007–2008 affected the ability and willingness of different sovereigns to meet such obligations, in different ways. Planet Tracker's research shows that nature dependence is partly useful for explaining this difference. Comparisons between HNDEs and LNDEs during this period reveals a divergence in credit worthiness for these categories. We show a link between countries' dependence on natural resources and credit ratings, a metric which is a key input in many investment decisions. The financial community could find this analysis useful for sovereign climate- or biodiversity-risk assessments.

We also found in NDE2022 that national characteristics and export behaviour are best grouped into renewable versus non-renewable exports. That is, countries focused on trade of renewables differ from those focused on non-renewables in terms of trade decisions and the organisation of economies and society in general. As such, we divide HDNEs and LNDEs into groups according to their renewable and non-renewable export shares and compare them for each group.

We show a **link** between **countries' dependence** on **NATURAL RESOURCES** and **credit ratings**



EMPIRICAL APPROACH

In this section, we discuss the empirical approach to clearly outline so that we are clear about our identification strategy and resulting estimate of impact what we are estimating. Our null and alternative hypotheses are:

Null hypothesis *(H_0):* The impact of the 2007–2008 global financial crisis on credit worthiness, as represented by a nation's credit rating, was the same for HNDE and LNDE groups.

Alternative hypothesis *(H_A):* The impact of the global financial crisis on credit worthiness as represented by a nation's credit rating was different for HNDE and LNDE groups[1].

The quasi-experiment gold standard for comparing the outcomes of two groups across time is the difference-in-differences (DD) approach[2]. The underlying concept is that find the first difference for a characteristic of interest before and after a treatment for the treatment group. Then we compare this to the second difference for the pre- and post-treatment for another control group or groups. This results in an impact estimate, which is the difference in their differences. In the DD approach, the 'treatment' is often either some exogenous global event or the implementation of a policy. This may seem intuitive: in fact, the idea behind the approach is quite old in terms of empirical strategies. It can be traced back to at least 1856 in Snow's study of reasons why cholera spread in some neighbourhoods of London but not others in 1854.[iii]

The modern empirical development of the DD approach begins with Ashenfelter[iv] (1978) and Ashenfelter and Card (1985).[v] However, it was Card and Krueger's (1994)[vi] study on whether minimum wage increases impact unemployment rates, which compares a state with and without such an increase, that made the DD approach popular. See also Angrist and Pischke (2009) for an approachable explanation.[vii] It is also an area of continuing development. One research area relevant for this paper is the question of how to arrive at more flexible estimation strategies. For example, in Mora and Reggio (2019),[viii] the authors explore the qualities of estimation strategies under different parallel pre-trend assumptions. However, the similarity or difference of pre-treatment trends can imply various things. In some contexts, it is critical for identification that the pre-event trends are parallel. In this study, however, non-parallel prior trends are expected and this raises an interesting point of discussion in what follows.

[1] To be clear, we would find support for H_A – that HNDEs and LNDEs had different impacts on their national credit ratings, if we can reject H_0 at commonly accepted levels of statistical significance based on acceptable empirical approaches.

[2] A quasi-experiment is one where we cannot assign our own people, nations or other groups of interest to treatment versus control groups, as this could introduce selection bias. Rather, we attempt to replicate an experimental design given the limitation of working with existing data. Preferably, the experiment groups should not be self-selected into either treatment or control group status, but we do what we can with the data available.

Building a Difference-in-Differences Approach

In this study, we take the additional step of building our DD estimator from scratch. In our estimator, we combine regression discontinuity (RD) (Thistlethwaite and Campbell, 1960[ix]) and regression kink (RK) (Nielsen, Sørensen, and Taber, 2010[x]; Card, Lee, Pei, and Weber, 2012[xi]) designs. The RD/RK-combination design allows the estimation of both a discontinuous jump between points and a change in the rate of change or slope for a variable following an event. We then build our DD approach by comparing the RD/RK outcomes of our two examined groups. By building our empirical approach in this manner it is quite clear what we are estimating and it allows a clear visualisation.

Let $Y_{i,t}$ be the relevant outcome in observation *i* during period t. $Y_{i,t}$ is a numerical version of the credit score of nation *i* in year *t*. Let x_t be an adjusted year, centred in the selected event, with the form $x_t = (time_i - k)$ where time is described in standard calendar form and *k* is the moment of the critical event. Here the 2007–2008 global financial crisis is our event, but the study can easily be updated with other events. For instance, in a few years the research design could study the impact of 2020–2022 coronavirus related national shutdowns. As the purpose of the model is to estimate the impact of the critical event at *k*, not the influence of primitives on *Y*, let a function $Yi,t = f(x_t)$ approximate the true relation $Y_{i,t} = g(X_{i,t})$ which has a potentially large vector of determinants of demand, $X_{i,t}$. We explore whether the global financial crisis at *k* fundamentally changes underlying determinants such that we can apply a binary indicator of form

(1)
$$D_t = \begin{cases} 1 \text{ if } year_t \geq k \\ 0 \text{ if } year_t < k \end{cases}$$

and can write the conditional expectation of *Y* for our two analysed groups, LNDEs vs HNDEs, as

(2)
$$E[Y_{LNDE,i,t}|x_t] = E[Y_{L0i}|x_t] + (E[Y_{L1i}|x_t] - E[Y_{L0i}|x_t])D_t$$

(3)
$$E[Y_{HNDE,i,t}|x_t] = E[Y_{H0i}|x_t] + (E[Y_{H1i}|x_t] - E[Y_{H0i}|x_t])D_t$$

where the first sub-notation notes whether they are in NDE group LNDE (L) or HNDE (H) and the second sub-notation indicates whether the 'treatment' of the global financial crisis has occurred. As the global financial crisis impacted all countries at approximately the same time, the moment of treatment is shared. Otherwise, we would use country-specific treatment points, which would not be difficult to implement if necessary. What equations (2) and (3) tell us is that we are modelling the expected outcome as the pre-event outcome, plus any change that occurs due to the global financial crisis. We are also allowing the before-and-after event outcomes to differ between LNDE and HNDE groups.

To keep the approach simple yet apparently sufficient, let the functional form of the pre-treatment conditional expectations for the LNDE and HNDE groups be

(4)
$$E[Y_{L0,i,t}|x_{t,} D_t = 0] = \alpha_{L0} + \beta_{L0}x_t$$

(5)
$$E[Y_{H0,i,t}|x_{t,} D_t = 0] = \alpha_{H0} + \beta_{H0}x_t$$

and let the post-treatment conditional expectations with both different slope and intercepts be

(6)
$$E[Y_{L1,i,t}|x_{t,} D_t = 1] = \alpha_{L1} + \beta_{L1}x_t$$

(7)
$$E[Y_{H1,i,t}|x_{t,} D_t = 1] = \alpha_{H1} + \beta_{H1}x_t$$

Substituting equations (4) through (7) into equations (2) and (3) and stating as their realisations results in

(8) $$Y_{L,i,t} = \alpha_{L0} + \beta_{L0}X_t + (\alpha_{L1} - \alpha_{L0})D_t + (\beta_{L1} - \beta_{L0})D_tX_t + \varepsilon_i$$

(9) $$Y_{H,i,t} = \alpha_{H0} + \beta_{H0}X_l + (\alpha_{H1} - \alpha_{H0})D_t + (\beta_{H1} - \beta_{H0})D_tX_t + \varepsilon_i$$

Equations (8) and (9) are the functional forms for the estimation of the RD and RK effects of the global financial crisis on LNDEs and HNDEs separately. The coefficients *($\alpha_{L1} - \alpha_{L0}$)* and *($\alpha_{H1} - \alpha_{H0}$)* identify any effect resulting in a discontinuity or 'jump' in LNDE and HNDE credit scores, respectively, and *($\beta_{L1} - \beta_{L0}$)* and *($\beta_{H1} - \beta_{H0}$)* show any change in the linear rates of change (changes in the slope) in their credit scores from the global financial crisis event *k* onward. Our impact estimate shows that for any divergence in HNDE versus LNDE credit scores due to the global financial crisis, there would be an instantaneous discontinuous drop *($\alpha_{H1} - \alpha_{H0}$) – ($\alpha_{L1} - \alpha_{L0}$)*, followed by any additional divergence or convergence in their rates of change as *($\beta_{H1} - \beta_{H0}$) – ($\beta_{L1} - \beta_{L0}$)*. We also provide a visualisation showing this impact estimate – see Figure 1.

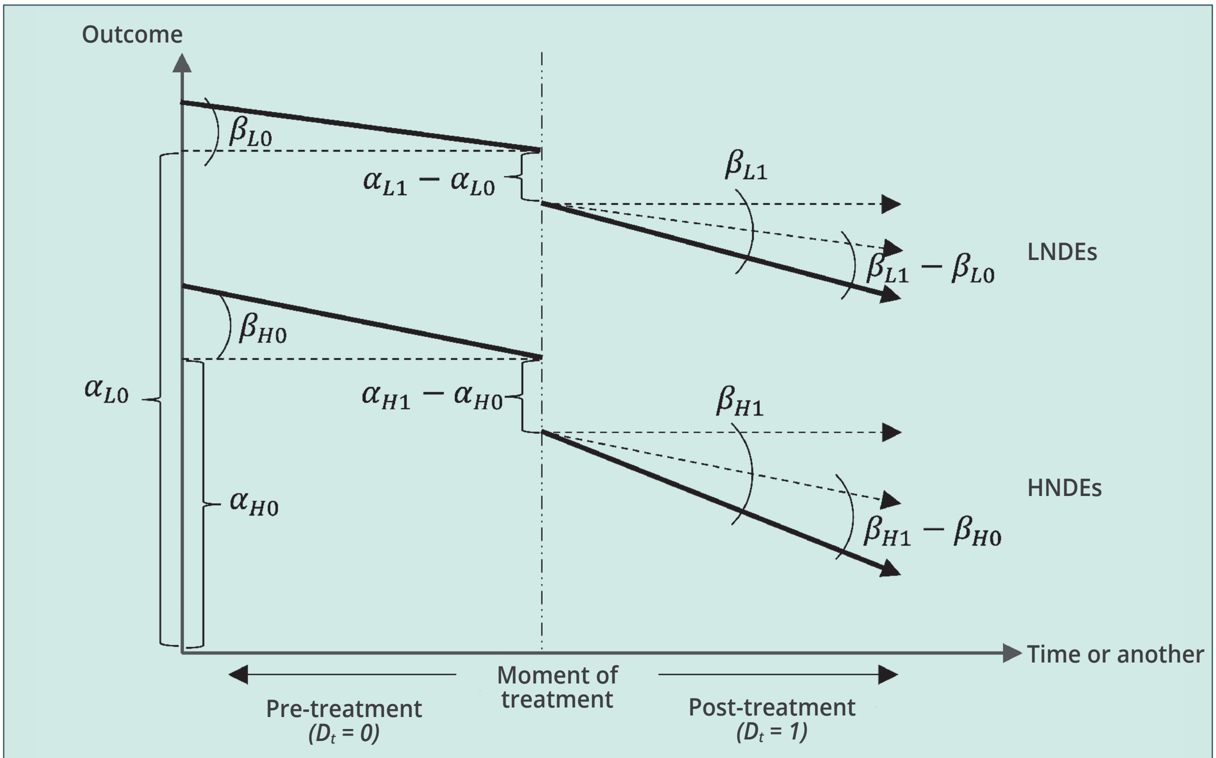


Figure 1: Visualisation of RD/RK-based DD estimation.
Source: Author depiction based on equations (8) and (9).

Notes: Interpretation of RD/RK coefficients:
α_{L0}, α_{H0}: level of the outcome immediately preceding the event at *k*
β_{L0}, β_{H0}: rate of change in the outcome over time preceding the event at *k*
($\alpha_{H1} - \alpha_{H0}$), ($\alpha_{L1} - \alpha_{L0}$): instantaneous impacts of the event on each group
($\beta_{H1} - \beta_{H0}$), ($\beta_{L1} - \beta_{L0}$): increase or decrease in the rate of change after the event on each group
Resulting DD coefficients:
($\alpha_{H1} - \alpha_{H0}$) – ($\alpha_{L1} - \alpha_{L0}$): difference in the instantaneous impact from the treatment on groups 0 and 1
($\beta_{H1} - \beta_{H0}$), ($\beta_{L1} - \beta_{L0}$): difference in the impact on the rate of change from the treatment on groups 0 and 1

To build the DD estimator, we then define another indicator variable for whether an observation is in the HNDE or LNDE group

(10) $$G_i = \begin{cases} 1 \textit{ if } \text{NDE} = \text{HNDE} \\ 0 \textit{ if } \text{NDE} = \text{LNDE} \end{cases}$$

What we ultimately want to explore is the difference in impact between the two groups. The conditional expectation of *Y* due to the treatment on the two NDE groups is of similar form to preceding equations (2) and (3), depicted as

(11) $$E[Y_{NDE,i,t} | NDE_i x_t] = [Y_{LNDE,i,t} | x_t] + ([Y_{HNDE,i,t} | x_t] - [Y_{LNDE,i,t} | x_t])G_i$$

This allows us to build a DD estimator from our preceding pair of RD/RK equations. Equation (11) illustrates that we have taken the LNDE group as the treatment group and then we estimate how the HNDE group is differently impacted.

It is important to define clearly what we mean by impact in this case, as the selection of countries in each group is not entirely exogenous. Whether a country is an LNDE or HNDE is clearly not imposed, but it is at least in part – often primarily – the result of the country's decisions. We can perhaps consider the selection groups a risk tolerance category associated with either higher or lower susceptibility to global financial shocks. The basis for this difference is that prices and demand for raw resources are historically more volatile than prices and demand for intermediary and finished goods. So, one might expect HNDEs to experience greater shocks and perhaps loss of confidence in their credit-worthiness due to global downturns.

Substituting equations (2) and (3) into equation (11) results in

(12) $$E[Y_{NDE,i,t} | NDE_i x_t] = (E[Y_{L0,i,t} | x_t] + (E[Y_{L1,i,t} | x_t] - E[Y_{L0,i,t} | x_t])D_t) + [(E[Y_{H0,i,t} | x_t] + (E[Y_{H1,i,t} | x_t] - [(E[Y_{H0,i,t} | x_t])D_t) - (E[Y_{L0,i,t} | x_t] + (E[Y_{L1,i,t} | x_t] - E[Y_{L0,i,t} | x_t])D_t)G_i$$

Let the functional form of the pre-treatment and post-treatment conditional expectations with different intercepts and slopes follow as before from equations (4) through (7). Substituting into equation (12) results in

(13) $$Y_{NDE,i,t} = (\alpha_{L0} + \beta_{L0}x_t + (\alpha_{L1} + \beta_{L1}x_t - (\alpha_{L0} + \beta_{L0}x_t))D_t) + [\,(\alpha_{H0} + \beta_{H0}x_t + (\alpha_{H1} + \beta_{H1}x_t - (\alpha_{H0} + \beta_{H0}x_t)) D_t) - (\alpha_{L0} + \beta_{L0}x_t + (\alpha_{L1} + \beta_{L1}x_t - (\alpha_{L0} + \beta_{L0}x_t))D_t)\,]G_i + \varepsilon_{i,t}$$

Which simplifies to

(14) $$Y_{NDE,i,t} = (\alpha_{L0} + \alpha_{L1}) + (\beta_{L0} + \beta_{L1})x_t - \alpha_{L0}D_t - \beta_{L0}x_tD_t + (\alpha_{H0} - \alpha_{L0})\, G_i + (\beta_{H0} - \beta_{L0})x_tG_i + [(\alpha_{H1} - \alpha_{H0}) - (\alpha_{L1} - \alpha_{L0})]\, D_tG_i + [(\beta_{H1} - \beta_{H0}) - [(\beta_{L1} - \beta_{L0})]\, x_tD_tG_i + \varepsilon_{i,t}$$

We might repurpose and simplify the notation a bit and restate our equation for estimation purposes as

(15) $$Y_{NDE,i,t} = \alpha_0 + \beta_0 x_t + D_0 + D_1 x_t + G_0 + G_1 x_t + \omega_0 + \omega_1 x_t + \varepsilon_{NDE,i,t}$$

where ω_0 and ω_1 are our DD discontinuous jump and slope change impact estimates, respectively.

The ordering of this process is important – we first formulate the RD/RK estimators and then compare them, not the other way around. Additionally, we centre the estimates around the *k* event, so intercept or 'jump' terms must be interpreted relative to the moment of the event. We might also consider whether a matching/synthetic control method – basically pairing nations based on a similarity index – would add useful information to the analysis to follow. However, comparing HNDE to LNDE groups as described here provides interesting results without this method. Before presenting our analysis, here is a quick note why we have not included a set of covariates when studying the impact of the global financial crisis on credit scores.

Whether to Include Additional Covariates

Both the RD/RK and DD approaches have an additive nature, so it's conceivable to add a set of controls, as in covariates describing other societal factors we may want to control for. These would enter into the prior equations as j-length sets of nation and year-dependent covariates, X'_{it}, resulting in an additional vector of estimates β_j. That is, the equations can be appended by $X'_{it}\beta_j$. Whether the estimates of βjs are statistically significant, depends on the strength of relationships between the covariates. It would not imply any corruption of the functional form presented here. If they are entirely independent, the coefficients will be unaffected. However, if they are highly dependent, leaving them out may substantially lead to biased results.

To decide whether to include covariates, we should consider the objective of the analysis. Sticking to the preceding forms of equations results in an estimate of the net effect of the underlying causes. In this case, these causes are changes in sovereign credit ratings due to changes in all underlying national factors. In contrast, including a large set of relevant covariates would instead result in an estimate of the impact on credit ratings after essentially factoring out other influences on the credit rating. But what would that actually mean? A credit rating is meant to be a summary statistic that includes data on many interrelated national factors that impact a nation's risk of default, among other possible outcomes. That is, most factors that we might include are rather mediators. If we were to factor out all the underlying causes of a national credit rating, we would be left with variation caused not by a nation's behavior, but by something else. Yet, we want to explore the relationship between a nation's vulnerability to global financial crises due to their export-side nature-dependency, which generally increases a nation's exposure to global economic volatility. So, we do not intend to explore a large set of covariates, as rigorous impact estimates on the net effect are instead the goal.

APPLICATION: MEASURING DIFFERENCES IN CREDIT RATING TRENDS

In this section, we apply the DD approach to study whether HNDE and LNDE credit scores had different corrections on average due to the 2007–2008 global financial crisis. We question whether nations with more or less exposure to international basic material markets experienced a greater loss of credit access going forward.

Data preparation and common empirical factors/adjustments

During preparation of the NDE2022 report, we collected credit worthiness score data at the national level.[xii] We assigned a numerical value to each credit rating across a 100-point scale, with 100 as the best score possible, a 100 to make the coefficients easier to interpret. Naturally, credit ratings would still be grouped tightly together, so for data visualization purposes in our scatterplots, we've added a bit of random variation so that observations aren't directly stacked on top of each other. While the variation may be thought to introduce errors in measuring credit worthiness over time, it only used as a visualization tool. In the empirical analysis, the data does not have additional variation added. For the numerical conversion of S&P sovereign credit ratings – see Table 2:

Table 2: S&P Sovereign Credit rating conversion.

Investment Grade		Speculative Grade	
AAA	100	**BB+**	63
AA+	93	**BB**	60
AA	90	**BB–**	57
AA–	87	**B+**	53
A+	83	**B**	50
A	80	**B–**	47
A–	77	**CCC+**	43
BBB+	73	**CCC**	40
BBB	70	**CCC–**	37
BBB–	67	**CC**	30
		C	20
		D	10

Note: Coverage 1995–2020 based on Sovereign Credit ratings local currency, from S&P Global as reported by Bloomberg. See discussion in the appendix to the NDE2022 report.

As identified in the NDE2022 paper, renewable and non-renewable exporter groups should be analysed separately, as their underlying decision drivers differ. However, it is important to note that the export shares of renewables versus non-renewables are strongly negatively correlated, with an export share correlation coefficient of negative 0.56. That is, when we are looking at renewable HNDEs, we are comparing them to renewable LNDEs, which are also often non-renewable HNDEs. The two groups are inversely linked, as many non-renewable nations are particularly specialised in terms of trade.

Here are several ways we adjust the data to address common issues. The collected data contains information on about 100 nations which had their credit worthiness reported on an annual basis. It is important to recognize that a nation's credit rating will be similar from year to year, when we conduct our empirical analysis. A standard process is to cluster the standard errors calculation at the national level. We also observe that the data indicates heteroskedasticity: the variance of the data changes across the period of observation. As such, we use an appropriate approach, White's standard errors. Finally, about 10 per cent of our observations occur at the upper bound of having perfect credit scores. At least mechanically, the data is censored from above, so we use the Tobit model as a common response to censored data. This only slightly impacts results by basically noting differences in observations that occur at the upper boundary.

Renewables

We begin with renewable credit score histograms before and after the global financial crisis - see Figure 2.

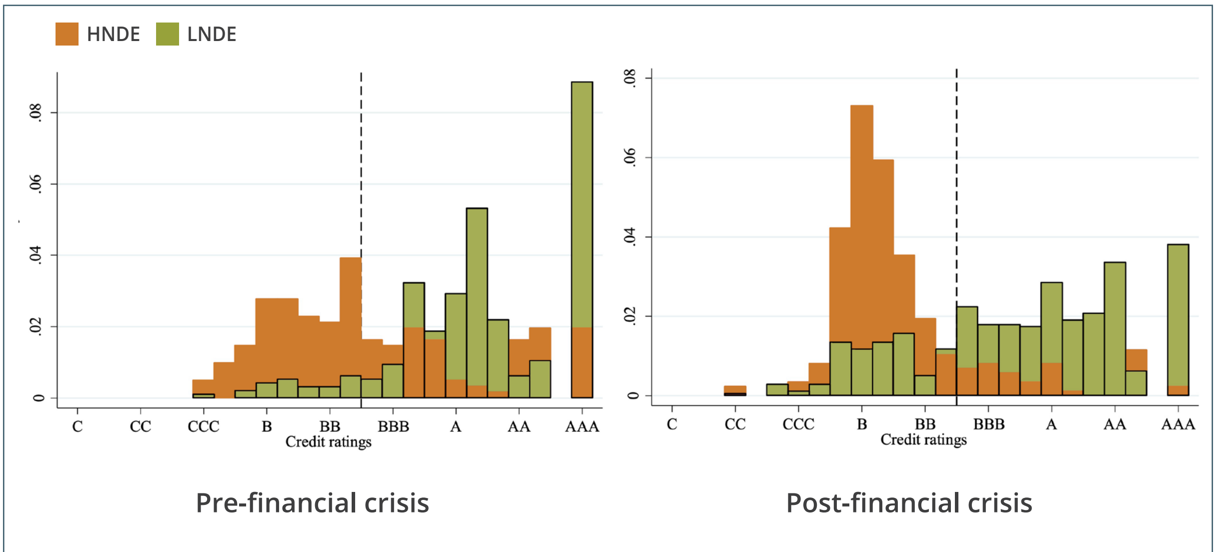


Figure 2: Distributions of credit ratings of renewable HNDEs versus LNDEs.
Source: Author calculations based on data prepared for the report NDE2022.

Notes: Renewable histograms with the same number of bins as credit rating scores. Credit scores of HNDEs (ochre) and LNDEs (green) pre- and post-global financial crisis. Dashed black line indicates the division between speculative and investment grade scores.

In essence, we present people's likely prior expectation for how the global financial crisis might have impacted sovereign credit worthiness before exploring the issue further. The histograms suggest that many nations including both LNDEs and HNDEs, but particularly the latter, had their credit scores downgraded. Note that these histograms contain about 1,400 observations which are from the roughly 100 nations that had been repeatedly sampled.

Next, we plot the numerical credit scores of the LNDE and HNDE groups separately over time – see Figure 3.

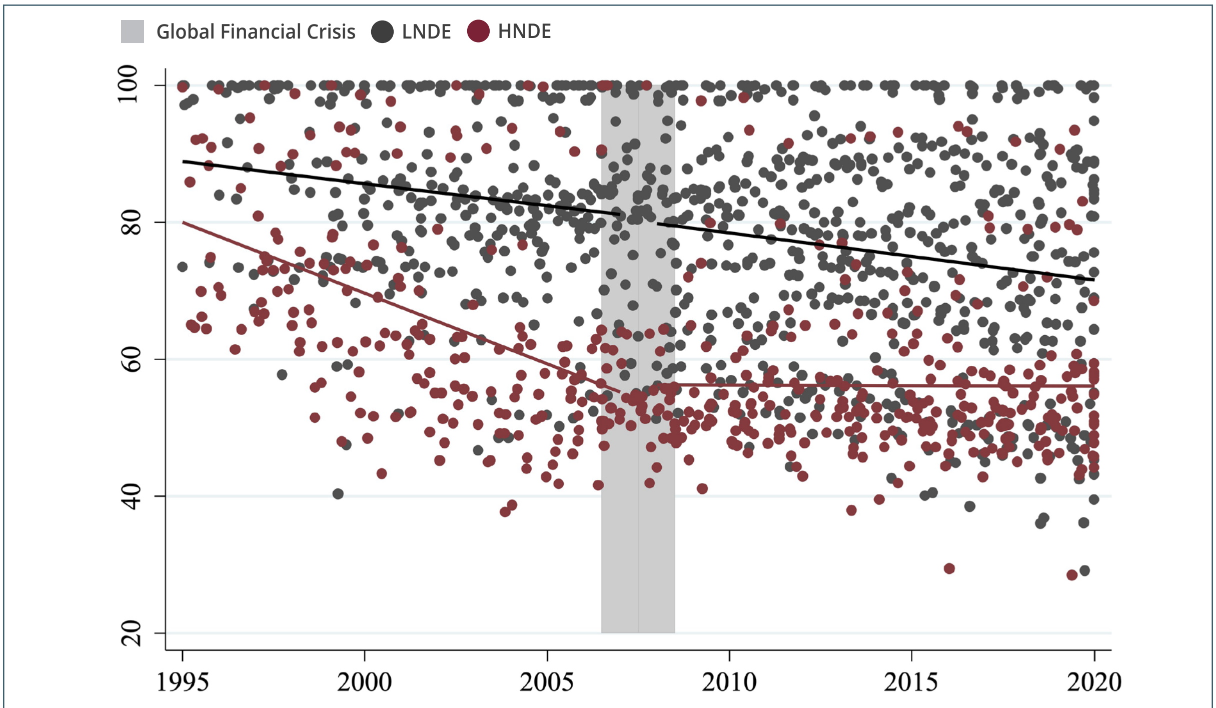


Figure 3: Credit ratings of renewable HNDEs versus LNDEs.
Source: Author calculations based on data prepared for the report NDE2022.

Notes: Annual data of numerical version of credit ratings at the national level for renewable HNDEs (red) and LNDEs (black) with group fitted lines. Small amount of random variation added to data to improve visualisation. 2007–2008 global financial crisis period in grey.

We can note, as in the histograms, that renewable HNDEs have worse credit ratings on average. However, there are a few in each group with very high scores. Generally, there is a lot of variation in the data, particularly among the renewable LNDEs. We will see that the opposite is the case for non-renewables in that the non-renewable HNDE data has more variation. This just further highlights the relationship between the groups: renewable LNDEs are often also non-renewable HNDEs.

Despite the scale of variation, we see an interesting trend emerge. Prior to the financial crisis, bother renewable HNDEs and LNDEs were experiencing a gradual degradation of credit scores. This implies there was an advance adjustment prior to the global financial crisis, as credit scores are intended to be forward-looking. We see in Figure 3, by the time of the crisis, the downward adjustment in credit scores for renewable HNDEs had ended, while the renewable LNDEs' credit scores continue to decline. We also don't see a particularly significant decline in credit scores during the financial crisis for most nations, which again fits the narrative that credit ratings change in anticipation of events.

We then pair DD-based estimates with the trends we have observed – see Table 3.

Table 3: DD Estimates on Changes in the Credit Ratings of Renewable Exporters.
Source: Author calculations based on data prepared for the report NDE 2022.

	Data	Coefficient	Unweighted
Constant	1	$\alpha_{L0} + \alpha_{L1}$	81.39^{***} (2.57)
Date, *x=(actual –k)*	x_i	$\beta_{L0} + \beta_{L1}$	-0.99^{**} (0.45)
RD: *D=1(actual ≥k)*	D_i	α_{L0}	−0.30 (1.98)
RK: year* D	$x_i D_i$	β_{L0}	0.26 (0.47)
	G_i	$\alpha_{H0} - \alpha_{L0}$	-27.50^{***} (3.98)
Parallel pre-trends test	$x_i G_i$	$\beta_{H0} - \beta_{L0}$	1.04^{**} (0.51)
DD estimates			
Discontinuity	$D_i G_i$	$(\alpha_{H1} - \alpha_{H0}) - (\alpha_{L1} - \alpha_{L0})$	3.31 (2.88)
Slope difference	$x_i D_i G_i$	$(\beta_{H1} - \beta_{H0}) - (\beta_{L1} - \beta_{L0})$	1.68^{***} (0.60)
		Observations	1,400
		Clusters (countries)	101
		R-squared*	0.34

Notes: (k=2008) Robust standard errors clustered at the country level in parentheses. 101 clusters/countries. *** Significant at the 1 per cent level, ** Significant at the 5 per cent level, * Significant at the 10 per cent level. R-squared calculated from OLS regression as Tobit Pseudo R-squared does not have an equivalent and familiar interpretation.

First, we can test whether the classic parallel pre-trends test holds. For this, we check to see if the estimate for data $\beta_{H0} - \beta_{L0}$ is statistically insignificant. This finding would suggest the two group's trends before the 2007–2008 financial crisis were was the same, statistically speaking. However, our parallel pre-trends test confirms our observation – that the credit ratings of renewable HNDEs were declining faster pre-financial crisis. This means we have to be careful in our interpretation of post-financial crisis slope change results.

We confirm that there was not a statistically significant 'jump' in scores. This is, in part but not entirely due to the large amount of variation in the renewable LNDE group. It also appears that credit rating agencies may have found that some renewable HNDEs to be less negatively impacted by the global financial crisis than expected, as there is a slight increase in their credit ratings. After the 2007–2008 financial crisis, renewable HNDE credit ratings remain nearly stable with the slope of their fitted line hovering at about zero. Meanwhile, renewable LNDEs continue to have a downward correction on average. Separate RD/RK analysis results are included in the appendix to confirm the separate group trends.

The net effect is that relative to LNDEs, the position of renewable HNDEs improves after the crisis. However, it is not a credit score increase as this improvement is relative to the credit ratings of the comparison LNDE group, which continue to decline. The mean renewable HNDE score is also still currently lower. The relative rate of divergence is that the position of renewable HNDEs improves relative to renewable LNDEs at a rate of one credit score full letter every $^{10}/_{1.68} \approx 6$ years and so we might expect convergence about a decade from now.

We next analyse non-renewable LNDEs and HNDEs for comparison.

Non-renewables

Our pre- and post-global financial crisis histograms once again to reflect common expectations about the impact of the global financial crisis on credit scores. This time, we're comparing non-renewable HNDEs versus LNDEs. We again observe that both groups have worse credit ratings on average in the post-crisis histogram. However, non-renewable HNDEs are particularly negatively impacted – see Figure 4.

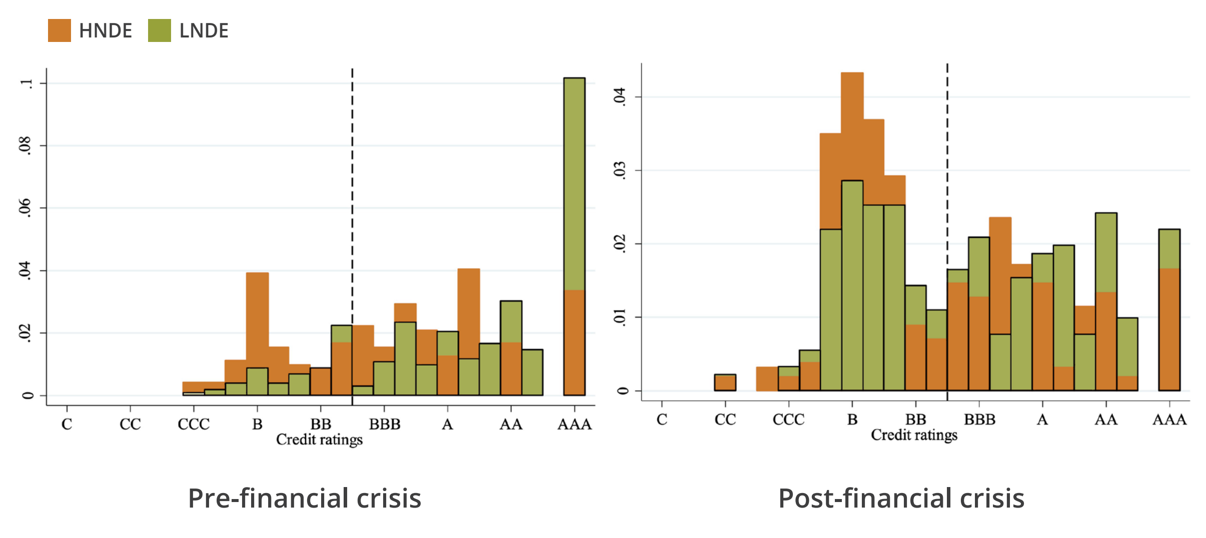


Figure 4: Distributions of credit ratings of non-renewable HNDEs versus LNDEs.
Source: Author calculations based on data prepared for the report NDE2022.

Notes: Non-renewable histograms with the same number of bins as credit rating scores. Credit scores of HNDEs (ochre) and LNDEs (green) pre- and post-global financial crisis. Dashed black line indicates the division between speculative and investment grade scores.

As a reminder, we found a strong negative correlation between nation-scale renewable and non-renewable export shares, so it makes sense that we observe opposite trends for renewables – see Figure 5.

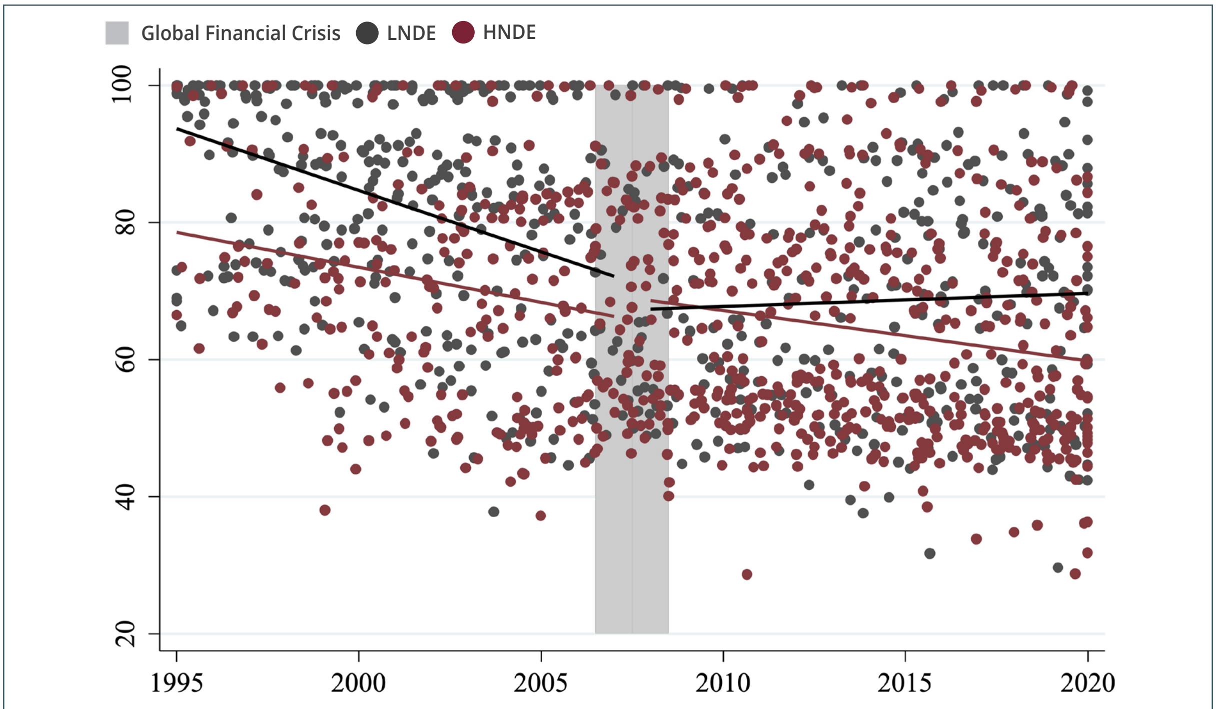


Figure 5: Credit ratings of non-renewable HNDEs versus LNDEs.
Source: Author calculations based on data prepared for the report NDE2022.

Notes: Annual data of numerical version of credit ratings at the national level for non-renewable HNDEs (red) and LNDEs (black) with group fitted lines. Small amount of random variation added to data to improve visualisation. 2007-2008 global financial crisis period in grey.

Here, we see that the credit ratings of non-renewable HNDEs undergo a downward trend pre-crisis, but here, the trend continues post-crisis as well. Forward-looking credit ratings suggest an outlook of continued decline for non-renewable HNDEs. We can note, however, that there is a lot of variance in the data and some non-renewable HNDEs maintain the highest sovereign credit ratings possible.

DD estimates again support the visual results – see in Table 4.

Table 4: DD Estimates on Changes in the Credit Ratings of Non-Renewable Exporters. Source: Author calculations based on data prepared for the report NDE 2022.			
	Data	Coefficient	Unweighted
Constant	1	$\alpha_{L0} + \alpha_{L1}$	69.30*** (4.12)
Date, *x=(actual −k)*	x_i	$\beta_{L0} + \beta_{L1}$	−2.49*** (0.43)
RD: *D=1(actual ≥k)*	D_i	α_{L0}	−1.06 (2.96)
RK: year* D	x_iD_i	β_{L0}	2.64*** (0.64)
	G_i	$\alpha_{H0} - \alpha_{L0}$	−2.70 (5.12)
Parallel pre-trends test	x_iG_i	$\beta_{H0} - \beta_{L0}$	1.48** (0.60)
DD estimates			
Discontinuity	D_iG_i	$(\alpha_{H1} - \alpha_{H0}) - (\alpha_{L1} - \alpha_{L0})$	3.59 (3.56)
Slope difference	$x_iD_iG_i$	$(\beta_{H1} - \beta_{H0}) - (\beta_{L1} - \beta_{L0})$	−2.39*** (0.81)
		Observations	1,372
		Clusters (countries)	107
		R-squared*	0.20

Notes: (k=2008) Robust standard errors clustered at the country level in parentheses. 107 clusters/countries. *** Significant at the 1 per cent level, ** Significant at the 5 per cent level, * Significant at the 10 per cent level. R-squared calculated from OLS regression as Tobit Pseudo R-squared does not have an equivalent and familiar interpretation.

We have a statistically insignificant 'jump' in the credit scores of HNDEs following the crisis, but then a statistically significant deterioration of non-renewable HNDE credit scores over time relative to LNDEs. The position of non-renewable HNDEs is particularly worse in comparison to their non-renewable LNDE competitors for international finance. The position of non-renewable HNDEs worsens relative to non-renewable LNDEs at a rate of one credit score full letter every $^{10}/_{2.39} \approx 4.2$ years. The groups had roughly similar ratings on average immediately after the crisis, but now continue to diverge.

DISCUSSION AND EXTENSIONS

We have explored how sovereign credit ratings changed over time, and therefore it is important to note, particularly with reference to the 2007–2008 global financial crisis, why credit risks change.

Our source for sovereign credit ratings, S&P Global, states: *"ratings change to reflect a current opinion of credit risk"* and *"they are seen to provide valuable opinions about current credit risk"*. Yet, after the global financial crisis, S&P Global, like other credit rating institutions, made some changes to their methodologies, *"driven by lessons learned from the financial crisis and new regulations introduced around the world"*.[ii] We therefore need to acknowledge that some post-crisis changes in credit ratings could be due to changes in assessment methodology. However, these changes are difficult to quantify.

To summarize briefly our observations, renewable HNDEs underwent a more drastic credit score correction leading up to the 2007–2008 global financial crisis. Post-crisis, the credit worthiness position of renewable HNDEs has been relatively stable, declining only slightly. In comparison, non-renewable HNDEs continue to experience substantially declining credit ratings. The underlying unsustainability of non-renewable production, transitions to renewable energy, increased rates of recycling and circular economy practices, and increasing social pushback against extreme levels of economic inequality that often accompany non-renewable resource extraction-focussed economies, likely all weigh negatively on the long-term outlook for non-renewable exporters.

To conclude the analysis, we explore what drives these national-level results, whether, the form or the sampling of the data. Considering the data employed are national-level export shares, the main analysis gives equal weight to small and large countries. To determine if results are independent of national scale, or at least independently distributed, we check if the results will be robust, given different forms of weighting.

For comparison, we might repeat the DD exercise where we instead use nation-specific weights, $w_{i,t}$, as

$$\sqrt{w_{i,t}}Y_{i,t} = \sqrt{w_{i,t}}f(x_t)$$

where the sum of the weights of all countries is one. The square root operation ensures that extreme outliers cannot drive the result either. Rather, we are providing more weight to nations with larger weights by any measure, but not letting the weights themselves drive the result.

We apply population, GDP, and export share weights to both the renewable and non-renewable analyses and provide the DD coefficient estimates – see Table 5.

Table 5: Weighted DD Coefficient Estimates.
Source: Author calculations based on data prepared for the report NDE 2022.

	Unweighted	Population weighted	GDP weighted	Export share weighted
Renewables				
Discontinuity	3.31 (2.88)	1.02 (5.73)	10.41 (8.65)	-0.97^{*} (0.59)
Slope difference	1.68^{***} (0.60)	1.31 (0.85)	−0.61 (1.14)	1.44^{**} (0.68)
Non-Renewables				
Discontinuity	3.59 (3.56)	−1.14 (5.05)	3.82 (6.30)	−1.04 (0.65)
Slope difference	-2.39^{***} (0.81)	−0.16 (1.07)	−0.39 (0.85)	−1.25 (0.85)

Notes: (k=2008) Robust standard errors clustered at the country level in parentheses. *** Significant at the 1 per cent level, ** Significant at the 5 per cent level, * Significant at the 10 per cent level. R-squared calculated from OLS regression as Tobit Pseudo R-squared does not have an equivalent and familiar interpretation.

We've also shared the full set of regression results in the appendix. We can interpret the coefficient changes in different ways. First, the weighted coefficients represent different perspectives: population weighted coefficients better represent what people experience, GDP coefficients reflect the experience of economically larger economies, and export share weights show the experience of nations more heavily engaged in resource exporting. If the estimated coefficients are larger under a given weighting scheme, larger nations in terms of the weighting basis reveal a greater impact, while smaller ones show a lower impact.

Using GDP as a measure, we can observe that smaller economies in the renewable HNDE group continue to have their credit ratings downgraded relative to larger renewable HNDEs. They are perhaps thought to be less capable of responding to future shocks. In terms of non-renewable resource exporters, we can observe that smaller nations in terms of all three weight types, population, total GDP, and export shares, are driving more of the result. In each case, the slope coefficient is negative, meaning that non-renewable HNDE credit ratings continue to worsen in relative terms, but the effect is greatest among small non-renewable HNDEs. These are again nations likely deemed to have a lower capacity to adapt to or overcome future shocks. However, we must again note that the data contains substantial variation.

Another issue to explore is how the data is sampled. Specifically, we question whether the results are more appropriately confined to the subset of nations that S&P provide credit ratings on, or whether the results describe a broader economic trend. To address this issue, we plot the number of nations for which S&P sovereign credit ratings are reported in each year – see Figure 6.

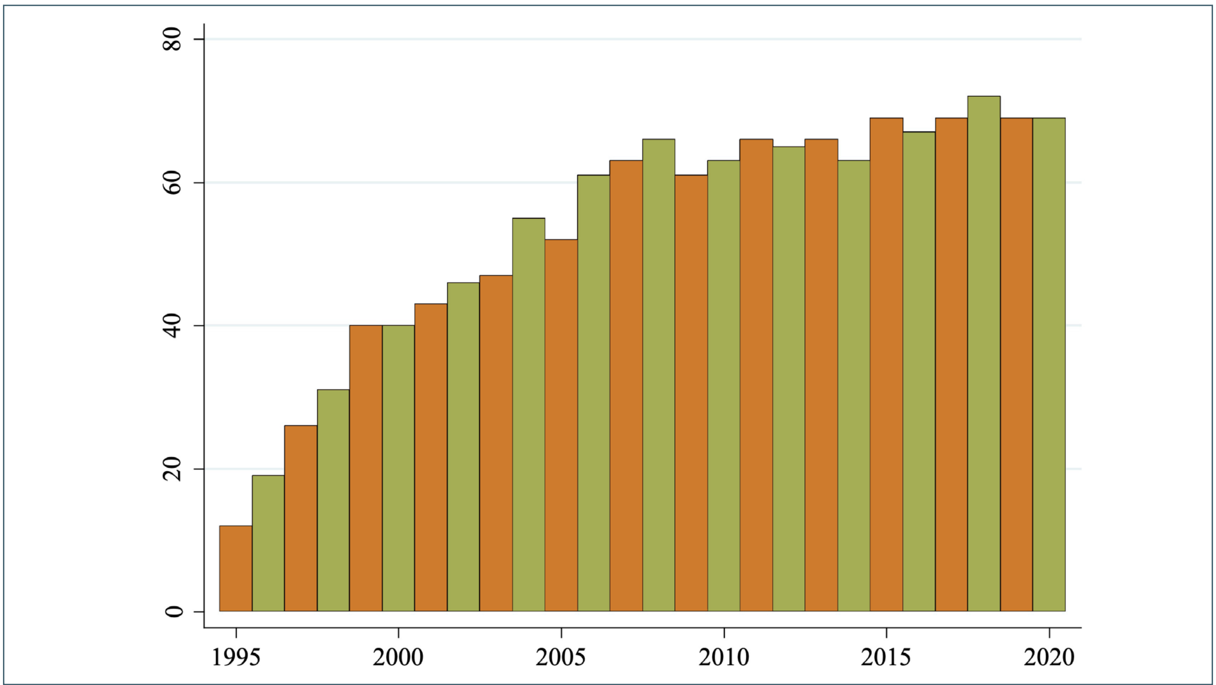


Figure 6: Number of Countries with credit ratings reported by year.
Source: Author calculations based on data prepared for the report NDE2022.

Notes: Annual data of number of credit ratings at the national level reported per year.

Clearly, the number of nations has increased markedly since the beginning of our sample in 1995. It's possible that the nations which had credit ratings since at least the beginning of our data, which are often comparatively larger, richer nations, have better credit ratings on average. Perhaps just as importantly, we assess whether the countries rated earlier are experiencing similar or different trends compared to more recently added countries, which are often smaller, poorer nations.

Due to the nature of the DD estimation method employed, only nations that have observations both pre- and post-global financial crisis are included. However, we can further divide the data set into nations with a longer history of credit ratings versus those rated for a shorter period of time. We put nations that were observed in year 2000 and earlier into an 'older' group, and we create a 'newer' group for those added post-2000.

We observe the renewable export data in the top row and the non-renewable data in the bottom row of our visualisation – see Figure 7.

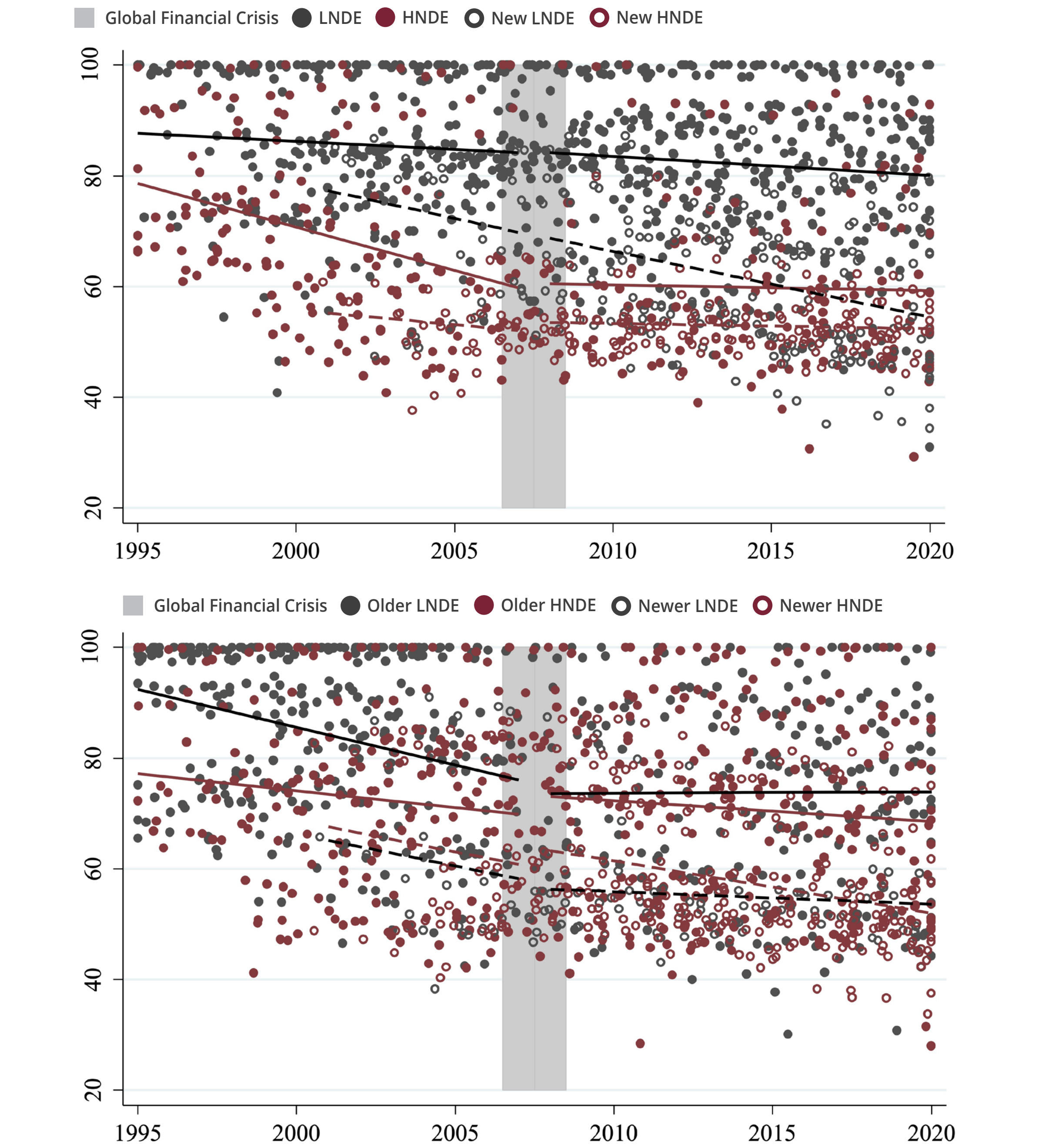


Figure 7: Credit ratings older and newer inclusions.
Source: Author calculations based on data prepared for the report NDE2022.

Notes: Annual data of numerical version of credit ratings at the national level for renewable (top row) and non-renewable (bottom row) HNDEs (red) and LNDEs (black) with group fitted lines. Small amount of random variation added to data to improve visualisation. 2007-2008 global financial crisis period in grey.

In both cases, the older rated groups are represented by solid lines and dots, and the newer rated groups with dashed fitted lines and hollow dots. Clearly, the early groups contain nations with higher credit ratings in both renewable and non-renewable cases. There are also differences in the correlation coefficients between renewable and non-renewable export shares: –0.30 for the older group and –0.67 for the newer group. That is, the later additions tend to be economies that are more specialised in either renewable or non-renewable exports, which is fitting for comparatively smaller nations.

Yet, despite difference in credit rating levels and degree of specialisation, we observe similar trends in the older and newer groups with regard to HNDEs versus LNDEs. Most importantly, we again see the continued downgrading of non-renewable HNDE nation credit ratings, before and after the global financial crisis. Our findings also show the majority of newly rated nations, particularly renewable HNDEs/non-renewable LNDEs, fall firmly in the speculative-grade rating group.

Next, we assign impact estimates to the trends we observe in Figure 7 to continue DD approach for this data set. One method is to include a set of indicator variables for one group or the other, which interact with our data set. The resulting coefficients would tell us how great the difference between the two groups is. The trade-off is that interpreting the results is more difficult and subject to mistakes in practice. Another method is to estimate coefficients for the older and newer rated groups separately and then compare the results. The trade-off is that the number of clusters would be small. However, with about 50 or less clusters standard error estimates tend to be too conservative and we would be more likely to reject what would otherwise be a statistically significant result. Instead, we discuss the results in general here and report the estimated coefficients in the appendix. These results are just a supplement to the primary results anyway.

As we have observed within the renewable group, the credit ratings of HNDEs and LNDEs in the older group diverge before the financial crisis. We also see that for the newer group, they slightly converge. For non-renewable exporters, we observe convergence in both the older and newer credit rating groups. We also observe that both older groups are different enough before the crisis to violate the parallel pre-trends requirement of classic DD approaches. After the financial crisis, we see (statistically insignificant) upward jumps in the credit ratings of all HNDE groups relative to their comparison LNDEs.

The continued effect of year-over-year credit score changes is perhaps more important. We observe continued convergence of renewable early and new group credit scores. Yet, interpretation requires care. The older group experienced a larger pre-trend correction among renewable HNDEs and then a minimal correction since. So, the rate of convergence relative to their LNDE counterparts is larger. In comparison, the newer group LNDEs experience a large but relatively constant year-over-year downward correction – both pre- and post-financial crisis – resulting in a small DD coefficient. By the end of the period of observation, the newly rated subgroup's HNDEs and LNDEs have about the same credit rating on average, while the convergence of those in the older group continues.

Within the non-renewable HNDE group, we see a continued downgrading of both the older and newer groups. However, the older group's credit ratings were converging at a faster rate before the financial crisis. The resulting DD coefficients suggest the divergence of non-renewable LNDEs versus HNDEs, as the latter continue to have their credit ratings downgraded. Unfortunately, the resulting slope coefficient for newly rated non-renewable LNDEs versus HNDEs is misleading. As we observed in the bottom row of Figure 7, the HNDE group had a higher (but statistically insignificant) pre-financial crisis credit ratings on average than the LNDE group. Since then, the newly rated HNDE group's credit ratings have declined rapidly after the financial crisis, becoming lower on average than newly rated LNDEs. The result is that the credit ratings of newly rated HNDEs and LNDEs are converging for much of the period, before beginning to diverge as the credit ratings of non-renewable HNDEs continue to drop.

CONCLUSION

As found in NDE2022, HNDEs often have lower credit ratings, for both the renewable and non-renewable groups, compared to their LNDEs counterparts. We also find that credit ratings have generally decreased (worsened) over the last 25 years.

While the scale of continued credit downgrading appears to be heterogeneous, we have identified two trends. First, **smaller economies tend to show a clearer downward trend in credit ratings, compared to larger economies in their respective NDE groups**. Second, **non-renewable HNDEs have experienced a faster rate of credit downgrading on average than their peers**. This second result holds true, whether we focus on specific experiences by weighting the data (by population, GDP, or export shares) or by dividing the data into groups receiving credit ratings for significantly longer timer periods versus shorter time periods.

We note that **there was not a particularly large downward correction in credit scores around the global financial crisis for most nations. However, the global financial crisis marked an inflection point in the long-term credit rating trajectories of some NDE groups. For example, the credit ratings of non-renewable HNDEs and LNDEs started diverging after 2007-2008**.

Nations that have been rated prior to 2000 often have higher credit ratings in both renewable and non-renewable export groups, compared to those that have received a credit rating within the last 20 years. The later additions tend to be economies that are more specialised in either renewable or non-renewable exports, and they're often comparatively smaller nations.

Some outliers retain great credit ratings throughout the period of analysis; e.g., Germany, Sweden and Switzerland. However, **we observe that many HNDEs, particularly non-renewable HNDEs, have experienced continued credit rating downgrades**. This implies that such nations may have trouble obtaining finance to fund economic transitions or recover from global climate change-related events going forward. We have not provided any possible responses, as that is beyond the scope of this report, but we highlight this emerging issue as it is of importance to capital markets.

We are aware that Planet Tracker's NDE categories represent only one way of describing a country's' dependence on nature. Certainly, more work needs to be done to explore complementary metrics that could provide a more comprehensive picture.

We do not know whether the credit rating agencies are aware of the possible importance of these nature dependent categories. **Planet Tracker believes that a good understanding of whether a country is highly dependent on renewable or non-renewable resources is necessary for assessing a sovereign's long term financial outlook. This will likely become more important in the next decade, as the challenges of climate change adaptation and mitigation, and of biodiversity loss, become more financially material**.

Supporting tables of RD/RK-based analyses and weighted regressions follow:

Table 6: RD/RK Estimates on Changes in the Credit Ratings of Renewable Exporters. Source: Author calculations based on data prepared for the report NDE2022.

	Data	Coefficient	LNDE	HNDE
Constant	1	α_{*0}	81.57*** (2.67)	53.84 (3.14)
Date, *x=(actual –k)*	x_i	β_{*0}	–1.04** (0.48)	–2.02*** (0.25)
RD: *D=1(actual ≥k)*	D_i	$\alpha_{*1} - \alpha_{*0}$	–0.30 (2.03)	3.01 (2.07)
RK: year* D	$D_i x_i$	$\beta_{*1} - \beta_{*0}$	0.30 (0.49)	1.94*** (0.37)
Derived DD estimates				
Discontinuity		$(\alpha_{H1} - \alpha_{H0}) - (\alpha_{L1} - \alpha_{L0})$	3.31	
Slope difference		$(\beta_{H1} - \beta_{H0}) - (\beta_{L1} - \beta_{L0})$	1.64	
		Observations	911	489
		Clusters (countries)	62	46
		Pseudo R-squared	0.09	0.21

Notes: (k=2008) Robust standard errors clustered at the country level in parentheses. *** Significant at the 1 per cent level, ** Significant at the 5 per cent level, * Significant at the 10 per cent level. R-squared calculated from OLS regression as Tobit Pseudo R-squared does not have an equivalent and familiar interpretation.

Table 7: RD/RK Estimates on Changes in the Credit Ratings of Non-Renewable Exporters. Source: Author calculations based on data prepared for the report NDE2022.

	Data	Coefficient	LNDE	HNDE
Constant	1	α_{*0}	69.32*** (4.20)	66.58*** (3.07)
Date, *x=(actual –k)*	x_i	β_{*0}	–2.54*** (0.46)	–0.99** (0.47)
RD: *D=1(actual ≥k)*	D_i	$\alpha_{*1} - \alpha_{*0}$	–1.01 (3.01)	2.51 (1.73)
RK: year* D	$D_i x_i$	$\beta_{*1} - \beta_{*0}$	2.70*** (0.66)	0.25 (0.55)
Derived DD estimates				
Discontinuity		$(\alpha_{H1} - \alpha_{H0}) - (\alpha_{L1} - \alpha_{L0})$	3.53	
Slope difference		$(\beta_{H1} - \beta_{H0}) - (\beta_{L1} - \beta_{L0})$	–2.45	
		Observations	619	753
		Clusters (countries)	53	61
		Pseudo R-squared	0.21	0.06

Notes: (k=2008) Robust standard errors clustered at the country level in parentheses. *** Significant at the 1 per cent level, ** Significant at the 5 per cent level, * Significant at the 10 per cent level. R-squared calculated from OLS regression as Tobit Pseudo R-squared does not have an equivalent and familiar interpretation.

Table 8: DD Estimates on Changes in the Credit Ratings of Renewable Exporters. Source: Author calculations based on data prepared for the report NDE2022.						
	Data	Coefficient	Unweighted	Population weighted	GDP weighted	Export share weighted
Constant	1	$\alpha_{L0} + \alpha_{L1}$	81.39*** (2.57)	79.76*** (2.97)	91.03*** (6.70)	83.84*** (3.61)
Date, *x=(actual –k)*	x_i	$\beta_{L0} + \beta_{L1}$	−0.99** (0.45)	−0.52 (0.77)	−0.75 (0.47)	−1.07** (0.54)
RD: *D=1(actual ≥k)*	D_i	α_{L0}	−0.30 (1.98)	4.90* (2.76)	0.55 (3.68)	−1.33 (3.00)
RK: year* D	x_iD_i	β_{L0}	0.26 (0.47)	−0.01 (0.66)	0.18 (0.48)	0.51 (0.59)
	G_i	$\alpha_{H0} - \alpha_{L0}$	-27.50*** (3.98)	-28.36*** (3.16)	-31.11*** (8.92)	-30.15*** (4.45)
Parallel pre-trends test	x_iG_i	$\beta_{H0} - \beta_{L0}$	−1.04** (0.51)	−1.20 (0.81)	−0.18 (0.71)	4.78 (3.60)
DD estimates						
Discontinuity	D_iG_i	$(\alpha_{H1} - \alpha_{H0}) - (\alpha_{L1} - \alpha_{L0})$	3.31 (2.88)	1.02 (5.73)	10.41 (8.65)	−0.97* (0.59)
Slope difference	$x_iD_iG_i$	$(\beta_{H1} - \beta_{H0}) - (\beta_{L1} - \beta_{L0})$	1.68*** (0.60)	1.31 (0.85)	−0.61 (1.14)	1.44** (0.68)
		Observations	1,400	1,323	1,323	1,400
		Clusters (countries)	101	96	96	101
		R-squared*	0.34	0.42	0.35	0.34

Notes: (k=2008) Robust standard errors clustered at the country level in parentheses. *** Significant at the 1 per cent level, ** Significant at the 5 per cent level, * Significant at the 10 per cent level. R-squared calculated from OLS regression as Tobit Pseudo R-squared does not have an equivalent and familiar interpretation.

Table 9: DD Estimates on Changes in the Credit Ratings of Non-Renewable Exporters.
Source: Author calculations based on data prepared for the report NDE2022.

	Data	Coefficient	Unweighted	Population weighted	GDP weighted	Export share weighted
Constant	1	$\alpha_{L0} + \alpha_{L1}$	69.30*** (4.12)	79.18*** (2.87)	90.04*** (6.25)	58.94*** (4.55)
Date, *x=(actual –k)*	x_i	$\beta_{L0} + \beta_{L1}$	−2.49*** (0.43)	−0.19 (0.74)	−0.98** (0.46)	−2.84*** (0.49)
RD: *D=1(actual ≥k)*	D_i	α_{L0}	−1.06 (2.96)	2.52 (4.48)	0.63 (5.85)	1.88 (3.14)
RK: year* D	x_iD_i	β_{L0}	2.64*** (0.64)	−0.28 (0.73)	0.33 (0.37)	2.96*** (0.69)
	G_i	$\alpha_{H0} - \alpha_{L0}$	−2.70 (5.12)	−12.36*** (4.31)	−11.90 (8.11)	−0.37 (5.80)
Parallel pre-trends test	x_iG_i	$\beta_{H0} - \beta_{L0}$	1.48** (0.60)	−0.25 (1.08)	0.11 (0.88)	1.19 (4.28)
		DD estimates				
Discontinuity	D_iG_i	$(\alpha_{H1} - \alpha_{H0}) - (\alpha_{L1} - \alpha_{L0})$	3.59 (3.56)	−1.14 (5.05)	3.82 (6.30)	−1.04 (0.65)
Slope difference	$x_iD_iG_i$	$(\beta_{H1} - \beta_{H0}) - (\beta_{L1} - \beta_{L0})$	−2.39*** (0.81)	−0.16 (1.07)	−0.39 (0.85)	−1.25 (0.85)
		Observations	1,372	1,321	1,321	1,372
		Clusters (countries)	107	103	103	107
		R-squared*	0.20	0.19	0.26	0.21

Notes: (k=2008) Robust standard errors clustered at the country level in parentheses. *** Significant at the 1 per cent level, ** Significant at the 5 per cent level, * Significant at the 10 per cent level. R-squared calculated from OLS regression as Tobit Pseudo R-squared does not have an equivalent and familiar interpretation.

Table 10: DD Estimates on Early versus Newly Rated Nation Groups. Source: Author calculations based on data prepared for the report NDE2022.						
			Renewable		Non-Renewable	
	Data	Coefficient	Early group	New group	Early group	New group
Constant	1	$\alpha_{L0}+\alpha_{L1}$	86.26*** (3.00)	67.91*** (3.27)	74.99*** (4.83)	56.31*** (5.73)
Date, *x=(actual −k)*	x_i	$\beta_{L0}+\beta_{L1}$	−0.48 (0.42)	−1.42** (0.68)	−1.95*** (0.40)	−1.34*** (0.45)
RD: *D=1(actual ≥k)*	D_i	α_{L0}	−0.47 (2.37)	1.32 (1.65)	−0.54 (3.20)	0.23 (2.84)
RK: year* D	x_iD_i	β_{L0}	0.12 (0.43)	0.43 (0.17)	1.98*** (0.60)	1.09** (0.41)
	G_i	$\alpha_{H0}-\alpha_{L0}$	-27.15*** (6.66)	−15.89*** (3.40)	−3.79 (6.45)	4.79 (6.54)
Parallel pre-trends test	x_iG_i	$\beta_{H0}-\beta_{L0}$	−1.05* (0.57)	1.02 (0.83)	1.40** (0.56)	0.57 (1.07)
DD estimates						
Discontinuity	D_iG_i	$(\alpha_{H1}-\alpha_{H0})-(\alpha_{L1}-\alpha_{L0})$	2.24 (4.38)	0.70 (2.63)	3.09 (3.77)	2.30 (3.79)
Slope difference	$x_iD_iG_i$	$(\beta_{H1}-\beta_{H0})-(\beta_{L1}-\beta_{L0})$	1.26 (0.79)	0.07 (0.97)	−1.78** (0.83)	1.30 (1.08)
		Observations	988	412	964	408
		Clusters (countries)	58	43	63	44
		R-squared*	0.31	0.34	0.13	0.10

Notes: (k=2008) Robust standard errors clustered at the country level in parentheses. *** Significant at the 1 per cent level, ** Significant at the 5 per cent level, * Significant at the 10 per cent level. R-squared calculated from OLS regression as Tobit Pseudo R-squared does not have an equivalent and familiar interpretation.

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Planet Tracker is a non-profit financial think tank producing analytics and reports to align capital markets with planetary boundaries. Our mission is to create significant and irreversible transformation of global financial activities by 2030. By informing, enabling and mobilising the transformative power of capital markets we aim to deliver a financial system that is fully aligned with a Net Zero, nature-positive economy. Planet Tracker proactively engages with financial institutions to drive change in their investment strategies. We ensure they know exactly what risk is built into their investments and identify opportunities from funding the systems transformations we advocate.

OUR FOOD SYSTEM TRANSITION PROGRAMME

As part of our overarching Food System Transition Programme, Food & Land Use Tracker changes the behaviours and business practices of global food system companies indirectly, by applying pressure on the financial institutions that provide their funding so that they pass that pressure on to the companies themselves. We provide them with information about the investment risks and opportunities that the transformation of the global food system will create, and we highlight the related reputational and operational risks that they themselves will be exposed to.

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