Climate-finance and climate transition risk: an assessment of China's overseas energy investments portfolio

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Abstract

The role of development finance institutions in low-income and emerging countries is fundamental to provide long-term capital for investments in climate mitigation and adaptation. Nevertheless, development finance institutions still lack sound and transparent metrics to assess the exposure of their projects to climate risks, as well as their impact on climate action. This information is crucial to allow them to deliver on their mandate, to preserve their financial position and to align beneficiary countries' economies to the climate goals. We contribute to fill in this gap by developing a novel climate stress-test methodology applied to the portfolios of overseas energy projects of two main Chinese policy banks. We estimate their exposure to two types of shocks, i.e. climate policy and balance sheet shocks, for individual energy projects across regions and energy sectors, under milder and tighter climate policy scenarios. Then, we provide several risk metrics. We find that the negative shocks are mostly concentrated on coal and oil projects and vary across regions between 4.2% and 22% of total loans value. Given the current leverage of Chinese policy banks, these losses are not negligible in comparison to banks' capital.

Keywords: overseas energy finance, climate transition risk, climate policy scenarios, climate stress-test, climate VaR, climate-finance.
JEL Codes: G01, G11, G32, G33.

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1 Introduction

Recently, development finance actors have identified the need to mainstream climate change in the financial assessment of their projects portfolios (Bonnel & Swann, 2015; European Bank for Reconstruction and Development, 2016). There is growing awareness that climate change could negatively impact on the value of investments and thus on the stability of the financial system (Carney, 2015; Draghi, 2017; European Systemic Risk Board, 2016). In particular, given the complexity of the international network of financial exposures (Battiston et al., 2012, 2016*b*,*a*) and the size of global development finance, neglecting to address climate risks may induce severe systemic risk (Battiston et al., 2017). In addition, development banks have also recognized the importance of assessing the opportunities generated by their projects in terms of impact on climate action (i.e. mitigation and adaptation), and their alignment to the Sustainable Development Goals (SDGs).

However, development finance institutions do not yet dispose of in-house, tailored metrics to mainstream climate risk assessment across all the phases of their projects evaluation. This gap represents a barrier for delivering on their mandate and to scale up private investments into climate-aligned sectors. Indeed, mining and fossil-fuels based energy and electricity production are the main responsible for the release of CO2 emissions in the atmosphere that, in turn, contribute to climate change.

Recent academic research has made progress in developing measures of financial portfolios' exposure to greenhouse gases (GHG) emissions, considering investors' market share (Monasterolo et al., 2017). There has been also progress on modeling the macroeconomic and distributive impacts of climate policies (Monasterolo & Raberto, 2018), and on the assessment of possible amplification of climate policies' shocks due to feedback loops within the financial system, in presence of high leverage and recovery rate lower than one, and the cascade effects on the real economy (Stolbova et al., 2018). However, targeted theoretical and empirical applications of these insights into development finance are still missing.

In order to fill in this gap, by building on Battiston et al. (2017), we develop the first climate stress-test methodology targeted to development finance institutions, and we apply it to the energy portfolio loans of two major Chinese policy banks, i.e. China Development Bank (CDB) and Export-Import Bank of China (CEXIM). With the climate stress-test, we can evaluate today the expected value of a loan exposed to a climate policy and a balance sheet shock. We first assess the exposure of CDB and CEXIM's portfolios to shocks induced by a sudden change in climate policy scenario (i.e. climate transition risk). This implies a shock on the project's market share that causes, in turn, a shock on the expected value of the loan today, thus affecting the probability of default associated to a specific project. Then, we consider a balance sheet shock on the borrower's side (idiosyncratic). This is led by operative fluctuations on companies delivering the project, thus affecting the probability of default on the borrower. Data on the banks' overseas energy portfolios are provided by the GEGI China Energy Finance database (Gallagher, 2017), which includes both fossil fuel-based and renewable energy projects worthy $228.105 billion (bn) in seven regions in low-income and emerging countries, from 2000 to 2018. Our modular methodology based on a simplified model is nevertheless able to capture the order of magnitude and sign of the shock on the project's value. First, we compute the exposure of individual portfolios of fossil fuel-based or renewable energy projects by region and year. Second, we estimate the change in market share of fossil fuel and renewable energy sectors in the regions considered under a set of climate policy scenarios, ranging from mild to severe, up to 2050, using the macroeconomic trajectories provided by four Integrated Assessment Models (IAMs) belonging to the LIMITS database (Kriegler et al., 2013). Third, we compute the shocks on each overseas energy project loan as a result of a sudden transition to a given climate policy scenario, in terms of relative magnitude and financial value. Each shock is conditional to a specific information set of models, regions, energy sector and climate policy scenario, across years. Fourth, conditional to a specific model and climate policy scenario, we develop and compute a project-based climate Value at Risk (VaR) to estimate the largest losses on projects' value. One advantage of our metrics is that they are transparent and thus replicable and customizable. They are concise and yet allow to capture the multiple relevant dimensions for climate-finance decision-making. The manuscript is organized as follows. Section 2 reviews the progress in mainstreaming climate risk metrics within development finance institutions. Section 3 describes the climate stress test methodology and its application to the Chinese policy banks' portfolios of overseas energy loans. Section 4 discusses the results of the exposures of CDB and CEXIM's portfolios to shocks under milder and tighter climate policy scenarios up to 2050, by beneficiary project, energy sector, amount and region. Section 5 concludes highlighting the policy implications.

2 Review of the state of the art: progress in mainstreaming climate risk metrics within development finance institutions

Since the COP21 UNFCCC conference held in Paris (2015), financial regulators and practitioners started to discuss the role of metrics and methods for climate-related financial disclosure. The G20s Financial Stability Board (FSB) introduced a Task Force for Climate-Related Financial Disclosures (TCFD) that highlighted the need for more transparency regarding investors' exposure to GHG emissions. In particular, in its final recommendations, the FSB TCFD suggested voluntary climate risk disclosure by financial actors as well as the introduction of tools (such as climate stress-test) to assess risks and opportunities related to climate change (TFCD, 2017). The FSB TCFD recommendations were recently followed by the results of the newly created European Commissions High-Level Expert Group on Sustainable Finance, which suggested the establishment of a common sustainability taxonomy at the EU level. In addition, it recommended the implementation of the TCFD disclosure recommendations at the EU level, also building on the positive experience of Frances Article 173 (High Level Experts Group on Sustainable Finance , HLEG). Development banks are recognizing the importance of assessing their portfolios exposure to climate risks, their impact on climate action (mitigation and adaptation), and their alignment with the SDGs. Six major development banks European Bank for Reconstruction and Development, the African Development Bank (AFB), the Asian Development Bank (ADB), the European Investment Bank (EIB), the Inter-American Development Bank Group (IDB) and the World Bank Group (WB) have been working together since 2011 to define a joint climate change finance tracking methodology. In particular, their strengths aimed to enhance joint tracking methodologies for climate change mitigation and adaptation, at the light of the Paris Agreement (European Bank for Reconstruction and Development, 2016). Further, several development banks have introduced formal targets for the climate action component of their annual lending activity (e.g. EIB stated a 25% minimum, the French Development Agency is aiming at 40% of its portfolio). Finally, EIB and the Green Finance Committee (GFC) of the China Society for Finance and Banking recently launched an official collaboration aimed at improving green finance definitions and standards with a view to facilitating cross-border green capital flows that resulted in a Joint White Paper (European Investment Bank and Green Finance Committee of China Society for Finance and Banking, 2017). Development banks' portfolios could be exposed to two main sources of climate-related risks:

- Physical risk, which derives from the location of the financed project (i.e. its exposure to damages deriving from climate change induced hazards) and the quality of the adaptation plan (according to the Nationally Determined Contributions (NDCs));
- Transition risk, which derives from the activity and sector that the project is going to finance (e.g. carbon-intense vs. renewable energy production).

Assessing the exposure of development banks portfolios to climate physical and transition risks is fundamental to allow the financial institutions to deliver on their mandate, as well as to meet their financial solvability objectives. Indeed, development banks need to preserve their AAA rating to access more favorable financing conditions on the markets. Therefore, the introduction of standardized metrics and methods to measure development banks progress towards climate action and the SDGs at the level of project portfolios could provide actionable information to development banks by assessing their progress in terms of (decreased) exposure to climate risks and (increased) impact on climate action. Regarding risk, it is crucial to integrate climate physical and transition risk factors into current financial risk metrics. Regarding impact, development banks need to assess the contribution of their projects portfolios to climate mitigation and adaptation objectives. Furthermore, in order to be able to capture the relevant dimensions for climate-finance decision-making, methods and metrics need to be transparent (thus replicable) and concise but not unidimensional.

3 Methodology and data

We build on the methodology introduced by Battiston et al. (2017) to develop a modular climate stress-test tailored to energy projects portfolios and applied to two major Chinese policy banks, i.e. CDB and CEXIM. We consider projects that are financed via loans, export credits, concessional and preferential loans.[1] The methodology allows us to i) compute the portion and value of the development banks portfolio (by number of projects, energy sectors and regions) that is exposed to climate transition risks under milder and tighter climate policy scenarios, up to 2050, and ii) to assess the maximum losses on portfolios' value incurred by fossil fuel and renewable energy projects by region and climate policy scenario.

3.1 Assessing portfolios' exposures to climate shocks

We consider a financial actor i (hereafter the bank) investing in a set of projects j through loan contracts. The valuation model for the loans includes three time steps t_0, t^*, T, where $t_0 < t^* < T$, with: t_0 denoting the time at which the valuation is carried out, t^* the time at which a climate policy shock potentially occurs, and T denoting the maturity of the loan contract. We then denote by $A_{ij}(t_0, T_j)$ the financial valuation at time t of the investment[2]. Accordingly, the valuation of actor i's projects portfolio is written as follows:

$$A_i(t_0) = \sum_j A_{i,j}(t_0, T_j). \tag{1}$$

In general, the valuation of a loan project j could be based on various approaches. For the sake of simplicity, here we consider the expected value of the loan, given the information at time t_0, so that:

$$A_{i,j}(t_0, T_j) = p_j(t_0, T_j) r_j F_{ij} + (1 - p_j(t_0, T_j)\, F_{ij} = F_{ij}\,(1 - (1 - r_j)\, p_j(t_0, T_j)), \tag{2}$$

where F_{ij} is the face value of the loan (already including the time discounted factor), r_j is the recovery

[1] The majority of investments (i.e. over 80% by amount) is delivered via loans.

[2] In our analysis, we simply take loans as the only investment type as loan size in our data takes up to 80% of the whole portfolio.

rate on the loan contract[3] and $p_j(t_0, T_j)$ is the default probability[4] of the borrower j of the loan with maturity T_j, based on the information available at time t, and conditional to the policy scenario P. We now introduce the notion of climate policy shock. At time t^*, a climate policy shock implies that the economy switches from a business-as-usual scenario (B) to a scenario P, which modifies the probability of default on each loan j. From Equation 2, it follows that the change in loan value as a result of the climate policy shock, is the product of its face value times the change in default probability,

$$\Delta A_{i,j}(t_0, T_j, P) = A_{i,j}(t_0, T_j, P) - A_{i,j}(t_0, T_j, B) = -F_{ij}(1 - r_j)\Delta p_j(P), \tag{3}$$

where $\Delta p_j(P)$ denotes the difference of the default probability going from scenario B to P.

In line with standard assumptions in the economic literature(Greenwald et al., 1984; Glasserman & Young, 2016), we assume that the default of the borrower j implies a legal procedure and hence a delay in the payments of the recovered assets to the creditors. Moreover, bankruptcy costs (e.g. legal costs, loss of assets and social capital) imply that the recovered assets can be significantly smaller in value than the face value of the contract, as reflected by a recovery rate r_j smaller than 1. In this context, a standard way of modeling the default of borrower j at the maturity T, is to consider it as the result of an exogenous stochastic shock, $\eta_j(T_j)$, hitting the asset side of the borrower, and observed at time T. Moreover, we want to take into account the effect of the policy shock occurring at time t^* and associated to the policy scenario P. We do so by means of an additional variable $\xi_j(t^*, P)$. Overall, at the maturity time T_j, the value of the loan is then described by the following equation,

$$A_j(T_j, P) = A_j(t_0, B) + \xi_j(t^*, P) + \eta_j(T_j). \tag{4}$$

In line with the literature on modeling default events (Battiston et al., 2016*b*), we assume that the borrower defaults at time T, under the policy scenario P, if its net worth $E_j(T_j)$ (defined as assets minus liabilities) becomes negative as a result of the shocks, i.e.

$$E_j(T_j, P) = A_j(t_0, B) + \xi_j(t^*, P) + \eta_j(T_j) - L_j < 0, \tag{5}$$

where the value of the liability L_j is considered independent of the policy scenario and of time (i.e. the debt is not restructured or revalued). Hence, the default probability is the probability that the

[3]The recovery rate is a standard notion in banking and finance used to indicate the ratio of the amount recovered by the lender upon default of the borrower, for instance after selling the collateral associated to the loan contract. Here we consider the recovery rate as exogenous, which sets our analysis of the size of potential shocks in a conservative boundary. Maximum losses are obtained with recovery rate equal to 0.

[4]The default probability serves as a key concept in this setting as it is affected both by a systematic shock from the climate policy change and by an idiosyncratic shock specific to the borrower. However, these two shocks occur at different points in time and influence the loan value via different channels.

idiosyncratic shock η_j at time T_j is smaller than a threshold value $\theta_j(P)$, which depends on j's liability and initial asset value at time t, and the policy shock ξ_j on its asset side at time t^*, as follows:

$$\eta_j(T_j) < \theta_j(P) = L_j - A_j(t_0, B) - \xi_j(t^*, P). \tag{6}$$

In case of no policy change, ξ_j equals 0, and the default condition becomes

$$\eta(T_j) < \theta_j(B) = L_j - A_j(t_0, B), \tag{7}$$

The default probability can thus be written as:

$$\mathbb{P}\{\eta_j < \theta_j(P)\} = \int_{\eta_{\text{inf}}}^{\theta_j(P)} p(\eta_j)\, d\eta_j, \tag{8}$$

where $p(\eta_j)$ is the probability distribution of the shock η_j, and η_{inf} is the lower bound of the support of the probability distribution. The difference in probability as a result of the policy shock can be expressed as

$$\delta\mathbb{P} = \int_{\theta_j(B)}^{\theta_j(P)} p(\eta_j)\, d\eta_j. \tag{9}$$

We assume that the policy shock impacts the borrower's balance sheet, and hence the expected value of the loan, via the transmission channel of a change in the market share of the economic sector of the project. We define a market share shock $u_{S,R}(P, M, t^*)$ as follows:

$$u_{S,R}(P, M, t^*) = \frac{m_{S,R}(P, M, t^*) - m_{S,R}(B, M, t^*)}{m_{S,R}(B, M, t^*)}. \tag{10}$$

The valuation $A_{i,j}(t_0, T_j)$ of the loan to a borrower j is subject to changes in the economic performance of sector S of the geographic region R in which it operates. More precisely, we assume that a relative change in the market share of the borrower j's sector S within the geographic region R, denoted by $u_{S,R}(P, M, t^*)$, implies an equal relative change in the value of j's net worth at time t^*. The justification for this assumption is that the net worth is the integral over time of profits and that, over one period of time, the relative change in net worth and in profit coincide, which can be expressed as

$$\frac{\Delta E_j}{E_j} = u_{S,R}(P, M, t^*). \tag{11}$$

In this paper, the trajectories of future values of market share are taken from the LIMITS database, considering combinations of models M (four different Integrated Assessment Models (IAM): GCAM, WITCH, IMAGE and REMIND) and climate policy scenarios (i.e. five scenarios characterized by a milder or tighter GHG emissions targets, see Section 3.3 for more details).

With the aim to illustrate the type of insights that can be gained with this analysis, we now assume that the probability distribution $p(\eta_j)$ of the shocks on the borrower's asset side follows a uniform distribution with support width δ, for a given model M, region and sector. In this case, the change in default probability from Equation 9 can be expressed as:

$$\delta\mathbb{P} = \frac{\theta_j(P) - \theta_j(B)}{\delta}. \tag{12}$$

From Equation 6, the difference in default threshold is the change in loan value due to the policy shock $\xi_j(t^*)$:

$$\Delta\theta_j = \theta_j(P) - \theta_j(B) = -\Delta E_j = -\xi_j. \tag{13}$$

In virtue of Equation 11, we then have

$$\Delta\theta_j = -\Delta E_j = -E_j u_{S,R}(P, M, t^*) \tag{14}$$

and the change in default probability becomes:

$$\delta\mathbb{P} = -\frac{E_j}{\delta}\, u_{S,R}(P, M, t^*). \tag{15}$$

Plugging Equation 15 into Equation 3, we obtain the change in expected value of the loan, conditional to a change from scenario B to scenario P:

$$\Delta A_{ij} = F_{ij}(1 - r_j)\frac{E_j}{\delta}\, u_{S,R}(P, M, t^*). \tag{16}$$

The above equation describes, under the two simplifying assumptions made at this stage, the change in the value of the loan to borrower j, conditional to a climate policy shock from scenario B to scenario P. Summing over the projects j in the portfolio, we obtain the *total change in loan value*:

$$\sum_j \Delta A_{i,j}(t_0, T_j, P) = \sum_j F_{ij}(1 - r_j)\frac{E_j}{\delta}\, u_{S,R}(P, M, t^*). \tag{17}$$

In principle, in order to compute the probability distribution of the total change in loan value (and from here some standard metrics of risk, such as the Value-at-Risk of the portfolio (Battiston et al., 2017)) one needs to know: (i) the joint probability distribution of shocks $\eta_j(T)$ (Equation 8), and (ii) the probability of occurrence of climate policy shocks.

At this stage, for the dataset analysed in the next section, none of these estimations are available. Thus it is not possible to apply the standard definition of Value-at-Risk. In order to provide a preliminary notion of the largest losses that could occur with a certain probability, we introduce a *Project-level climate Value at Risk (VaR)* defined as follows.

Definition. Consider a set of project loans, with $j = 1, ..., n$. We define the *Project-level Climate VaR* as the value (VaR) such that, conditional to the same climate policy shock for all n projects, the fraction of projects leading to losses larger than the VaR equals the confidence level c:

$$|\{j|\Delta A_{ij}(t_0, T_j, P, B) \geq VaR\}| \ /n = c. \tag{18}$$

Note that in the following, we set $c = 5\%$.

One interpretation of the notion of Project-level Climate VaR is that if projects mature and default independently, then the probability of any given project to be associated with a loss larger than VaR is smaller than c. This notion has several limitations but it provides a preliminary notion of the largest exposure of the portfolio under specific conditions.

We also consider other complementary statistics, i.e. (i) the *maximal loss (gain)* from individual projects (see results in the next section), and (ii) the *total positive (negative) change in loan values*, defined as the sum of loan values with positive (negative) change in value associated to the climate policy shock.

The methodology described in this section is subject to further developments in order to relax the simplifying assumptions considered so far. For instance, the assumptions on the relation between the shocks on energy sectors' market share and the borrower's net worth, as well as those on the probability distribution of shocks on net worth at the maturity, deserve more attention. However, already at this stage, our approach allows to establish the order of magnitude as well as the sign of the change in value of loans, conditional upon changes in climate policies. To our knowledge, this is the first attempt to develop such a methodology and fills in a major gap in the literature.

3.2 Mapping China's overseas energy finance

For our analysis, we use financial flows data provided by the GEGI database, which includes information on 199 overseas investments by two major Chinese policy banks from 2000 to the beginning of 2018, amounting to \$228.105 bn in total, across 7 world regions (63 countries). The annual sum peaked in year 2009 and 2016 at \$42 and \$47bn respectively. In 2009, the main beneficiaries were Russia and Brazil with \$25 bn and \$10 bn oil investments respectively. In 2016, the largest investments were a \$12 bn gas project in Russia and a \$10 bn oil project in Brazil.

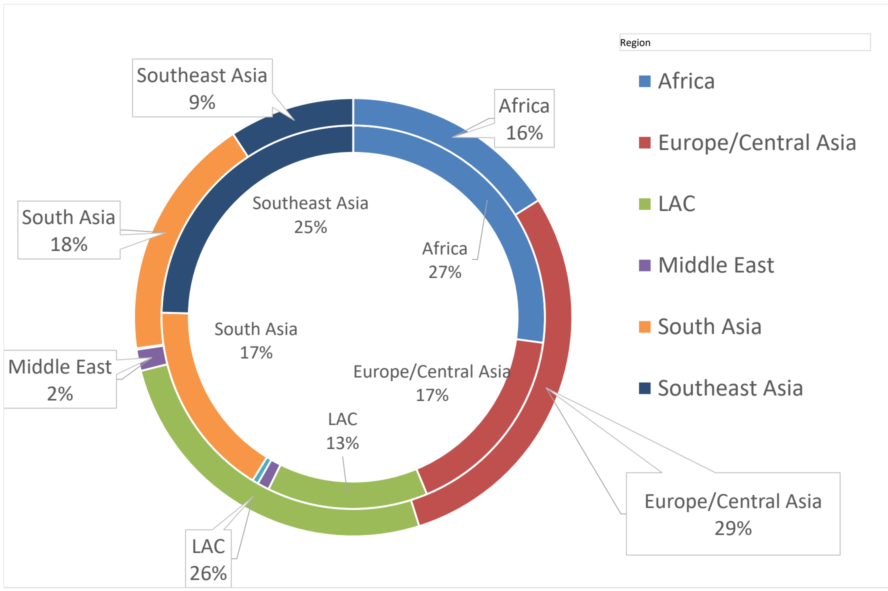

Figure 1: Regional Distribution of China's oversea energy finance. Data source: GEGI

Figure 1 shows the the shares of each region in terms of project numbers (inside circle) and invested amounts (outside circle). Africa and Southeast Asia together have more than half of the total projects while Europe/Central Asia and Latin America received more than half of the invested amount. The top three beneficiary countries are Russia, Brazil and Pakistan, with the sum of the investments located within these three accounting for 47% of the whole Chinese policy banks' overseas energy portfolios. Figure 2 shows the allocation of overseas energy loans by value, lender and energy sector, according to the reclassification we did from very brown (i.e. coal) to very green (i.e. solar). All the projects are displayed in relation to the energy source that they contribute to finance. We grouped coal, gas/LNG and oil as fossil fuel sources, and combined hydro-power, solar, thermal and wind as renewable energy sources.[5] The gap between the share of fossil fuel-based and renewable investment emerges more clearly in favor of the former when we consider the financial value of the project: fossil fuel based energy projects represent 51.26% of the projects but 72.09% of portfolio's value. Thus, fossil fuel energy projects tend to have much larger financial value than renewable energy projects. Indeed, the average size of an oil investment (USD 3830 million, mln) is almost 20 times as large as the average size of a thermal investment (USD 194 mln). In Fig. 3 We illustrates each region's investment

[5]Electric and electricity represent only 1.74% of the total amount of the projects. Therefore, we excluded them.

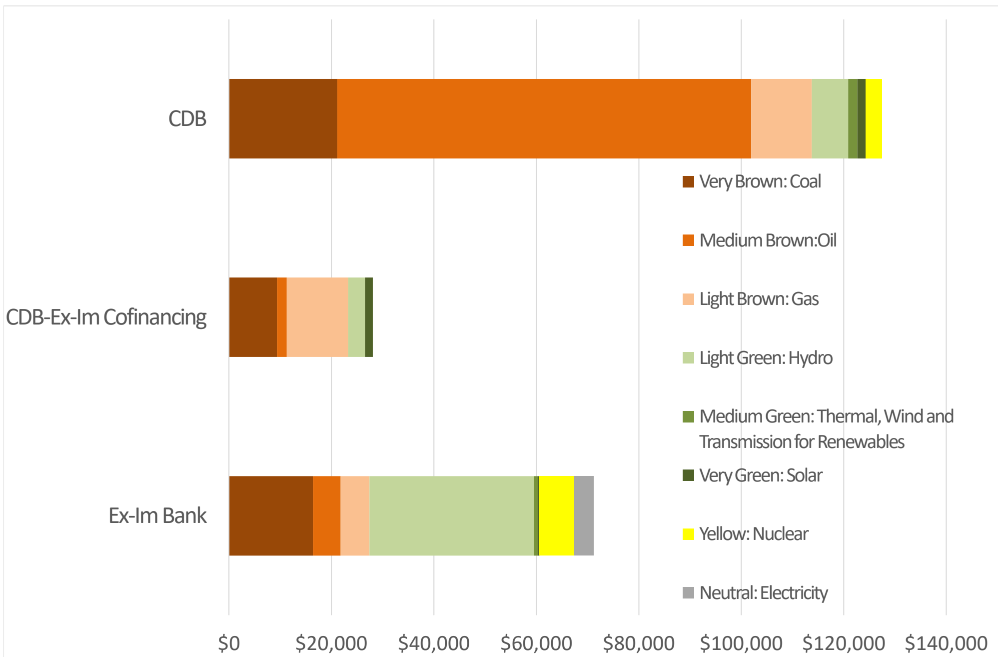

Figure 2: CDB and CEXIM's overseas energy portfolios Unit: million. Data source: GEGI

according to their energy source. The color gradient represents the energy category from the most polluting energy source in terms of CO2 emissions, i.e. coal (very brown), to the least polluting, e.g. solar (very green). Nuclear energy projects represent 4.4% of the total portfolio and are highlighted in the figures in bright yellow.

The lenders included in the GEGI dataset are CDB, CEXIM, CDB-CEXIM co-financing, CEXIM and unknown (below 1%). We focus on the three major funding sources. CDBs oversea energy financing is the largest lender with USD $127 bn, followed by CEXIM with USD $71 bn, and the co-financing between the two amounting to USD $28 bn. In Figure 2 we see that all lenders are highly exposed to fossil energy, with oil investments representing alone 63.38% of CDBs portfolio. The overall fossil fuel energy share of these three funding sources is up to 73%. The highest share among renewable sources belong to hydro-power projects, with a total of USD$43 bn, 75% of which are provided by CEXIM.

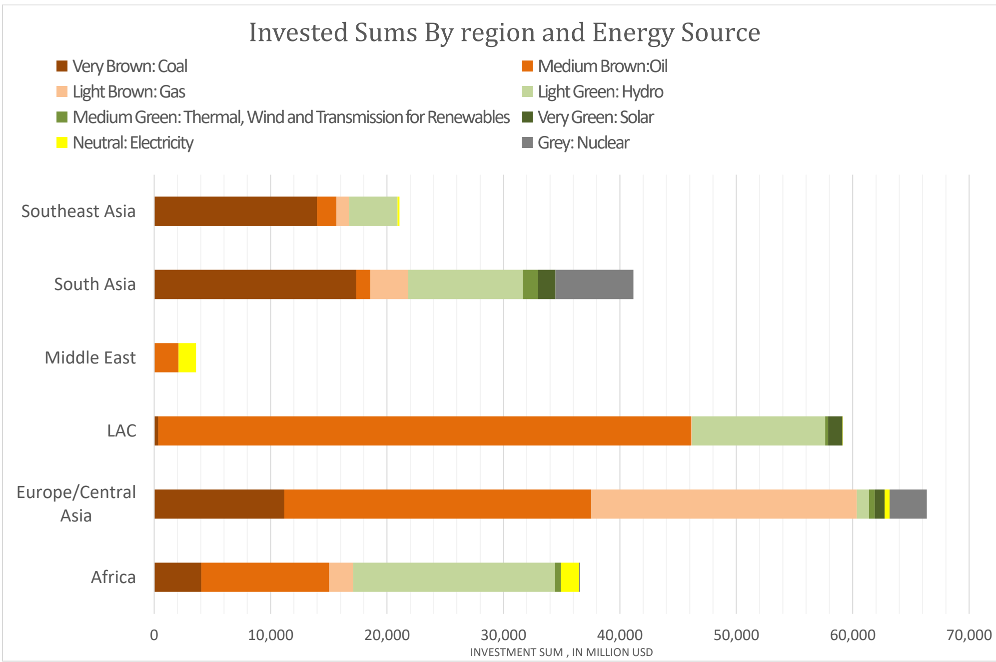

Figure 3: Region and Energy Sector of China's oversea energy finance. Source: GEGI

3.3 Shocks on macroeconomic trajectories of energy sectors based on LIMITS's climate policy scenarios

With the aim to assess the exposure of CDB and CEXIM's overseas energy finance to climate policy shocks, we select four climate policy scenarios (from milder to tighter) from the LIMITS database, as well as a baseline of no stable climate policy introduction (i.e. the Base scenario), see Table 1.

We use the LIMITS project database (Kriegler et al., 2013) to obtain the macroeconomic trajectories (in terms of market share) for fossil fuel and renewable energy sectors covered by the China's overseas energy portfolio, under twelve climate policy scenarios identified by the LIMITS project. The market share trajectories both in the fossil fuel and renewable energy sectors are influenced by the introduction of domestic and international climate policies. Then, we estimate the impact of a shock (i.e. the change in climate policy trajectory from the Base) on the value of each fossil fuel and renewable energy project.

Scenario Name	Scenario Class	Target before 2020	Target between 2020 and 2100
Base	No climate policy	None	None
RefPol-450	Countries Fragmented, Immediate Action	Lenient	450 ppm: 2.8W/m2 in 2100, overshoot allowed
StrPol-450	Countries Fragmented, Immediate Action	Strengthened	450 ppm: 2.8W/m2 in 2100, overshoot allowed
RefPol-500	Countries Fragmented, Immediate Action	Lenient	500 ppm: 3.2W/m2 in 2100, overshoot allowed
StrPol-500	Countries Fragmented, Immediate Action	Strengthened	500 ppm: 3.2W/m2 in 2100, overshoot allowed

Table 1. Selected climate policy scenarios from the LIMITS database. Table 1 shows the four climate policy scenarios that we considered (plus the Base scenario) in our analysis, i.e. RefPol-450, RefPol-500, StrPol-450, StrPol-500. The scenarios are characterised by i) fragmented and lenient or strengthened climate action across countries, and ii) milder or tighter emissions targets to be achieve, respectively 500 parts per million (ppm) and 450 ppm. The emissions target provides the likelihood to achieve the 2 degrees C objective by the end of 21st Century, i.e. 70% with 450 ppm, and 50% with 500 ppm.

A change in climate policy through time can lead to a change in the sectors' macroeconomic trajectory, inducing a shock in the market share of different primary and secondary energy sources that could differ in sign and magnitude. We consider a shock occurring in the period between 2005 and 2050, affecting the market shares of the sectors of the China's overseas energy projects portfolio. The market share shocks induced by the introduction of a climate policy are then translated in shocks in the loans' value that could be negative (i.e. meaning losses in project's value) or positive (i.e. gains in the market-value of the loan). Figure. 4 shows the drop in the market share of coal energy in year 2020 and 2030 in Africa due to the change from policy scenario baseline to a tighter climate policy scenarios (in this figure, we consider LIMITS-450 and LIMITS-500). In this scenario, fossil fuel energy's market share would drop while renewable energy's market-share would gain. Then, we compute the maximum value of losses and gains on each portfolio for each shock, considering a specific information set composed by a model, a regions, a sector and a climate policy scenario, for each five years' time step. We obtain a range of variation of losses and gains across projects for each model and climate policy scenario. Finally, we compute the *Project-level climate VaR* to highlight the largest losses on projects that could occur associated to a specific climate policy scenario and model.

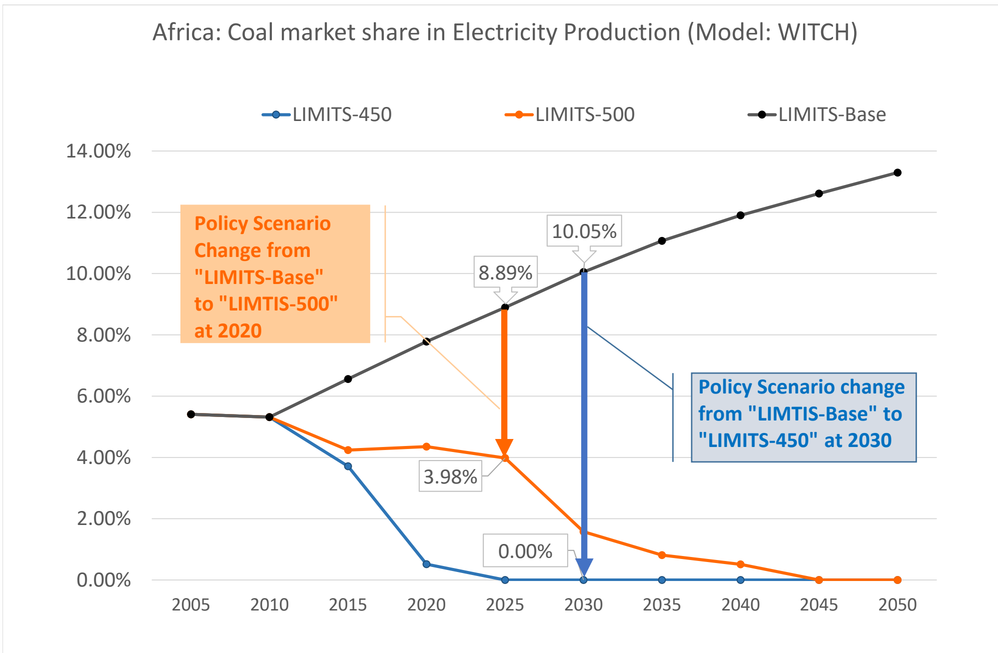

Figure 4: Africa: Coal Market Share in Electricity Production. Figure 4 provides an example of the computation of the market-share for an energy sector, i.e. coal for electricity production, in a specific region, i.e. Africa, and conditioned to the WITCH model, under three climate policy scenarios.

4 Results

By computing the shocks on each Chinas overseas energy project, we find that the magnitude (in percentage and financial value) varies considerably across models and the climate policy scenarios considered.

In the following, we present the preliminary results of our analysis for two models, i.e. CGAM and WITCH, and for a milder (i.e. RefPol500) and a tighter (i.e. StrPol450) climate policy scenario. At this stage, we find that both positive and negative shocks on energy projects are more pronounced in the WITCH model than in the CGAM model, both in the RefPol-500 and tighter StrPol-450 climate policy scenarios considered. In addition, the way in which the sectors are affected by the shocks vary across models.

Table 2 reports some aggregate descriptive statistics on the portfolio shocks in each combination of model and policy scenario. Notice that the maximum positive shock always corresponds to an

model	scenario	minshock	maxShock	totNegShock	totPosShock	totRelNegShock	projectVaR
GCAM	LIMITS-RefPol-450	-1582	6500	-12176	22338	-0.05	-830
WITCH	LIMITS-RefPol-450	-3965	6500	-50778	42809	-0.22	-3878
GCAM	LIMITS-RefPol-500	-1180	6500	-9484	21957	-0.04	-711
WITCH	LIMITS-RefPol-500	-3503	6500	-31343	46723	-0.14	-2710
GCAM	LIMITS-StrPol-450	-1585	6500	-13275	23742	-0.06	-1001
WITCH	LIMITS-StrPol-450	-3852	6500	-49281	42954	-0.22	-3587
GCAM	LIMITS-StrPol-500	-1192	6500	-10838	23360	-0.05	-893
WITCH	LIMITS-StrPol-500	-3482	6500	-31139	46745	-0.14	-2721

Table 2. Statistics of portfolio shocks in USD mln.

individual nuclear project in Pakistan (see Conclusion for a discussion on the limitations of the LIMITS market share projections for the nuclear sector in low-income and emerging countries). The sum of negative shocks ranges from about USD 50 bn to about 9 bn. In contrast, the sum of the positive shocks ranges from about USD 22 bn to about 47 bn. Further, the values of VaR obtained range from - USD 3878 mln to - USD 711 mln. This means that the capital to be kept aside by the Chinese lenders in order to maintain their financial performance on individual projects varies by a factor close to 5 across climate policy scenarios and models.

In the GCAM RefPol500 scenario (Figure 5), the most positive shock is led by a nuclear power generation project in Pakistan (light blue), followed by a solar project in Pakistan (light green). In contrast, the most negative shocks in value are experienced by coal-based power generation and transmission projects. In particular, the most negatively affected project is a power generation oil project (Russia and China oil pipeline). By increasing the policy severity, thus moving to scenario GCAM StrPol450, we notice an increase in the value of the negative shocks (see Figure 6).

In contrast, the WITCH RefPol500 scenario displays an amplification in the value of shocks, in particular the negative ones, and more homogeneous spread across energy sectors (Figure 7). Negative shocks affect only projects in the coal and gas generation sectors, with peaks in a gas project in Russia and a coal project in India. At the level of individual projects, the most positive shock is due to the nuclear power generation project in Pakistan. Nevertheless, in aggregate, the hydro-power sector is subject to the most positive shocks, also in comparison to the GCAM scenarios. Interestingly, also primary and secondary energy oil projects are affected by positive shocks. Summing up, by increasing the climate policy severity, thus moving to scenario WITCH StrPol450 (Figure 8), we notice an increase in the value of the negative shocks in comparison to the previous scenarios. In addition, secondary gas, secondary and primary energy oil are subject to both negative and positive shocks. Further, the largest positive shock is on hydro-power energy, followed by nuclear energy.

We then consider the geographical distributions of shocks by project, amount, policy scenario

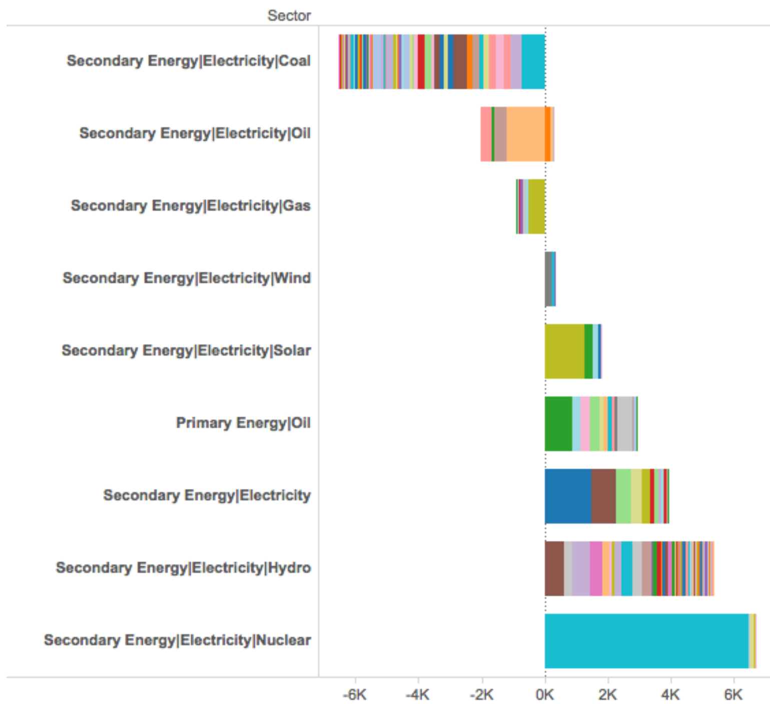

Figure 5: Shocks on portfolios by project, GCAM, RefPol500, in USD mln. The shock values range between a total loss of USD 9483,9 mln and approximately USD 21957,2 mln of total gains on projects. Negative shocks are spread across projects in coal power generation, and in few oil and gas power generation project. All the other sectors are affected by positive shocks, in particular in nuclear and hydro-power sectors.

and model. In GCAM RefPol500 (Figure 9) the positive shocks overtake the negative ones, and are located in the "India+" region (red) that includes Bangladesh, India, Nepal, Pakistan, Sri Lanka, in the nuclear and hydro-power sectors. Positive shocks also affect hydro-power in Africa (blue). In contrast, the negative shocks are most severe in the coal power generation, in particular in "India+", Rest of Asia (light green) and Reforming Economies (gray, and including transition countries in Eastern Europe and in ex-URSS). Reforming economies also experience negative shocks in oil and gas power generation. With the increase in severity of the climate policy scenario (i.e. StrPol450), we see an increase in the range of the shocks on projects' value, in particular in coal power generation in China plus and in oil and gas power generation in Reforming Economies.

In WITCH, in the RefPol500 scenario the most positive shock is associated again at the nuclear project in Pakistan, while the negative shocks are prevalently allocated on coal and oil power generation projects and are distributed across regions (China plus, but also Rest of Asia, Reforming Economies and Latin America). The relative position of the other positive and negative shocks across regions

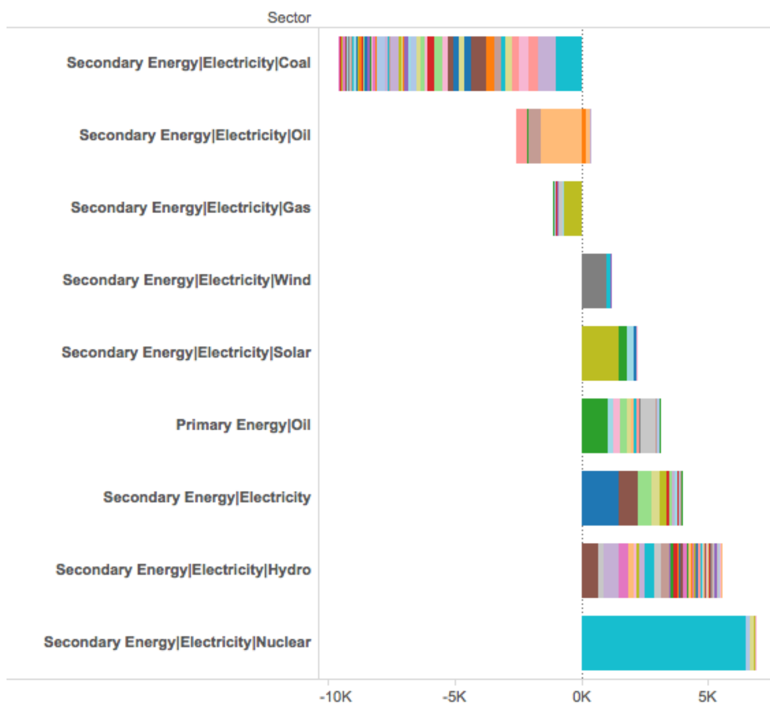

Figure 6: Shocks on portfolios by project, CGAM, StrPol450 in USD mln. The shock values range between a loss of USD 13275,3 mln and approximately USD 23742,4 mln of gains. As a difference from Figure 5, negative shocks affect also primary and secondary oil projects, while positive shocks in the hydro-power equal those in nuclear projects. The relative position of solar and wind projects remains unchanged.

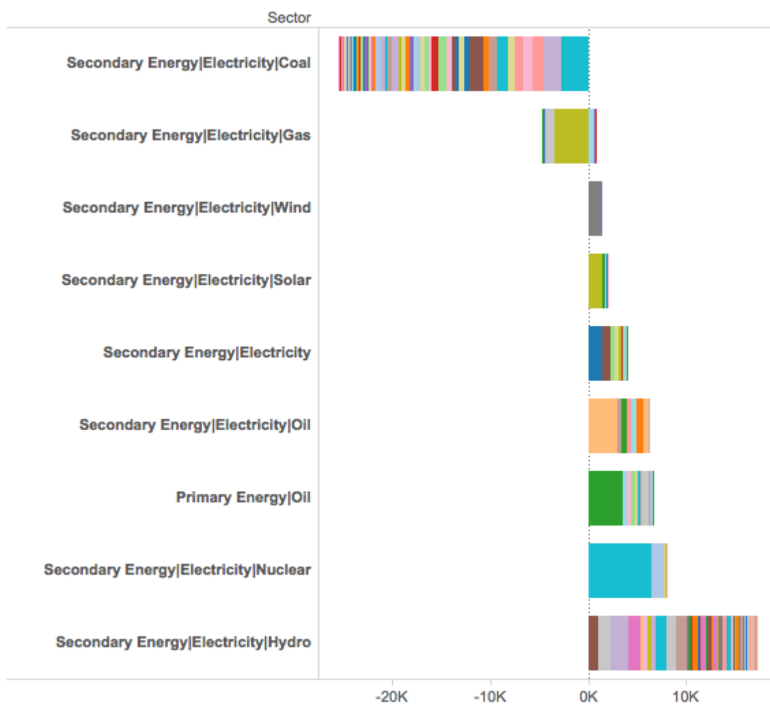

Figure 7: Shocks on portfolios by project, WITCH, REfPol500, in USD mln. The shock values ranges between a total loss of USD 31343,4 mln and approximately a total USD 46722,9 mln. Negative shocks are spread across projects in coal power generation, and in a few gas power generation projects. All the other sectors are affected by positive shocks, in particular in nuclear projects, and in the hydro-power sector. Solar and wind renewable energy projects are the least beneficiary from positive shocks.

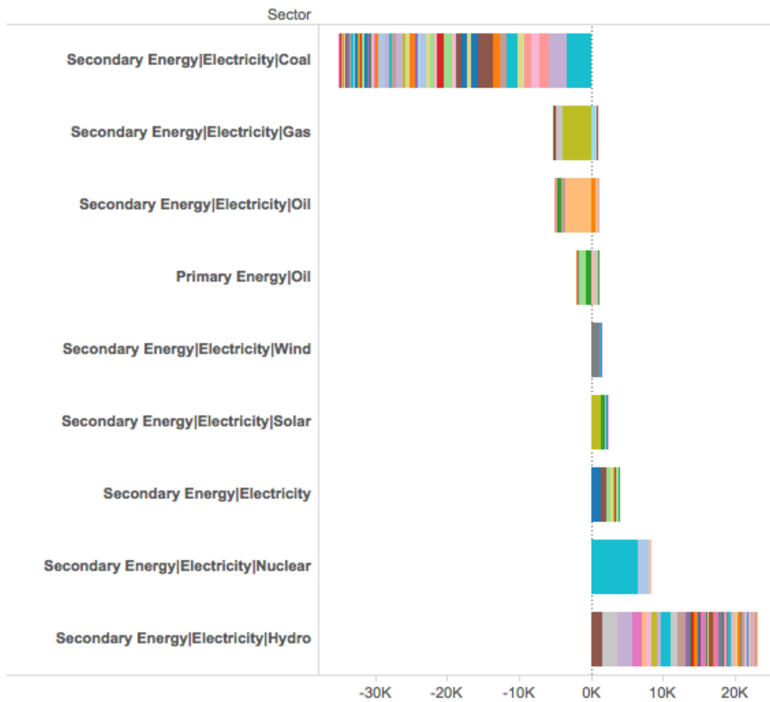

Figure 8: Shocks on portfolios by project, WITCH, StrPol450, in USD mln. Total value of negative shocks reaches USD 49280 mln, while the value of positive shocks reaches USD 42953,5 mln. As a difference from Figure 7, negative shocks affect also primary and secondary oil projects, while positive shocks in the hydro-power equal those in nuclear projects. The relative position of solar and wind projects remain unchanged.

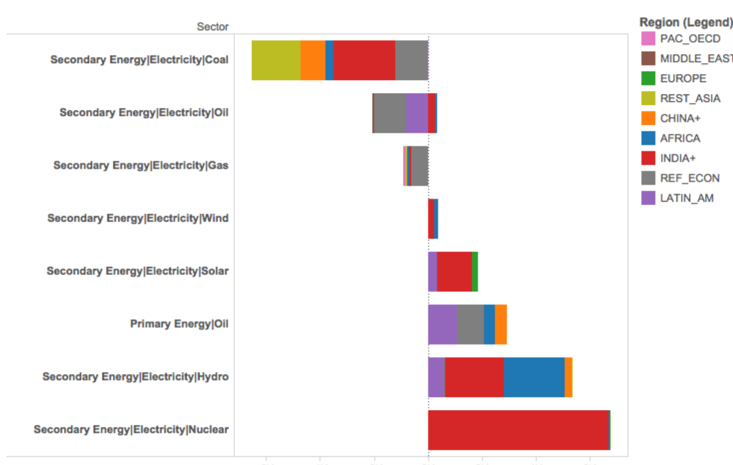

Figure 9: Shocks on portfolios by region, GCAM, RefPol500, in USD mln.

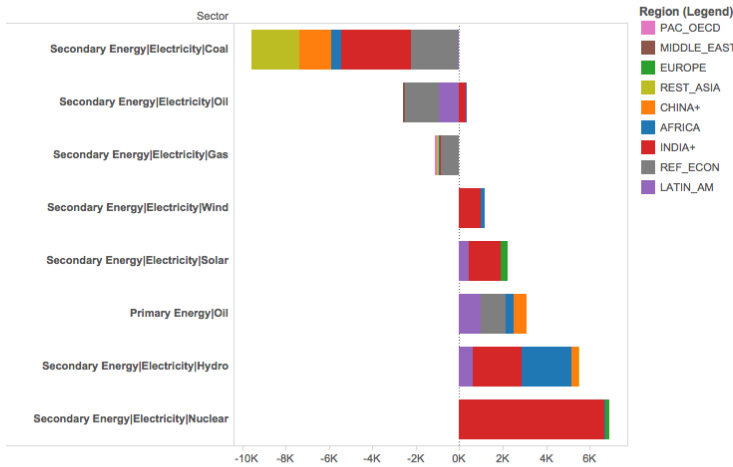

Figure 10: Shocks on portfolios by region, GCAM, StrPol450, in USD mln.

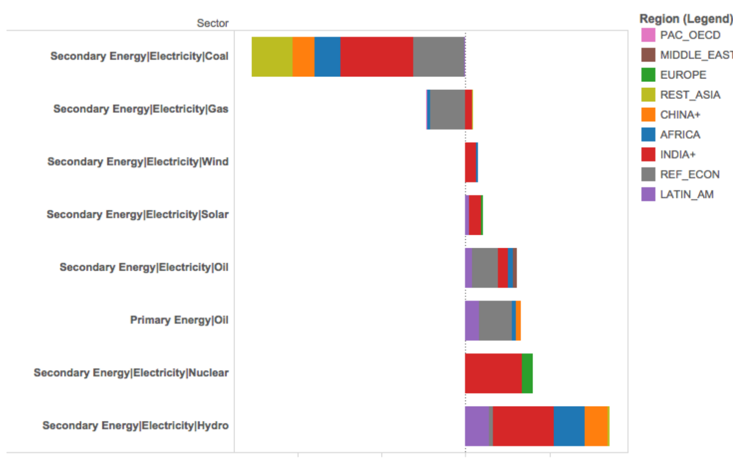

Figure 11: Shocks on portfolios by region, WITCH, RefPol500, in USD mln.

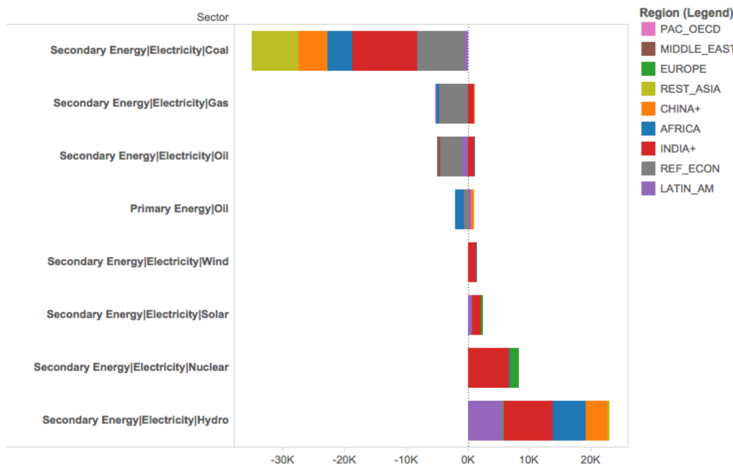

Figure 12: Shocks on portfolios by region, WITCH, StrPol450, in USD mln.

and sector don't change considerably from the GCAM regional scenarios (see Figures 10,11).

Moving to a WITCH tighter climate policy scenario, i.e. StrPol450 (see Figure 12) we notice more variability in the value of the shocks and in the relative position of sectors and regions. Negative shocks extend to primary energy production via oil. However, primary oil, gas and oil power generation are both affected by positive and negative shocks. In the secondary energy coal sector, projects affected by negative shocks are spread across several regions, while in the secondary energy gas and oil sectors they are concentrated in Reforming Economies and "India+". In contrast, positive shocks are associated to the nuclear sector in Pakistan (red) and in the UK (green) and spread across four regions in the hydro-power sector. Positive shocks on solar and wind renewable energy sources are concentrated in "India+".

At this stage of the analysis we are not able to identify general patterns on the shocks across climate policy scenarios and countries. However, the results presented so far illustrate the kind of insights that can be gained with our methodology.

5 Conclusions and policy implications

Our article provides the first development of a climate stress-test applied to the overseas energy loans of two major Chinese policy banks, i.e. CDB and CEXIM. Our methodology allows development banks to assess the order of magnitude and the sign of the change in value of each loan to energy projects, conditional upon a shock determined by a change in climate policy, using sectors market shares trajectories provided by four IAMs included in LIMITS. Then, it allows us to compute the maximum expected loss on portfolios' value introducing a novel definition of a *Project-level climate VaR*. For development banks, applying our climate stress methodology is important for three reasons: i) to estimate the exposure of their projects' portfolio to climate transition risks, ii) to assess the alignment of their portfolio with their mandate, and iii) to derive implications as regards their financial solvability. Indeed, the information provided by the climate stress-test would allow them to identify sources or climate-related financial risks, and thus to shift their portfolios' allocation, thus building resilience and maximizing the value for money. In the context of climate finance, previous work has also investigated the valuation of complex contracts in the presence of shocks on the price of emission allowances and cost of technology (Chesney et al, 2016).

However, such work has not considered portfolios of contracts and the possibility of climate policy shocks occurring in the future. Here, we focus on the simple case of the one-time valuation of energy project's loan contracts, while leaving the valuation of more complex contracts for the future. The results of our climate stress-test show that the magnitude of losses in CDB and CEXIM portfolios' values is influenced by the magnitude of the shocks related to the timing and stringency of climate policies aimed to limit global GHG emissions by 2050. We considered both negative (i.e. meaning losses in project's value) and positive (i.e. gains in the market-value of the loan) shocks. In addition, the sign and magnitude of the shock is subject to high variability, which depends on the projects location by region, the energy sub-sector (in the fossil fuel and renewable energy categories), and the model used. Overall, the value of losses range between 4% and 22% of the portfolios' value. Both projects losses and gains are amplified using the WITCH model. Highest losses are experienced by projects in coal, oil and gas power generation, in particular in Asia, in transition economies and in Latin America. In contrast, the highest gains are reported by hydro-power and for nuclear power generation projects, the latter depending on one project located in Pakistan. Finally, the value of climate VaR ranges from - USD 3878 mln to - USD 711 mln, implying a variation of factor close to 5 across models and climate policy scenarios. Some remarks apply to this analysis, which should then be considered as preliminary for the following reasons. First, further work is ongoing in order to relax the assumptions on the transmission of shocks on sectors market share (now assumed to be linear), on the valuation of project loans (for which we consider the expected value, but more sophisticated methods could be applied, e.g. the Net Present Value), and on the distribution of balance sheet shocks on projects (that we assume to be uniform). Current work is being developed to introduce a Poisson probability distribution of climate policy shocks, in order to refine also the project-based climate VaR methodology (Bretschger & Soretz, 2018). Second, the high positive shocks on the value of a single nuclear power generation project in Pakistan should rise concern in terms of validity of the LIMITS IAMs definition of the climate policy scenarios and their implementation (in terms of assumptions on renewable and nuclear capacity installation needed to achieve the emissions targets), as well as in terms of policy recommendations. Indeed, in the last decade, technological shocks made renewable energy sources (e.g. oil and wind) cost and productivity-competitive with fossil fuel energy sources and nuclear. In low-income and emerging countries struggling to build resilience against climate change, renewable energy sources are considered as a fundamental investment by development finance institutions. Our results have relevant implications on the financial performance of the Chinese policy banks (and thus of the public and private financial institutions connected to them), as well as for the achievement of the Paris Agreement and the SDGs in the beneficiary countries. On the one hand, for instance, with a current leverage (intended as assets on equity) equal to 12 for CDB, a shock causing 10% of losses on portfolios value would be enough to lead the Chinese policy banks to financial stress on their overseas energy portfolios. This, in turn, could have negative repercussions both on the financial stability of the lender, which would need to go on financial markets to access finance, and on the countries credit worthiness and sovereign debt. On the other hand, the high exposure of China policy banks overseas energy portfolios to fossil fuel-based energy sectors in the beneficiary low-income and emerging countries, represents a misalignment with the ambitious Paris Agreement pledges ad the SDGs. Indeed, fossil fuel-based energy projects contribute to lock-in the economies of beneficiary countries in a high-carbon path, increasing the exposure to the risk of carbon stranded assets. Finally, the way in which the climate policy scenarios are designed and implemented via investment patterns matters for the policy relevance of the results.

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Appendix. Further information on methodology and data

Regions classification according to the LIMITS database

In the shock estimation part, we employed economic projections under different scenarios and models from LIMITS database. To be consistent, we adopt the ten ’super regions’ (plus a rest of world region) as LIMITS. Here we build a correspondence between each LIMITS region and the countries covered by the China overseas energy projects within the GEGI’s database.

- AFRICA: all models contain Sub-Saharan Africa; some models also include North African countries, others do not. This is not a big problem with GEGI because projects in North Africa have a sum of $ 2675.03 million compared to $ 2.7 billion Africa total. The complete list of countries in AFRICA region is as follows: Angola, Benin, Togo, Cameroon, Cote d'Ivoire, DRC, Egypt, Equa. Guinea, Ethiopia, Gabon, Ghana, Guinea, Kenya, Malawi, Mali, Mauritius, Morocco, Niger, Nigeria, Republic of Congo, South Africa, South Sudan, Sudan, Uganda, Zambia and Zimbabwe.

- CHINA+: This group refers to countries of centrally-planned Asia, primarily China for LIMITS database. In our GEGI analysis, this category includes Cambodia, Vietnam, Laos and Myanmar.

- RREST ASIA: Fiji, Indonesia, Malaysia, Papua New Guinea and Philippines.

- PAC OECD: Only Australia in our country list

- MIDDLE EAST: Iran and Jordan

- INDIA+: primarily India, it also includes Bangladesh, India, Nepal, Pakistan and Sri Lanka.

- REF ECON: This group includes countries from the Reforming Economies of Eastern Europe and the Former Soviet Union; primarily Russia, Belarus, Bosnia & Herzegovina, Kazakhstan, Kyrgyzstan, Serbia, Tajikistan, Turkmenistan, Ukraine and Uzbekistan.

- LATIN AM: Countries of Latin America and the Caribbean, in this paper specifically Argentina, Bolivia, Brazil[6], Chile, Ecuador, Guyana, Peru and Venezuela.

- EUROPE: Only three recipient countries in GEGI fall into this classification: Bulgaria, Italy, United Kingdom.

Scenarios and models from the LIMITS database

We adopt the climate policy scenarios from the LIMITS project. Base scenario is the baseline scenario which implies no climate policy, i.e., a business as usual track. The four climate policy scenarios chosen in this paper are constructed to line out the possible pathways for the economy in both the short and long run. StrPol and RefPol refers to policy regimes until 2020. Until then, individual regions follow domestic climate and technology policies that include emissions reduction targets for the year 2020. Lenient (RefPol) or stringent policy (StrPol) regimes imply different GHG emissions reduction targets, renewable energy shares in power generation or final energy, and renewable and

[6] In IMAGE, Brazil is listed alone, which could be a potential problem. However, in this analysis, model IMAGE is not included

nuclear capacity installation targets for 26 world regions (see details of the Kriegler 2013 paper). In these scenarios, a global climate mitigation regime would only emerge after a period characterised by fragmented policies implemented at the country or regional level. 450 ppm gives a likely to very likely (70%) chance of reaching the 2 degrees C target, while a 500 ppm gives a as likely not (50%) chance of reaching the 2 degrees C target. More information on scenarios and models can be found in LIMITS PROJECT website [7].

[7] http://www.feem-project.net/limits/