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Working Paper

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Irene Monasterolo
Vienna University of Economics and Business, Austria, and Boston University, USA

Jiani I. Zheng
Dept. of Banking and Finance, University of Zuerich, Switzerland

Stefano Battiston
Dept. of Banking and Finance, University of Zuerich, Switzerland

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Irene Monasterolo *[1], Jiani I. Zheng[2], and Stefano Battiston[2]

[1]Vienna University of Economics and Business, Austria, and Boston University, USA
[2]Dept. of Banking and Finance, University of Zuerich, Switzerland

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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 their projects' exposure to climate risks and their impact on global 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 with the climate goals. We contribute to fill in this gap by developing a novel climate stress-test methodology applied to the loans 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 idiosyncratic shocks, that could affect individual energy projects across regions and energy sectors, under climate policy scenarios consistent with the 2 degrees C target. 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 could lead to severe financial distress for them, with implications on macroeconomics and finance.

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JEL Codes: G01, G11, G32, G33.

1 Introduction

There is growing awareness among development finance institutions of the need to factor and integrate climate-related financial risks in the financial assessment of their projects portfolios (Bonnel & Swann, 2015; European Bank for Reconstruction and Development, 2016) Indeed, it is now widely recognized by academics and financial stakeholders 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; Battiston et al., 2017). In particular, given the complexity of the international network of financial exposures (Battiston et al., 2012, 2016b,a) and the interconnectedness with expanding global development finance (featuring new actors, such as the Asian Infrastructure and Investment Bank), the introduction of climate risks consideration into financial risk metrics is fundamental to tame potential 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 (mitigation, adaptation), and their alignment to the Paris Agreement and 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 for scaling up private investments into low-carbon sectors. In particular, the energy sector is fundamental for a smooth low-carbon transition. On the one hand, fossil fuels extraction and the of burning of coal, natural gas, and oil for electricity and heat are the largest single source of global greenhouse gas (GHG) emissions, equal to 35% of the total in 2010 (IPCC, 2014). In turn, the concentration of GHG emissions in the atmosphere is the main responsible of worsening climate change. On the other hand, investments into fossil fuels energy sectors constrain the beneficiary country's economy on a high carbon path and also represent a risk for investors' financial solvability, in case of climate physical or transition risk. Academic research has made progress in developing measures of financial portfolios' exposure to greenhouse gases (GHG) emissions, considering investors' market share in carbon-intensive sectors that could become stranded assets (Monasterolo et al., 2017). There has been also progress on modeling the macroeconomic and distributive impacts of climate policies (Monasterolo and Raberto, 2018; Dafermos et al., 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 Euro-Area economy (Stolbova et al., 2018). Finally, recent research highlighted the role of network analysis to assess the impact of carbon stranded assets across financial and economic sectors (Campiglio et al., 2017). 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 overseas energy 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 balance sheet shock linked to the beneficiary's business operations, and a climate policy shock led by the introduction of a milder or tighter climate policies aimed to stay place the economies within the 2 degrees C target. Our methodology is modular and based on a simplified model but 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 banks' portfolios to fossil fuel-based or renewable energy projects by region and year. Second, we estimate the change in the market share of fossil fuel and renewable energy sectors by regions under a set of climate policy scenarios consistent with the 2 degrees C target up to 2050, using the macroeconomic trajectories provided by four Integrated Assessment Models (IAMs) of the LIMITS project (Kriegler et al., 2013). Third, we consider a balance sheet shock on the borrower's side (idiosyncratic) led by operative fluctuations on companies delivering the project and affecting the probability of default on the borrower. Fourth, we add the climate policy shocks resulting 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. Finally, conditional to a specific model's forecasts 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. In particular, they allow us to consider circularity between climate policies and market actors' investment decisions, and to consider situations of departure from rational expectations. Data on the banks' overseas energy loans worthy $228.105 billion (bn) in seven regions in low-income and emerging countries, from 2000 to 2018, are provided by the GEGI China Energy Finance database (Gallagher, 2017). The results have relevant implications for China's macroeconomic and financial performance because domestic and foreign energy investments are crucial for Chinese economic development. In particular, foreign energy investments are part of the Chinese geopolitical strategy and narrative on climate-finance, and imply opportunities and challenges for Chinese public and private capital allocation. Thus, our analysis can inform the discussion on the role of China in the low-carbon energy transition, by allowing the comparison between the Chinese energy transition narrative and the actual investment strategy domestically vs. overseas, in particular in low-income and emerging countries. In addition, it helps to identify potential sources of financial instability, being the Chinese policy banks supported by the Chinese central bank and the government. 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. Section 5 concludes discussing 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 including the European Bank for Reconstruction and Development, the African Development Bank (AfDB), 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-finance tracking methodology. In particular, they 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 losses from climate-led hazards) and the quality of the adaptation plan (according to the Nationally Determined Contributions (NDCs));

- Transition risk, which derives from the technology of the sector that the project is going to finance (e.g. carbon-intense vs. renewable energy), and by the introduction of climate policies.

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 and on their financial solvability objectives. Indeed, development banks need to preserve their AAA rating to access more favorable financing conditions on the markets and thus to be able to provide better lending conditions to the beneficiary countries. Therefore, the introduction of standardized metrics and methods to measure development banks progress towards climate action and the SDGs at the project level could provide them actionable information through the assessment of 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 and thus in their financial risk management. 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 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 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. Our methodology allows to i) compute the portion and value of the development banks portfolio (by energy sectors, number of projects, 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 energy projects by region and policy scenario.

3.1 Valuation framework for loan contracts in presence of climate policy shocks

We consider a financial actor i (hereafter, the bank) endowed with a portfolio of investments in a set of projects through loan contracts. For the point of view of credit risk, each project is represented here as a distinct borrower j. We aim to carry out a valuation of the portfolio that takes into account climate policy shocks. The valuation model includes three time steps, t_0, t^*, T_j, with $t_0 < t^* < T_j$. t_0 denotes the time at which the valuation is carried out, t^* denotes the time at which a climate policy shock potentially occurs, and T_j denotes the maturity of the loan contract to the borrower j. We then denote by $A_{ij}(t_0, T_j)$ the financial valuation at time t_0 of the investment of bank i in the project j, with maturity T_j. Accordingly, the valuation of actor i's projects portfolio can be 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 simple approach based on the expected value of the loan, given the information available to the bank 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-discounting factor), r_j is the recovery rate on the loan contract[1] and $p_j(t_0, T_j)$ is the probability, based on the information available at time t_0, that the borrower j defaults on the loan at the maturity T_j.

In line with standard assumptions in the economic literature, 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 (Greenwald et al., 1984), 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_j, 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_j.

3.1.1 Climate policy shocks

We now introduce the notion of climate policy shock. At time t^* (intermediate between the time of the valuation and the time of the maturity) the occurrence of a climate policy shock (e.g. the introduction of a carbon tax or the coordination of several countries on GHG emission targets) implies that the economy switches from a business-as-usual scenario characterized by no climate policy (B) to a scenario P where the market shares of some economic sectors are affected. We assume that this transition modifies the probability of default of the borrower j through changes in the market share of the economic sector of j. This assumption will be elaborated more in detail later on in this section. For now, we want to point out that from Equation 2 (taken as conditional to a given climate policy

[1] The recovery rate is a standard notion in banking that indicates the ratio of the amount recovered by the lender upon default of the borrower, for instance after liquidating the collateral associated to the loan contract. Here we consider the recovery rate as exogenous (thus setting the size of potential shocks in a conservative boundary), while maximum losses are obtained with recovery rate equal to 0.

scenario) it follows that a change in default probability implies a proportional change in the expected value of the loan value:

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

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

3.1.2 Borrower's default condition

In order to take into account the effect of the climate policy associated with a scenario P, we model the total assets $A_j(T_j)$ of the borrower j at time T_j as a stochastic variable described by the following equation,

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

where $A_j(t_0)$ is the value of the asset at time t_0, $\xi_j(t^*, P)$ is a shock occurring at time t^* associated with the climate policy, and $\eta_j(T_j)$ is an idiosyncratic shock occurring at time T_j. In line with the literature on modeling default events (Battiston et al., 2016*b*), we assume that the borrower defaults at time T_j, if its net worth (called also book equity and defined as assets minus liabilities) at the maturity $E_j(T_j)$ becomes negative as a result of the two shocks, i.e.

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

where the value of the liability L_j is assumed to be independent of the policy scenario and of time, i.e. the debt can not restructured or repurchased by the borrower.

In this formulation, for a given policy shock $\xi_j(t^*, P)$, the conditioned default probability of the borrower is the probability that the 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 net worth value at time t_0, and the magnitude of the climate policy shock ξ_j on its asset side at time t^*. Formally, the default condition reads:

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

Indeed, the borrower defaults at the maturity T_j if the idiosyncratic shock is lower than the initial equity value summed to the policy shock. In case of no policy shock, ξ_j equals 0 and the default condition becomes:

$$\eta(T_j) < \theta_j(B) = -(E_j(t_0). \tag{7}$$

The default probability can thus be written as:

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

where $p(\eta_j)$ is the probability distribution of the idiosyncratic 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

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

3.1.3 Profitability and shocks on market share

We now 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:

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

It is intuitive that the valuation $A_{i,j}(t_0, T_j)$ of the loan to a borrower j can be affected by changes in the economic performance of sector S of the geographic region R in which the borrower operates. Indeed, from a theoretical accounting perspective, under the assumptions of 1) constant demand, 2) constant prices and 3) constant returns to scale, a decrease x in the market share of firm i translates in a relative decrease x in its sales and therefore in its profits.

Here, 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 a proportional relative change in the profitability of the j's. The assumption is justified by a body of empirical literature which has found a strong and positive empirical relation between market-share and profitability (Szymanski et al., 1993; Venkatraman and Prescott, 1990). Notice that since the net worth is the integral of profits over one period of time, the relative change in net worth and in profit coincide. Therefore, it is equivalent to assume that a relative change in net worth is proportional to the relative shock in market share:

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

where χ denotes the elasticity of profitability with respect to market share. The literature has estimated the magnitude of the elasticity coefficient of profitability with respect to market share for several business sectors (including banks and insurance) and it has found it to be heterogeneous and dependent on several factors such as firm size (Venkatraman and Prescott, 1990). In principle, in our approach, the elasticity coefficient could be estimated empirically for the specific sectors and regions of the borrowers in the portfolio. In this work, the data to carry out this estimation was not available. Since in this paper we aim to provide an estimation of the upper bounds of the magnitude of the shocks due to climate policies, we have assumed a value of χ constant and equal to 1 (typical empirical values range between 0.2 and 0.6).

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 and mean μ, 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 climate 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

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

and the change in default probability becomes:

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

The idiosyncratic and the climate policy shocks are assumed here to be independent, for the sake of simplicity. In reality the two shocks could be interdependent. The effect of the climate policy shock is to shift (either left or right) the probability distribution of the idiosyncratic shocks, with positive or negative effects, respectively, for the default probability. 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:

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

The above equation describes, under the 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.

3.1.4 Portfolio value

Summing over the projects j in the portfolio, we obtain the *total change in loan value* [2]:

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

The selection of the parameter values for the application described in this paper is discussed in Appendix. 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. Therefore, 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

[2] For a description of the parameters, please refer to the Appendix

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

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 investments peaked in 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.

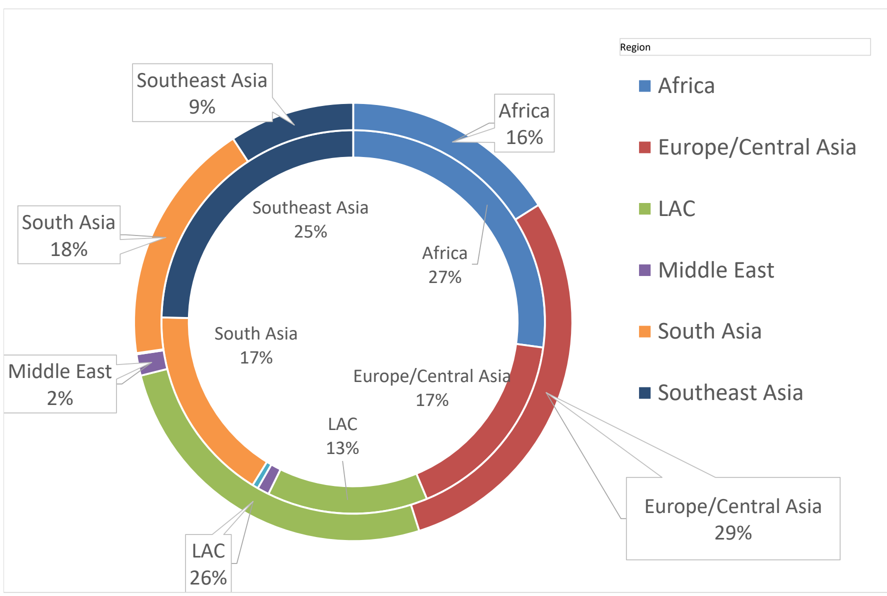

Figure 1: Regional Distribution of China's oversea energy finance. Data source: GEGI

Figure 1 shows the regional share 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 that account for 47% of the Chinese policy banks' portfolios. Figure 2 shows the allocation of overseas energy loans by value, lender and energy sector,

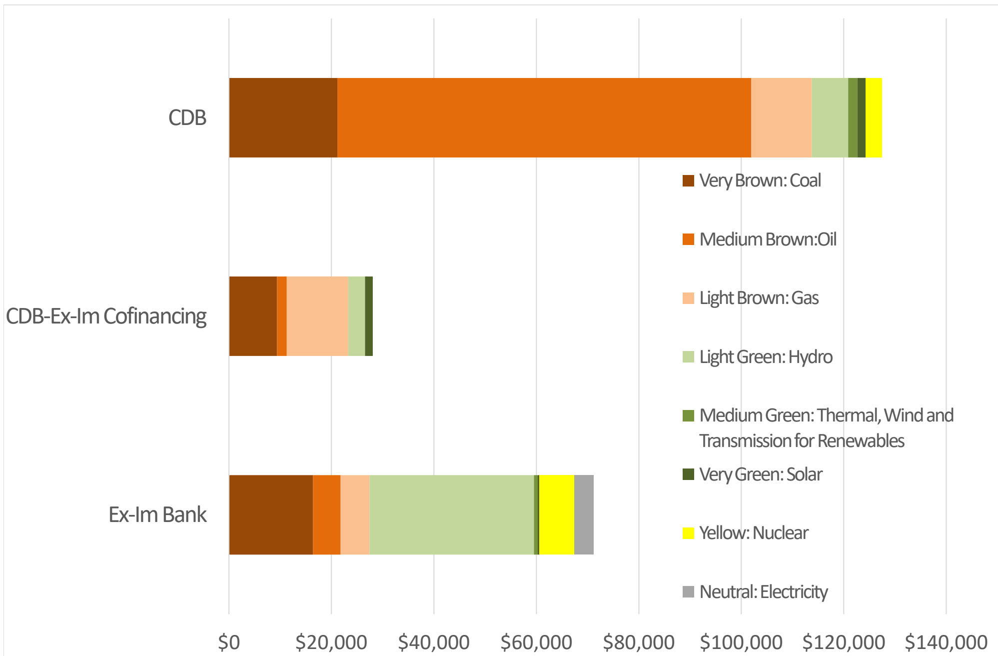

Figure 2: CDB and CEXIM's overseas energy portfolios Unit: million. Data source: GEGI

according to our classification based on the energy technology. We grouped coal, gas/LNG and oil as fossil fuel sources, and combined hydro-power, solar, thermal and wind as renewable energy sources.[3] The financial value of fossil fuel-based investments clearly overtake that of renewable ones: fossil fuel based energy projects represent 51.26% of projects but 72.09% of portfolio's value. 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 Figure 3 we illustrate each region's investment according to their energy source. The color gradient represents the energy category from the most CO2 emissions' intense, i.e. coal (very brown), to the least one, i.e. solar (very green). 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, i.e. CDB (USD $127 bn), followed by CEXIM (USD $71 bn) and the co-financing between the two (USD $28 bn). Figure 2 shows that all lenders are highly exposed to fossil energy (oil investments represent 63.38% of CDBs portfolio). Hydro-power projects represent the highest share of renewable sources (USD $43 bn), 75% of which are funded by CEXIM.

[3]We excluded electric and electricity projects because they represent only 1.74% of the total amount

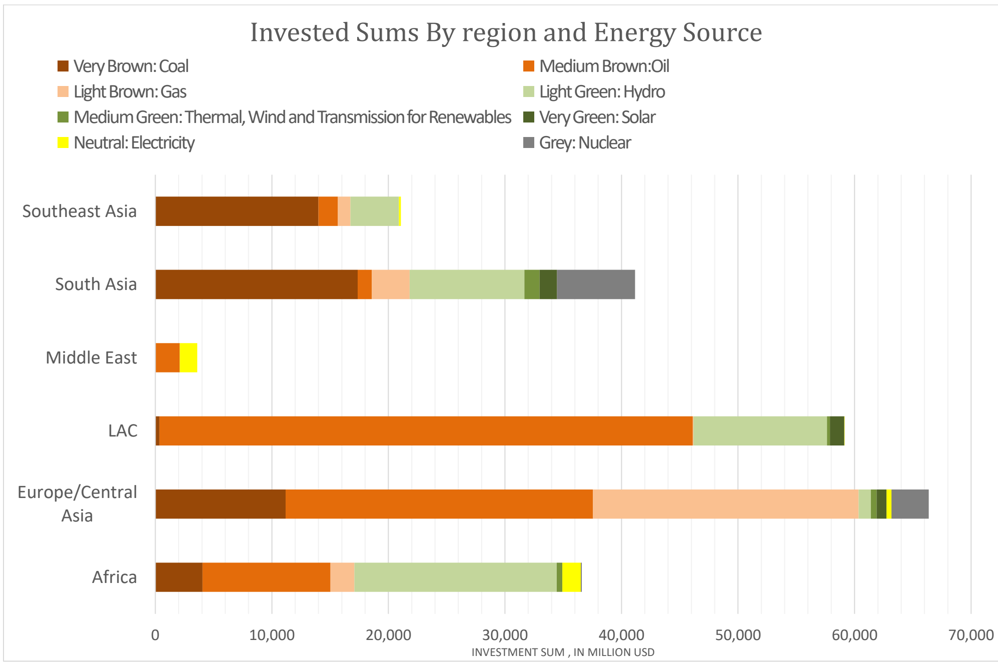

Figure 3: Region and Energy Sector of China's oversea energy finance. Source: GEGI

3.3 Sectors' market shares trajectories subject to 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 in terms of CO2 emissions concentration) from the LIMITS database that are aligned to the 2 degrees C target, and we also consider a baseline of no climate policy (i.e. the Base scenario), see Table 1. We use the LIMITS project database (Kriegler et al., 2013) to obtain the market shares trajectories for fossil fuel and renewable energy sectors included in the China's overseas energy portfolios influenced by the introduction of domestic and international climate policies (a full description of the climate policy scenarios is provided in the Appendix). In particular, the two emissions concentration targets chosen under the so-called milder and tighter climate policy scenarios (i.e. 500 and the 450 parts per million (ppm)), determine the amount of CO2 to be emitted in the atmosphere by 2100 that would allow the achievement of the 2 degrees C path. These targets are associated to a probability of exceeding the 2 degrees C target by 35-59% and 20-41% respectively (Meinshausen et al., 2009). Thus, the choice of specific emissions concentration targets could be considered as a proxy for the stringency of the global emission cap imposed by potential climate treaty.

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 considered (plus the Base scenario), i.e. RefPol-450, RefPol-500, StrPol-450, StrPol-500. The emissions concentration targets (500 vs 450 ppm) provide 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 implies a change in the sectors' macroeconomic trajectory, and thus in the market share of primary and secondary energy sources, and could differ in sign and magnitude. We consider a shock occurring in the period between 2005 and 2050, affecting the market shares of the China's overseas energy projects sectors. The market share shocks induced by the introduction of a climate policy are then translated in shocks in the loans' value. Figure. 4 shows the drop in the market share of coal energy in year 2020 and 2030 in the African region 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 an IAM, 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.

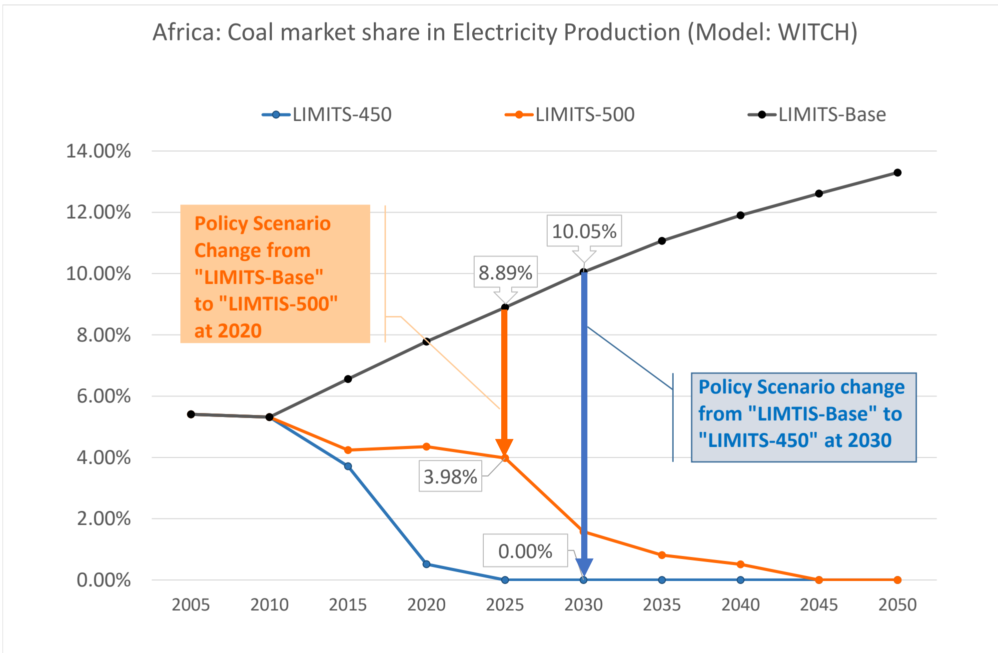

Figure 4: Africa: Coal Market Share in Electricity Production. Figure 4 provides an example of the computation of the market-share for an energy sector, i.e. coal for electricity production, in a specific region, i.e. Africa, and conditioned to the WITCH model, under three climate policy scenarios.

4 Results

In the following, we present the results of our analysis based on two classes of IAMs, i.e. CGAM and WITCH, and for two climate policy scenarios: a milder one (i.e. RefPol500) and tighter one (i.e. StrPol450).[4] We find that both positive and negative shocks on energy projects are more pronounced in WITCH than in CGAM, both under the RefPol-500 and tighter StrPol-450 climate policy scenarios. In addition, the policy shocks' transmission on the fossil/renewable energy sectors vary across models. Table 2 reports some descriptive statistics on the shocks in each combination of models and policy scenarios considered. The maximum positive shock always corresponds to an individual nuclear project in Pakistan (see Conclusion for a discussion on the limitations of IAMs' market share projections). 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 VaR values range from

[4]For a discussion of the characteristics and differences between the two IAMs, see the Appendix.

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.

- 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), positive shocks are led by a single nuclear power generation project in Pakistan (light blue), followed by a solar project in Pakistan (light green). In contrast, negative shocks in value are led by coal-based and oil based power generation and transmission projects (in particular, 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, led by a gas project in Russia and a coal project in India. In contrast, the most positive shock is led by a nuclear power generation project in Pakistan. Nevertheless, in aggregate, positive shocks are led by the hydro-power sector. Interestingly, also primary and secondary energy oil projects are affected by positive shocks. This result is due to the characteristics of the IAMs used to compute the change in sectors' market shares. In conclusion, the increase in climate policy severity, i.e. moving to scenario WITCH StrPol450 (Figure 8), leads to an increase in the value of the negative shocks. Secondary gas, secondary and primary energy oil are subject to both negative and positive shocks, while the largest positive shock affects hydro-power and nuclear energy. We now consider the geographical distributions of shocks by project, amount, policy scenario 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, negative shocks are most severe in the coal power generation, in particular in "India+", Rest of Asia (light green) and Reforming Economies (grey, including transition countries in Eastern Europe and in ex-URSS), which also experience negative shocks in oil and gas power

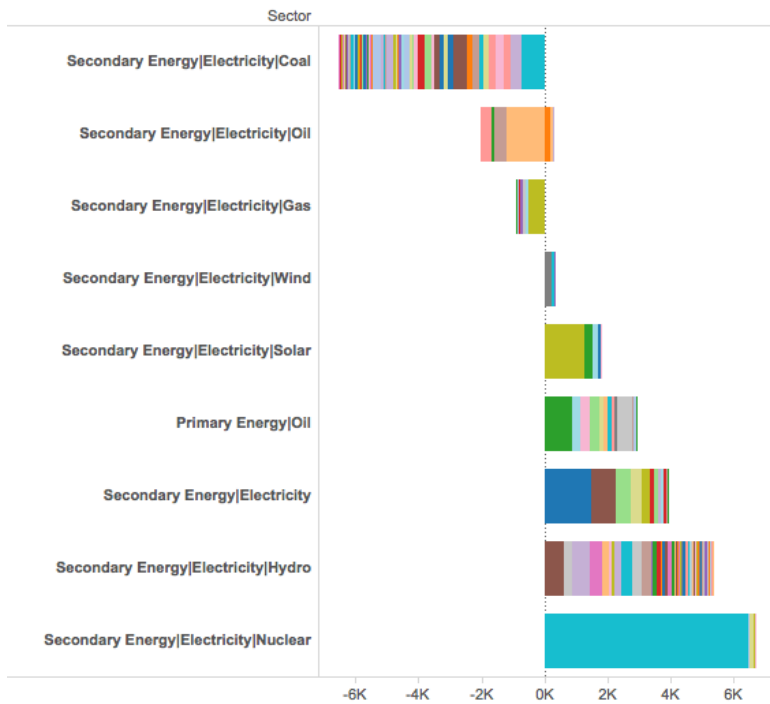

Figure 5: Shocks on portfolios by project, GCAM, RefPol500, in USD mln. The shock values range between a total loss of USD 9483,9 mln and approximately USD 21957,2 mln of total gains on projects. Negative shocks are spread across projects in coal power generation, and in few oil and gas power generation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

generation. With the increase in severity of the climate policy scenario (i.e. StrPol450), the severity of shocks on projects' value increases, in particular in coal power generation in China+ and in oil and gas power generation in Reforming Economies.

In WITCH, in the RefPol500 scenario, positive shocks are associated at the nuclear project in Pakistan, while negative shocks are associated to coal and oil power generation projects, and are distributed across regions (China+, but also Rest of Asia, Reforming Economies and Latin America). The relative position of the other positive and negative shocks across regions and sector don't change considerably from the GCAM regional scenarios (see Figures 10,11).

Moving to a tighter climate policy scenario, i.e. StrPol450 (see Figure 12) we notice a change 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

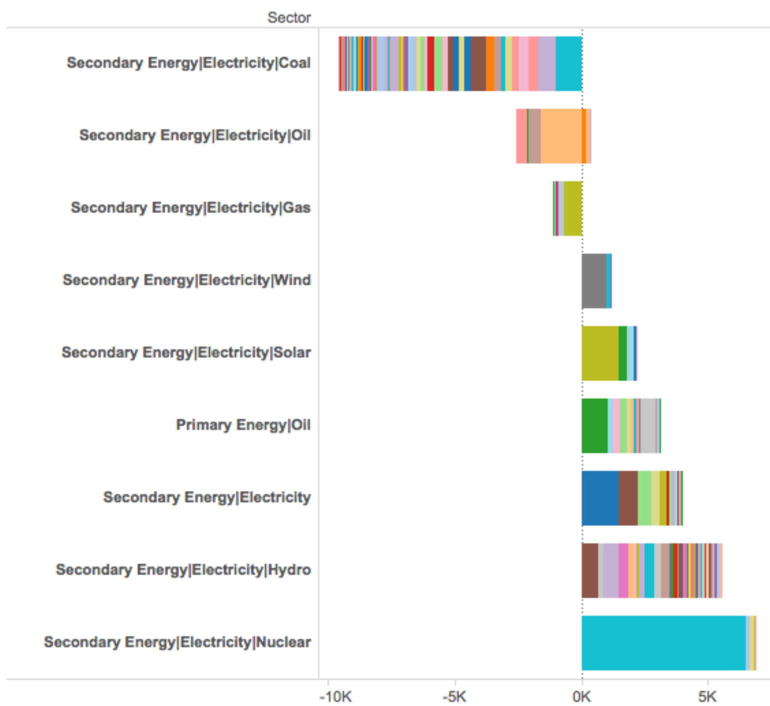

Figure 6: Shocks on portfolios by project, CGAM, StrPol450 in USD mln. The shock values range between a loss of USD 13275,3 mln and approximately USD 23742,4 mln of gains. As a difference from Figure 5, negative shocks affect also primary and secondary oil projects, while positive shocks in hydro-power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

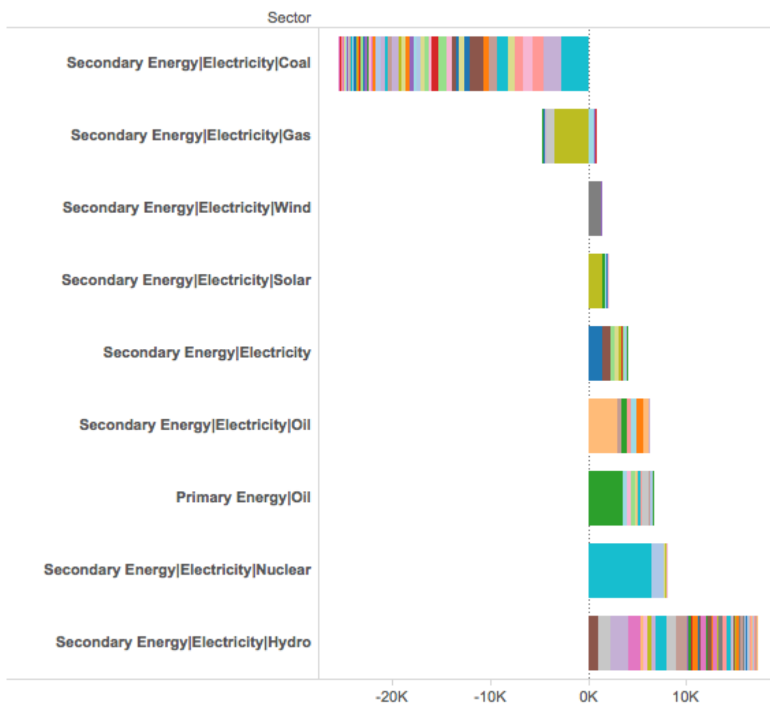

Figure 7: Shocks on portfolios by project, WITCH, REfPol500, in USD mln. The shock values range between a total loss of USD 31343,4 mln and USD 46722,9 mln. Negative shocks are spread across projects in coal power generation and gas power generation projects. The other sectors are affected by positive shocks, in particular nuclear and hydro-power projects, while solar and wind projects benefit the least.

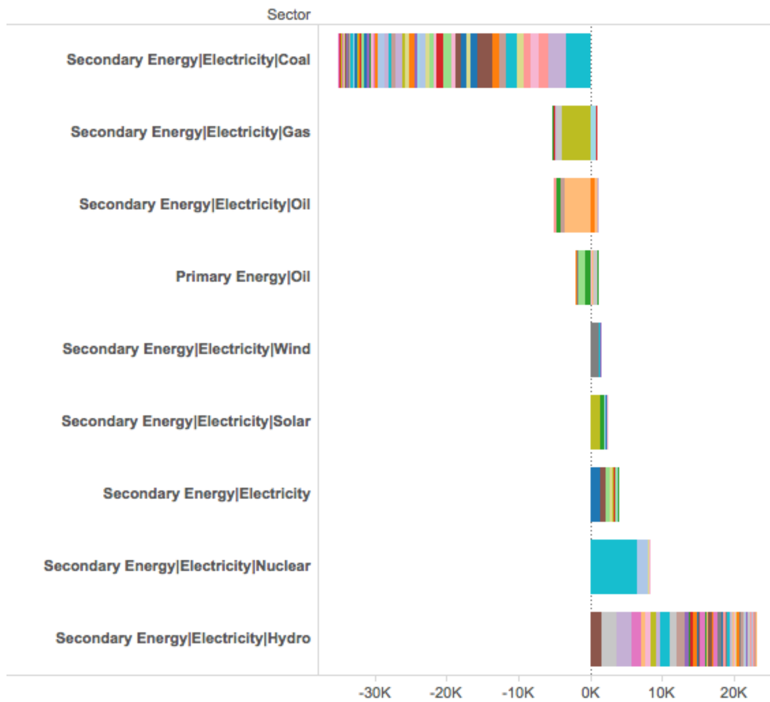

Figure 8: Shocks on portfolios by project, WITCH, StrPol450, in USD mln. Total value of negative shocks reaches USD 49280 mln, while the value of positive shocks reaches USD 42953,5 mln. As a difference from Figure 7, negative shocks affect also primary and secondary oil projects, while positive shocks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

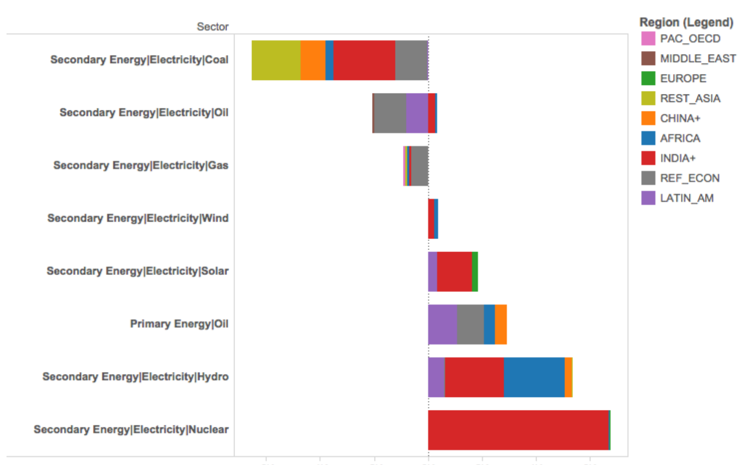

Figure 9: Shocks on portfolios by region, GCAM, RefPol500, in USD mln.

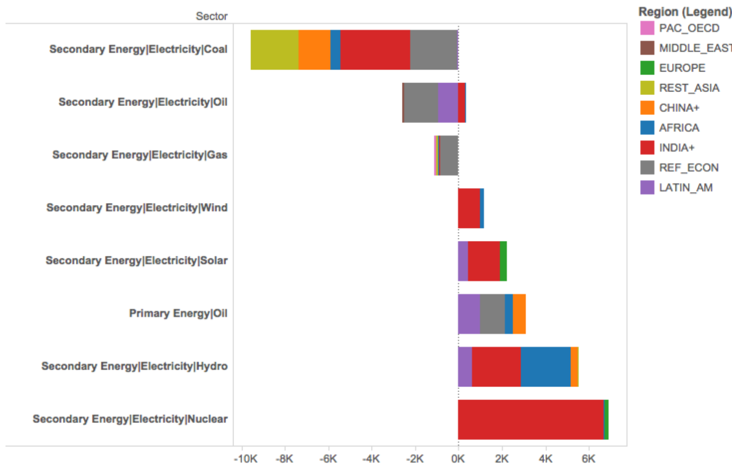

Figure 10: Shocks on portfolios by region, GCAM, StrPol450, in USD mln.

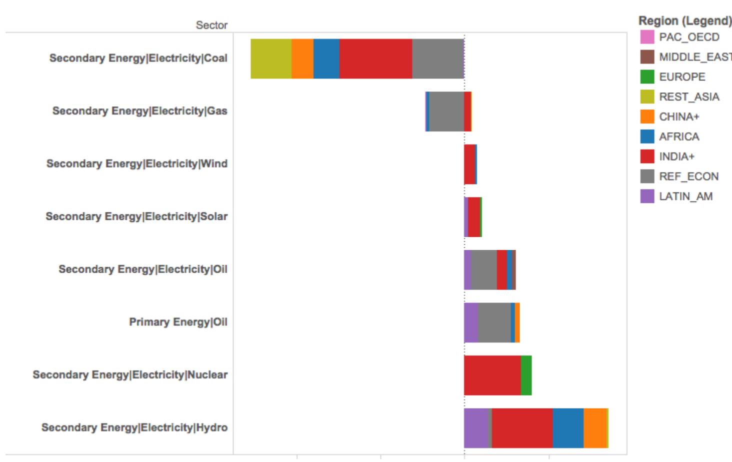

Figure 11: Shocks on portfolios by region, WITCH, RefPol500, in USD mln.

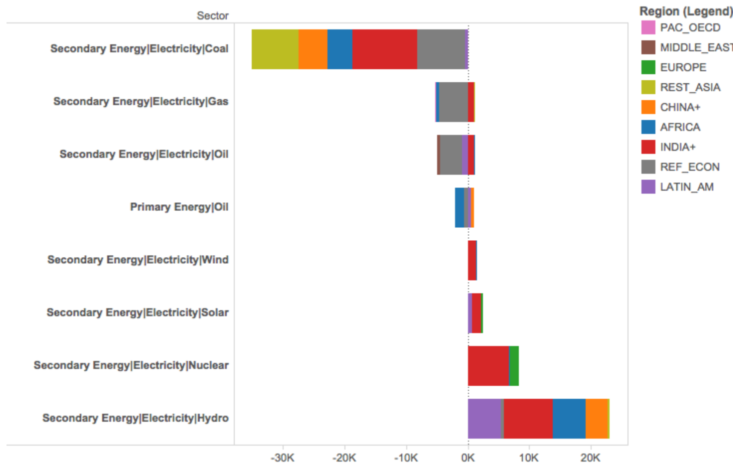

Figure 12: Shocks on portfolios by region, WITCH, StrPol450, in USD mln.

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), while they are 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 shocks' general patterns across climate policy scenarios and regions. However, the results presented so far illustrate the kind of insights that can be gained with our methodology and could be improved with more granular data.

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 modular methodology represents an advancement on the state of the art because it 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 IAMs. Then, it allows to compute the maximum expected losses on portfolios' value associated to specific energy projects 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 on their financial solvability. This information is policy relevant in so far it helps identify the sources of portfolios' climate-related financial risks that could have systemic implications, and thus to inform climate-resilient portfolios' risk management strategies.

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 near future. Here, we focus on the simple case of the one-time valuation of banks' energy loans' contracts, while leaving the valuation of more complex contracts for future analysis. The results of our climate stress-test show that the magnitude of losses in CDB and CEXIM portfolios' values is influenced by the shocks related to the timing and stringency of climate policies aligned to the Paris Agreement. The sign and magnitude of the shock is subject to high variability, which is conditioned to the projects location by region, the energy sub-sector (i.e. in the fossil fuel and in the renewable energy categories), and the IAM used to estimate the change in market shares. Overall, the losses range between 4% and 22% of the portfolios' value. 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. Positive and negative results are amplified using the WITCH IAM.

Some remarks apply to this analysis, which should then be considered as preliminary for the following reasons. First, we are working to relax the assumptions on the transmission of shocks on sectors market share (which is 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), on the distribution of the balance sheet shocks on projects (that we assume to be uniform), as well as the introduction of a Poisson probability distribution of climate policy shocks (according to (Bretschger & Soretz, 2018)) with the aim to refine the project-based climate VaR methodology. 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 IAMs climate policy scenarios and their implementation in terms of assumptions on renewable and nuclear capacity installation needed to achieve the 2 degrees C aligned emissions targets, and on policy recommendations. Indeed, in the last decade, technological shocks made renewable energy sources cost and productivity-competitive with fossil fuel energy sources and nuclear. In low-income and emerging countries that struggle to build resilience against climate change and to lift the population out of energy poverty, renewable energy sources are considered as a fundamental investment sector by development finance institutions. Our results have policy implications for China policy banks portfolios risk management strategies under climate transition risk. Chinese policy banks overseas energy portfolios are highly exposed to fossil fuels investments that could become stranded once technological improvements in renewable energy and climate policies aligned with the Paris Agreement are introduced. In order to decrease the exposure to carbon stranded assets, Chinese policy banks might want to rebalance their overseas energy portfolios moving from very brown (coal and oil) to green energy sectors (solar and wind). This strategy would bring three advantages to Chinese policy banks. First, it would help them align their overseas energy investments to their sustainability narrative and mandate, thus driving the economic development of the beneficiary countries into a low-carbon path. Second, by decreasing their portfolios exposure to carbon stranded assets, they could increase their portfolios resilience to climate transition risk. Third, by rebalancing their overseas energy portfolios toward low-carbon projects and sectors, Chinese policy banks would contribute to preserve their financial solvability, with positive implications on Chinese macroeconomic and financial stability, being Chinese policy banks tightly linked to the Chinese government and central banks policies. Indeed, if we consider the current leverage of 12 (defined as assets on equity) of China Development Bank, even an average shock of 10% on its loans portfolio could induce financial distress, with 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. Finally, given the high level of interconnectedness of Chinese financial institutions, potential risk spread and systemic implications from the exposure of other Chinese financial institutions to Chinese policy banks could occur.

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Appendix. Further information on models, methodology and data

In the results section, we display the shocks on project loans' values obtained using two of the four IAMs considered, i.e. GCAM and WITCH. In general, GCAM provides a more detailed representation of the agriculture and energy sectors from an engineering point of view than WITCH, but it is more approximative in the representation of the economy and technological change. The two models differ in terms of macroeconomic core (partial equilibrium in GCAM vs general equilibrium in WITCH), the treatment of technological change (which is exogenous in GCAM and endogenous in WITCH), the definition of expectations (based on recursive dynamics in GCAM and on perfect foresight in WITCH), the details of the agricultural and energy value chains (which are highly detailed in GCAM and less in WITCH), the representation of the GHG and aerosol emissions (GCAM considers a full basket of greenhouse gases, precursors, and aerosols while WITCH includes CO2, CH4, N20, fluorinated gases and SO2 aerosols) and of negative emissions technologies (Carbon capture storage is considered for both electricity and hydrogen production in GCAM but only in electricity production in WITCH). These differences in models specification affect the difference in results in the estimation of the change in sectors market shares under the climate policy scenarios considered in our analysis. For a comprehensive analysis of the differences between the two models, see Kriegler et al. (2013).

Selection of the parameters' values.

The following parameters depend on the individual borrower: the face value of the loan F_{ij} and the initial equity level E_j the recovery rate r_j and m that characterize the distribution of the idiosyncratic shocks, according to the following relation $F_{ij}(1-r_j)\frac{E_j}{\delta}\,\chi\, u_{S,R}(P,M,t^*)$. The initial equity level E_j of the borrower can be observed from the balance sheet. The face value of the loan F_{ij} is also observable because it is negotiated between the borrower and the lender (the bank) at the moment of the granting the loan contract.

The elasticity χ is sector specific and can be estimated from sectoral data on profitability and market share.

The recovery rate r_j and the parameters of the distribution of shocks hitting the borrower are more difficult to observe but could be estimated based on the historical values for borrowers in the same project's sector and region. Indeed, we can assume that the default of borrowers in the same sector and in the same region (e.g. coal-based electricity producers in Poland) can be described by parameters that are much closer than those describing borrowers in different sectors and regions.

Since these data are not available at this stage of our analysis, we have made some assumptions on the plausible range of values that they could take.

We have set $E_j/delta$ =1, corresponding to the assumption that the magnitude of the initial net worth and width of the distribution of the idiosyncratic shocks are comparable. We have also set the recovery rate as r_j=0. This case corresponds to the upper bound of the loss incurred on a given loan.

Regarding the elasticity coefficient between profitability and market share we have assumed a value of χ constant and equal to 1.

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[5], 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 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 [6].

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

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