Journal of Economic Interaction and Coordination
https://doi.org/10.1007/s11403-024-00425-z

REGULAR ARTICLE

Project finance or corporate finance for renewable energy? an agent-based insight

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Received: 3 January 2023 / Accepted: 19 August 2024

Abstract
State-of-the-art macroeconomic agent-based models (ABMs) include an increasing level of detail in the energy sector. However, the possible financing mechanisms of renewable energy are rarely considered. In this study, an investment model for power plants is conceptualized, in which energy investors interact in an imperfect and decentralized market network for credits, deposits and project equity. Agents engage in new power plant investments either through a special purpose vehicle in a project finance (PF) structure or via standard corporate finance (CF). The model portrays the growth of new power generation capacity, taking into account technological differences and investment risks associated with the power market. Different scenarios are contrasted to investigate the influence of PF investments on the transition. Further, the effectiveness of a simple green credit easing (GCE) mechanism is discussed. The results show that varying the composition of the PF and CF strategies significantly influences the transition speed. GCE can recover the pace of the transition, even under drastic reductions in PF. The model serves as a foundational framework for more in-depth policy analysis within larger agent-based integrated assessment models.

Keywords Agent-based modeling · Energy finance · Financial network interactions · Heterogeneity

1 Introduction

Numerous countries are grappling with the challenge of expanding their renewable power generation capacities to meet climate objectives and sustainability ambitions, requiring huge investments in generation infrastructure (McCollum et al. 2013; Peake and Ekins 2017; Thacker et al. 2019). Financing costs constitute a large

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Published online: 09 September 2024

fraction of the total costs of renewable power projects, and are often a key figure in the risk assessment of sustainable technologies (Egli et al. 2018; Hirth and Steckel 2016). The coordination of energy finance is a key factor for a successful transition (Polzin and Sanders 2020). In 2023, the total investment for financing energy world-wide amounted to 1.7 trillion US dollar, and it is imperative to sustain high investment volumes in the upcoming years in order to achieve a global warming target below 2 °C (IEA 2023; McCollum et al. 2018). A significant share of these investment efforts will be directed toward transforming the power market, enhancing renewable electricity generation. Most power markets, even if widely liberalized, are subject to regulatory measures supporting renewable power plants (Hu et al. 2018; Nicolli and Vona 2019). The policy design of these measures plays a vital role in achieving an optimal balancing between public subsidies and private investments. In this regard, agent-based integrated assessment models (IAMs) are a useful analysis tool. Effectively integrating the factors driving renewable energy finance into agent-based IAM frameworks is an essential prerequisite. A main challenge in modeling is to incorporate the bottom-up market aspects of energy investments in sufficient detail, while maintaining the simplicity and generality of a modeling framework.

When modeling energy investments, the related barriers and risks have to be considered for a set of heterogeneous investors (Mustaffa et al. 2021; Semieniuk et al. 2021). Empirically grounded research has developed an understanding about the composition of investors' balance sheets and cost of capital for renewable energy finance (Steffen 2020; Kempa et al. 2021), and has widely demystified real-world investors' risk perception and attitudes toward power market support schemes as well as the underlying financing conditions (May and Neuhoff 2017; Polzin et al. 2019; Taghizadeh-Hesary and Yoshino 2020).[1]

Here, agent-based models (ABMs) are particularly suitable, as they naturally incorporate bottom-up transition dynamics and actors' behavior under heterogeneity (Vasileiadou and Safarzynska 2010; Farmer et al. 2015; Dosi and Roventini 2019; Nieddu et al. 2022). Conversely, some of these empirically grounded insights on energy finance have not yet entered the domain of macro-ABMs of the energy transition. For a reliable identification of policy settings which incentivize the expansion of renewable energy investments, macro-ABMs and agent-based IAMs need to be charged with more real-world evidence about the energy investment behavior. Recent literature has elaborated several open research gaps in the ABM modeling context. Castro et al. (2020) point out a lack in agent-based modeling of climate-energy policy. Sanders et al. (2022) and Savin et al. (2023) identify missing parts from other disciplines such as electricity market modeling. However, only few contributions have been made in the direction of concrete model designs for (macro) ABMs linking financial markets and electricity markets.[2]

The model of this paper is an attempt for improvement in this direction. Two aspects of renewable energy finance are highlighted: heterogeneity in investors and technologies, and the investment risk related to power market premium schemes.

[1] The risk aspect is especially important for energy projects which have difficulties to hedge against risk otherwise, for example through bilateral power purchase agreements (Hollmén et al. 2022).

[2] See appendix A for a more detailed literature review.

First, power generation technologies are heterogeneous and therefore need to be considered as different asset classes. Typically, macroeconomic models only separate between “clean and dirty” (or “green and brown”) technologies, blurring out the heterogeneous technological specifications of different types of power plants. For example, solar photovoltaic investments may offer relatively lower upfront costs and shorter project times compared to onshore wind power projects, whereas wind power plants may run over a higher number of hours per year (Hirth et al. 2016). The physical and technological boundaries of electricity generation naturally result in a certain degree of heterogeneity among energy investors. In addition, there can be an information asymmetry on the credit market between the investors, who are familiar with their technological parameters, and the credit lenders, who apply best-practice rules to assess project risks in a more generalized fashion. Without further financial intermediaries being engaged, this can lead to a significant mismatch (In et al. 2020). Thus, heterogeneity in energy investors and their financing strategies might induce institutional and market-related barriers for mobilizing private finance for low-carbon technologies (Barazza and Strachan 2020; Azhgaliyeva et al. 2023; Mazzucato and Semieniuk 2018).[3] As a result of variations in operational and non-operational (financing) expenditures among different investors and technologies, the cash flow of power plant projects differs from one project to another.

Second, investment risk is linked to power market support schemes and the occurrence of insecure revenue streams. Whereas most models assume an exogenous power price or a fixed feed-in premium, a typical feature employed in real-world power markets is the sliding market premium.[4] One-sided power market premium designs allow for windfall profits of renewable energy plants whenever expensive fossil power is price-setting, while securing a lower bound of revenue streams if electricity prices fall below a certain strike price. Under one-sided premium schemes, renewable energy investors must therefore account for the insecurity of acquiring excess profits or not. According to the pecking order theory of investment (Myers and Majluf 1984), when confronted with insecure future revenue streams investors will be restricted to equity-based financing and do not make use of (typically cheaper) debt-based financing or retained past earnings. This aspect is also connected to the use of project finance (PF) (Pollio 1998; Steffen 2018; Gatti 2023). The latter offers an opportunity to de-risk an investor’s balance sheet by splitting off parts of its funds to a subsidiary, a so-called special purpose vehicle (SPV). SPVs are economic entities which exist as an isolated financial frame for the underlying energy project, therefore being evaluated for their individual performance rather than the investor’s financial leverage or past performance. There are also some more intrinsic reasons for using PF, related to the organizational structure of an investment. Citizen energy projects for wind and solar are typical example for SPV architectures and high equity to debt shares, whereas most utility-scale coal- and gas-fired

[3] Because different power plant types can attract different types of investors, they also play a role in the decentralization of power and a shift toward local and regional authorities, see (Iskandarova et al. 2021; Schlindwein and Montalvo 2023; Romero-Castro et al. 2023).

[4] For example, see (Gawel and Purkus 2013; Purkus et al. 2015; Klobasa et al. 2013) for a more detailed analysis of the market premium on the German electricity market.

power plants classically make use of corporate finance (CF) (Steffen 2018). In summary, the de-risking of energy investments often results in different combinations of financing strategies (CF/PF) and debt-to-equity compositions among the heterogeneous investors, depending on the power market layout.

In order to address these two under-researched aspects, this paper considers six different power generation technologies and a stylized power market with a one-sided sliding premium mechanism. Investors and banks are matched bottom-up on imperfect financial markets in order to account for stickiness and information asymmetry. Both the PF and the CF strategy are considered.

The remainder of this paper is structured as follows: In Sect. 2, we address our model structure and equations, and the timeline of events is constructed. Further, model results for a baseline setting and two alternative scenarios with less project finance and with an additional credit easing scheme are discussed (Sect. 3). We summarize our results and discuss the potential for further research in Sect. 4.

2 Model

The model of this paper adopts two distinct levels of detail, employing stylized, representative agents for the government, central bank and rest of economy on the macroeconomic level, while utilizing microeconomically interacting agents for energy investors, SPVs and banks. Figure 1 provides a comprehensive overview of the model architecture, illustrating the relations and financial transactions between the agents, as well as the market interactions. This model uses a stock-flow consistent framework, meaning that the financial balances of agents are coherent, and liabilities of one agent are consistently treated as assets for another.[5] Investors either follow the Project Finance (PF) or the Corporate Finance (CF) strategy, conditional on the generation technology they aim to invest in. CF investors can directly invest into new power plants. PF Investors follow a more indirect strategy, as they search for project opportunities (which are represented by newly forming SPVs) via the market for equity, and invest in new power plants using SPVs as intermediaries. SPV projects and CF investors interact with banks via the credit market in order to obtain credits for new projects. The interaction dynamics influence the cost of equity and cost of debt for each individual power plant. Banks pay and receive interest and principle payments. The evaluation of new bank loans is subject to the macro-prudential regulation of the bank reserves, as well as to the risk perception of the banks about the projects to be financed. Once power plants have been built up, they are added to the supply side of the power market. When the power market is cleared, power is consumed and revenues from sales are distributed to the investors. It is important to note two dynamic properties of our model regarding the agent types and number of agents. First, investors can switch between PF and CF strategies over time, such that there is no strict separation between CF investors and PF investors. Second,

[5] Our model does not include a fully fledged macroeconomy with all economy-wide agents being explicitly modeled. Therefore, some transactions are open-ended (they never enter the system again), but these are tracked and we never violate stock-flow consistency.

the number of SPVs is growing over time, i.e., whenever an SPV is successfully launched, the old SPV exits the active market, and a new SPV enters the market.[6] The old SPV, however, remains in the simulation until the end of the project lifetime. The number of the banks is kept fixed over the entire simulation period, and defaulted banks are replaced by new entrants if necessary.

Our model is set up using Python and the (*xxx*) open-source package for agent-based modeling (*citation blinded*). Each agent represents an isolated financial entity, possessing its own balance sheet and cash flow accounting. The balance sheet matrix (Table 7 in appendix B.1) defines the asset and liability entries for each agent class. Stock-flow consistency is tracked by only making use of pre-defined, consistent transactions throughout the simulation (see Table 8 in appendix B.2 for an overview).

The following subsections address the behavioral rules for each agent class in detail.

2.1 Investors

The energy investors, indexed with j, are the core agents of the model, taking part in most of the transactions. In the beginning of the simulation, the initial deposits and credits are registered at randomly selected banks. To account for a heterogeneous starting distribution in size of the investors, the initial size of investor agents is sampled from a Pareto distribution (see appendix F for a more detailed description). The financial structure of investors changes as a result of different activities. Besides looking for new investment opportunities, investors have to provide interest and tax payments, and conduct operational efforts on existing power plant projects. Investors act on the deposit market, the credit market and the project equity market. In the beginning, each agent is assigned a favorite bank for deposits and a favorite bank for credits. It deposits all its available liquidity $D_{j,k(j)}$ on the favorite bank for deposits, $k(j)$, and will start asking for credits (accounted as financial liabilities $L_{j,k'}$) from the favorite bank $k'(j)$ for credits. However, as time evolves, the investors can select new favorite banks, and therefore the credits of investor j will be stored at a finite set of banks $\mathcal{B}_j$. This is because power plant project-related loans are not allowed to be relocated from their original bank: Re-financing does not occur and interest rates are fixed per project. Investors which are equity holders of an SPV receive a return on their investment in form of dividend payments. SPVs are registered as equity on the asset side of the investors' balance sheets. When operating power plants, a physical quantity $Y_{p,t}$ equivalent to the plant p's nominal power yield, is generated. The plant owner pays the operational costs of the plants. Finally, a fraction $\varphi_{p,t}$ of the plant's physical yield is sold at the price $\tilde{p}^{el}_t$ at the power market. The operational costs sum up to $C_{p,t}(\varphi_{p,t}, Y_{p,t})$.[7] The investors pay a fixed part θ of their positive after-tax profits $\Pi_{j,t}$ to the rest of economy agent as dividends. The remainder of profits is held on the deposit account as retained earnings.

[6] For simplicity, there is only one power plant project per SPV.

[7] The costs of a power plant are split into fixed and variable costs, see also section 2.4.

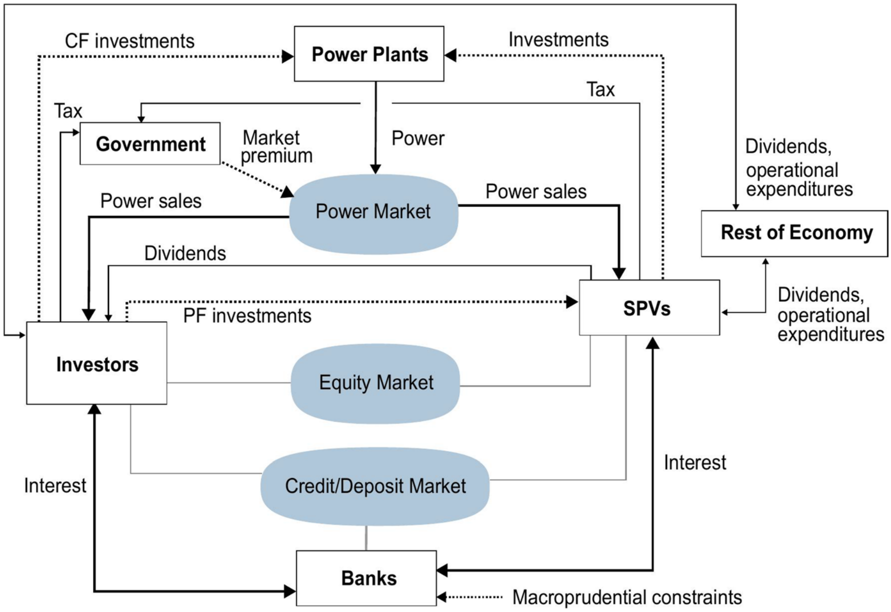

Fig. 1 Overview of the model structure. Boxes represent agent classes, blue ovals represent market interactions

In summary, the net income of an investor is composed of financing, power plant operation and taxes:

$$\Pi_{j,t} = \underbrace{r^{\delta}_{k(j),t} D_{j,k(j),t-1} - \sum_{k \in \mathcal{B}_j} \sum_{p \in \mathrm{CF}_{j,k}} r^{\ell}_{k,p,t} L_{j,p,k,t-1}}_{\text{financing}} + \underbrace{\sum_{p \in \mathrm{CF}_j} (\varphi_{p,t} Y_{p,t} \tilde{p}^{el}_t - C_{p,t}(\varphi_{p,t}, Y_{p,t})) + \sum_{i \in \mathrm{PF}_j} (E_{i,j}/E_i)\Pi_{i,t}}_{\text{power plant operation}} - \underbrace{T_{j,t}}_{\text{taxes}}$$

Here, $\mathrm{CF}_{j,k}$ denotes the set of corporate-financed power plants of investor j, with loans held at bank k, and PF_j its set of SPVs (project-financed power plant projects). The rates $r^{\delta}_{k(j)}$ and $r^{\ell}_{k,p}$ are the bank-specific rates on deposits and credits, respectively. It can be seen from Eq. (1) that the project-financed cashflows are encapsulated in the SPV structure. Corporate taxes $T_{j,t}$ are charged on positive net profits (financing and operation cash flows) at a fixed rate τ_0. Investor dividends $Div_j = \theta \max\{0, \Pi_{j,t}\}$ are paid to the rest of economy. SPV dividends are paid out to investor j from the profits $\Pi_{i,t}$ of an SPV i, depending on the quantity invested $E_{i,j}$ weighted by the total equity E_i contained in i.

Using a nested random choice experiment, investors take the decision to invest in certain technologies, choose a financing strategy and compute a suitable balancing of debt and equity. Figure 2a shows an overview of the nested decision process for investors. In this paper, it is assumed that decisions of investors are not fully rational and therefore follow immutable habits in their choice of the technology and financing structure,[8] determined using a fixed exogenous choice probability. However, the portion of debt vs. equity (D/E ratio) is endogenously linked to the power market risk. The decisions of technology and financing strategy are discrete, and the D/E ratio varies continuously. Investors plan new power plants according to the following three-step sequence. First, there is an initial decision about the technology to invest in, drawn randomly from the set of available technologies using technology-specific weighting factors. For simplicity, the relative frequency of each technology is set equal to the exogenous technology mix $\mathcal{T}$, such that the political capacity expansion target is practically internalized to the investors' technology choice τ: $P(\tau) = p_\tau$ for $\tau \in \mathcal{T} =$ {solar, wind onshore, wind offshore, lignite, hard coal, natural gas}, $\sum_{\tau \in \mathcal{T}} p_\tau = 1$ where $P(\tau)$ is the probability of choosing technology τ. The technology decision is only revised after an investor has succeeded in building a new power plant, or if it has not succeeded for a fixed number of $N^\dagger$ periods. Second, the investors' financing strategy (CF or PF) is determined. The strategy choice is conditional on the technology choice, and the probability to favor PF over CF is specified according to a simple lookup table for each of the technologies (see Table 1), reflecting the relative frequencies of project finance for a given technology[9]: $P(\mathrm{PF}|\tau) = p_{0,\mathrm{PF}|\tau}$, $P(\mathrm{CF}|\tau) = 1 - p_{0,\mathrm{PF}|\tau}$. Third, the share of equity vs. debt is endogenously determined, depending on the expected revenues of the technologies at the power market. This step also takes the market premium mechanism for electricity prices into consideration, re-evaluated in each simulation period. A detailed treatment of this decision step is given in section 2.5.1.

After this multi-step procedure, investors with the CF strategy will directly ask for loans at their current favorite bank for credits (the credit mechanism is described in Sect. 2.5.3). Once a bank accepts to issue the required credits to the investor, the power plant project is started and the required financial deposits are converted into fixed assets via a transaction with the rest of economy (where the machinery and construction service sector can be thought of). Investors with PF strategy must search for a newly opening SPV fitting their technology, transfer the required equity share and wait for the SPV to obtain a bank loan (or possibly additional equity funds), and to start the project independently (for more details see Sect. 2.5.2).

Investors operate in their normal business until their deposits turn zero: At any financial transaction demanding more deposits than available, an illiquidity bankruptcy event is triggered, in which the investor tries to restore its balance sheet. If

[8] This assumption is backed by empirical evidence about energy investors, concluding that investment decisions can be more intrinsic and irrational, see e.g., (Gamel et al. 2016; Holstenkamp and Kahla 2016) on community energy and (Frei et al. 2018) on large-scale utilities. Further decision factors could be regional differences, social responsibility and desire for local energy supply. The exogenous choice of technology and financing structure allows for an architectural design of the transition conditions by the modeler (Andersen et al. 2023).

[9] Mind that the values provided just serve as an illustrative setting and only roughly reflect the real-world situation. We therefore refrain from providing any particular policy advice and focus on the theoretical features of the model.

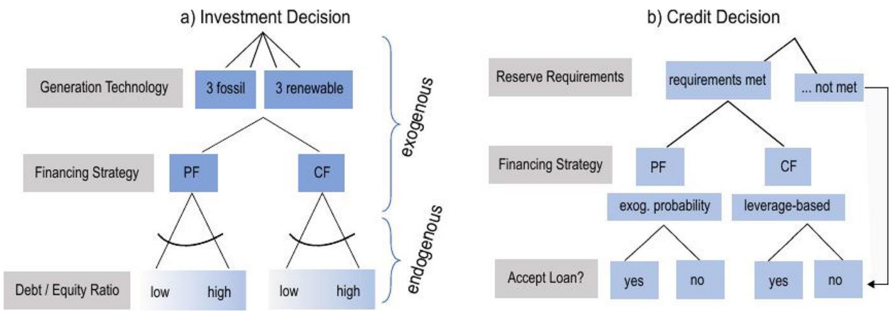

Fig. 2 Illustration of the three-step decision process of investors (**a**) and the credit granting mechanism of banks (**b**)

financing expenditures cannot be covered, the corresponding amount is registered as a bad debt loss at the bank.[10] Any negative liquidity is assumed to be cushioned by the rest of the economy. Insolvency bankruptcy occurs at negative net worth. After a bankruptcy event (either illiquidity or insolvency), the investor reconsiders its running power plant projects. From the set of running projects, investors dump existing power plants which are currently producing negative cashflows, starting at the fossil CF plants, then moving on to the renewable CF plants, and finally to the PF plants. Projects with negative cashflow are prematurely terminated. Such unconventionally terminated projects are stranded capacities and no longer contribute to the power supply. Related loans turn into non-performing loans.

2.2 Banks

Banks (indexed with k) serve as lenders for credits and are demanders for deposits. They hold both deposits of the rest of economy (subscript R, involving all non-energy finance) and the energy-specific deposits and loans. Initially, each investor is assigned a random bank for deposits and a random bank for loans, shaping the initial pools of depositors and debtors and determining the initial leverage factor of the banks (more details about the initialization sequence are given in appendix F).

Banks compete for liquidity at the deposit market, as they are obliged to hold sufficient liquidity reserves. Besides deposits, banks can obtain additional liquidity reserves in form of central bank loans C_k, such that reserves can be expressed as $R_{k,t} = D_{k,R,t} + \sum_{j \in \mathcal{D}_k} D_{j,k,t} + C_{k,t}$, where $\mathcal{D}_k$ denotes the set of depositors (microeconomic clients) of bank k. The required central bank credits are subject to the reserve requirement, such that ideally $R_{k,t} \geq \kappa_{\min} L_{k,t}$:

$$C_{k,t} = max\{0, \kappa_{\min} L_{k,t} - D_{k,t}\}. \tag{1}$$

A global and exogenous interest $r^{\star}$ is charged on central bank credits. In order to make profits, banks take the central bank rate as the lower bound for the interest

[10] For simplicity, loans, even if non-performing, remain at the bank they originate from and are not resold.

Table 1 Parametrization of the exogenous investment choices–technology mix and project finance choice probability. Source: own assumptions

	Technology Mix $P(\tau)$	PF Choice Probability $P(PF\|\tau)$
1. Solar	0.29	0.28
2. Wind Onshore	0.56	0.24
3. Wind Offshore	0.05	0.15
4. Lignite	0.0	0.0
5. Hard Coal	0.0	(0.07)
6. Natural Gas	0.10	0.02

rate on loans. The set of debtors (investors and SPVs) of bank k is called $\mathcal{L}_k$. In the standard business of a (healthy) bank, its cash flow consists of interest payments on deposits and interest payments on performing loans (i.e., excluding non-performing loans $L^\dagger$), as well as interest payments on central bank credits and government bonds. Bank k's change in cash flow can be written out as

$$\Pi_{k,t} = r^{\ell}_{k,p,j,t}\left(L_{k,R,t} + \sum_{j\in\mathcal{L}_k}\sum_{p\in\mathcal{P}_{jk}} \left(L^{p}_{j,k,t} - L^{\dagger,p}_{j,k,t} \right) \right) - r^{\delta}_{k,t}\left(D_{k,R,t} + \sum_{j\in\mathcal{D}_k} D_{j,k,t} \right) - r^{\star} C_{k,t} + r_b B_{k,t}. \tag{2}$$

where $\mathcal{P}_{jk}$ describes the set of power plants owned by investor or SPV j, financed at bank k. $L_{k,R,t}$ and $D_{k,R,t}$ are the credits and deposits held in the rest-of-economy sector. For simplicity, profits are retained within each bank and not further distributed. Banks can influence their market shares by adjusting the deposit and credit rates offered at the financial markets. Each bank has an idiosyncratic perception about its strategic position in the markets and therefore offers individual interest rates on loans (r^{ℓ}_k) and deposits (r^{δ}_k). Interest rates are periodically adjusted at the financial markets, and only count for the current period t. However, if a power plant is financed at time t', its owner receives a fixed interest rate $r^{\ell}_{k,t'}\ \forall\, t \in [t', t' + (T-1)]$ on credits throughout the lifetime T of the project for this project-related loan. In contrast, at later points in time, an investor or SPV will not be guaranteed the same interest rate from its favorite bank for further projects, and will instead be offered a new interest rate for each follow-up period, depending on the banks' dynamic changes. Therefore, agents are constantly in search of banks offering a better interest rate than the current favorite bank, inducing competition among banks. An analogous rule holds for deposits—if agents find a bank offering higher interest on deposits, agents decide to shift all their deposits to this new bank. More details about the financial markets are given in Sect. 2.5.3.

Figure 2b shows the two-step decision procedure of banks when evaluating requests for new credits. It involves the following steps:

1. In the first step, the bank determines its own ability to issue further credits. It computes its capital adequacy ratio ($\kappa_{k,t} = R_{k,t}/L_{k,t}$) and continues to the second step if reserves are sufficient ($\kappa_{k,t} \geq \kappa_{\min}$).

2. In the second step, the bank distinguishes between corporate-financed and project-financed credit requests. It does so by investigating the financial leverage of the applicant. Figure 3 shows a typical balance sheet of an energy investor. Whereas the PF-financed part on an investor's balance sheet is not further regarded in more detail (it is hidden in the SPV), the corporate loans related to preexisting CF projects are classified as risky. Requests of SPVs for project-financed plants are therefore simply accepted at a probability p_0 as a rule of thumb followed by the banks, however, for corporate loans, the evaluation is more complex and a calculation of the investor's default probability p_d takes place. $p_d(j)$ is calculated as a function of investor j's financial leverage[11]:

$$p_d(j) = 1 - \varrho_1^{L'_j/(D_j+L'_j)}. \tag{3}$$

In the latter equation,

$$L'_j = L_j + (1 + \varrho_2(r^* + r^\ell_k))\Delta L \tag{4}$$

represents both the current loans and an additional weighted term based on the amount of the new loans and the current bank-specific rate r^ℓ_k. In summary, a credit is accepted at probability p_0 for PF projects and at probability $1 - p_d$ for CF projects.

3. If the credit is accepted, the interest rate is computed as the bank-specific interest rate, plus an investor-specific risk mark-up (which is equal among all banks). In the PF case, this mark-up is zero, whereas CF investors' mark-ups are equal to $r^\ell_{k,j} = r^\ell_j = \varrho_3 \cdot \left(L_j/(L_j + D_j)\right)^\lambda$, such that finally the project-specific interest rate offered amounts to

$$r^\ell_{k,p,j} = r^* + r^\ell_k + r^\ell_j \tag{5}$$

where r^* denotes the central bank base rate. The general pattern behind the functional form of Eqs. (3–5) parametrized by $(\varrho_1, \varrho_2, \varrho_3, \lambda)$ is that increasingly leveraged investors exhibit high default probabilities, and even if they are granted a credit, they are charged a risk mark-up on the interest rate to hedge against bankruptcies. Whereas the higher default probability directly affects an investor's ability to access new credit, the mark-up on interest rate worsens the financing conditions for debt.[12]

As a consequence of the shifts in the financial market (changes in deposits and loans), banks need to adjust their reserves. If a bank has more reserves than required by the macro-prudential regulation, it first sells a fraction of its central bank credits, then buys new government bonds B_k (yielding interest payments r_b), and finally

[11] We omit the time period index t for better clarity of the equations.

[12] The nonlinear functional form influences discriminative power of the banks' mechanism to determine whether a firm is well-performing or prone to default. We leave the exploration of different credit ratings or functional forms of p_d and $r^\ell_{k,j}$ to future research.

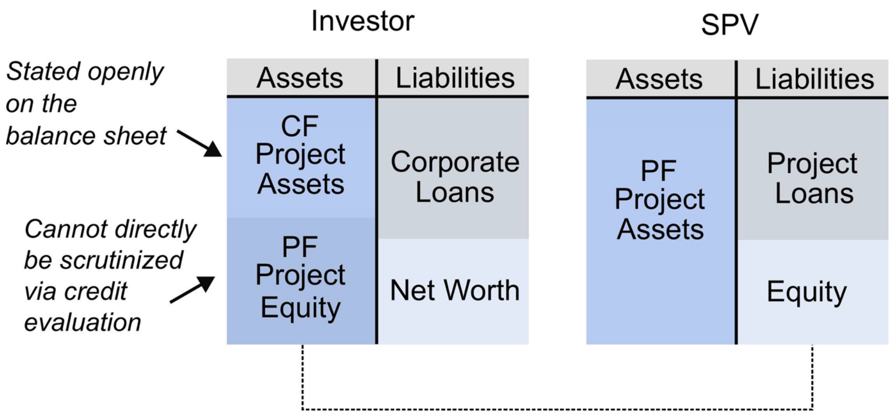

Fig. 3 Left: Overview of a typical balance sheet of a power plant investor, containing both project-financed (PF) and corporate-financed (CF) assets. Right: balance sheet of a special purpose vehicle (SPV) isolating a part of the project assets

issues new loans to the rest of economy.[13] In turn, if the bank has less reserves than required, it first sells parts of its bonds and secondly purchases an amount of new central bank credits equal to a certain fraction of missing reserves. As banks use adaptive rules, they cannot instantly fix their reserve requirements but manage the amount of reserves gradually over time.[14]

For simplicity, throughout the simulation, the number of banks is held constant, and bank losses are not forwarded to the non-financial system. At some point, certain poor-performing banks will reach negative net worth (this case has no further consequences). If a bank reaches negative liquidity reserves (due to non-profitable business activity and/or large-scale bank runs of depositors), it goes bankrupt and exits the market. It is then replaced by a new entrant to keep the number of banks in the simulation fixed. The new bank inherits the client network of the old one, and receives a starting capital equal to the net worth of the smallest bank at the beginning of the simulation. The negative reserves are cushioned by the banking system, where the contribution of each bank is weighted by the size (net worth) of the bank. If the excess reserves of the banking system are not sufficient to cover the starting capital, the government takes up new debt to cover the expenses.

[13] Bonds not held by the bank are bought by the central bank. For simplicity, we set $r_b = 0$ for our simulations, and do not include yield curves or any other temporal dimension.

[14] The exact parameters are given in appendix C.

2.3 SPVs

In the initial phase of their existence, Special Purpose Vehicle (SPV) agents can be thought of as empty frames for future power plant project opportunities.[15] Within each SPV, a technology is determined from a random choice experiment, in complete analogy to the investors' technology choice, and computations are conducted about how much debt and equity is needed to secure the investment.[16] SPVs start by collecting funds from investors on the equity market until they reach the required level of equity from which the project can start (see 2.5.2 for a detailed description of the market protocol). Subsequently, they apply for a loan at their favorite bank for credits. In each period in time, all new SPVs attempt to invest in a power plant. If enough funding is available and if the SPV has successfully acquired a bank loan, the project is launched and the SPV is moved to the list of actively running SPV agents, blocking its availability for further investments. Otherwise, the SPV keeps searching for further investors. If this process remains unsuccessful for $N^{\dagger}$ periods, the agent decides to re-consider its investment choice (technology and equity ratio).[17] To match the relative frequency of target technologies in investors, SPVs use the same probability weights as corporate investors for the choice of technologies.[18] Random combinations in technology choice between SPVs and investors introduce a certain difficulty for the SPV agents to find appropriate investors matching their technology, but might allow for a quick debt financing once the investors are set up because PF projects are not evaluated by financial leverage. In contrast, corporate investors might encounter difficulties in finding appropriate banks or in receiving a loan at their favorite bank, but do not face the matching barrier with SPVs. The cash flow of SPVs is similar to the investors; however, SPVs only contain at most one power plant as a fixed asset for simplicity. Net profits are paid out to the project shareholders $\mathcal{S}_i$ (after taxes), weighted by the relative share of equity provided by each shareholder.[19] The net income of an SPV reads

$$\begin{aligned}\Pi_{i,t} = & \underbrace{r^{\delta}_{k(i)} D_{i,k(i),t-1} - r^{\ell}_{k'} L_{i,k'(i),t-1}}_{\text{financing}} \\ & + \underbrace{\varphi_{p,t} Y_{i,t} \tilde{p}^{el}_t - C_{i,t}(\varphi_{p,t} Y_{i,t})}_{\text{power plant operation}} - \underbrace{T_{i,t}}_{\text{taxes}} .\end{aligned} \tag{6}$$

[15] In the real world, these entities can be imagined as a newly opened generation site, a new citizen initiative or just a regular business opportunity. Project developers have specialized in setting up SPV-like financing structures for a large class of power plant projects (Mohamadi 2021).

[16] Sect. 2.5.1 provides a more in-depth treatment of the equity ratio calculations.

[17] For simplicity, the SPV does not return the previously collected equity, and is allowed to switch the target technology.

[18] The mechanism for SPVs is the same as for investors, but technology weights of SPVs are multiplied with the PF choice probability because SPVs only engage in PF investments.

[19] Mind that this creates a gap between expected and actually realized shareholder dividends. The perception of PF investors about expected revenues is therefore technically only relevant in the market matching success on the market for project equity.

Here, $D_{i,k(i)}$ are the deposits at the favorite bank $k(i)$ of the SPV for deposits, $L_{i,k'(i)}$ are the project-specific loans at the favorite bank $k'(i)$ for loans, and $\varphi_{i,t}$ is the share of generated power sold at the power market. The operational costs $C_{i,t}(Y_{i,t})$ are evaluated identical to the corporate investors. As SPVs are only financial vehicles, net profits of each SPV are forwarded to the equity shareholders, weighted by their relative investment volume: $Div_{i,t} = \sum_{j \in \mathcal{S}_i} (E_{i,j}/E_p)\Pi_{i,t}$. Taxes $T_{i,t}$ are charged on any positive profits at the same rate τ_0 as for CF investors.[20]

2.4 Power plants

Power plants (index p) represent physical electricity generation sites. Running power plants are registered as fixed (non-financial) assets of the agent owning the plant (an investor or SPV, power plants are owned by exactly one agent each). Further, each power plant is specified by the generation technology (solar, wind offshore, wind onshore, lignite, hard coal or natural gas), the amortization time (lifetime) of the project,[21] the full-load hours, the exogenous capacity (identical for all units of the same technology) and operational expenditures (fixed and variable). The starting time of a power plant p is denoted $t_0(p)$. Each plant has a fixed capacity factor ($\tilde{Y}$), and its size is set to a standard capacity $\hat{K}$ which is identical for all units of the same technology, such that its physical power yield $Y_{p,t}$ amounts $Y_{p,t} = \tilde{Y}_p \cdot \hat{K}_p \varphi_{t,p}$. The generation costs associated with this yield are $C(\varphi_{t,p} Y_{p,t}) = C^{var}_{p,t} \varphi_{t,p} Y_{p,t} + C^{fix}_{p,t}$. After each discrete time period, one power generation process takes place in the power plants, revenues of each plant are computed. The net cash flow of a power plant project is given by revenues minus operational and financing expenditures

$$V_{p,t} = Y_{p,t} p^{el}_t - C(\varphi_{t,p} Y_{p,t}) - r^{\ell}_{k,p,t} L_{p,t} \tag{7}$$

where L_p denotes the total outstanding debt of the project.[22] Congestion of power might occur, albeit unsold power is not assigned any additional cost beyond fixed operational costs and financing costs in this model.[23] Mind that renewable plants, once built, are close-to-zero marginal cost producers, whereas fossil plants have to deal with high variable operational costs for each additional marginal unit of power produced. Technology specifications are detailed out in the appendix (Table 11).[24] The factors $\varphi_{t,p} \in [0, 1]$ depend on the merit order in the power market and are explained in Section 2.5.1.

[20] Note that the dividends paid to the investors can be both positive and negative, depending on the power price level and the various financing factors. Therefore, there is no bankruptcy condition for the SPVs as there is for energy investors or banks.

[21] In this model, power plant lifetimes exceed the temporal scope of the simulation. Project lifetimes can therefore be thought of as close to infinity.

[22] Debt is re-paid in every period according to a standard annuity scheme, i.e., the annuity due in period t is $L_{p,0}(1-(1+r)^{-T})/((1+r)^{t-1}r)$ with $L_{p,0}$ being the initial credit volume, r being the credit rate and T representing the number of periods the power plant runs (the project lifetime).

[23] Renewable energy is highly variable throughout a weather year (Tong et al. 2021). However, this is of minor importance for investments going over maturities of many years or decades, potentially averaging fluctuations. We leave the investigation of resilience to extreme weather events to future research.

[24] This paper highlights the theoretical modeling aspects of the energy sector. The exact choice of parameters tailored to a specific real-world situation is left to future research.

2.5 Markets

In the model of this paper, agents are matched bottom-up on decentralized financial markets. The financial market matching protocols for deposits, credits and equity organize a one-on-one random matching of supply and demand agents, where each agent has only access to a limited pool of matching partners. This results in bipartite networks (Namatame and Chen 2016) for credits and deposits, which do not rely on an equilibrium assumption and allow for information asymmetry and heterogeneous interest rates. Table 2 shows the supply and demand side of each market employed in the model. The power market works different from the financial markets and determines the power price level in each period (see Sect. 2.5.1). The project equity market for matching PF investors with SPVs is addressed in Sect. 2.5.2. The financial markets for credits and deposits are explained in Sect. 2.5.3.

2.5.1 Power market

The power market operates as a clearing house for physical units of electricity. Figure 4a shows a demand-supply diagram for this market. Just as in any economic market, the power market aims at matching supply and demand, the latter being exogenously fixed, as represented by a vertical line.[25] The power market mechanism serves two purposes: It determines the price of electricity p^{el} and it determines the functions $\varphi_{t,p}$ for each power plant, indicating the ratio between the maximum output and actual amount of electricity sold.

Clearing Protocol To determine a base price, the long-term price level is computed as a linear function of the renewable generation share. This effect is known as the long-term merit order effect (Sensfuß et al. 2008). Whenever the residual load (the amount of fossil supply) is low (cf. Figure 4b), the supply curve is shifted toward the right, resulting in lower clearing price levels compared to situations with little renewable feed-in (cf. Figure 4a).[26] The concept of merit order refers to the sorting of power plants on the supply side in a discrete pecking order—power plants are first sorted, and power supply is additively accumulated, beginning with the first plant, until the physical demand is fulfilled.

The detailed sequence of events is as follows:

1. All power producing plants are sorted by the merit order rank, depending on their technology, in the following order: solar, wind onshore, wind offshore, lignite,

[25] There is improvement potential for future modeling at this point. Changes in production level, production efficiency of energy intensive firms and changes in energy import rates might provide a moderate elasticity in demand, slightly deviating from a vertical line.

[26] Mind that in real-world power markets, this is typically a short-term effect. The long-term merit order hypothesizes that this effect is transferable to wider time horizons. One simulation period in this model can be considered mid- to long-term in this respect.

hard coal, natural gas.[27] This yields the actual, discrete supply curve (gray areas in Fig. 4a, b).

2. Iterate over all plants. The potential electricity supply of a plant p is given by $Y_p^\star = \tilde{Y}_p \cdot \hat{K}_p$. The maximum needed generation capacity $Y_p = \max(L - \hat{Y}_p, 0)$ is computed for each plant, where L denotes the exogenous power demand (load) and $\hat{Y}_p$ the cumulative electricity production of all plants with higher rank than p. The load factor results in $\varphi_{t,p} = Y_p / Y_p^\star \in [0, 1]$.
3. Repeat the process until the demand is met or no plants are left.[28] The resulting clearing price in each period t is approximated as a linear function

$$p_t^{el} = \beta_0 - \beta_1 \psi_t \tag{8}$$

where $\psi_t = (\sum_{\mathrm{RE}} \varphi_{t,p} Y_p^\star)/L = Y_t^{RE}/L$ is the overall share of renewable energy provided. Here, β_0 corresponds to the marginal cost of the most expensive fossil power plant in the system, and β_1 determines the strength of the long-run merit order effect.

To refine the power price dynamics, short-term price fluctuations are added by a mean-reverting stochastic process (see Sect. E.1 for more details). All plants with $\varphi_{t,p} > 0$ are assigned the market value p_t^{el} for this period (the remaining plants have zero market value because they are not required).

Market Premium and Ratio of Equity We expect from the long-term merit order effect that the investments in renewable generation technology will lower the power price level. This, however, can be a possible burden for investors as the expected profits from power sales gradually decrease over time. In order to support the renewable energy investors, a sliding premium is employed. This sliding premium can be thought of as a financial option contract, granting at least a minimum strike price $S_{\tau,t}$, such that the effective selling price for renewable plants is never below this bound. Fossil generation is not included in this premium scheme. The effective price results in

$$\tilde{p}^{el} = \begin{cases} p_t^{el} & \text{if } \tau \in \{\text{lignite, hard coal, natural gas}\} \\ \max(S_{\tau,t}, p_t^{el}) & \text{if } \tau \in \{\text{solar, wind offshore, wind onshore}\} \end{cases} \tag{9}$$

where $S_{\tau,t}$ is a value which depends on the respective technology τ and p_t^{el} denotes the (wholesale) clearing price without market premium. Figure 4c schematically depicts the relation between the project value of renewable power plants and the composition of debt and equity. In contrast to the fossil counterparts, renewable electricity is generated at very low marginal costs, such that their market value (their selling price at the power market) tends to be low in times of high shares of renewable energy and high whenever expensive fossil plants are in the market alongside. If there is no premium, renewable power plants make high revenues if power prices are

[27] The order in this model is fixed. We sort plants by technologies in analogy to marginal generation costs. Within groups of power plants possessing the same rank, plants are randomly shuffled.

[28] In case there are no plants left (which does not happen in the scenarios analyzed in this paper), it can be assumed that energy imports are used to cover the remaining load.

Table 2 Overview of the markets in the model and mapping of supply and demand

Market	Supply	Demand
Deposits	Investors, SPVs	Banks
Loans	Banks	Investors, SPVs
Project Equity	Investors	SPVs
Power	Power Plants	Rest of Economy (fixed)

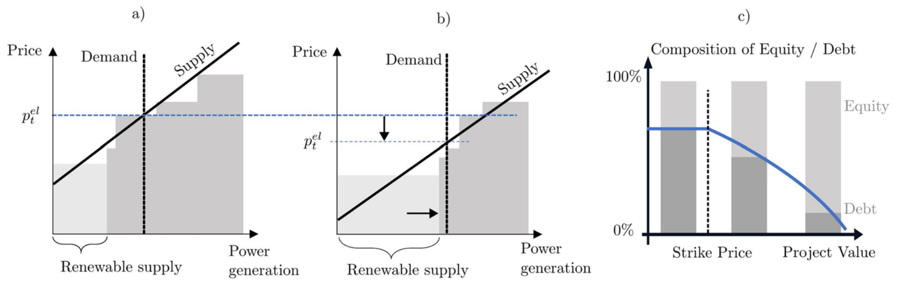

Fig. 4 Left: Power prices when the renewable energy supply is low (**a**) and high (**b**). The gray areas indicate the supply curve. Right: Composition of debt and equity as a function of the market value of a project relative to the strike price (**c**)

high and close to zero revenues if power prices are low. With the premium active, plants can theoretically receive revenues with no upper bound, but the minimum revenues are secured. Any positive difference between strike price and market value is paid by the consumer (here: rest of economy). This ensures the profitability of renewable power plants, even under permanently high shares of renewable energy and thus low power price levels. If the expected revenue of a power plant is higher than the level of the strike price S, excess revenues occur. Under the assumption that banks are fully risk-averse with respect to the financing of renewable energy projects, such additional fluctuations in revenues have to be backed using equity instead of conventional bank debt (due to the pecking order theory of capital, see Myers and Majluf (1984)). The equity required for a project under a sliding market premium is therefore equal to the uncertain additional revenues beyond S, which can be also interpreted as a minimal risk level. The required equity is mathematically given by the expectation value of revenues higher than the strike price.[29] Here, it is assumed for simplicity that all power plants receive the market premium, and the strike price is set equal to an equilibrium value, which is obtained by requiring that the premium can just cover the technology costs.[30] Therefore, S is chosen optimally by the government such that the investment I can be on average covered from the sum of debt and equity:

[29] For a more rigorous mathematical treatment see appendix E.2.

[30] The real-world strike price is auctioned between a state institution and the investors. The implementation of the actual coordination mechanism to determine S if left to future research.

$$S_{\tau,t} = \operatorname{argmin}_{S'_\tau} \left| I_\tau - (D_t(S'_\tau) + E_t(S'_\tau)) \right| \tag{10}$$

$$\text{s.t. } D_t = f(\tilde{Y}_\tau (S'_\tau - C_{\text{var},\tau}) - C_{\text{fix},\tau}, \langle r^\ell \rangle_t, \langle r_e \rangle_t) \tag{11}$$

$$\text{s.t. } E_t = g(\tilde{Y}_\tau, S'_\tau, \phi_\tau, \langle r_e \rangle_t) \tag{12}$$

where the expected level of debt D and equity E depends on the distribution of expected market values for a technology τ. For solving this optimization problem, the method developed by Neuhoff et al. (2022) is used.[31] The intuition is that the strike price is chosen such that renewable power plants can raise sufficient debt to cover their operational costs, where a technology-specific optimal output $\tilde{Y}_\tau$ is assumed, derived from the annual load hours of the technologies included (see Table 11 in the appendix).[32] The constraints f and g incorporate the average financing conditions in the economy, i.e., the average equity rate $\langle r_e \rangle_t$ and credit rate $\langle r^\ell \rangle_t$ of all investor, SPV and bank agents (see appendix E.2). Further, the distribution of expected market values ϕ_τ beyond the strike price S is included in the calculation for the fraction of equity (constraint g). Note that E_t rises as market values grow and D_t increases with increasing strike price. Therefore, at higher market values relative to the strike price, the expected share of equity for investments rises, as schematically depicted in Fig. 4c.

Once the strike price is set by the government, investors compute their individual levels of debt and equity using their idiosyncratic financing conditions $r_{e,j}$, as well as r^ℓ_j and S_τ such that $D_{j,t}(S_{\tau,t}, r_{e,j,t}, r^\ell_{j,t})$ and $E_{j,t}(S_{\tau,t}, r_{e,j,t})$ fluctuate around the equilibrium assumption in Eqs. (11) and (12) for each investor j as a consequence of the financial market imperfections. SPVs follow the same systematic, using the average equity rate of their envisaged shareholders.[33] The equity rate is obtained from the expectation value formed by the investors, i.e., $r_{e,j,t} = \mathbb{E}_t[r_e(j,\tau)]$, as will be further elaborated in Sect. 2.5.2. For their perception of r^ℓ_j, investors take only their current favorite bank into account.

2.5.2 Project equity market

In order to collect equity, SPVs have to find suitable investors on the market for project equity. PF investors compete for SPVs by stating their desired shareholder return (return on equity), based on their expectations. The expected return rate on

[31] A more in-depth treatment of this algorithm is given in appendix E.2.

[32] The parameter $\tilde{Y}$ has a constant value, related to the optimal operation modes of each technology, rather than the actually obtained market shares at the power market. It therefore differs from φY mentioned earlier in this section. It is obtained by dividing the average annual full-load hours of a technology by 8760 (number of hours per year), see Table 11.

[33] It is ensured at all times that the optimization objective is always close to zero, such that $D(S_\tau) + E(S_\tau) = I_\tau$ holds within very small numerical errors. The fluctuations in debt and equity used for financing can therefore be solely attributed to the imperfections on the financial market.

equity $\mathbb{E}[r_e(j,\tau)]$ of investor j for a technology τ is computed using a capital asset pricing model (CAPM, cf. Gatti (2023), Kitzing and Weber (2014)), such that investors can gauge the relationship between risk and return:

$$\mathbb{E}_t[r_e(j,\tau)]' = r_f + \beta_j^e \cdot \max\{0, \mathbb{E}_t[r_{j,\tau}^m] - r_f\} \tag{13}$$

$$\mathbb{E}_t[r_e(j,\tau)] = \alpha_e \mathbb{E}[r_e(\tau)]_0 + (1-\alpha_e)\mathbb{E}_t[r_e(j,\tau)]' \tag{14}$$

where $r_f = r_b$ denotes a risk-free rate.[34] The expected market return rate $\mathbb{E}_t[r_{j,\tau}^m]$ at the equity market for technology τ is approximated by the net cumulative cash flow $\tilde{V}_{p',t} = \sum_{t'=t_0(p')}^{t} V_{p',t'}$ divided by the invested capital E_p', averaged over all existing power plants $p' \in \mathcal{P}_\tau$ of this technology,

$$\mathbb{E}_t[r_{j,\tau}^m] = \frac{1}{|\mathcal{P}_\tau|} \sum_{p' \in \mathcal{P}_\tau} \tilde{V}_{p',t} e^{-\delta_m a_{p'}} / E_{p'}, \tag{15}$$

weighting the power plants according to their age $a_{p'}$. Hence, $\mathbb{E}_t[r_{j,\tau}^m]$ varies over time as the values for V_p' change over time. Investors are conservative in their expectation formation, weighting the currently perceived return rates on equity (Eq. 13) with their intrinsic beliefs $\mathbb{E}[r_e(\tau)]_0$, as included in Eq. (14). The (levered) equity beta β_j^e is linked to the asset beta β_j^a via the following equation:

$$\beta_j^e = \beta_j^a \left(1 + (1-\tau_0)\left(\frac{D_j}{E_j}\right)^*\right) \tag{16}$$

where β_j^a is the asset beta factor assigned to investor j.[35] This parameter reflects heterogeneity in asset classes (technical designs, regional effects etc.). Equation (16) considers that interest payments can be deducted from tax, and therefore the targeted debt-to-equity ratio $(D_j/E_j)^*$ and the corporate tax rate τ_0 must be taken into account.[36] The market matching protocol brings together supply and demand in the following sequence of events:

---

[34] The 10-year government bond yield is typically used in practice. In our model, we assume a constant value.

[35] β_j^a is re-assigned from a uniform distribution $u \sim (\beta_{\min}^a, \beta_{\max}^a)$ each time an investor redecides the target technology.

[36] For simplicity, investors are conservative in their expectations and assign $(D/E)^* = (1-\alpha)/\alpha$ as a fixed proxy factor, α being the minimum required equity share of a project. This also avoids a circular dependence between the level of equity used and the expected return on equity. Although in our model, the assumptions underlying the capital asset pricing model are not entirely fulfilled—for example there is no fully efficient market and no full rationality—investors have this formula at hand when it comes to estimating the return on equity they expect from their power plant investments. Therefore, our model reflects a certain limited rationality of the market actors who do not fully take advantage of their individual market situation, but rather tend to apply common-practice decision making.

1. Iterate over a subset of SPVs with relative size $0 \leq \chi_E \leq 1$, randomly selected from the demand pool. For each SPV, a new random subset of relative size χ_E of investors (equity suppliers) is matched.
2. Out of the random subset of investors seen by an SPV, the best investor candidates are chosen using the following systematic:

   - Investors with matching technology choice are selected as suitable candidates.
   - Second, those investors are filtered who provide sufficient financial means to fully meet the entire demand, given by the SPV's target equity, considering preexisting funds of the SPV already collected earlier. If there are suitable candidates, the best match is chosen according to the lowest expected return on equity of the investor.
   - If no single investor meets the criteria to support funds on its own, the market algorithm attempts to fill up the SPV's demand by attempting to create a joint venture from smaller investors, accumulating their potential equity supply until the demand is met, or until the pool of supply agents is exhausted. These smaller investors are selected at random from the available pool.

It is worth noting that the SPVs cannot directly choose among investors, but can only send applications to their favored matches. Investors will then go through their offers in chronological order and put their funds into the joint venture (or possibly single venture).[37] In order to avoid overly lumpy investments, investors are only allowed to put at maximum a share of ξ_E of their available deposits into one SPV at a time. Further, an SPV can only request up to $\hat{N}$ investors per market clearing round. After obtaining sufficient funding in terms of shareholder equity, the SPV will apply for a bank credit in order to obtain the required remaining funding from debt. As soon as the SPV receives a credit via the credit market, the SPV purchases a power plant at the rest-of-economy agent and starts operating the power plant (which is assumed to be available immediately after, i.e., at zero construction time).[38] If the searching of the SPV is not successful for a period of $N^{\dagger}$ periods, the SPV redecides its investment choice and target technology. This decision is in full analogy to the random choice experiment of the corporate investors.

2.5.3 Deposit and credit market

The main idea of the deposit and credit market is that banks alter their offered interest rates in order to expand their business and regulate their attraction toward potential clients.[39]

[37] This mechanism is similar to the "brochure mechanism" of the Schumpeter Meeting Keynes model, see Dosi et al. (2010).

[38] The rest of economy agent can be thought of as providing machine parts to construct the power plant. Also, planning and construction times can significantly delay the renewable capacity expansion. This aspect will be included in future versions of the model.

[39] The deposit and credit market are similar, but not fully identical to the matching protocols of Riccetti et al. (2015).

Deposit Market On the deposit market, banks are demanders, and investors and SPVs are matched from the supply side. As a result of the matching, depositors find new favorite banks for deposits. Banks are initially assigned a random value $r^{\delta}_{k,0} \in u(r^{\delta}_{min,0}, r^{\delta}_{max,0})$ as their current offer for the interest rate on deposits. When re-matching the deposit market, the sequence of events is as follows:

1. A random subset of size $0 \leq \chi_D \leq 1$ relative to the total number of demand agents (banks) is drawn. The selected banks update their offered deposit rates. Banks prefer attracting deposits over central bank loans, as the interest rate on deposits is by design lower than the interest rate on central bank loans. As a consequence of competition to other banks, each bank tries to set the interest rate on deposits as low as possible and as high as necessary to attract depositors. Thus, if liquidity requirements are not met, i.e., $R_{k,t} < \kappa_{\min} L_{k,t-1}$, or if there is not more than one client, the bank aims at attracting more depositors. This mechanism works also in reverse: lowering the interest rate will dis-incentivize depositors from choosing this bank. Also, if the deposits just match the reserve requirements, the banks increases the interest rate to be able to expand its liquidity available for new loans in the next period:
$$r^{*\delta}_{k,t} = \begin{cases} r^{\delta}_{k,t-1}(1 + u(0, \alpha^{\uparrow}_{d})) \text{ if } R_{k,t-1} \leq \kappa_{\min} L_{k,t-1} \text{ or } N_{\text{clients}} <= 1 \\ r^{\delta}_{k,t-1}(1 - u(0, \alpha^{\downarrow}_{d})) \text{ if } R_{k,t-1} > \kappa_{\min} L_{k,t-1} \text{ and } N_{\text{clients}} > 1 \end{cases} \tag{17}$$
   The interest rates on deposits move between the legs $(\bar{r}^{\delta}, r^{\star})$ with $r^{\delta}_{k,t} = min(r^{\star}, max(\bar{r}^{\delta}, r^{*\delta}_{k,t}))$. $\alpha^{\uparrow}_{d}, \alpha^{\downarrow}_{d}$ are learning speed parameters for the upward and downward adjustment of deposit rates, and $u(0, x)$ is a uniform random value between 0 and x.
2. We loop over suppliers in a randomly drawn subset of relative size $0 \leq \chi'_D \leq 1$. Each depositor in this subset is randomly assigned a pool of banks with relative size χ_D. Banks in this subset are sorted according to their interest rate on deposits. The bank with the highest rate wins. The supplier will transfer all its deposits to the bank with the highest offered rate if the rate is at least as high as the current rate. Otherwise, the old bank is kept.

The protocol just outlined is processed separately in a market for investors and a market for SPVs. Despite this separation, the deposit market does not further distinguish between SPVs and investors. After the market clearing for the micro-economically modeled agents, the deposits in the rest of economy are shifted. Each bank is compared with a number N_m other banks at random. A share η^R_D of the economy's deposits is transferred from the current bank to the bank offering the best conditions in the subset (if different from the current bank). The number of clients of each bank is equal to the number of depositors in the current period.

Credit Market The credit market mechanism is similar to the deposit market. Banks are initially assigned a random value $r^{\delta}_{k,0} \in u(r^{\ell}_{min,0}, r^{\ell}_{max,0})$ as their current offer for the interest rate on credits. The sequence of events of the market protocol is as follows:

1. A random subset of relative size $0 \leq \chi_C \leq 1$ is selected from the banks, who are allowed to adapt their interest rates, based on the past experience. The interest rate on loans is adjusted as follows:

$$r^{\ell}_{k,t} = \begin{cases} r^{\ell}_{k,t-1}(1 - u(0, \alpha^{\downarrow}_{\ell})) \text{ if } r_{s,k} < \langle r_s \rangle \text{ or } R_{k,t-1} \geq \kappa_{\min} L_{k,t-1} \\ r^{\ell}_{k,t-1}(1 + u(0, \alpha^{\uparrow}_{\ell})) \text{ if } r_{s,k} > \langle r_s \rangle \text{ and } R_{k,t-1} < \kappa_{\min} L_{k,t-1} \end{cases} \tag{18}$$

   using the up- and downward adjustment speed $\alpha^{\uparrow}_{\ell}, \alpha^{\downarrow}_{\ell}$ for the credit rate. The interest rate of a bank k is raised if the matching success rate $r_{s,k}$ of this bank is larger than the average matching success rate $\langle r_s \rangle$. If the success rate is relatively low, or if there is enough liquidity present in the bank, the interest rate is lowered in order to attract new credit takers.
2. A subset of relative size $0 \leq \chi'_C \leq 1$ is randomly drawn from the demand set. We loop over each investor/SPV in the demand set. Demanders which have nonzero demand for credits are filtered out. For all remaining demanders, a random subset, of relative size χ_C each, is drawn from the supply set. The bank offering the lowest interest rate in this subset is chosen as a potential candidate. The investor/SPV changes to the candidate bank as a new favorite bank for credits if its credit rate is below the investor's current credit rate, i.e., the rate it would obtain for a new credit a the current favorite bank.

   If this is the case, it is a success for the new bank and a failure for all remaining banks in the visible subset. Otherwise, a matching failure for the entire subset is registered.

The credit market matching success rate is determined by dividing the number of successes of banks by the sum of successes and failures in the past five simulation periods. In equivalence to the deposit market, there is a separate credit market for investor and SPVs. After the market clearing for the microeconomically modeled agents is done, the credits of the rest of economy are updated in full analogy to the rest-of-economy deposit market. Here, a share η^R_L of credits is relocated if one in the randomly selected N_m other banks considered offers a lower or equal credit rate.

The market activities for deposits and credits lead to a heterogeneous distribution of deposit and credit rates, and agents are not able to observe the whole market in a simulation period.

2.6 Sequence of events

Before the actual simulation, an initialization sequence takes place. This involves the following steps[40]:

[40] Macroeconomic agent-based models typically require a 'burn-in' phase, in which the quasi-steady state is reached beginning from a roughly posed parameter set. We try to keep this phase short by experimenting with different theoretical ranges of parameters.

1. Agents and their corresponding balance sheets are set up in a consistent manner.
2. An initial power generation mix is set up.[41]
3. Market links for credits and deposits are initialized: In the beginning, favorite banks for investors and SPVs are completely random.

After the initialization has taken place, the main model loop is iterated:

1. Each investor (SPV) receives revenues from last period's business and pays dividends to the shareholders (rest of economy or the parent investor)
2. The power market clears and strike prices are updated. Each power plant updates its production yield for this period.
3. Power plants update their cash flows from power generation (revenues net generation costs). New expectations about the market return are formed.
4. The markets for deposits, credits and project equity clear.
5. PF and CF Investors try to invest in new power plants, SPVs apply for loans at the banks.
6. Cash flows from taxes and interest payments are updated.
7. Banks attempt to repair their reserves by buying or selling central bank loans, bonds or loans from the rest of economy.
8. Bankrupt investors and banks are restored.

Each model run consists of a total of 1000 simulation periods.

3 Results

The purpose of this section is to study the simulation output and to check some qualitative stylized facts. Subsection 3.1 starts by showcasing two representative baseline model runs. Additionally, to illustrate the statistical properties of our results, we present the outcomes of 100 Monte Carlo simulations. Subsection 3.2 continues with the analysis of two alternative scenarios, in which the impact of a lowered probability of project finance, as well as an enhanced green credit granting probability (green credit easing) are investigated.

3.1 Baseline model

In the baseline setting, the economic system is set up such that most of the model dynamics, like e.g., the credit rate or the investor failure rate, are in a quasi-steady state.[42] Two independent runs of the model are observed in order to give an intuition

[41] These initial power plants are not owned by the investors but are exogenous. Their revenues and losses are forwarded to the rest-of-economy agent.

[42] Albeit there are empirically reasonable parameters included, the model is not calibrated to fit any particular empirical statistics or historical data. We leave this task to future research. See (Fagiolo et al. 2006, 2019; Lamperti 2018; Vandin et al. 2021) for a treatment of calibration methods for agent-based

about the model output and to sketch the possible variation among model runs. The analysis of the results follows a two-step procedure. First, the functioning and stability of the financial markets, as well as the resulting financing conditions for power plant investors is investigated. Second, we inspect the number of capacity additions for electricity generation, the transition of power mix toward renewable power plants and the evolution of power prices.

Figure 5 shows some key financial market indicators of the model. To ensure a proper functioning of the deposit market, banks need to have enough competitiveness such that the market concentration does not favor one bank at all times, with all the others having zero clients.[43] Figure 5a shows the financial market concentration measured by the Herfindahl-Hirschman index (HHI) of the distribution of bank clients. The market concentration exhibits endogenous cycles for both of the simulations, ranging between 0.05 (all banks have approximately equal market size) and 0.5 (two banks share the market power). The model output suggests that the chosen baseline parametrization is able to sustain relatively stable cycles of higher and lower concentration throughout the simulated period.[44] The matching success rate (Fig. 5c), measured as the ratio between successful interactions on the credit market and the total number of interactions taken place, requires a burn-in up to approximately $t = 250$, from whereon it remains relatively stable slightly above 20%. Bank failures are infrequent events, suggesting that there are small-scale endogenous bank crises, but the model does not yield collateral damage to the banking system, with more than six of the 20 banks failing within a time window of ten modeling periods. These results of the financial markets are in line with other decentralized matching models in literature, obtaining endogenous business cycles as well as occasional firm and bank failures, see e.g., (Riccetti et al. 2015, 2022). The mean leverage of investors is shown in Fig. 5b, remaining relatively stable between 46 and 49% along the entire time span of the simulation. This indicates that the investment risk of the power plant projects is relatively constant, reflected in the debt share of the investments.

Further, the financing conditions for power plants are analyzed (Fig. 6). There is a slight increase in credit rates, as well as a stable development in expected return on equity almost no long-term trend component. Interest rates on credits are influenced by the tightening reserves of banks in the second half of the simulation ($t > 500$). The falling electricity price (Fig. 6c), the main dynamic parameter of power plant revenue streams, exhibits clearly visible short-term fluctuations and a long-term downward trend, as expected from Eq. (8). The strike prices for solar and wind energy (Fig. 6d) rise until approximately $t = 500$, exceeding the wholesale market price at around $t = 300$. In the more mature phase of the transition, strike prices

Footnote 42 (continued)
models. We characterize the quasi-steady state by a visually stable development of the stochastic model output for the first 200 time steps in two representative runs.

[43] Clients are defined as agents storing this bank as their favorite bank for deposits.

[44] For more detailed studies on the emergence of market concentration in agent-based models, we forward the interested reader to (Santos and Nakane 2021; Terranova and Turco 2022).

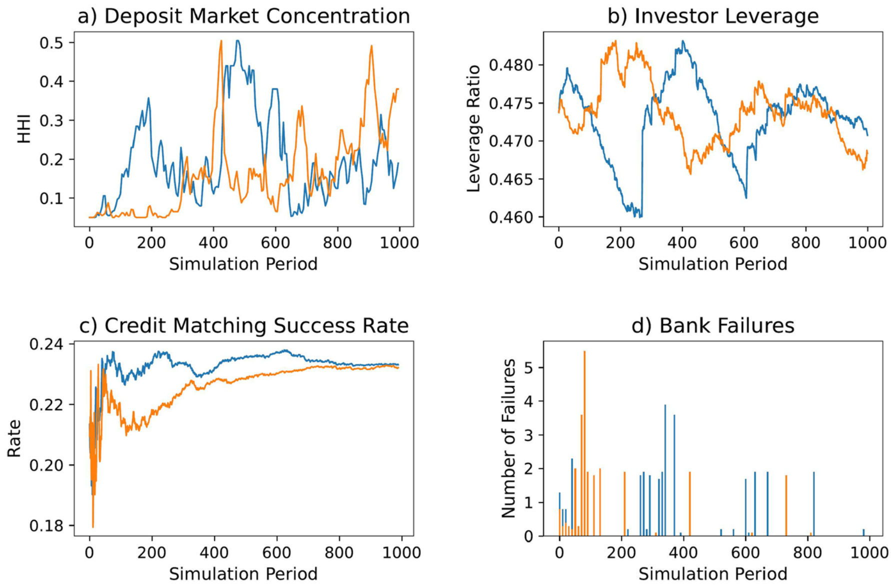

Fig. 5 Financial market indicators of two distinct runs of the baseline model (blue and orange curve). **a** Deposit market concentration (Herfindahl-Hirschman index of number of clients per bank), **b** investor leverage, **c** average credit market matching success rate, **d** average number of bank failures. The values shown for the bank failures are ten-period averages to provide sufficient statistics and to improve visual clarity

almost saturate toward the technology costs. Whereas the strike price for solar and wind onshore energy are in the same order of magnitude, wind offshore prices reach significantly higher levels, due to the high technology costs, thus lower profitability, of the offshore wind technology.

In Fig. 7a-b, the number of power plants and the resulting renewable energy share of total generation is plotted for two representative runs. In the first run (blue curve), there is an investment plateau at around $t = 400$ and another at $t = 600$. This plateau is not existent in the second simulation (orange curve); however, a slight kink after $t = 400$ is visible. The second run reaches full renewable power generation before the end of the simulation ($t < 1000$). Apart from the temporary disruptions, the power plant expansion is rather linear, and the growth rate of PF projects (solid lines in Fig. 7 exceeds the one of the CF projects (dashed lines). In Fig. 7c, the number of bankrupt investors per simulation period is plotted. For the blue curve, it is clearly visible that the bankruptcies are highly correlated with the phases of low power plant capacity expansion. This bankruptcy wave is anticipated in the rejected credit requests, which endogenously emerge between $t = 200$ and $t = 400$ (Fig. 7d, blue curve). As can be seen in the blue curve in Fig. 5b, the investor leverage also experiences a boom between $t = 200$ and $t = 500$ and a subsequent bust until $t = 600$, the point where the investment plateau ends. This is not observable for the other simulation run, indicating that this type of crisis is an emergent phenomenon of the model. In fact, this contagion dynamic is a typical feature of bank-investor network,

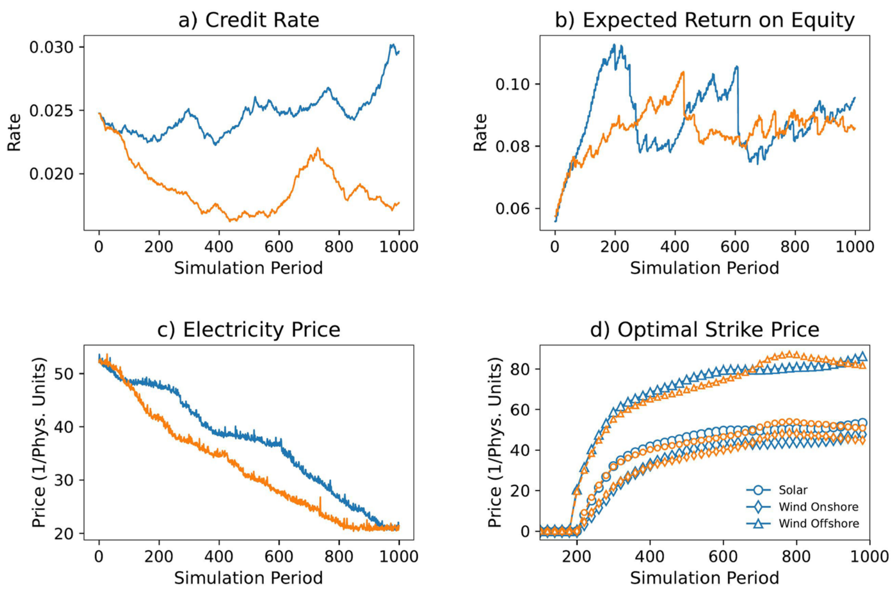

Fig. 6 Financial composition and financing conditions for two distinct runs of the baseline model (blue and orange curve). **a** Ratio of debt to total assets for SPVs and investors, **b** average credit rates, **c** electricity price development, **d** strike prices for the power market premium of the renewable technologies

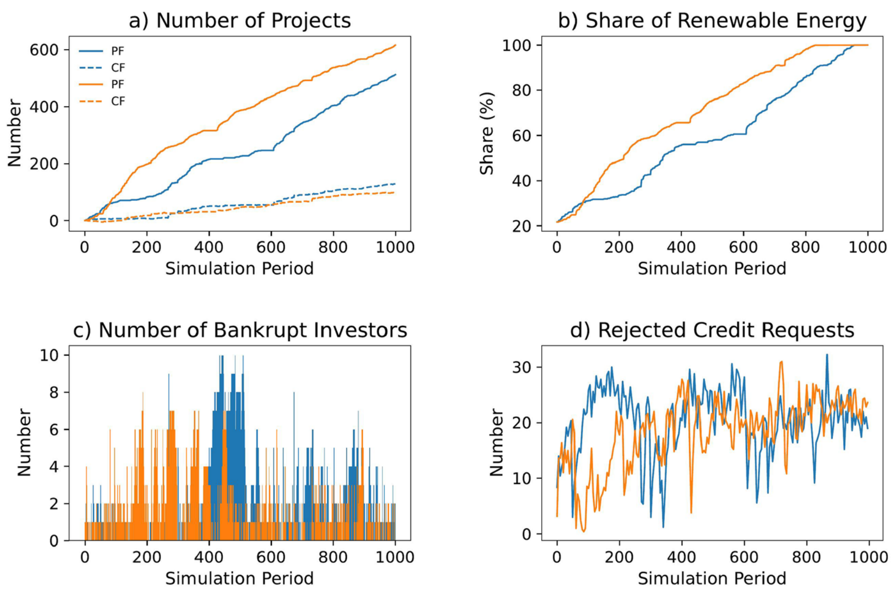

Fig. 7 **a** Number of power plants, **b** share of renewable energy generated, **c** number of bankrupt investors per simulation period, **d** rejection rate of credit requests (absolute count). The blue and orange curve represent two distinct runs of the baseline model

as corroborated by earlier research (Acemoglu et al. 2015; Lux 2016; Bottazzi et al. 2020).[45] In order to find a possible point where the model stabilizes and continues a steady, almost linear expansion in power generation capacity, we perform a Zivot Andrews test for the identification of structural breaks. This test yields the existence of a structural break in almost all of the model runs, located between the periods 440 and 590, depending on the variable used for the test (variables tested were: credit and deposit rate, project growth, renewable project growth, deposit market concentration). Comparing this result with the evolution of the power mix (Fig. 8d, panel A), it can be seen that this is where the second last fossil technology is phased out. This suggests that, in reality, there are actually two structural breaks, each placed where a fossil generation technology drops out of the merit order. Therefore, there is a feedback effect from the fossil drop-out on the financial well-being of investors, thus affecting also renewable installments.[46]

Table 3 shows an overview of the model statistics. For a better intuition of the simulation phases, we separate the simulation window into four equal ranges (I–IV), representing 250 iterations each. Within the modeling period of 1000 iterations, the renewable energy share rises from 37 to 80% in the baseline scenario. The average capital adequacy ratio of banks stays mostly within the target range of 8%. The rows labeled *Premium* indicate the percentage of sliding premium paid by the consumer as a fraction of the total consumer power price (composed of wholesale electricity price and premium).This is also the part of the electricity which could be securely financed using debt-based financing methods. For most indicators, standard deviations tend to be larger in the range I than in range II–IV, indicating a higher initial instability of the model in this phase. To investigate the model properties further, we run a series of statistical tests.[47] A Dickey fuller test is run on selected variables, suggesting non-stationarity of most of the output time series, pointing toward the existence of structural changes and persistent crises. We also look at auto- and cross-correlation of the model variables (filtered for the cyclical component), and run a Johansen test, revealing a cyclical correlation of investor leverage and credit rates, as well as a negative relation between investor defaults and credit rates.[48] Investor defaults tend to be negatively correlated with the growth of energy projects because the defaulting investors are not the ones able to invest in new projects in the same period of bankruptcy.

[45] It has been shown that the density of interconnections affects the way in which financial distress propagates the network. There is also an effect of the inter-bank connections, which we do not structurally investigate in this paper, but has been explored in (Grilli et al. 2015; Pallante et al. 2024).

[46] A possible expansion of the model could be the introduction of green-minded investors who do not experience such structural breaks due to intentionally sustainable investment portfolios. In our simulation, portfolios are random and heterogeneous.

[47] Due to length restrictions, not all statistical results can be shown. We invite the interested reader to request more information directly from the authors.

[48] This could be interpreted as follows: Defaulting investors are replaced by smaller agents in the course of the exit-entry process, banks experience a credit gap and have to lower the interest rates in order to attract new investors from the credit network.

An overview of the stylized facts generated in the model can be obtained from Table 4.[49] First, energy investments are lumpy, i.e., investors cannot build a partial power plant but must afford the entire upfront budget in order to expand the generation capacity (SF1). There is also a certain "lumpiness" in the composition of equity and debt, as investors have to provide both to end up with a successful projects. Further, investment is affected by the financial structure of the investors (SF2), as described in Section 2.2. Running a Jarque-Bera test on the average level of deposits for investors clearly reveals a non-normal distribution of investor sizes. This is both due to the Pareto-distributed initial setting and due to the model dynamics, yielding fat-tailed distributions.[50] Investors are allowed to change their initial choice on target technologies, resulting in a variety of power plants of different technologies being built by a single investor. This results in a strong heterogeneity among investors (SF4). Their bankruptcies, as an indirect measure of risk-taking, are closely connected to the growth in capacity (SF5). The latter stylized fact is a result of the bad credit rating highly leveraged investors receive. Investors who are in or close to bankruptcy are typically declined further credits, which reduces systemic risk but hinders the renewable transition.

In conclusion, the baseline model operates as expected and is able to replicate stylized facts about energy investments.

3.2 Scenario analysis

In this section, we explore the outcomes of the agent-based model under two alternative scenarios to understand the impact of various financial structures on renewable energy investments. This analysis includes two small additional scenarios deviating from the baseline: The "Less Project Finance" scenario and the "Less Project Finance with Green Credit Easing" (GCE) scenario. The objective is to examine how reducing the availability of project finance and introducing supportive financial policies for corporate finance affect the dynamics of renewable energy investment, power generation mix, and overall system stability. A summary of the changes made with respect to the baseline parameter setting can be found in Table 5. The structural changes made to the model in the context of the scenario analysis refer to the choice probability for project finance of the investors, as well as the banking parameters for applicants aiming at renewable technology investments which determine risk markup-ups on interest rates and the assessment of default probabilities. Figures 8 and 9, along with Table 6,

49 Because the macroeconomic dynamics are not fully covered, we cannot give information about potential additional stylized facts that would emerge in a complete model, such as the volatility of gross domestic product or other cross-correlations with macro-variables such as employment. However, some microeconomic stylized facts are already included and can be seen from the model results.

50 Skewed and fat-tailed distributions are a typical emergent result in agent-based models, see for example Fagiolo et al. (2008) and Lamperti and Mattei (2018) for fat-tailed growth distributions in macro-ABMs.

Table 3 Statistics (mean with standard deviation in brackets) of the Monte Carlo simulation in the baseline scenario

Range	I ($t = 0 - 249$)	II ($t = 250 - 499$)	III ($t = 500 - 749$)	IV ($t = 750 - 999$)
Share PF	0.80 (0.08)	0.82 (0.00)	0.81 (0.00)	0.80 (0.01)
RE Share	0.37 (0.09)	0.61 (0.06)	0.78 (0.04)	0.91 (0.03)
Investor Leverage	0.48 (0.00)	0.47 (0.00)	0.46 (0.01)	0.45 (0.00)
Credit Market Success Rate	0.23 (0.04)	0.23 (0.00)	0.23 (0.00)	0.23 (0.00)
Capital Adequacy Ratio (%)	8.11 (1.58)	8.16 (0.59)	7.97 (0.46)	7.98 (1.26)
Credit Rate (%)	2.29 (0.08)	2.21 (0.01)	2.32 (0.05)	2.45 (0.03)
Equity Rate (%)	7.86 (0.92)	8.97 (0.13)	8.91 (0.14)	9.26 (0.10)
Bank Defaults per Period	0.83 (0.63)	0.13 (0.14)	0.07 (0.10)	0.14 (0.14)
Investor Defaults per Period	1.41 (0.56)	2.03 (0.20)	1.32 (0.26)	0.91 (0.20)
Electricity Price (1/phys. units)	46.41 (3.63)	36.72 (2.23)	29.82 (1.76)	24.79 (1.25)
Strike Price (Solar)	1.22 (3.74)	37.28 (7.09)	47.15 (1.21)	50.90 (0.94)
Strike Price (Wind Onshore)	0.55 (1.69)	28.66 (7.99)	40.62 (1.43)	44.92 (1.07)
Strike Price (Wind Offshore)	5.43 (11.43)	62.80 (8.17)	75.53 (1.97)	81.83 (1.62)
Premium (Solar) %	0.00 (0.00)	1.04 (1.53)	12.81 (4.55)	27.66 (4.16)
Premium (Wind Onshore) %	0.00 (0.00)	0.03 (0.09)	6.13 (3.65)	20.47 (4.56)
Premium (Wind Offshore) %	0.00 (0.00)	1.50 (1.33)	11.32 (4.59)	27.70 (4.83)

present a detailed comparison of the model outputs from these scenarios across several key metrics from a total of 100 Monte Carlo runs.

Less Project Finance In the "Less Project Finance" scenario, the number of PF projects is significantly reduced, compelling a greater dependence on CF. This scenario aims to evaluate the resilience and effectiveness of the financial market and investment behavior when PF is less prevalent. In detail, the PF choice probability of each technology is reduced to 1/30 of the original value (see Table 11 of the appendix), which however effectively results in reducing the PF share from roughly 80% in the baseline model to approximately 40% (see Table 6). Figure 8a (panel A) and b (panel B) shows the number of CF projects and PF projects resulting in both the baseline and alternative model run. The results indicate that while the total number of projects financed through CF increases, the overall growth in renewable energy capacity is slower compared to the baseline. We attribute this to coordination issues in the CF channel. As can be seen from Table 6, the credit market success rate drops from 23% (baseline) to around 19–21%, indicating that slightly less agents are able to acquire credits at the financial markets. The long-term merit order is not as predominant. Instead, the power price exhibits a

Table 4 Overview of the stylized facts replicated by the model

Stylized fact	Description	References
SF1	Energy investments are lumpy	Gallagher et al. (2011)
SF2	Investment is affected by the financial structure of the investors	Fazzari et al. (1988) and Brunnschweiler (2010)
SF3	Right-skewed (fat-tailed) investor size distribution	Fagiolo et al. (2008), Lamperti and Mattei (2018)
SF4	Energy heterogeneity across investors	Iskandarova et al. (2021), Schlindwein and Montalvo (2023), Romero-Castro et al. (2023)
SF5	Investors' risk-taking affects energy capacity growth	Bonfim (2009), Wang et al. (2024)

Table 5 Overview of the alternative scenario settings

Scenario	Change in PF	$\Delta\rho_3^{RE}$	$\Delta\rho_1^{RE}$	$\Delta\kappa_{min}^{RE}$
Less PF	~ 1/2 of baseline	–	–	–
Less PF + GCE	~ 1/2 of baseline	− 0.01	+ 0.025	− 0.005

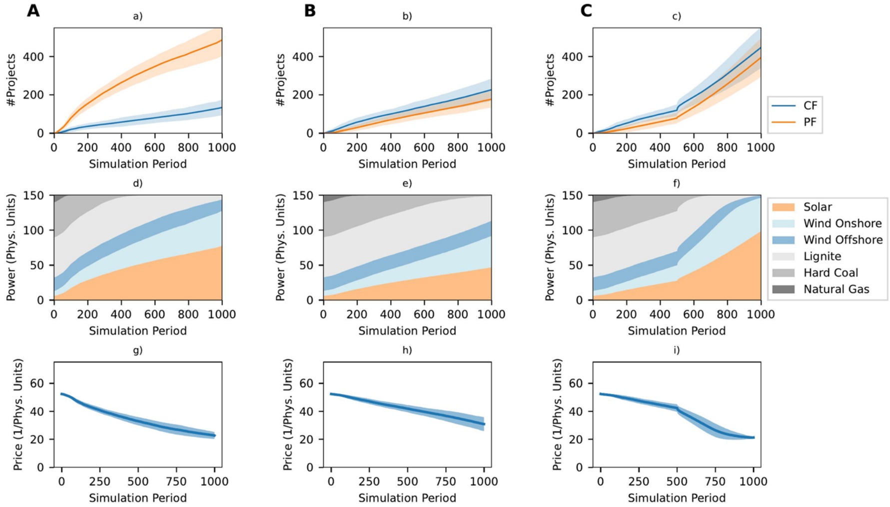

Fig. 8 Overview of the number of projects (**a**–**c**), mix in power generation (**d**–**f**) and power prices (**g**–**i**) for the baseline and alternative scenarios. Panel A: Baseline, Panel B: Less PF, Panel C: Less PF + GCE at $t = 500$. Solid lines indicate the means across 100 Monte Carlo runs, shaded areas behind the line plots represent one standard deviation

slow but linear decline as a consequence of the moderate renewable energy (RE) expansion. Further, there is almost no usage of the power market support mechanism, solely making up 7–13% of the RE power price at the end of the simulation.

Whereas the bank default rate is not significantly affected (the banking system seems to be on average effective in controlling its reserves in order to not run into a financial crisis), the investor default rate is actually lower than in the baseline scenario in the beginning of the simulation, and slowly adjusts to higher values toward the end. As can be seen from the box plots (Fig. 9i), in some of the simulations, bankruptcy crises appear, in which there is a much larger bankruptcy rate, not fitting into a normal distribution. These extreme events are less present in the less PF scenario with respect to the baseline scenario, indicating that the possibility of risk hedging via SPV structures might be throttled in the alternative scenario with less PF. The risk of renewable plants is also less as power prices remain at higher levels compared to the baseline setting. A similar occurrence of crises can be observed from the bank defaults (Fig. 9h) and the capital adequacy ratio of banks (Fig. 9d), where toward the end of the simulation (phases III–IV),

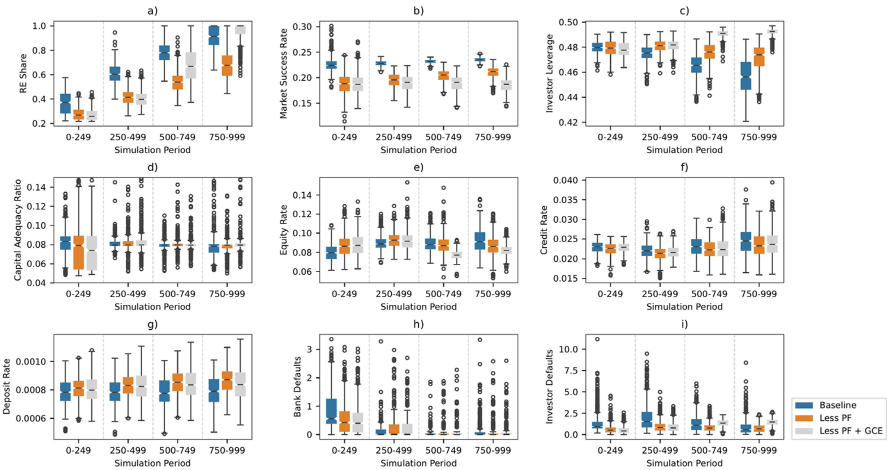

Fig. 9 Boxplots of 100 Monte Carlo samples of the baseline scenario (blue), the alternative scenario with less project finance (orange) and the alternative scenario with less project finance and green credit easing (GCE) at $t = 500$ (gray) for different model variables. Results are shown for four different simulation horizons: I (t =0–249), II (250–499), III (500–749) and IV (750–999). **a** Share of renewable energy (RE), **b** credit market success rate (ratio of successful to total number of requests), **c** mean investor leverage, **d** mean capital adequacy ratio of banks, **e** mean expected equity rate of investors, **f** mean credit rate of banks, **g** mean deposit rate of banks, **h** average number of bank defaults, **i** average number of investor defaults

there is a large spread of default rates among the Monte Carlo runs. The latter is similar to the baseline case.

Green Credit Easing Support Instrument Due to the immaturity of technologies and high individualism of renewable energy projects, green CF investors often face difficulties when searching for financial capital. As an alternative to PF, green credit easing (GCE) might guide green CF investors toward a successful launch of a debt-intensive project (Lamperti et al. 2021; Alharbi et al. 2023) but is also linked to increased fragility and risk in the financial system (Del Gaudio et al. 2022). The introduction of Green Credit Easing (GCE) in the "Less Project Finance with GCE" scenario aims to mitigate the adverse effects of reduced PF by improving access to credit for green projects. This policy intervention is designed to guide green CF investors toward successful debt-intensive project launches, thereby sustaining investment momentum. We technically do so by changing the parameters ρ_1 and ρ_3 in the credit mechanism (Eqs. 3 and 5), and alleviating the reserve requirements $\kappa_{\min}$, see Table 5. We introduce the modifications ρ_1^{RE}, ρ_3^{RE}, $\kappa_{\min}^{\mathrm{RE}}$ for renewable energy such that the new bank parameters depend on the technology choice τ:

Table 6 Statistics (mean with standard deviation in brackets) of the Monte Carlo simulation in the alternative scenarios with less PF, and less PF with green credit easing (GCE)

Range	Less PF				Less PF + GCE			
	I	II	III	IV	I	II	II	IV
	($t = 0 - 249$)	II ($t = 250 - 499$)	($t = 500 - 749$)	($t = 750 - 999$)	($t = 0 - 249$)	($t = 250 - 499$)	($t = 500 - 749$)	($t = 750 - 999$)
Share PF	0.26 (0.10)	0.40 (0.02)	0.43 (0.00)	0.44 (0.00)	0.24 (0.09)	0.36 (0.02)	0.42 (0.02)	0.46 (0.01)
RE Share	0.28 (0.04)	0.42 (0.04)	0.54 (0.04)	0.68 (0.04)	0.27 (0.04)	0.40 (0.04)	0.68 (0.11)	0.95 (0.04)
Investor Leverage	0.47 (0.00)	0.47 (0.00)	0.47 (0.00)	0.47 (0.00)	0.47 (0.00)	0.47 (0.00)	0.49 (0.00)	0.49 (0.00)
Credit Market Success Rate	0.19 (0.04)	0.19 (0.00)	0.20 (0.00)	0.21 (0.00)	0.19 (0.04)	0.19 (0.00)	0.19 (0.00)	0.18 (0.00)
Capital Adequacy Ratio (%)	7.90 (1.96)	8.59 (1.82)	8.11 (0.68)	8.05 (0.90)	7.91 (2.50)	8.72 (1.91)	8.08 (0.67)	8.19 (1.15)
Credit Rate (%)	2.25 (0.09)	2.13 (0.02)	2.23 (0.03)	2.35 (0.03)	2.29 (0.07)	2.17 (0.01)	2.27 (0.06)	2.40 (0.02)
Equity Rate (%)	8.54 (1.18)	9.30 (0.08)	8.83 (0.12)	8.65 (0.05)	8.65 (1.23)	9.27 (0.10)	7.74 (0.27)	8.20 (0.07)
Bank Defaults per Period	0.60 (0.32)	0.22 (0.23)	0.10 (0.13)	0.13 (0.14)	0.55 (0.27)	0.26 (0.23)	0.11 (0.14)	0.12 (0.13)
Investor Defaults per Period	0.63 (0.23)	0.97 (0.12)	0.83 (0.11)	0.73 (0.12)	0.53 (0.20)	0.87 (0.13)	1.34 (0.38)	1.45 (0.14)
Electricity Price (1/phys. units)	49.95 (1.60)	44.44 (1.46)	39.36 (1.46)	33.90 (1.72)	50.22 (1.44)	44.96 (1.48)	33.77 (4.28)	23.00 (1.50)
Strike Price (Solar)	0.95 (2.92)	35.05 (8.12)	46.80 (1.22)	50.35 (0.91)	0.95 (2.92)	35.10 (8.19)	46.68 (1.14)	50.16 (0.89)
Strike Price (Wind Onshore)	0.29 (0.88)	23.66 (8.46)	39.32 (2.03)	44.26 (1.07)	0.30 (0.91)	23.76 (8.47)	39.30 (2.00)	44.06 (1.03)
Strike Price (Wind Offshore)	5.41 (11.39)	62.55 (8.14)	75.15 (1.79)	80.91 (1.55)	5.45 (11.47)	62.97 (8.19)	74.97 (1.64)	80.58 (1.52)
Premium (Solar) %	0.00 (0.00)	0.00 (0.00)	3.12 (2.17)	13.65 (3.89)	0.00 (0.00)	0.00 (0.00)	14.66 (9.40)	43.23 (5.04)
Premium (Wind Onshore) %	0.00 (0.00)	0.00 (0.00)	0.10 (0.26)	7.30 (4.01)	0.00 (0.00)	0.00 (0.00)	6.02 (6.73)	33.95 (5.96)
Premium (Wind Offshore) %	0.00 (0.00)	0.28 (0.31)	2.56 (0.94)	8.90 (3.21)	0.00 (0.00)	0.29 (0.29)	9.34 (6.27)	31.95 (4.25)

$$\rho'_1 = \begin{cases} \rho_{1,\tau} + \Delta\rho_1^{RE} \text{ if } \tau \text{ is RE} \\ \rho_1 \text{ else} \end{cases},$$
$$\rho'_{2,\tau} = \begin{cases} \rho_2 + \Delta\rho_2^{RE} \text{ if } \tau \text{ is RE} \\ \rho_2 \text{ else} \end{cases}, \tag{19}$$
$$\kappa'_{\min,\tau} = \begin{cases} \kappa_{\min} + \Delta\kappa_{\min}^{\mathrm{RE}} \text{ if } \tau \text{ is RE} \\ \kappa_{\min} \text{ else.} \end{cases}$$

This structural modification starts at $t = 500$, when the government likely notices that the phase-out is not happening as fast as expected from the baseline scenario, and therefore introduces short-handed measures to recover the transition pathway. The GCE results in a more optimistic evaluation of default probabilities, as well as a lower risk mark-up for levered investors. However, these improved conditions are only granted to renewable investors. Further, we allow banks to slightly "overstrain" their capital adequacy ratios when lending for green investments ($\Delta\kappa_{\min}^{\mathrm{RE}}$). The remaining mechanisms of banks and investors stay unchanged. As depicted in Fig. 8c and f, the number of renewable energy projects and the power mix show a much more inclined growth trajectory as soon as the GCE is introduced, approaching the levels of renewable share and power price observed in the baseline scenario by the end of the simulation period. Therefore, GCE effectively bridges the financing gap created by reduced PF, enabling continued investment in renewable energy projects. Interestingly, the credit market success rate stay approximately the same with GCE, indicating improved availability and accessibility of financing for green projects, but an approximately equal overall success rate in credits. The rate of investor defaults is slightly higher but more stabilized with respect to the other scenarios, suggesting a balanced risk environment for investors facilitated by GCE. Even though the average value of bank defaults slightly reduces in periods I and II, the occurrence of bank default crises persists (see Fig. 9). However, the banking system seems to effectively steer its credit granting toward green investors, shielding the fossil investments, while maintaining a low-risk level of reserves.[51] In summary, the GCE policy effectively mitigates the negative impact of reduced PF, promoting a steady growth in renewable energy investments. This scenario suggests that combining PF with supportive financial policies like GCE might enhance the resilience and effectiveness of the financial system in driving the sustainable energy transition. GCE helps maintain a high investment rate while managing risk, underscoring the importance of policy interventions in sustainable finance.

[51] The reason behind this shielding effect could potentially lie in the design of the capital reserve buffer. We leave the exploration of the influence of the behavioral parameters of the banks, like $\kappa_{\min}^{\mathrm{RE}}$ for future research.

4 Conclusions and outlook

In summary, this paper has developed and employed an agent-based model to study the effects of different financial structures on renewable energy investments. The model's detailed representation of investor behavior, financial market interactions, and power market risk allows for an analysis of the roles of PF and CF in the renewable energy transition. By integrating elements such as project-specific risks, investor heterogeneity, and a market premium design, the model provides a comprehensive framework to understand the financial mechanisms driving sustainable energy investments, and is able to reproduce basic stylized facts about energy investments. The findings suggest that project finance is essential for rapid renewable energy deployment, as it enables a second financing channel for power plants. Without PF, the investment pace slows down significantly, and achieving sustainability targets becomes more challenging. However, also GCE can effectively support renewable energy investments by improving access to green credit and reducing financial risks, creating a robust financing environment that can accelerate the transition to renewable energy. These results suggest that PF is suitable for fostering renewable energy growth due to its ability to manage and distribute financial risks through special purpose vehicles (SPVs).

Future research should further explore the model's parameter space in order to find an optimal mix of financial mechanisms and policy interventions to enhance the resilience and effectiveness of the financial system in supporting renewable energy investments. This includes investigating the interplay between various forms of financing, regulatory frameworks, and market conditions. Additionally, expanding the model to include other forms of renewable energy technologies such as storage and grid technology, and different power market policies will provide deeper insights into more complicated energy systems. Moreover, addressing the observed endogenous crises situations in financial indicators will be crucial for developing robust strategies to mitigate financial risks. By identifying the conditions that lead to extreme values and financial instability, policymakers and financial institutions can better design interventions to ensure a smooth and continuous transition to a sustainable energy future. Further expansions could include the combination of this model with an integrated assessment model, or a further dis-aggregation of the rest-of-economy agent. Finally, the role of energy trade has remained unexplored, for which the analysis of financial stability in the context of geopolitical risks is left to future research. A further expansion of the model could be the introduction of alternative banking mechanisms, such as the evaluation of investors according to the expected operating cashflow instead of the financial leverage.

In conclusion, this study unveils the role of PF in driving the renewable energy transition and the role of policy interventions like GCE in supporting this process. This model suggests a balanced approach that leverages the strengths of PF, supplemented by targeted financial policies, to effectively address the challenges of financing renewable energy projects and contribute to achieving an economy's sustainability goals. The model represents a good basis for further analyses or usage as an energy module in a larger integrated assessment model.

Appendix

Appendix A: Expanded literature review

The linkage between power market aspects and agent-based integrated assessment modeling is elaborated in this paragraph, extending the literature review of the main article.

In models focusing on finance, bank lending plays a superior role over techno-economic aspects. Investment mechanisms are closely linked to changes in the balance sheet of investors and banks. This research stream addresses the question for possible external finance of carbon-friendly firms from a perspective of commercial banks, through the channels of conventional bank lending, market debt (i.e., green bonds) and market equity investments (Campiglio 2016; Campiglio et al. 2018). Further, D'Orazio and Popoyan (2019) propose the decarbonization of banks' balance sheets in a macro-prudential policy context. The authors draw conclusions for central banking and related reserve requirements.

In agent-based electricity market models, the expansion planning of power generation capacities is typically determined via the net present value of power plant projects, based on the electricity price. Developments in market price levels can be modeled subject to temporal supply scarcity or as a response to specific market mechanisms (Kraan et al. 2018; Chappin et al. 2017; Jimenez et al. 2024). Thus, the reaction of heterogeneous power suppliers to market incentives can be analyzed (Purkus et al. 2015; Jonson et al. 2020; Barazza and Strachan 2020), but minor modeling focus is attributed to the actual financing form and balance sheet composition resulting from these market incentives.

Representing yet another stream of literature, full-sized macro-ABMs aim at a more holistic understanding of the economy in the context of sustainable transitions. For example, in (Nieddu et al. 2022; Ponta et al. 2018; Raberto et al. 2019) and (Lamperti et al. 2020, 2021), green financial policies in ABMs with heterogeneous firms and banks are investigated. However, these types of ABM are able to address the energy-economy-climate nexus in a highly integrated fashion, minor attention is attributed to the electricity market clearing mechanisms and associated investment risks, neither are different generation technologies addressed. Similarly, Ciola et al. (2023) consider the introduction of windfall profits and changes in fossil fuel prices, but do not mirror long-term merit order effects.

Generally, in ABMs, the bridge between power market premia and alternative financing structures for renewable energy (in particular project finance) is seldom built. Solely Ari and Koc (2019) have presented a first agent-based model for sustainable financing for Qatar solar farms. The model includes a representative bank and a finite number of uniformly distributed agents, who can make use of equity-based financial intermediaries or conventional bank loans. In a follow-up work, the authors also consider a model with a philanthropic crowdfunding organization (Ari and Koc 2021). Whereas the authors aim at describing wealth developments, they exogenize assumptions about government incentives and risk accommodation.

In summary, models considering sustainable finance in agent-based macroeconomic modeling have been identified in literature, as well as models incorporating capacity investments in the context of power markets. Nevertheless, a research gap lies in the combination of energy finance, power market incentives and technological heterogeneity. This paper aims at providing a contribution toward filling this gap.

Appendix B: Model details

Appendix B.1: Balance sheet matrix

Table 7 shows the balance sheet matrix of the model.

Table 7 Balance sheet matrix showing the balance sheet entries for banks, investors, special purpose vehicles (SPVs), the central bank (CBank), the government and the rest of economy (RoE)

	Bank		Investor		SPV		CBank		Govern-ment		RoE	
	A	L	A	L	A	L	A	L	A	L	A	L
Deposits		D	D_I		D_S						D_R	
Loans	L			L_I		L_S						L_R
Central Bank Loans		C					C					
Currency in circulation								M				
Bonds	B									B		
Project Equity			E_p			E_p						
(Power Plant Assets)			K_I		K_S							
Net Worth		NW_B		NW_I		NW_S		NW_C		NW_G		NW_R

Appendix B.2: Transactions-flow matrix

Table 8 shows the transactions-flow matrix of the model.

Table 8 Transactions flow matrix including the current account (CA) and capital account (KA) of banks, investors, special purpose vehicles (SPVs), the central bank (CBank), the government and the rest of economy (RoE)

Transaction	Bank		CBank		Government		Investor		RoE		Spv		Total
	CA	KA	CA	KA	CA	KA	CA	KA	CA	KA	CA	KA	
Dividends	$-Div_b$						$-Div_I + Div_S$		Div_R		$-Div_S$		0
Electricity Consumption							$+Ele_I$		$-Ele$		$+Ele_S$		0
Power Plant Operation							$-\mathcal{C}(Y)_I$		$+\mathcal{C}(Y)$		$-\mathcal{C}(Y)_S$		0
Interest Bonds	$+r_bB$				$-r_bB$								0
Interest Cb Creds	$-r_cC$		$+r_cC$										0
Interest Credits	$+Intr_\ell$						$-r_{\ell,I}L_I$		$-r_{\ell,R}L_R$		$-r_{\ell,S}L_S$		0
Interest Deposits	$-Intr_d$						$+r_dD_I$		$+r_dD_R$		$+r_dD_S$		0
Investment							$-I_I$	I_I			$-I_S$	I_S	0
Taxes					T		$-T_I$				$-T_S$		0
Bailout	$+bo - bo_B$				$-bo_G$								0
Retained Earnings	$-(Ret_B)$	$+(Ret_B)$	$-(Ret_C)$	$+(Ret_C)$	$-(Ret_G)$	$+(Ret_G)$	$-(Ret_I)$	$+(Ret_I)$	$-(Ret_R)$	$+(Ret_R)$	$-(Ret_S)$	$+(Ret_S)$	0
Δ Deposits		$-\Delta D_B$						ΔD_I		ΔD_r		ΔD_S	0
Δ Loans		ΔL_B						$-\Delta L_I$				$-\Delta L_S$	0
Δ Project Equity								ΔE				$-\Delta E$	0
Δ Central Bank Loans		$-\Delta C$		$+\Delta C$									0
Δ Bonds		ΔB				$-\Delta B$							0
Total	0	0	0	0	0	0	0	0	0	0	0	0	0

Appendix C: Structural model parameters

Table 9 summarizes the values and descriptions for the structural parameters of the model. Table 10 shows the fractions of reserves sold or bought by banks to optimize their composition of reserves with respect to the macro-prudential requirements.

Table 9 Parametrization of the power market model. Source: own values

Variable	Description	Value
θ	Fraction of investor profits paid out as dividends	0.6
τ_0	Tax rate	0.3
$r^\star$	Central bank rate	0.0
r_b	Government bond yield	0.0
$\kappa_{\min}$	Reserve requirement	0.08
χ_E	Subset sampling size on the equity market	0.10
χ_C, χ'_C	Subset sampling size on the credit market	0.20, 0.05
χ_D, χ'_D	Subset sampling size on the deposit market	0.15, 0.05
$N^\dagger$	Number of attempts before rethinking an investment decision	4
$\hat{N}$	Maximum number of equity market requests per SPV	2
ξ_E	Maximum share of equity funds put into one SPV	0.2
η_D^R, η_L^R	Share of rest of economy credits/deposits shifted	0.005
α_e	Weighting factor for expected return on equity	0.9
N_m	Random number of banks in rest of economy financial markets	2
$\beta^a_{\min}, \beta^a_{\max}$	Asset beta distribution	0.8, 1.0
$\alpha_d^\uparrow, \alpha_d^\downarrow$	Learning speeds (deposit market)	0.057, 0.050
$\alpha_\ell^\uparrow, \alpha_\ell^\downarrow$	Learning speeds (credit market)	0.002, 0.14
β_0, β_1	Power price starting level and merit order slope	60.0, 40.0
$r^\delta_{min,0}, r^\delta_{max,0}$	Initial interest rate parameters (deposits)	(0.004, 0.006)
$r^\ell_{min,0}, r^\ell_{max,0}$	Initial interest rate parameters (credits)	(0.015, 0.025)
ϱ_1	Bank parameter (credit evaluation)	0.5
ϱ_2	Bank parameter (credit evaluation)	0.001
ϱ_3	Bank parameter (credit evaluation)	0.03
λ	Bank parameter (credit evaluation)	4
p_0	SPV credit acceptance probability	0.85
ζ_d, ζ_c	Fraction of credits and deposits of the RoE agent shifted on the financial markets	0.005
L	Power load	150

Table 10 Overview of the fractions of reserves sold and bought by banks to reach their reserve requirement goals. Source: own assumptions

Parameter	φ_L	φ_B^{buy}	φ_B^{sell}	$\varphi_{CB}^{\text{buy}}$	$\varphi_{CB}^{\text{sell}}$
Value	0.9	0.6	0.6	0.8	0.98

Appendix D: Technology parameters

Table 11 Technology data used in this paper: Typical system size (MW), annual full-load hours (h), probability of project finance ($p(PF)$) in the baseline scenario (BL) and the alternative scenarios with less project finance (PF), probability of technology choice $p(T)$, fixed operational costs (kEUR/kW), variable operational costs (kEUR/kWh) and capital expenditures (kEUR/kW). Sources: own assumptions

Technology	Size $\hat{K}$ (MW)	Load Hours (h/year)	p(PF) BL / less PF %	p(T) %	C^{fix} (Eur/kW)	C^{var} (Eur/kWh)	Capex
Solar PV	50	1130	28.8/0.96	29	20	0.0	700
Wind Onshore	40	2570	24.0/0.8	56	19	0.002	1800
Wind Offshore	100	2820	15.0/0.5	5	70	0.004	3000
Lignite	75	6970	0.0/0.0	0	40	0.0009	2300
Hard Coal	100	6550	6.6/0.22	0	42	0.018	1900
Natural Gas	50	2600	1.8/0.06	10	25	0.050	800

Appendix E: Power market details

Appendix E.1: Short-term power market dynamics

The clearing price of the market is approximated as a linear function of the renewable share in the power plant pool, such that $P_0 = \eta_1 - \eta_2 Y_{\mathrm{RE}}/(Y_{\mathrm{RE}} + Y_{\mathrm{fossil}})$, where parameters η_1, η_2 determine the strength of the merit order effect. A second price term is added to account for fluctuations in weather and regional heterogeneity not explicitly modeled. This short-term power market model is adapted from literature (Kitzing and Weber 2014), employing a two-factor stochastic model, where the logarithm of the power price is divided into a long-term and a short-term component, i.e.,

$$\ln P_t = \xi_t + \chi_t \tag{20}$$

$$d\bar{P}_t = \bar{P}_t\left(\mu_\xi + \frac{1}{2}\sigma_\xi^2\right)dt + \bar{P}_t\sigma_\xi dz_\xi \tag{21}$$

$$d\chi_t = -\kappa\chi_t dt + \sigma_\chi dz_\chi \tag{22}$$

where $d\bar{P}$ is a long-term Brownian motion and $d\chi_t$ is a mean-reverting short-term process, in particular an Ornstein–Uhlenbeck process.[52] In our model, we use the

[52] As the Phelix future market is barely used in recent years (2021–2022), a smoothed spot price as a proxy for the base price. The calibration process for this model is described in (Kitzing and Weber 2014). In this paper, we only make theoretical assumptions about the short-term parameters.

arbitrary parameters $\xi = 3.7, \chi = 0.5, \mu_\xi = 0.001, \kappa = 0.5, \sigma_x i = 0.1, \sigma_\chi = 0.1$ and overlay the resulting short-term fluctuations with the long-term clearing price to account for more stochastic (and thus closer-to-reality) revenue streams of the investors.

Appendix E.2: Numerical determination of financing conditions

For computing the strike price endogenously, we make use of the algorithm derived by Neuhoff et al. (2022).[53] This method sums over the distribution ϕ of all expected market values of power plants to yield the required amount of equity (E) in the project, given the strike price S:

$$a_e E(S) \stackrel{!}{=} \tilde{Y} \int_S^\infty \phi(p')dp'. \tag{23}$$

Equation (23) states that the equity-serving cash flow equals the expected revenue streams from a power plant beyond the strike price S, yielding its physical output $\tilde{Y}$ for a given period. Here, a_e is the equity-serving factor (the expected fraction of equity to be paid to shareholders in each financing period). This equation reflects that insecure revenue streams are backed by equity. The distribution ϕ influences how strict this rule applies. If expectations are relatively stable, ϕ might be a function with a sharp peak around S, and equity will only account for a short right tail. If expectations are fuzzy, ϕ exhibit a broader tail beyond S and the amount of equity required increases. In this paper, $\phi(p_i) \sim N(\mu_\phi, \sigma_\phi)$ is a normal distribution of expected market values across power plants of the same technology,[54] where μ_ϕ is given by last period's power price level and the standard deviation $\sigma_\phi (= 2.0)$ is an indicator of heterogeneity in expectations. Mind that this is a conservative and myopic strategy as market values tend to fall with increasing renewable ramp-up in the long run. The portion of debt D in the investment covers at least the costs of electricity generation:

$$\tilde{a}_d D(S) \stackrel{!}{=} \tilde{Y}(S - C^{var}) - C^{fix}. \tag{24}$$

Here, the costs C^{var} and C^{fix} for variable and fixed operational costs are included. The debt-serving factor a_d and equity-serving factor a_e read[55]

[53] We forward the interested reader to this article, which represents a thorough derivation and investigation of the method summarized here. The only difference in our model is that also fixed expenditures are covered by debt.

[54] We approximate the integral in equation 23 over a discrete distribution of expected market values.

[55] The debt and equity-serving factors result from the geometric sum over discounted cash flows in the entire project lifetime T, i.e., $D = \sum_{t=1}^{T_p} a_d D/(1 + r^\ell)^t, E = \sum_{t=1}^{T_p} a_e E/(1 + r_e)^t$. A more thorough derivation can be found for example in Götze et al. (2008).

$$a_d(r_\ell) = \frac{r_\ell(1+r_\ell)^{T_p}}{(1+r_\ell)^{T_p}-1}, \quad a_e(r_e) = \frac{r_e(1+r_e)^{T_p}}{(1+r_e)^{T_p}-1} \tag{25}$$

$$\tilde{a}_d(r_\ell, r_e) = (1-\alpha)a_d + \alpha a_e \tag{26}$$

where the adjusted debt-serving factor $\tilde{a}_d$, introduced by Neuhoff et al. (2022), includes the assumption that a minimum share $\alpha(=0.2)$ of equity is required in all cases to secure the project debt, and T_p denotes the project lifetime.[56] Equations (23) and (24) can be interpreted as the constraints f (equation 12) and g (Eq. 11) from the main text when solved for E and D, respectively:

$$E = g(\tilde{Y}, S, \phi, r_e) = \frac{1}{a_e(r_e)}\left(\tilde{Y}\int_S^\infty \phi(p')dp'\right), \tag{27}$$

$$D = f(y, r_\ell, r_e) = \frac{y}{\tilde{a}_d(r_\ell, r_e)} \tag{28}$$

$$\text{where } y := \left(\tilde{Y}(S - C^{var}) - C^{fix}\right). \tag{29}$$

These equations are used in two different ways in this model. The government determines the optimal strike price, using average financing rates. Investors then take this optimal strike price as given, and compute D and E using their individual financing conditions, as explained in section 2.5.1. For the calculation of debt and equity for a specific investor j, S is taken as given. In the latter case, consider an investor j. In equation (25), the interest rate $r_\ell = r^\ell_{k'(j)}$ of the current favorite bank for credits and the expected per-period return on equity $r_e = \mathbb{E}[r_e(j,\tau)]$ were used. We determine $\mathbb{E}[r_e(j,\tau)]$ by plugging in equation (14) for the technology τ investor j aims to invest in.

Appendix F: Initialization of stocks

In the beginning of the simulation, the deposits and loans of investors are set up. Investors are businesses of varying size in employees, and the number of persons in this business is directly linked to its initial financial wealth.[57] The simulation contains in sum 100 investor agents. Each investor j is initialized by providing an equity

[56] In our model, project lifetimes exceed the end of the simulation and are therefore not regarded. Mind that $a_d \approx r_\ell$ and $a_e(j) \approx r_e$ for $T_p \gg 1$.

[57] As we do not include a labor market, the number of employees has no further effect on the model dynamics.

Table 12 Financial parameters for banks: total assets (monetary units)

Bank Index	0	1	2	3	4	5	6	7	8	9
Total Assets	1348	519	490	462	287	241	220	169	163	154
Bank Index	10	11	12	13	14	15	16	17	18	19
Total Assets	45	27	26	19	19	16	15	12	12	12

ratio η_j^0 and a number of employees n_j, sampled randomly from a Pareto distribution with probability density $p(n_j) = am^a/x^{a+1}$ with scale $m = 1$ and shape $a = 1$. The net worth is scaled linearly between a minimum value $\bar{E} = 100$ and maximum value $\hat{E} = 3000$ (monetary units) such that the net worth of investor j matches the ratio between j's number of employees and the maximum number of employees in the simulation, $\hat{n}_j$: $E_{j,0} = n_j/\hat{n}_j \cdot (\hat{E} - \bar{E}) + \bar{E}$. The ratio $\eta_j^0 = 0.1$ of each agent determines the total assets, which are linked to total deposits via $D_{j,0} = E_{j,0}/\eta_j^0$. The initial loans of each agent are computed via $L_{j,0} = A_{j,0} - E_{j,0} = D_{j,0} - E_{j,0}$ Note that, for consistency of the stocks, each investor requires a bank for deposits and a bank for loans. Each agent chooses a random bank k in the beginning, and all loans are issued by a second random bank k', such that $L_{j,0} = L_{j,k'}, L_{j,\kappa} = 0\ \forall \kappa \neq k'$ and $D_{j,0} = D_{j,k}, D_{j,\kappa} = 0\ \forall \kappa \neq k$.

Banks (indexed with k) have an initial set of loans and deposits stemming from both the investors and the rest of the economy. We sample 20 commercial banks given a list of total assets $A_{k,0}$ for each bank (cf. Table 12). The composition of total assets of the bank k reads $A_{k,t} = \sum_j L_{j,k,0} + L'_{k,t} + R_{k,0}$ where j indexes the bank's clients for loans. To determine the quantity of reserves at each bank, we apply fixed exogenous shares, i.e., $R_{k,0} = \eta_r A_{k,0}$. Finally, we compute the loans stemming from the rest of the economy (not from the energy investors) L' as the residual $L'_{k,0} = A_{k_0} - R_{k,0} - \sum_j L_{j,k,0}$. On the liability, side, banks are assigned a share for central bank loans, η_{cb}. The liabilities of bank k are initially $L_{k,0} = \sum_j D_{j,k,0} + D'_{k,0} + L^{CB}_{k,0}$ such that the rest of the economy's deposits become $D'_{k,0} = L_{k,0} - \sum_j D_{j,k,0} - L^{CB}_{k,0}$. The initial equity of banks finally reads $E_{k,0} = A_{k,t} - L_{k,0} = \sum_j L_{j,k,0} + L'_{k,0} + R_{k,0} - \left(\sum_j D_{j,k,0} + L^{CB}_{k,0}\right)$. If the equity resulting from this procedure is lower than a minimum share $\eta_A = 0.01$ of total assets, reserves of the missing amount are added to the bank's balance sheet in order to meet this requirement. For simplicity, $\eta_{cb} = 0$ is set in the beginning of the simulation and $\eta_r = 0.03$ as a fraction of initial reserves for all banks. Initial rates on credits and deposits are sampled from uniform distributions ($r^{\ell}_{k,0} \sim u(0.020, 0.030)$, $r^{\delta}_{k,0} \sim u(0.0001, 0.0015)$).

The initial distribution of power plants is an approximate scaled-down version of the German energy system.[58] In order to reduce computational resources, the

[58] This representation is very stylized and therefore cannot be used for direct policy analysis for a specific country.

Table 13 Initial number of power plants by technology

Technology	Solar	Wind Onshore	Wind Offshore	Lignite	Hard Coal	Natural Gas
Count	40	25	25	40	28	30

characteristic generation capacity is scaled up artificially with respect to the real-world capacity. Table 13 gives an overview of the initial power plant distribution employed in the model. In total, there are 188 initial power plants.

Acknowledgements The authors acknowledge the funding by DLR internal funds in the project NagSys (part of the Helmholtz Program "Energy System Design"). We further thank researchers at Scuola Superiore Sant'Anna and at the university of Graz for their valuable feedback on our modeling work during workshops and conferences. We acknowledge the valuable feedback provided by the participants of the WEHIA 2022 conference on an early version of the model. Special thanks go to the anonymous reviewers, who helped to improve the quality of this article significantly. Further we acknowledge the help of Tobias Naegler, Kristina Nienhaus, Karsten Müller and Jonas Eschmann for their valuable discussions and feedback.

Funding Open Access funding enabled and organized by Projekt DEAL.

Declarations

Conflict of interest There are no competing financial or non-financial interests related to the work submitted.

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