From metal ores to financial risk: a macro-evolutionary model of the energy transition with energy, financial and commodity markets

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June, 2024

Acknowledgments.
We acknowledge financial support from the National Science Centre, Poland, grant no. 2019/35/B/HS4/00140.

Abstract

Most studies of the energy transition ignore metals and minerals as a production factor in the energy sector. However, investments in renewable power plants are many times more metal-intensive than investments in fossil fuels. As a result, progressive metal scarcity can undermine the future cost of renewable energy and financial stability. In this paper, we present a macro-evolutionary agent-based model to study the impact of commodity market on the low-carbon transition. The model includes the final goods sector, the banking sector, the capital sector, the energy sector, which is composed of renewable and fossil-fuel power plants, and the commodity sector, which includes material firms and mining sites. We show that achieving a 100% share of renewable energy in the electricity system increases the cost of mining metal ores, which can have a negative impact on financial stability, i.e., the number of non-performing loans and the loan-to-deposit ratio in the economy. The greater the competition in the commodity market, the lower the prices of material goods. However, this comes at the cost of a higher bankruptcy rate for material firms. Reducing material intensity in sectors other than energy, e.g., through improvements in resource efficiency, or the discovery of new, more productive mining sites, can minimize transition risks.

1. Introduction

A transition to a low-carbon economy is unprecedented. Previous energy transitions, e.g., from coal to oil or from oil to natural gas, took about 50-60 years. The transition to renewable energy is particularly challenging for several reasons (Hall et al., 2014): global energy consumption, and thus the scale of investment to support a low-carbon transition, is 20 times greater than previous transitions; renewables tend to be intermittent, lack sufficient energy density, have a low energy return on investment (EROI), and require large investments in the supporting infrastructure. On the positive side, innovation and economies of scale have rapidly reduced the cost of clean energy technologies such as solar PV and batteries (Way et al., 2022).

There are concerns that the cost of clean energy technologies may increase in the future due to a surge in metal prices. Current mineral supplies and investment plans are insufficient for energy sector transformation (IEA, 2021). Lithium and cobalt prices more than doubled in 2021, and copper, nickel, and aluminum prices increased by 25% to 40% (Kim, 2022). Many minerals critical to emerging technologies have become scarce due to political tensions or shortages (Massari and Ruberti, 2013) or are in a decline in the quality of metal ores (Michaux, 2021). This could have a substantial impact on the financing needs of low-carbon technologies and financial stability (Boer et al., 2021). Most studies of the energy transition ignore metals and minerals as an input of production of capital investments in the energy sector. Only recently, the problem of metal scarcity has achieved attention in the theoretical models (see Chazel et al., 2023; Fabre et al., 2020, and Pommeret et al., 2022). The general conclusion emerging from this line of the literature is that the scarcity of metals impacts the optimal path of the energy transition, while metal recycling can reduce its cost. These studies provide an important first step in the assessment of the role of metals in the low-carbon transition. However, they rely on integrated assessment and computational general equilibrium models that lack money, banking, and the financial system. As a result, they are ill-equipped to study how metal scarcity due to the low-carbon transition can affect financial stability.

Against this background, we develop a macro agent-based model to examine the role of the commodity market in the low-carbon transition. The model includes the final goods sector, the capital sector, the banking sector, the energy sector composed of renewable and fossil-fuel power plants, and the commodity sector, which includes material firms and mining sites. The model is stock-flow consistent, meaning all financial transactions are recorded in the balance sheets of the commercial bank, and monetary flows sum to zero. Capital producers constantly engage in R&D activities to improve their productivity, and the productivity of capital goods offered to firms in different sectors. Metals constitute a production input for capital goods, which differ in terms of the ratio of metal-to-capital, i.e., the material intensity. In particular, capital goods for the renewable energy sector are more metal-intensive than for the fossil fuel or final goods sectors. An important novelty of our model that distinguishes it from previous studies is that metals are produced. In the commodity market, heterogeneous material firms compete for clients. Each firm owns one mining site from which it extracts metal ores. The cost of extraction in each site increases with the progressing metal ore scarcity. Firms use metal ores to produce material goods that constitute production input in other sectors.

In our model, investments in renewable energy accelerate metal scarcity, increasing ore extraction costs and material prices. Higher metal prices affect the ability of firms to repay the loans and increase the average loan size. As a result, the larger the share of renewable energy, the more financially unstable the economy, which we examine by looking at the number of non-performing loans, the rate of firms' bankruptcies, and the loan-to-deposit ratio in the economy. Our analysis shows that the commodity market can contribute to or mitigate the transition risk. For instance, the greater the competition in the commodity market, the lower the price of material goods, which results in less debt in the economy. However, this comes at the cost of a higher rate of firm bankruptcies as more material firms entering the market also entail a higher rate of their failures. Other factors affecting a low-carbon transition include the distribution of ore extraction costs across existing mines, the likelihood of exploration of mining sites, and decisions on market entry by new material firms.

Our work relates to two lines of the literature: the climate-economy assessment using Integrated Assessment Models (IAMs), and a recent wave of agent-based models of climate policies. IAMs dominate climate policy advice. Such models describe how the accumulation of carbon dioxide emissions due to production activities in various sectors affects global temperature, which in turn reduces GDP and consumption (Nordhaus, 1994; Tol, 1995). The most influential examples of such models are DICE, FUND, and PAGE (Nordhaus, 2008, 2017; Stern, 2013). IAMs rely on aggregate equations that represent a single representative agent, e.g., a consumer or a producer. Agents are rational and forward-looking, performing complex optimization of their decisions over long time horizons. Such models have been used to derive the optimal climate policy, for instance, the social cost of carbon or subsidies for renewable energy (Golosov et al., 2014; Rezai and van der Ploeg, 2016). Most IAMs models ignore the role of metals in the energy transition. Only recently, minerals as capital inputs in the energy sector have been included in the climate-economy models (see Chazel et al., 2023; Fabre et al., 2020; and Pommeret et al., 2022). It has been shown that cumulative emissions can exceed the carbon budget if policymakers ignore the potential scarcity of minerals embedded in green capital (Pommeret et al., 2022). Another important insight from this literature is that the progressing resource scarcity can undermine the low-carbon transition. For instance, Chazel et al. (2023) extends the model of Golosov et al. (2014) to study the role of rare minerals, namely copper, in energy transitions. The authors show that even in the case of a 100% recycling rate, green energy production is 50% lower than in the scenario with unlimited primary copper. In addition, Fabre et al. (2020) find that the greater the recycling rate of minerals, the more the energy mix should rely on renewable energy, and the sooner should investment in the renewable capacity take place.

IAMs lack a financial system, money, and banking. As a result, they are ill-suited to examine the transition risks, namely the impact of climate change or mitigation policies on financial stability. The approach requires that climate change impacts and their financial consequences are studied separately. For instance, Dietz et al. (2016) use the DICE model to predict global GDP growth with and without climate change. Subsequently, the authors calculate financial losses due to climate change, using a measure of climate value-at-risk (VaR). The authors find that with a 1% probability, climate-related losses would exceed 16.9% of global financial assets, i.e., the 99th percentile global climate VaR is $24.2 trillion. However, this approach does not capture the feedback mechanism from financial losses to economic growth, or how the risk spreads through the financial networks, which has been typically studied using agent-based models (ABMs).

In macro ABMs, sectors are modelled as networks of heterogeneous agents, whose interactions can be a source of emergent properties that are not reducible to the behavior of individual agents (Arthur, 2021; Axtell and Farmer, 2022). Innovation at the level of individual firms lies at the core of economic growth (see an overview in Dawid and Delli Gatti, 2018). For instance, in the work by Dosi et al. (2010,2013), the economy consists of a machinery-producing sector and a consumer goods sector composed of heterogeneous firms and workers. Capital firms produce heterogeneous machinery and follow simple production routines. Consumer goods firms use machinery purchased from capital firms to produce final products. The main feature of such models is that innovations are endogenous to economic dynamics, as capital firms invest in R&D activities. Macro ABMs are typically stock-flow consistent, which implies that all monetary flows between firms and banks are captured in interconnected balance sheets, while all transactions within the economy are zero-sum (Godley and Lavoie, 2012; Nikiforos and Zezza, 2017).

ABMs have enriched the understanding of pandemics (Epstein, 2009), systemic risk in financial and housing markets (Franke and Westerhoff, 2012; Thurner and Poledna, 2013), business cycles and industry dynamics (Russo et al., 2010, 2016; Botta et al., 2021), and job search and matching in labor markets (Cardaci et al., 2015; Russo et al., 2016). Recently, agent-based models have been used to examine the impact of climate change and policies for economic and financial stability (Aglietta and Espagne, 2016; Dafermos et al., 2017; Ponta et al., 2018; Monasterolo et al., 2019; Roncoroni et al., 2021; Safarzynska and van den Bergh, 2017; Ciola et al., 2023; Turco et al., 2023). For instance, Lamperti et al. (2019) use an agent-based climate-economy model to examine how climate shocks to labor productivity and the capital stock of individual firms impact their profitability and ability to repay loans, which in turn affects the public cost of bailing out banks. The authors show that climate change will increase the frequency of banking crises (26-248%) while bailing out insolvent banks will lead to an additional fiscal burden of about 5-15%

of GDP per year. As another example, Safarzynska and van den Bergh (2017) propose an agent-based macroeconomic model that captures the interactions between energy, finance, and technology. The energy sector consists of heterogeneous power plants that generate electricity from different energy sources: gas, coal, or renewables. Each time a new firm enters the market, it receives a loan from a bank to cover the cost of the initial investment. The authors show that when loans to the energy sector are concentrated in a few banks, the insolvency of renewable energy producers can trigger a cascade of insolvencies through the financial network. This effect depends on the price of energy. If the price is too low, the profits generated by renewable energy producers are too low to pay their debts. Finally, a recent paper by Turco et al. (2023) proposes a macro agent-based model with multiple sectors to study the role of fiscal and monetary policies in stabilizing the economy in response to energy shocks. The model includes the capital and energy sectors, and the public sector which consist of the government and the central bank. The authors find that in the absence of stabilization policies, energy shocks lead to inflation and a reduction in GDP. Energy subsidies promote a fast economic recovery but at the expense of financial instability.

The remainder of the paper is as follows. Section 2 presents the structure of the model and describes the main assumptions. Section 3 presents the results from model simulations. Section 4 concludes.

2. Model Description

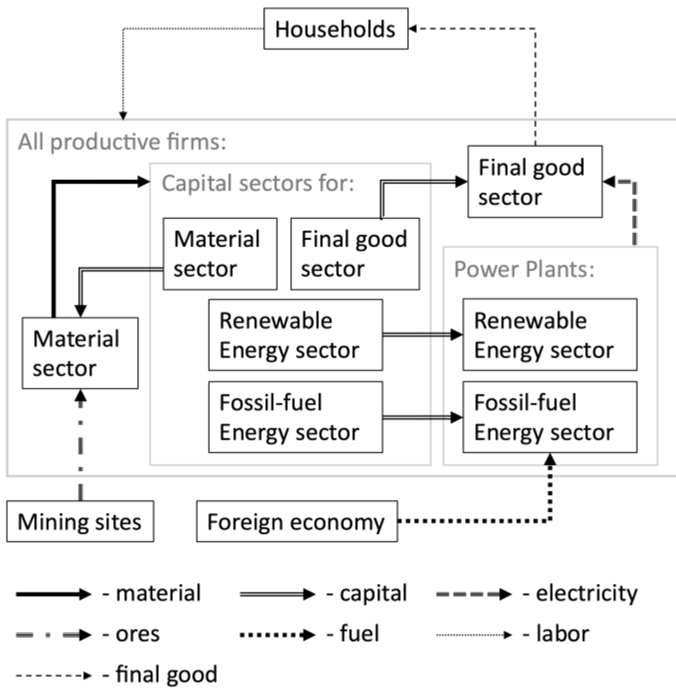
In this section, we discuss the model assumptions. We discuss the dynamics in the final goods sector in Section 2.1, the behaviour of consumers/households in Section 2.3, the dynamics in the energy sector in Section 2.4, the commodity market in Section 2.5, and the capital and banking sectors in Section 2.6 and 2.7, respectively. Figure 1 summarizes the flows of goods and services in the model. Firms in the final goods sector produce homogenous products using labour, energy, and capital goods. If their production capacity is insufficient to meet the desired demand, firms invest in capital expansion. On the capital market, firms produce capital goods using labour, and material inputs. They engage in R&D activities to improve their labour productivity and the productivity of capital goods (machinery) offered to firms in different sectors. Each capital firm specializes in capital goods designed specifically for one of the sectors of the economy.

The energy sector consists of renewable and fossil-fuel producers. Power plants leave the market if they reach their maximum lifespan or go bankrupt. New power plants can enter the market at any time. They embody energy technology (renewable or fossil fuel) based on the net present value (NPV) of investment. Investments in renewable energy are characterized by a higher initial cost than fossil fuels as they are more material-intensive. The commodity sector is modelled as a vertically integrated sector that includes mining sites extracting metal ores and material firms producing homogenous material goods, which can be thought of as metals. Material firms are assumed to own the mining sites and incur the ore extraction cost. For each mining site, the extraction cost depends on the depletion of metal ore deposits. We assume that new mining sites can emerge at any time. The initial ore reserves and the initial extraction cost are drawn randomly for each new site. Material sectors invest in capital goods. As capital goods firms use metals as an input for production, this creates the simultaneity of material goods as inputs and outputs.

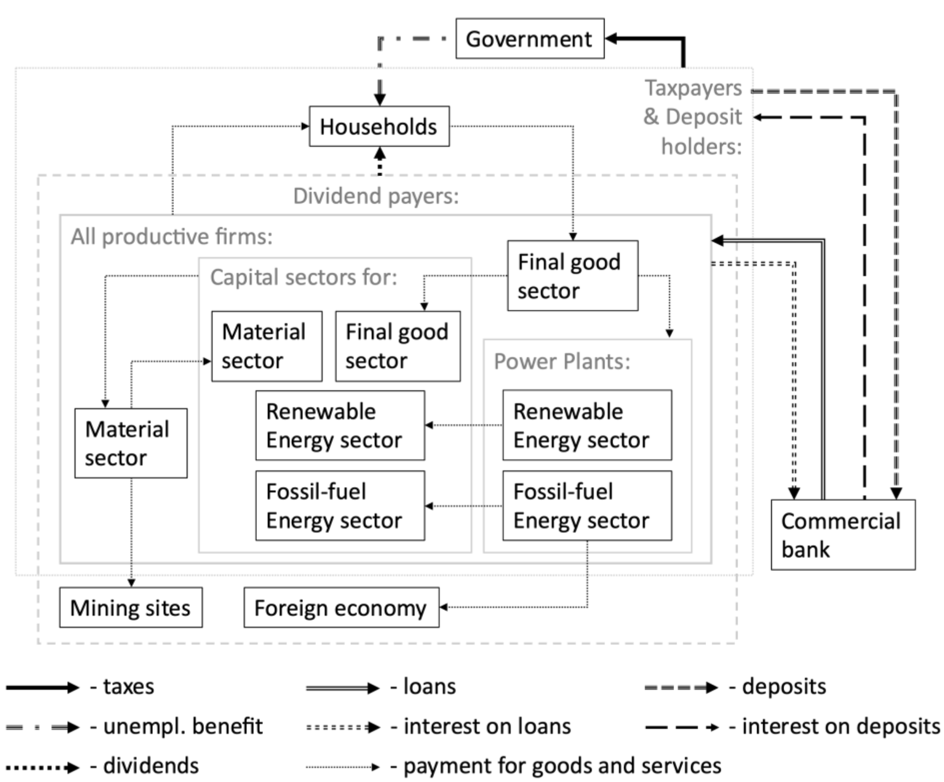
Figure 1(b) depicts the flows of money in the economy. Each firm and household has a deposit account at the commercial bank and receives interest on their deposits. For simplicity, we assume only one commercial bank. Firms with insufficient liquidity apply for loans for capital expansion. Loan approval depends on the leverage ratio of the borrower. In addition, the amount of credit issued by the commercial bank is limited by deposits of firms and households. Firms expenditures on inputs that are not produced in the model, such as fossil fuel or metal ores, are distributed as dividends to households to ensure the closure of financial flows.

Figure 1. Structure of the model

(a) flow of goods and services



(b) money flow



2.1. Final Goods Sector

The final good market is composed of heterogenous firms offering homogenous goods that differ with respect to prices. The dynamics in this market work as follows. First, households compute desired consumption budget $\tilde{C}_{h,t}$, and select a final good firm that has a positive inventory with the probability that depends on firms' prices. This way, consumers attempt to buy the cheapest product available on the market. After all consumers make their purchasing decisions, firms compute the expected demand and invest in capital expansion if necessary.

The final goods producers use labor $N_{i,t}$, electricity $E_{i,t}$ and capital goods as inputs. The production function is given by:

$$Y_{i,t} = \min\left(\sum_{v \in V_{i,t}} \kappa_v K_{v,t}\,, \alpha^{FG} N_{i,t}, \varepsilon E_{i,t}\right), \tag{1}$$

where $Y_{i,t}$ is the output of the firm, κ_v and $K_{v,t}$ are the productivity and the quantity of capital good v in the firm's capital stock $V_{i,t}$, α^{FG} is the labor productivity in final good sector, and ε is the energy productivity in the final good sector. Based on the expected demand $Q^*_{i,t}$, final good firms set their desired production $\tilde{Y}_{i,t}$ as:

$$\tilde{Y}_{i,t} = Q^*_{i,t}(1 + \beta_{FG}) - inv_{i,t}, \tag{2}$$

where β_{FG} is the final good inventory buffer parameter, and $inv_{i,t}$ is the output inventory of the firm.

The expect demand $Q^*_{i,t}$ is computed using the adaptive expectation function:

$$Q^*_{i,t} = Q^*_{i,t-1} + \alpha_{exp}\left(Q_{i,t-1} - Q^*_{i,t-1}\right), \tag{3}$$

where $Q_{i,t-1}$ is the past demand, and α_{exp} is the adaptive expectation parameter.

Firms' production is constrained by their capital stock. The capital stock of each firm is composed of vintages v of different capital goods. The maximum output that firm *i* can produce at time *t* is equal to:

$$\hat{Y}_{i,t} = \sum_{v \in V_{i,t}} \kappa_{v,t}\, K_{v,t}, \tag{4}$$

where $\hat{Y}_{i,t}$ is the maximum output, $\kappa_{v,t}$ is the capital productivity of the capital good v, and $K_{v,t}$ is the quantity of the capital good v in the firm's capital stock $V_{i,t}$. Each capital stock depreciates at the constant rate $\delta^{K_{FG}}$:

$$K_{v,t} = (1 - \delta^{K_{FG}}) \cdot K_{v,t-1}. \tag{5}$$

After firms set their production, they hire workers:

$$\tilde{N}_{i,t} = \min\left(\hat{Y}_{i,t}, \tilde{Y}_{i,t}\right) \cdot 1/\alpha^{FG}, \tag{6}$$

where $\tilde{N}_{i,t}$ is labor demand, and α^{FG} is the labor productivity in the final good sector. Firms also order energy:

$$\tilde{E}_{i,t} = \min(\hat{Y}_{i,t}, \tilde{Y}_{i,t}) \cdot 1/\varepsilon, \tag{7}$$

where ε is the energy productivity. In both equations, $\min(\hat{Y}_{i,t}, \tilde{Y}_{i,t})$ indicates the level of current production, which is set as the minimum of the desired ($\tilde{Y}_{i,t}$) and the maximum attainable production ($\hat{Y}_{i,t}$).

The unit cost of production consists of input expenditures, and fixed costs such as capital depreciation and interests paid on loans:

$$\begin{aligned} c_{i,t}^{FG} &= \frac{wN_{i,t} + \bar{p}_{i,t}^{E} E_{i,t} + \Delta_{i,t}^{depr} + \Lambda_{i,t}^{int_{pmt}}}{Y_{i,t}} \\ &= \frac{w}{\alpha^{FG}} + \frac{\bar{p}_{i,t}^{E}}{\varepsilon} + \frac{\Delta_{i,t}^{depr} + \Lambda_{i,t}^{int_{pmt}}}{Y_{i,t}}, \end{aligned} \tag{8}$$

where w is wage, $\bar{p}_{i,t}^{E}$ is average price at which firm i bought electricity from different power plants weighted by the amount purchased, $\Delta_{i,t}^{depr}$ is the depreciation of the capital stock, and $\Lambda_{i,t}^{int_{pmt}}$ is the interest payments on loans.

Each firm sets its price $p_{i,t}^{FG}$ by imposing a markup over its unit cost of production:

$$p_{i,t}^{FG} = c_{i,t}^{FG} \cdot (1 + \mu_{i,t}), \tag{9}$$

where $c_{i,t}^{FG}$ is the unit cost of production, and $\mu_{i,t}^{FG}$ is the markup over the unit cost of production. The markup changes depending on the market share of firm *i*:

$$\mu_{i,t}^{FG} = \begin{cases} \mu_{i,t-1}^{FG}(1 + \mu_t^{FN}) & \text{if } f_{i,t} > \bar{f}_t \text{ and } \Delta f_{i,t} > 0 \\ \mu_{i,t-1}^{FG}(1 - \mu_t^{FN}) & \text{if } f_{i,t} < \bar{f}_t \text{ or } \Delta f_{i,t} < 0 \\ \mu_{i,t-1}^{FG} & \text{otherwise,} \end{cases} \tag{10}$$

where $f_{i,t}$ is the market share of firm i, $\bar{f}_t$ is the average market share, $\Delta f_{i,t}$ is the change in market share, and $\mu_t^{FN} \sim FN\left(\mu_{FN_{markup}}, \sigma^2_{FN_{markup}}\right)$ is a random value draw from the folded normal distribution.

If firm's desired production exceeds its production capacity, a firm orders capital goods on the capital market. A final good producer selects capital good v with the probability inversely proportional to its price (see Section 2.2). The desired level of capital investment $\tilde{K}_{i,t}$ is equal to:

$$\tilde{K}_{i,t} = \max(0, \tilde{Y}_{i,t+dt^{C_{FG}}} - \hat{Y}_{i,t+dt^{C_{FG}}}) \cdot 1/\kappa_v, \tag{11}$$

where $\hat{Y}_{i,t+dt^{C_{FG}}}$ is the future productive capacity at time $t + dt^{C_{FG}}$ equal to the expected future desired production ($\tilde{Y}_{i,t}$), κ_v is the capital productivity of new capital good v, and $t + dt^{C_{FG}}$ is the arrival time of a new capital good in the final good sector.

If firm's liquidity is insufficient to finance capital expansion, a firm borrows money from the bank. The desired loan amount is computed as:

$$\tilde{L}_{i,t} = \max\left(0, p_v \tilde{K}_{v,t} - \frac{D_{i,t}}{1 + \beta_{cash}}\right), \tag{12}$$

where p_v is the price of the capital good v, $D_{i,t}$ is the deposit balance of the firm, and β_{cash} is a cash buffer calculated as a fraction of its deposit balance, following Assenza et al. (2015). The capital ordered arrives after $dt^{K_{FG}}$ periods.

Firms that have negative equity are declared bankrupt and exit the market. They attempt to repay loans using remaining liquidity. Unrepaid loans become non-performing loans for the commercial bank. Each period, a new final good firm can enter the market with probability $prob^{FG}$ or in case the total number of final good firms is lower than the number of firms operating in the first period of model simulations ($\#_{FG}$).

2.2. The matching algorithm

In the model, all interactions occur at the decentralized markets, where firms compete for clients, while consumers compete to purchase the cheapest products. The probability of agent i being matched with agent j is given by:

$$P[\text{agent } i \text{ selects supplier } j\ ] \equiv P_{i\mapsto j}\left(\mathbb{S}_{i,t}, \Psi_{j,t}\right) = \frac{\exp\left(-\gamma^{logit}\log\left(\Psi_{j,t}\right)\right)}{\sum_{k\in\mathbb{S}_{i,t}}\exp\left(-\gamma^{logit}\log\left(\Psi_{k,t}\right)\right)}, \tag{13}$$

where $j \in \mathbb{S}_{i,t}$, is the set of suppliers, γ^{logit} is the logit competition parameter, and $\Psi_{k,t}$ indicates a cost or a price of supplier k. The equation implies that the cheapest suppliers have the highest probability of being selected.

2.3 Households

Households purchase final goods and save money in banks. Consumption of household h is equal to:

$$C_{h,t} = c_Y^{HH}\left(Y_{h,t} + div_{h,t}\right) + c_D^{HH} D_{j,t}, \tag{14}$$

where c_Y^{HH} is the propensity to consume out of income, $Y_{h,t}$ is the household's wage income before tax or unemployment benefit if household did not receive wage, $div_{h,t}$ is dividend income, c_D^{HH} is the propensity to consume out of wealth, and $D_{h,t}$ is the deposit balance of the household.

Firms randomly hire workers until labor demand is satisfied or there is no more labor available. Households are employed by firms for one period only. Afterwards, they enter the labor market again. The wage rate w per unit of labor is fixed. Formally, households are endowed with $lab_t \in (0,1]$ labor units allocated to one or more firms proportionally to the ratio of aggregate labor demand to labor supply ($\frac{\sum_j \widetilde{N}_{j,t}}{\#_{HH}}$):

$$lab_t = \min\left(1, \frac{\sum_j \widetilde{N}_{j,t}}{\#_{HH}}\right), \tag{15}$$

where $\sum_j \widetilde{N}_{j,t}$ is the total labor demand by all sectors, and $\#_{HH}$ is the number of households. Each worker can be employed by multiple firms as long as the total employment of an individual worker at different firms does not exceed lab_t.

2.4. Energy Sector

The energy sector *E* is composed of renewable *RE* and fossil-fuel *FE* producers. Due to different unit costs, the power plants have different marginal costs of electricity generation and sell electricity at different prices. Matching between power plants and their consumers is modelled using the matching algorithm described in Section 2.2.

Energy production of a power plant embodying energy technology E ($Y_{i,t}^E$) is given by:

$$Y_{i,t}^E = \min\left(\kappa_{v,t} K_{v,t}, \alpha^E N_{i,t}^E, \phi^{FE} F_{i,t}\right), \quad (16)$$

where $\kappa_{v,t}$ and $K_{v,t}$ are the productivity and the quantity of the installed capital, α^E is the labor productivity in sector *E*, and $N_{i,t}^E$ is the labor force in sector *E*, ϕ^{FE} is the thermal efficiency, i.e., the energy-to-output ratio, and $F_{i,t}$ is fuel. We assume that *RE* plants do not use fuel such that $Y_{i,t}^E = \min\left(\kappa_{v,t} K_{v,t}, \alpha^E N_{i,t}^E\right)$. $E \in \{RE, FE\}$

The price of fuel $p_{fuel,t}$ follows the Geometric Brownian Motion process:

$$dp_{fuel,t} = \mu_{fuel} p_{fuel,t} dt + \sigma_{fuel} p_{fuel,t} dW_t, \quad (17)$$

where μ_{fuel} and σ_{fuel} are the drift and volatility terms of the stochastic process, and W_t is the standard Wiener process.

Each power plants sets the desired level of production $\tilde{Y}_{it}^E$ as:

$$\tilde{Y}_{it}^E = Q_{i,t}^*(1 + \beta_E), \quad (18)$$

where $Q_{i,t}^*$ is firm *i*'s expected demand, and β_E is the energy buffer. The expected demand is computed using eqn. 3. The maximum output of each power plant $\hat{Y}_{i,t}^E$ depends on the capital stock $K_{v,t}$ and its productivity $\kappa_{v,t}$:

$$\hat{Y}_{i,t}^E = \kappa_{v,t} K_{v,t}, \quad (19)$$

Unlike firms in the final good sector, power plants do not invest in capital expansion nor their capital stock depreciates over time. Each power plant has a limited lifespan, equal to $\tau^{K_{RE}}$ and $\tau^{K_{FE}}$ periods in case of renewable and fossil-fuel power plants, respectively. After this time, the plant becomes obsolete.

Based on the production plan, power plants compute labor demand $\widetilde{N}_{i,t}^E$ as:

$$\widetilde{N}_{i,t}^E = \tilde{Y}_{it}^E \cdot 1/\alpha^E, \quad (20)$$

where α^E is the labor productivity in sector E.

The fuel demand $\tilde{F}_{i,t}$ by fossil-fuel power plants is equal to:

$$\tilde{F}_{i,t} = \tilde{Y}_{it}^{FE} \cdot 1/\phi^{FE}, \tag{21}$$

where $\tilde{Y}_{it}^{FE}$ is the desired production, and ϕ^{FE} is the fuel productivity.

The unit cost of production of power plant *i* embodying fuel E s is equal to:

$$c_{i,t}^{E} = \frac{w}{\alpha^{E}} + \frac{p_{fuel}}{\phi^{FE}} + \frac{\Lambda_{i,t}^{int_{pmt}} + p_v K_{v,t}/\tau^{C_{xE}}}{Y_{i,t}^{E}}, \tag{22}$$

where $\Lambda_{i,t}^{int_{pmt}}$ are interest payments on loans, and τ^{C_E} is the lifespan of the power plant. The second term of the above equation disappears for renewable power plants that do not incur fuel costs.

2.4.1. The exit and entry of power plants

Power plants leave the market once they reach their maximum lifespan. At any time, a new power plant can enter the market, depending on the expected future gap in the energy demand and supply.

The total energy gap is defined as:

$$\mathbf{E}_{t+dt^{C_E}}^{gap} = \max\left(0, \sum_{j \in FG_{firms}} \tilde{E}_{j,t} - \sum_{j \in PowerPlants} \hat{Y}_{j,t+dt^{C_E}}\right). \tag{23}$$

In the eqn. 23, the future electricity demand is assumed to be equal to its current level, while the future supply is calculated by summing the maximum production capacity of all power plants that will be operating on the market after dt^{C_E} periods, which is the time needed to build a new power plant embodying fuel $E \in \{RE, FE\}$.

A new power plant enters the market if the gap is greater than zero: $\mathbf{E}_{t+dt^{C_E}}^{gap} > 0$. If this the case, an energy owner decides on the type of energy to be embodied in a new power plant. The decision is made by comparing the Net Present Value (NPV) of investments in renewable NPV_v^{RE} and fossil-fuel power plants NPV_v^{FE}, computed as:

$$NPV_v^{E} = -p_v \tilde{K}_{v,t} + \sum_{j=0}^{\tau^{K_{xE}-1}} \left(\frac{\bar{p}_E \kappa_v \tilde{K}_{v,t} - w \cdot \kappa_v \tilde{K}_{v,t}/\alpha^{E} - p_{fuel,t} \kappa_v \tilde{K}_{v,t}/\phi}{(1+r_L)^{j+dt^{C_E}}}\right), \tag{24}$$

where $\bar{p}_E$ is the expected electricity price, $p_{fuel,t}$ is the fuel price equal to 0 if $E = RE$. In general, the NPV of investments in a new power plant v depends on the difference between the current cost of capital, the present value of future net cash flows, and the interest rate r_L. After the values of both NPV_v^{RE} and NPV_v^{FE} are compared, the more profitable power plant enters the market.

2.5. Materials Sector

The materials sector extracts metal ores from mining sites and uses them to produce material goods that constitute an input for production in other sectors. Each material firm initially has access to one mining site. In case ores therein become depleted, the firm invests in the exploration of new mining sites. Material firms can also abandon the existing mining site, if the cost of extraction becomes too high, and invest in a new mining site.

The production function of firms in the material sector $Y_{i,t}^{M}$is defined as:

$$Y_{i,t}^{M} = \min\left(\sum_{v \in V_{i,t}} \kappa_{v,t} K_{i,v,t}\,, \alpha^{M} N_{i,t}^{M}, \rho R_{i,t}\right), \tag{25}$$

where $\kappa_{v,t}$ and $K_{v,t}$ are the productivity and the size capital good v, $N_{i,t}^{M}$ is the labor force, α^{M} is the labor productivity in the material sector, ρ is the ore productivity in material sector, and $R_{i,t}$ is the quantity of ore available to firm *i*. Based on the expected demand $Q_{i,t}^{*}$ (see eqn. 3), material firms set their production plan $\tilde{Y}_{i,t}^{M}$:

$$\tilde{Y}_{i,t}^{M} = Q_{i,t}^{*}(1+\beta_{M}) - inv_{i,t}, \tag{26}$$

where β_{M} is the material inventory buffer parameter, and $inv_{i,t}$ is the inventory of the firm.

The maximum output $\hat{Y}_{i,t}^{M}$ of firm *i* in the material sector is constrained by its capital stock composed of different vintages v of capital goods:

$$\hat{Y}_{i,t}^{M} = \sum_{v \in V_{i,t}} \kappa_{v,t}\, K_{v,t}, \tag{27}$$

where $\kappa_{v,t}$ is the capital productivity of the capital good v, and $K_{v,t}$ that belongs to firm *i*'s capital stock $V_{i,t}$.

After setting the desired production level, the firm hires workers:

$$\tilde{N}_{i,t}^{M} = \min\left(\hat{Y}_{i,t}^{M}, \tilde{Y}_{i,t}^{M}\right) \cdot 1/\alpha^{M}, \tag{28}$$

where $\min\left(\hat{Y}_{i,t}^{M}, \tilde{Y}_{i,t}^{M}\right)$ is the total output equal to the minimum of the desired production ($\tilde{Y}_{i,t}^{M}$) and the maximum feasible output ($\hat{Y}_{i,t}^{M}$), and α^{M} is the labor productivity in the material sector.

The demand for ore $\tilde{R}_{i,t}$ is equal to:

$$\tilde{R}_{i,t} = \min\left(\hat{Y}_{i,t}^{M}, \tilde{Y}_{i,t}^{M}\right) \cdot 1/\rho, \tag{29}$$

where ρ is the ore productivity in material sector.

The unit cost of production is equal to:

$$c_{i,t}^{M} = \frac{w}{\alpha^{M}} + \frac{c_{i,t}^{ore}}{\rho} + \frac{\Delta_{i,t}^{depr} + \Lambda_{i,t}^{int_{pmt}}}{Y_{i,t}^{M}}, \tag{30}$$

where w is wage, $c_{i,t}^{ore}$ is the cost of ore extraction, α^M is the labor productivity in the material sector, ρ is the ore productivity in material sector, $\Delta_{i,t}^{depr}$ is the depreciation of the capital stock, and $\Lambda_{i,t}^{int_{pmt}}$ is the interest payments on loans.

The cost of ore extraction $c_{i,t}^{ore}$ increases with the depletion of ores in each mining site:

$$c_{i,t}^{ore} = \gamma_{1,t}^{ore} \left(\frac{\hat{R}_i^D}{R_{i,t}^D}\right)^{\gamma_2^{ore}} , \tag{31}$$

where is the cost of ore extraction, $\gamma_{1,t}^{ore} \sim FN(\gamma_1^{ore}, \sigma_{\gamma_1^{ore}}^2)$ is the ore extraction cost parameter 1, γ_2^{ore} is the ore extraction cost parameter 2 that determines the growth rate of the ore extraction cost, $\hat{R}_i^D$ is the initial ore deposit of the mining site, and $R_{i,t}^D$ is the remaining ore deposit of the mining site. The cost of ore extraction is distributed to the households in the form of dividends.

If the desired ore extraction exceeds the remaining reserves $R_{i,t}^D$, then the firm extract all ores from the available site, and move to a new mining site, while keeping its capital stock. In the beginning of each simulation run, there are $\#_M$ mining sites. Each timestep there is a probability pr^{ore} of a new ore deposit being discovered. The amount of ores in a new mining site, including those existing at the start of the simulation, is drawn from:

$$\hat{R}_i^D = FN\left(\mu_{R^D}, \sigma_{R^D}^2\right), \tag{32}$$

where μ_{R^D}, σ_{R^D} are the mean and the standard deviation of the folded normal distribution.

A new material firm evaluates if it would be profitable to enter the market. Formally, it selects a new mining site randomly with the probability inversely proportional to the cost of extraction in each site (see Section 2.2). The firm invests in a new mining site if the expected price $p_{M,t}^*$ of material goods would be higher than the expected price it can charge due to investments in a new mining site $p_{i,t}^*$, namely: $p_{i,t}^* < p_{M,t}^*$. The expected price of materials follows the adaptive expectation equation:

$$p_{M,t}^* = p_{M,t-1}^* + \alpha_{exp}^M\left(p_{M,t-1} - p_{M,t-1}^*\right) \tag{33}$$

where $p_{M,t-1}$ is the average price of material goods weighted by the shares of their sales in total sales, and α_{exp}^M is the adaptative expectation parameter. The expected price of firm i after investing in a new mining site is equal to:

$$p_{i,t}^* = \left(1 + \mu_{M,0}\right) c_{i,t}^* , \tag{34}$$

where $\mu_{M,0}$ is the markup imposed on the expected cost $c_{i,t}^*$, which follows:

$$c_{i,t}^* = \frac{w}{\alpha^M} + \frac{c_{i,t}^{ore}}{\rho} + \sum_{v \in V_{i,t}^*} (\delta^{K_M} + r_L) \frac{p_{v,t}}{\kappa_{v,t}} , \tag{35}$$

where w is wage, α^M is the labor productivity in the material sector, $c_{i,dt}^{ore}$ is the ore extraction cost of the new mining site, ρ is the ore productivity, δ^{K_M} is the material capital depreciation rate, r_L is the loan interest rate, and $p_{v,t}$, $\kappa_{v,t}$ are the price and productivity of capital good v that belongs to firm i's potential capital stock $V_{i,t}^*$.

2.6. Capital Sector

On the capital market, firms compete for clients by engaging in R&D activities to improve the productivity of capital goods. The R&D process is modeled following a seminal work by Nelson and Winter (1982), according to which firms invest in innovation and imitation of other firms' techniques. An important novelty of our model concerns that capital firms use material goods as a production input. Moreover, the material intensity of capital goods depends on the sector for which the capital good is intended. In particular, each capital firm C_x specializes in producing capital goods for specific sector $x \in \{FG, M, FE, RE\}$. This assumption allows us to model investments in fossil fuels to be more material-intensive than renewable energy investments.

The production function of capital firm goods C_x takes the following form:

$$Y_{C_x,t} = \min\left(\alpha_{C_x,t} N_{C_x,t}^Y, m^{C_x} M_{C_x,t}\right) \tag{36}$$

where x is the sector for which capital producers offer capital goods, i.e., renewable/fossil energy, material or final good producers, $\alpha_{C_x,t}$ is the labor productivity of capital firm C_x, $N_{C_x,t}^Y$ is the number of workers, m^{C_x} is the material intensity of sector x, and $M_{C_x,t}$ is the material input used for production by capital firm C_x.

Unlike other sectors, capital firms collect orders, which sum defines their desired production $\tilde{Y}_{C_x,t}$ as:

$$\tilde{Y}_{C_x,t} = \begin{cases} \sum_{j \in FG} I_{j,t-dt^{C_{FG}}} & \text{if } x = FG \\ \sum_{j \in RE} I_{j,t-dt^{C_{RE}}} & \text{if } x = RE \\ \sum_{j \in FE} I_{j,t-dt^{C_{FE}}} & \text{if } x = FE \\ \sum_{j \in M} I_{j,t-dt^{C_M}} & \text{if } x = M \end{cases}, \tag{37}$$

where dt^{C_X} stands for the delivery time of capital goods in sector x.

Capital firms order material goods according to the equation:

$$\widetilde{M}_{C_x,t} = \tilde{Y}_{C_x,t} / m^{C_x}, \tag{38}$$

where $\widetilde{M}_{C_x,t}$ is the desired material stock at period t. The amount of available materials at time t $M_{C_x,t}$ defines the maximum output $\hat{Y}_{C_x,t}$ as:

$$\hat{Y}_{C_x,t} = m^{C_x} M_{C_x,t}. \tag{39}$$

The demand for production labor $\widetilde{N}^{Y}_{C_x,t}$ is computed as:

$$\widetilde{N}^{Y}_{C_x,t} = \min(\hat{Y}_{C_x,t}, \tilde{Y}_{C_x,t}\ )/\alpha_{C_x,t}, \tag{40}$$

where $\alpha_{C_x,t}$ is the labor productivity of capital firm C_x.

The unit cost of production of the capital firm, which specialized in capital goods for sector x, is equal to:

$$c_{C_x,t} = \frac{\bar{p}_{M,C_x,t}}{m^{C_x}} + \frac{w}{\alpha^{C_x}_{i,t}} + \frac{wN^{R\&D}_{C_x,t} + \Lambda^{int_{pmt}}_{C_x,t}}{Y_{C_x,t}}, \tag{41}$$

where $\bar{p}_{M,C_x,t}$ is the average price of materials weighted by the respective quantities in the inventory, w is wage, $N^{R\&D}_{C_x,t}$ is labor allocated to R&D, and $\Lambda^{int_{pmt}}_{C_x,t}$ are the interest payments.

Capital firms invest a fraction of their profits in R&D activities to improve their labor productivities, or productivities of capital goods offered to their clients. Firms engage in two types of R&D activities: innovation $IN_{C_x,t+1}$ and imitation $IM_{C_x,t+1}$. The amount of finance allocated to both types of activities is defined, following Dosi et al. (2010) and Terranova and Turco (2022), as:

$$\begin{aligned} R\&D_{C_x,t+1} &= \nu^{R\&D}\pi^{net}_{C_x,t} \\ IN_{C_x,t+1} &= \left(1-\chi^{imit}\right)R\&D_{C_x,t+1}, \\ IM_{C_x,t+1} &= \chi^{imit}R\&D_{C_x,t+1} \end{aligned} \tag{42}$$

where $\nu^{R\&D} \in (0,1]$ and $\chi^{imit} \in (0,1)$. The R&D budget defines the number of workers $\widetilde{N}^{R\&D}_{C_x,t+1}$ hired to perform innovation activities:

$$\widetilde{N}^{R\&D}_{C_x,t+1} = \frac{R\&D_{C_x,t+1}}{w}. \tag{43}$$

Innovation follows a stochastic two-step process. In the first step, a firm engages in either innovation or imitation with the following probabilities:

$$\begin{aligned} P[\text{firm } C_x \text{ innovates}] &= 1 - e^{-\rho^{R\&D} IN_{C_x,t}} \\ P[\text{firm } C_x \text{ imitates}] &= 1 - e^{-\rho^{R\&D} IM_{C_x,t}}, \end{aligned} \tag{44}$$

where $\rho^{R\&D} \in (0,1]$ is a parameter defining the probability that the R&D process will be successful. In the second step, in case the innovation draw was successful, the capital and labor productivity change according to:

$$\kappa_{C_x,t+1}^{inn} = \kappa_{C_x,t}\left(1 + x_{C_x,t}\Delta_\kappa\right), \text{where } \Delta_\kappa = FN\left(\mu_{FN_{innov}^{product}}, \sigma^2_{FN_{innov}^{product}}\right)$$
$$\alpha_{C_x,t+1}^{inn} = \alpha_{C_x,t}\left(1 + x_{C_x,t}\Delta_\alpha\right), \text{where } \Delta_\kappa = FN\left(\mu_{FN_{innov}^{process}}, \sigma^2_{FN_{innov}^{process}}\right), \quad (45)$$

where $x_{C_x,t} = \max\left(\frac{\kappa_{C_x,t}}{\bar{\kappa}_t},\ 2\right)$ indicates the position of a firm in the distribution of capital productivities among all capital firms in sector C_x, with $\bar{\kappa}_t$ describing the average capital productivity among them, $\mu_{FN_{innov}^{product}}$ and $\sigma^2_{FN_{innov}^{product}}$ are the mean and variance parameters in the folded normal distribution describing product innovation, and $\mu_{FN_{innov}^{process}}$ and $\sigma^2_{FN_{innov}^{process}}$ are parameters in the folded normal distribution corresponding to process innovation, respectively.

If firm C_x draws an imitation activity, it randomly selects the most successful competitor j (see eqn. 3). It adopts his technology, which changes $\kappa_{C_x,t+1}^{imi} = \kappa_{j,t}$ and $\alpha_{C_x,t+1}^{imi} = \alpha_{j,t}$. Finally, in case both innovation and imitation draws are successful, a firm chooses technology that yields the highest productivity of production such that $\kappa_{C_x,t+1} = \max\left(\kappa_{C_x,t+1}^{inn},\ \kappa_{C_x,t+1}^{imi}\right)$ and $\alpha_{C_x,t+1} = \max\left(\alpha_{C_x,t+1}^{inn},\ \alpha_{C_x,t+1}^{imi}\right)$.

2.7. Banking Sector

The banking sector is composed of one bank, in which all agents (consumers and producers) hold their accounts. Each period, the accounts are updated to reflect financial flows on the market. Agents also earn interest on their deposits and pay interest on their loans. The bank grants loans for capital investments to firms that don't have sufficient liquidity. In case of short-term liquidity needs, the bank grans a short-term loan that is being repaid after η^{short} periods. The probability of receiving a loan is modelled using an S-shaped function that depends on the leverage ratio $\frac{\mathcal{L}_{j,t}}{\mathcal{E}_{j,t}+\mathcal{L}_{j,t}}$ of a borrower and the loan-to-deposits ratio $\frac{\sum_k L_{k,t}}{\sum_k D_{k,t}}$ of the lending bank:

$$P[\text{bank grants loan to firm } j] = \begin{cases} \dfrac{1}{1 + e^{\lambda_2^{loan}\cdot\left(\frac{\mathcal{L}_{j,t}}{\mathcal{E}_{j,t}+\mathcal{L}_{j,t}} - \lambda_1^{loan}\right)}} & \text{, if } \dfrac{\sum_k L_{k,t}}{\sum_k D_{k,t}} < \lambda_3^{loan} \\ 0 & \text{, otherwise} \end{cases}, \quad (46)$$

where $\mathcal{L}_{j,t}$ are liabilities of firm j at time t, $\mathcal{E}_{j,t}$ is the equity of firm j at time t, λ_1^{loan} is the critical value of the leverage ratio above which the probability of granting a loan becomes less than 50%, λ_2^{loan} is the sensitivity parameter, λ_3^{loan} is the maximum loan-to-deposit ratio of a bank, and $L_{k,t}$ is the sum of loans (including non-performing ones) issued to firm k, and $D_{k,t}$ is firm/household k's deposits.

The time by which loans needs to be repaid η^x is sector-specific, it corresponds to the capital lifespan in sector x (η^x=τ^{C_x}). The loan principal payment per period is equal to:

$$\Lambda_{i,t}^{prin_{pmt}} = \sum_{j=t-\eta^x}^{t-1} L_{i,j-dt^x} \frac{1}{\eta^x}. \tag{47}$$

The total balance of loans, i.e., an outstanding principal amount that has not yet been repaid, is computed as:

$$\Lambda_{i,t}^{balance} = \sum_{j=t-\eta^x}^{t-1} L_{i,j-dt^x} \left(1 - \frac{t-(j+dt^x)}{\eta^x}\right), \tag{48}$$

while interest payments on loans as:

$$\Lambda_{i,t}^{int_{pmt}} = \sum_{j=t-\eta^x}^{t-1} r_L \cdot L_{i,j-dt^x} \frac{\eta^x - \big((t-1)-j\big)}{\eta^x}, \tag{49}$$

where r_L is the interest rate on loans, η^x is the loan duration, and dt^x is the capital delivery time. Until capital is received, the loan interest and the principal payment are not being paid. In case of a short-term loan, η^x is replaced with η^{short}, while $dt^x = 0$.

3. Results

In this section, we present the results from the model simulations. We examine how the transition to a low-carbon economy is affected by different factors. In Section 3.1., we study the effect of the relative material intensity of investments in renewable power plants to fossil-fuel power plants and the dynamics of fuel prices on the low-carbon transition. Section 3.2 discusses the impact of competition in the material market and the entry of new mining sites on financial stability. In both sections, the average ore extraction cost increases over time with the progressing metal ore scarcity. In Sections 3.3 and 3.4, we relax this assumption in the absence and presence of (exogenous) geopolitical shocks that make some mining sites temporarily unavailable, respectively. We run the model 100 times for 200 timesteps. Each time step represents one year. Supplementary Table ST6 reports the mean results from Monte Carlo analysis for each experimental condition. In particular, we report the mean results from the last 50 periods from each simulation repeated 100 times to control for the presence of the stochastic factors in our model.

3.1. Material intensity of investments in the energy sector

Figure 2 illustrates the model dynamics depending on the relative material intensity of investments in renewable energy and fossil fuels. Formally, in the baseline scenario, the coefficient of the capital-to-material ratio, i.e., an inverse of the material intensity of the renewable energy capital ($m^{C_{RE}}$), is equal to 1.25, which is reduced to 0.75 in the 'high R material intensity' scenario and increased to 2 in the 'low R material intensity' scenario. The inverse of the material intensity of investment in fossil-fuel power plants ($m^{C_{FE}}$) is equal to 15, and thus such investments are always less material intensive than investments in renewable energy regardless of the considered scenario.

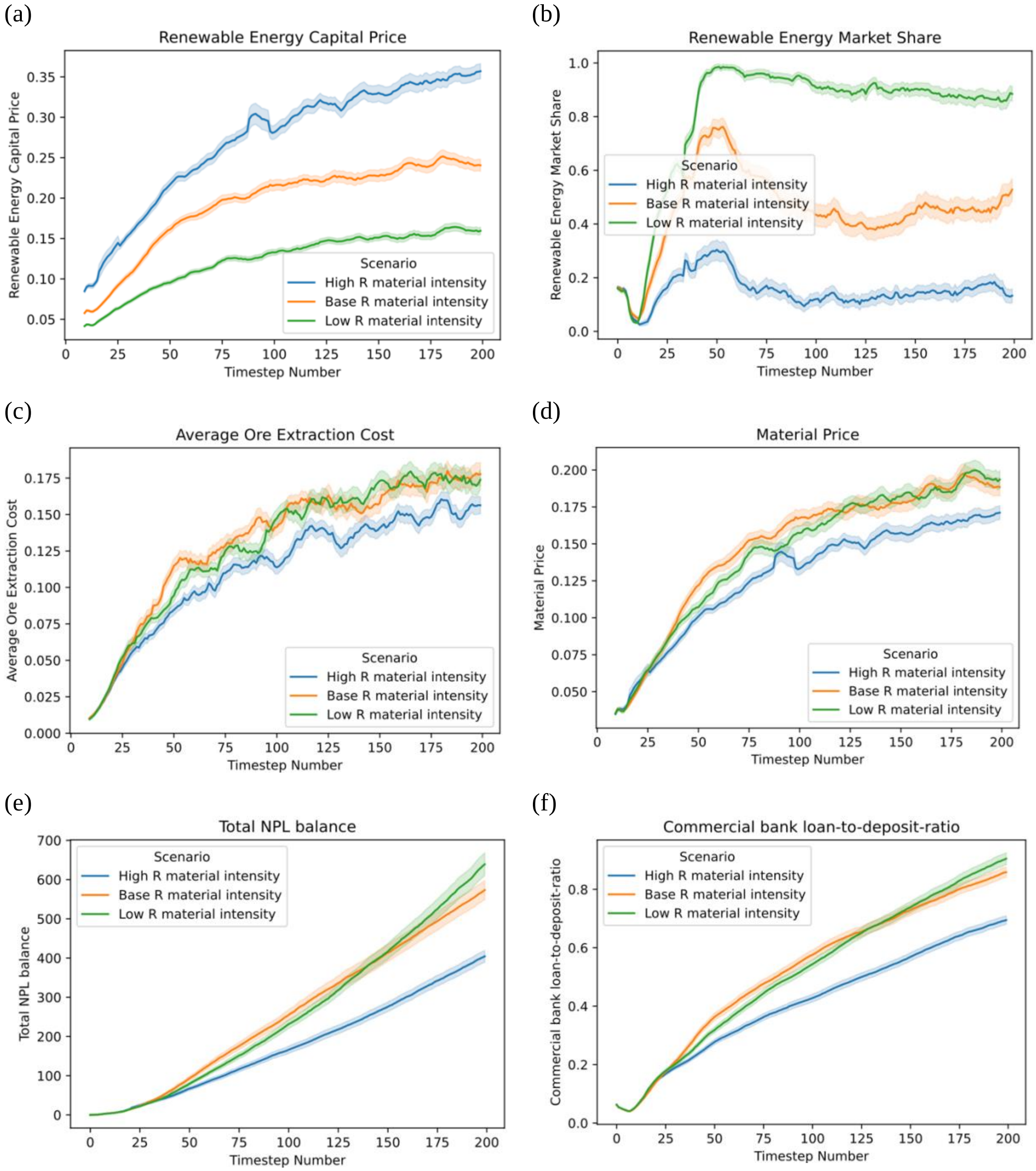
Figure 2(b) shows that in the baseline scenario, the transition to renewable energy accelerates in the first 50 years, after which period, the share of renewable energy declines until it reaches 50% of the energy market. This can be explained by an increasing price of metal ore extraction over time (due to metal scarcity), which reduces the attractiveness of investments in renewable energy. In the baseline scenario, we set the material intensities of capital investments in the energy sector so that the NPVs of investments in renewable energy and fossil fuel are similar. Under such a condition, small fluctuations in material prices and/or changes in the cost of capital goods can shift the cost advantage towards renewable energy or fossil fuels. As a result, the probability of a new renewable power plant entering the market is about 50%. Increasing the value of the material intensity of investments in renewable energy relative to fossil fuels prevents the transition from occurring in the 'high R material intensity' scenario while reducing it ensures that renewable energy reaches a 100% share of the energy market in the 'low R material intensity' scenario.

Our results indicate that the 'high R material intensity' scenario with the low level of investments in renewable energy results in a more financially stable economy than economies characterized by higher shares of such investments, confirming the previous results from the literature. For instance, Safarzynska and van den Bergh (2017) show that renewable power plants are more prone to bankruptcy, which can negatively affect the stability of the banking sector that provides loans to energy producers. This effect depends on the impact of the energy mix on the price of electricity and the ability of renewable power producers to repay their loans. In our model, the mechanism through which investment in renewable energy undermines financial stability is different. Investments in renewable energy accelerate metal scarcity, increasing ore extraction costs and material prices. In turn, higher metal prices affect the ability of firms to repay the loans and increase the average loan size. As a result, the total balance of non-performing loans and the loan-to-deposit ratio are much lower in the 'high R material intensity' scenario compared to other scenarios (Figures 2(e) and 2(f)). In addition, in the 'high R material intensity' scenario, the low level of metal ore extraction results in lower ore extraction costs and less volatile household disposable income due to more stable dividends from the extraction sector.

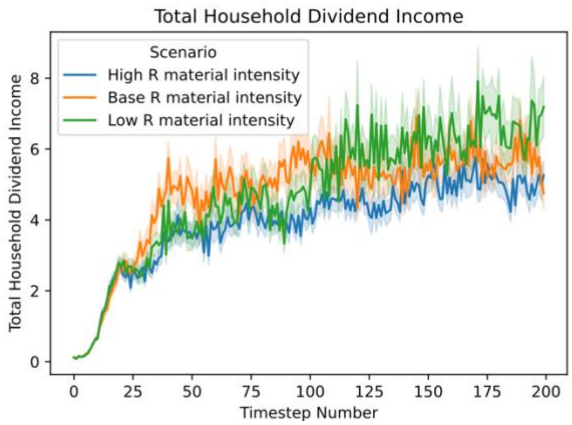
In all scenarios, the price of fossil fuels changes according the geometric Brownian motion equation (eqn. 17). Figure 3 presents the results from the model simulations, where we change the value of the drift parameter in this equation. In the baseline scenario, this parameter is equal to $\mu_{fuel} = 0.002$, which we increase to $\mu_{fuel} = 0.006$ in the 'high fuel price growth' scenario, and reduce to $\mu_{fuel} = 0.0003$ in the 'low fuel price growth' scenario. As a result, the price of fossil fuels increases faster in the 'high fuel price growth' scenario compared to the baseline scenario, while in the 'low fuel price growth' scenario, the fossil fuel price is relatively stable over time (Figure 3(a)). Figure 3(b) shows that the higher the price of fossil fuels, the greater the share of investments in renewable energy. In particular, higher fossil fuel prices reduce the net present value of fossil fuel investments.

Figures 3(e) and 3(f) illustrate that the higher the fuel prices, the greater the total balance of non-performing loans and the loan-to-deposit ratio due to more volatile and higher electricity prices, which increases the number of bankruptcies in the final good sector (Figure 3(i)). Interestingly, the 'high fuel price growth' scenario not only results in the highest share of renewable energy but also the highest price of electricity compared to other scenarios. This is the opposite pattern to the one observed in Figure 2, where the higher the share of renewable energy, the lower the electricity price. In particular, the 'high fuel price growth' scenario results in renewable energy reaching 80-90% of the market, with the remaining share of electricity supplied by fossil fuels. Although the share of fossil fuels in electricity generation is relatively small compared to other scenarios considered in Figure 3, a very high fuel price in this scenario offsets the reduction in the electricity price caused by investment in renewable energy.

Figure 2. Material intensity of renewable energy capital



(g)



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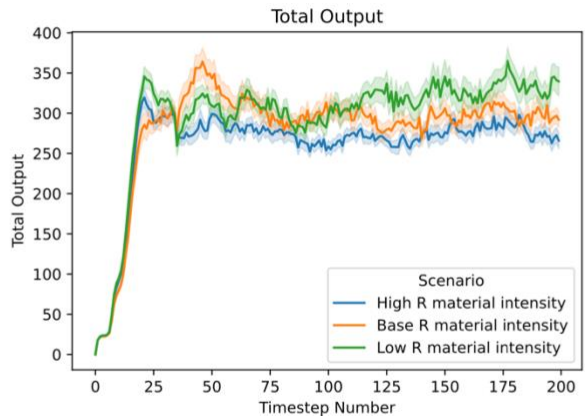
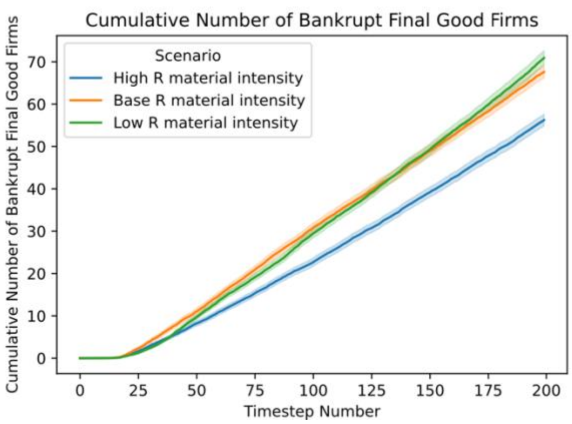
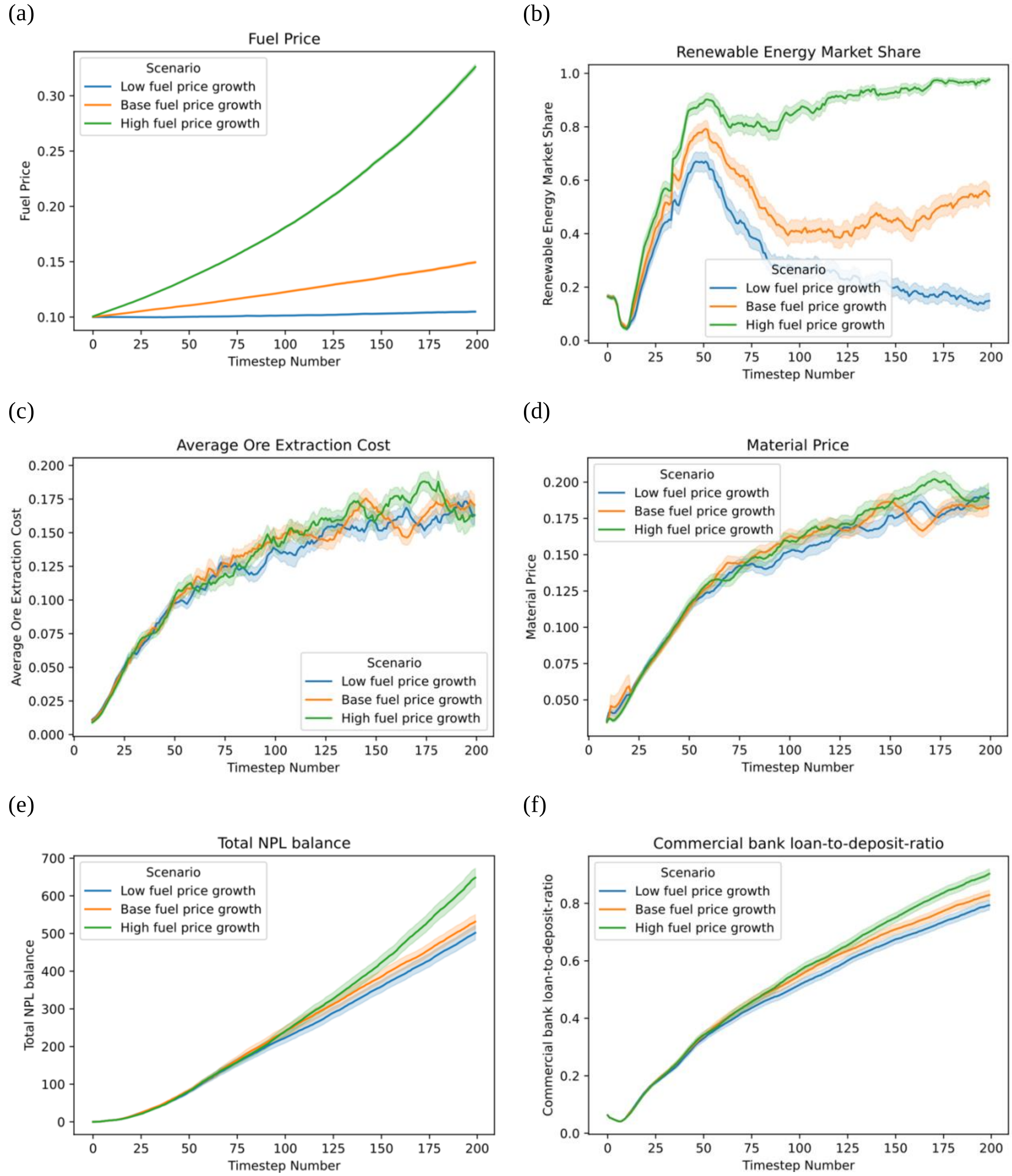


(i)



Note: The results in each figure represent the mean of the variable in question from the Monte Carlo repetitions for each experimental condition. The shadow area corresponds to the standard error. Figures (a), (c) and (d) show ten-year averages.

Figure 3. The impact of the rising cost of fossil fuels



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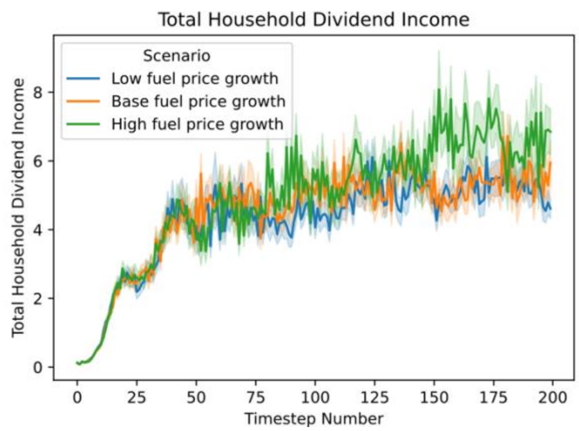

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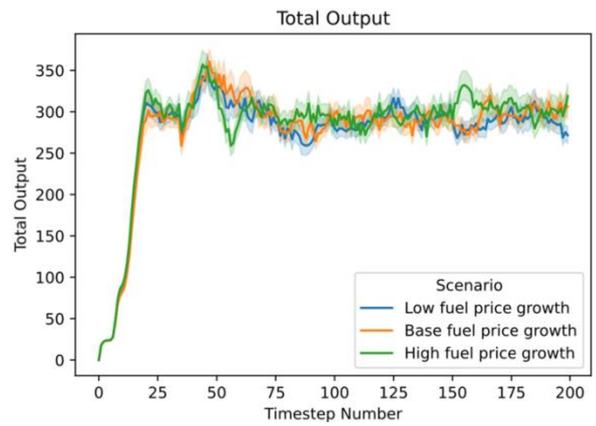
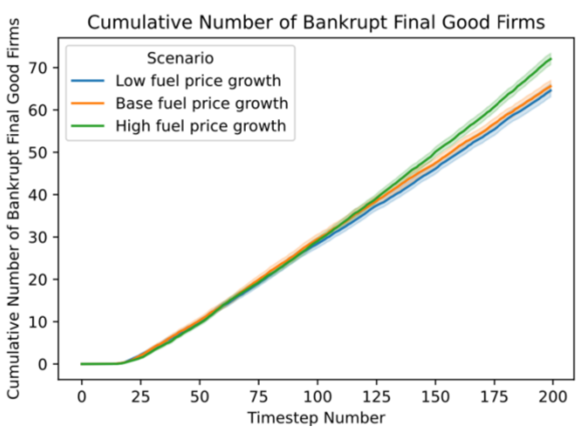


(i)



Note: The results in each figure represent the mean of the variable in question from the Monte Carlo repetitions for each experimental condition. The shadow area corresponds to the standard error. Figures (c) and (d) show ten-year averages to smooth the lines.

3.2. The entry of new mining sites and competition among material firms

The results of model simulations indicate that our results are sensitive to the dynamics of the entry of new mining sites and competition among material firms. Supplementary Table ST6 summarizes the results from the sensitivity analysis, where we examine if our results are robust to changes in key parameter values. This includes: the probability of new mining site exploration (pr^{ore}), the average and variance of the initial ore extraction cost ($\gamma_1^{ore}, \sigma^2_{\gamma_1^{ore}}$), the rate at which depletion of resources affects the cost of extraction (γ_2^{ore}), and the mean size of the mining site (μ_{R^D}).

In our model simulations, each new mining site is assigned an initial cost of extraction drawn from the folded normal distribution $FN(\gamma_1^{ore}, \sigma^2_{\gamma_1^{ore}})$, where γ_1^{ore} and $\sigma^2_{\gamma_1^{ore}}$ are the mean and variance, respectively. All new entering mining sites, on average, have the same initial cost of extraction. However, the cost of extraction of incumbent firms increases over time with the progressing ore scarcity in each mining site. In this setting, the lower the probability of entry of new mining sites (pr^{ore}), the higher the average ore extraction costs. On the other hand, a higher entry rate of new mining sites reduces the average cost of extraction but at the cost of a higher bankruptcy rate among material firms. In particular, the more material firms compete for clients, the higher the probability that the entry of new cost-competitive material firms will push some incumbent material firms into bankruptcy.

The results in Table ST6 indicate that reducing the mean of the initial ore cost increases the share of renewable energy and improves financial stability. In particular, it lowers the rate of firms' bankruptcies, the number of non-performing loans, and the loan-to-deposit ratio. Similarly, increasing the variance from which the initial ore cost is drawn facilitates the energy transition. This is because the greater diversity of material prices allows capital firms to choose among cheaper material suppliers on the market, lowering the mean extraction cost. However, the greater variety also increases the rate of firms' bankruptcies. The results in Supplementary Table ST6 show that reducing the value of variance $\sigma^2_{\gamma_1^{ore}}$ from 0.03 to 0.005 lowers the cumulative number of firms' bankruptcies from 87 to 69 by reducing the incentives of material firms to enter the market.

The model is also sensitive to the parameter governing the impact of extraction on ore extraction cost, i.e., the convexity of extraction costs (γ_2^{ore}). A high value of this parameter increases the mean extraction cost while reducing the share of renewable energy. Simultaneously, it increases the value of dividends from the material sector to households, boosting demand and final output. However, this comes at the cost of financial instability. The rate of firm bankruptcies, NPLs, and the loan-to-deposit ratio increase due to higher ore extraction costs and higher volatility of household dividends, which makes profits of final good producers more unpredictable. Finally, a higher average initial ore deposit of new mines (μ_{R^D}) increases investment in renewable energy as more ore deposits slow down the growth of ore extraction costs (see Eq. 31). The variance of initial ore deposits $\sigma^2_{R^D}$ has a negligible impact on the model dynamics.

As another finding from our sensitivity analysis, we find that the model is sensitive not only to changes in the material intensity of investments in renewable energy (inverse of $m^{K_{RE}}$) but also to changes in the material intensity of final good producers (inverse of $m^{K_{FG}}$). The higher the material intensity of the final good sectors, the greater the depletion of ores in the existing mines, which increases the average ore extraction cost. As a result, increasing the value of material intensity in this sector results in a more financially unstable economy.

Finally, the competition among material firms affects the energy transition. Before entering the market, each material firm estimates the future price of materials and compares it to its expected costs (see Eqns. 33 and 35). The adaptive expectation parameter α^m_{exp} determines the impact of past material price fluctuations on the current price. Higher values of this parameter are associated with a higher bankruptcy rate due to the more frequent entry of new material firms. In addition, the logit competition parameter (γ_{mining}^{logit}) describes how sensitive is the selection of metal ore suppliers by material firms to the meal ore price. The low value of this parameter increases the randomness in the selection process of new mining sites. Less randomness lowers the ore extraction costs and facilitates the energy transition.

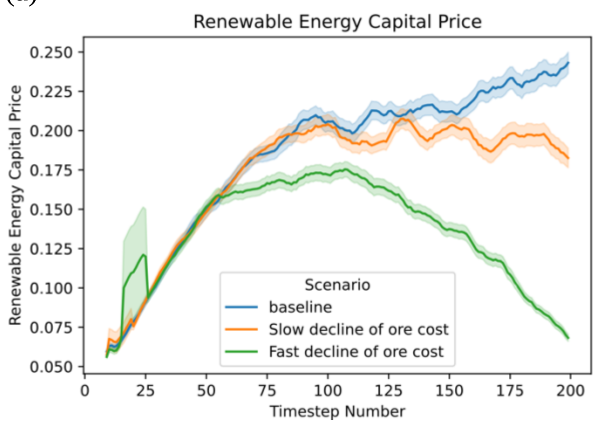
3.3. A declining price of ore extraction costs

In this section, we examine the effects of declining costs of metal ore extraction on the low carbon transition. In the previous section, the initial cost of ore extraction of each new mining site was drawn from the folded normal distribution. As a result, the ore extraction cost was increasing over time, as the cost of incumbent material firms was increasing with the progressing metal ore scarcity. In this section, we report the result from model simulations, where the initial ore extraction cost is drawn from $FN(\gamma_{1,t}^{ore}, \sigma_{\gamma_1^{ore}}^2)$, where $\gamma_{1,t}^{ore} = \gamma_{1,x}^{ore} \cdot (1 - \vartheta t)$ and ϑ captures the speed of a decline of initial metal ores extraction costs, while x is the period when the last mining site was explored. This implies that, on average, all new entering mining companies face a lower initial cost of extraction than incumbent firms. We consider three scenarios: the baseline ($\vartheta = 0$); and 'the slow' and 'the fast' decline in metal ore extraction costs, where we set $\vartheta = \frac{1}{400}$ and $\vartheta = \frac{1}{200}$, respectively. The exogenous decline in metal ore extraction costs may be interpreted as a result of public investment in the efficiency of mining technology, or the cost declining due to learning-by-doing.

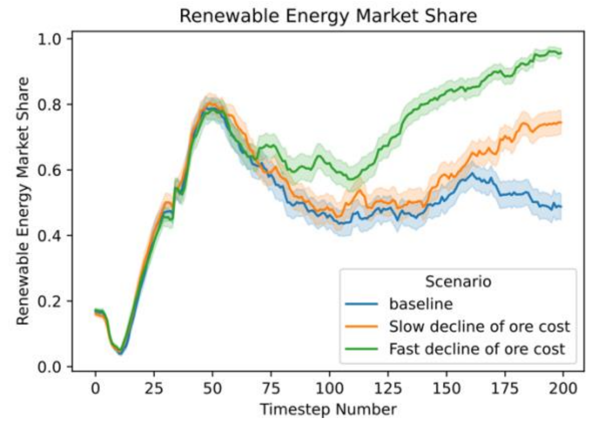
Figure 4(c) illustrates that the faster the decline in metal ore extraction costs translates into a higher share of renewable energy (Figure 4(b)), the lower total balance of non-performing loans (Figure 4(e)), and the lower loan-to-deposit ratio (Figure 4(f)) compared to other scenarios. A declining material ore cost disproportionately favors renewable energy, increasing its share in the energy mix. It also increases the number of material firms entering the market, and the rate of bankruptcy among material firms. However, financial stability improves as the higher rate of bankruptcy of material firms is offset by a reduction in bankruptcies of firms in the final good sector. In particular, the declining ore extraction translates into a lower electricity price, which reduces demand for loans. As a result, the total balance of NPLs and the loan-to-deposit ratio is lower, the faster the decline in the material ore price (Figures 4(e) and (f)).

Figure 4. A declining metal ore extraction costs

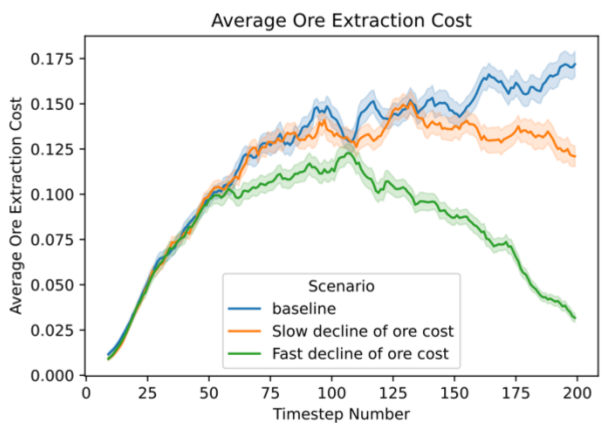
(a)



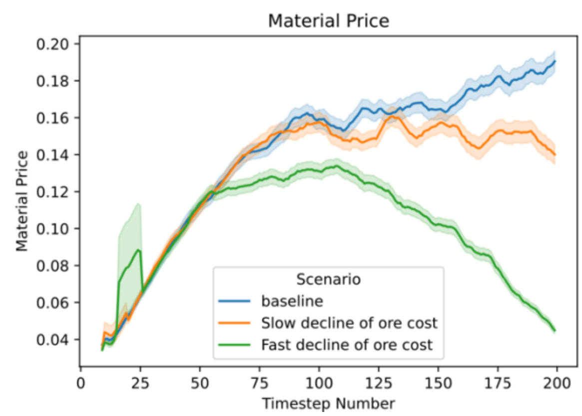
(b)



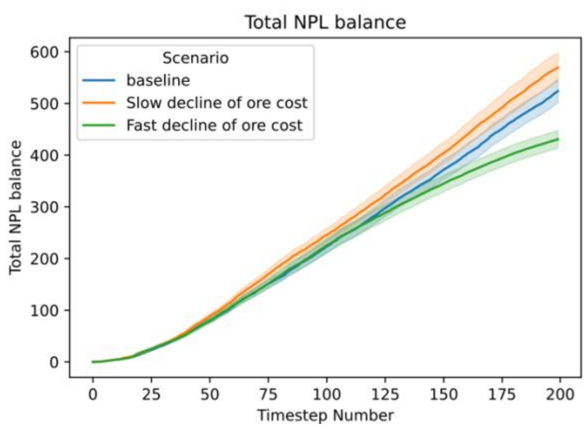
(c)



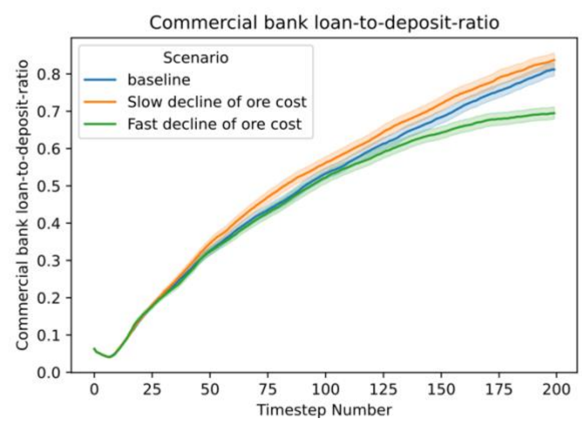
(d)



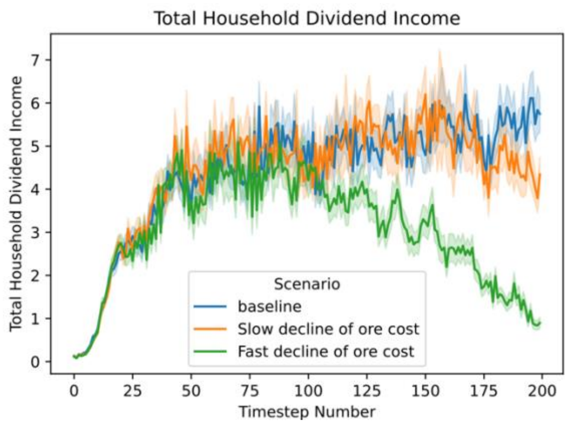
(e)



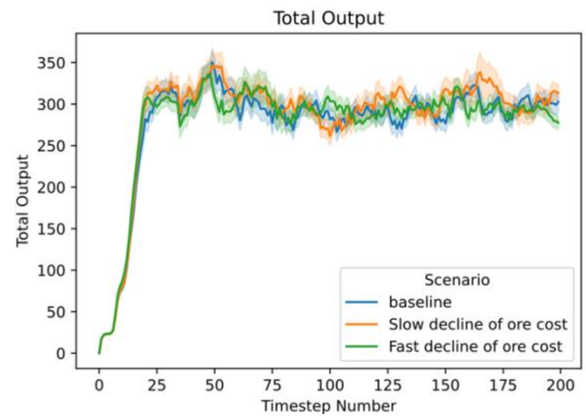
(f)



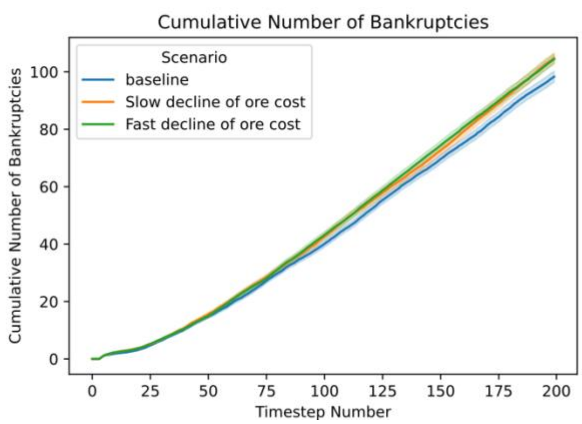
(g)



(h)



(i)

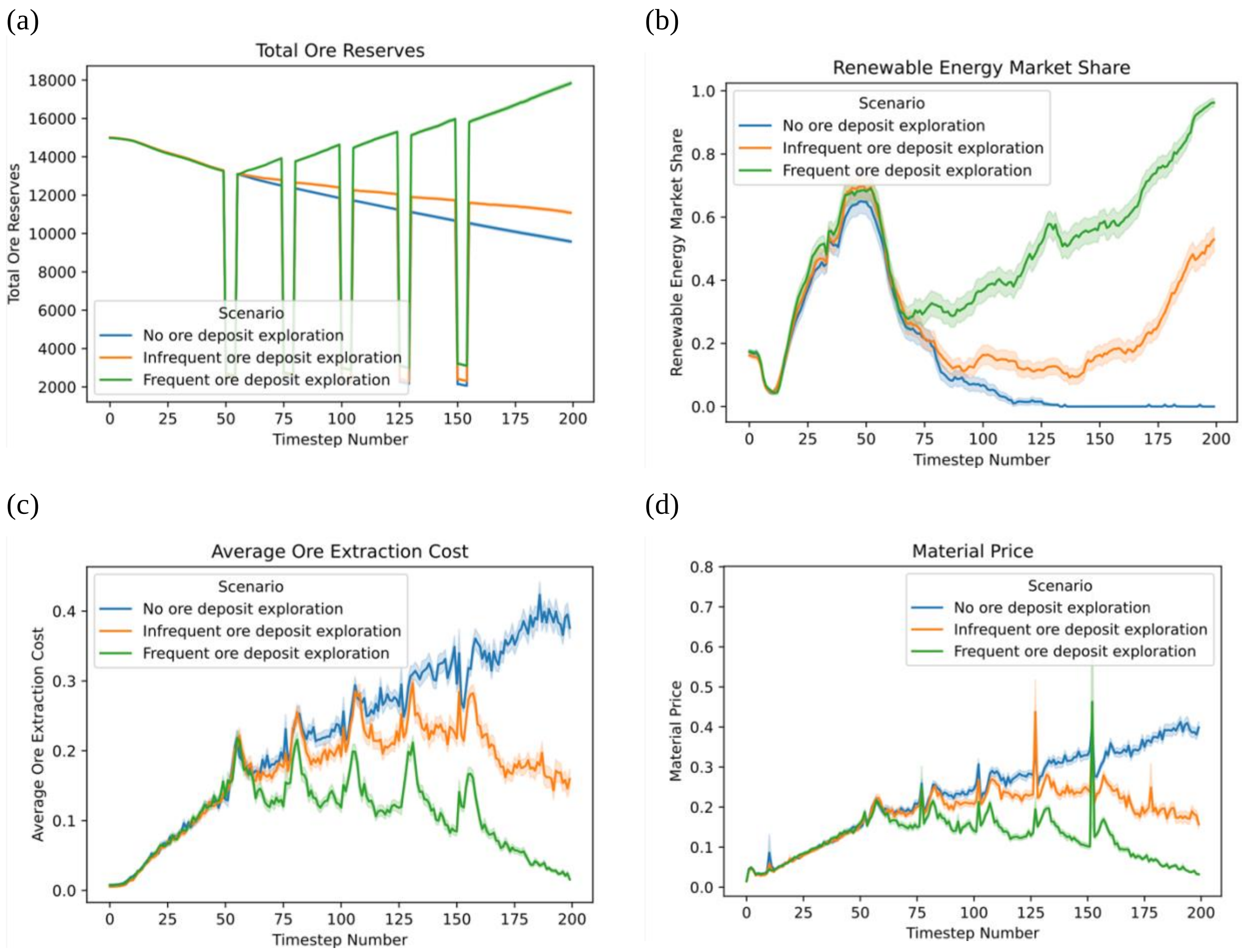


Note: The results in each figure represent the mean of the variable in question from the Monte Carlo repetitions for each experimental condition. The shadow area corresponds to the standard error. Figures (a) and (d) show ten year averages.

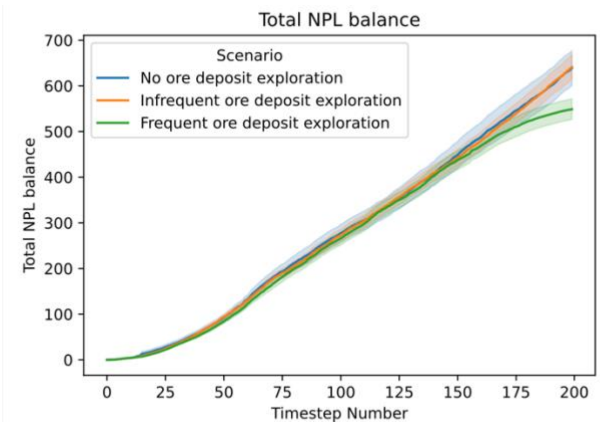
3.4. Geopolitical risk

In this section, we report the results from model simulations, where geopolitical risk makes some mining sites become temporarily unavailable. As in Section 3.3, we assume that the initial cost of new entering mining sites decreases over time. Formally, we set $\vartheta = \frac{1}{200}$ in the equation describing the decline of initial ore extraction cost ($\gamma_{1,t}^{ore} = \gamma_{1,x}^{ore} \cdot (1 - \vartheta t)$). In addition, we introduce shocks to total ore reserves, where between periods 50 and 150 every 25 periods, there is an 80% probability that each of the existing mining sites will not mine ore for the next 5 consecutive periods. We compare the results from three scenarios: 'with no entry', where the probability of the entry of new mining sites is set to zero ($pr^{ore} = 0$), 'with the infrequent entry' ($pr^{ore} = 0.1$), and 'with the frequent entry' ($pr^{ore} = 0.5$). The results in Figure 5 show the 'no entry' scenario results in the ore extraction cost increasing over time. In other scenarios, the mean ore extraction cost declines over time. The pace of decline depends on the probability of entry. The main result of the model simulations reported in this section is that geopolitical risks undermine the low-carbon transition due to the reduced availability of metal ores. If the probability of exploration of new mining sites is sufficiently high, the share of renewable energy will gradually increase (Figure 5(b)). However, this comes at the cost of increasing the number of bankruptcies in the material sector (Figure 5(i)), and less dividend income received by households (Figure 5(g))) driven by lower ore extraction costs.

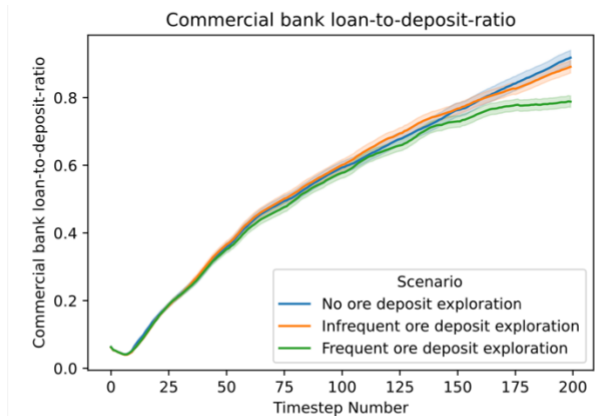
Figure 5. The impact of geopolitical risks on macroeconomic stability



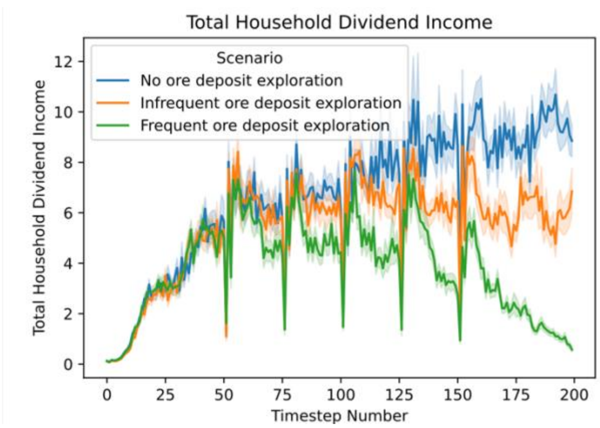
(e)



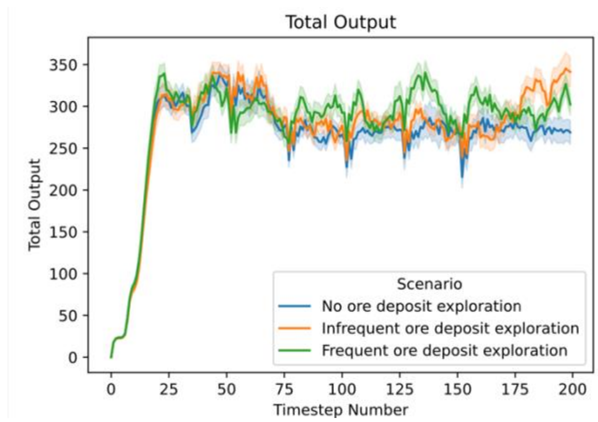
(f)



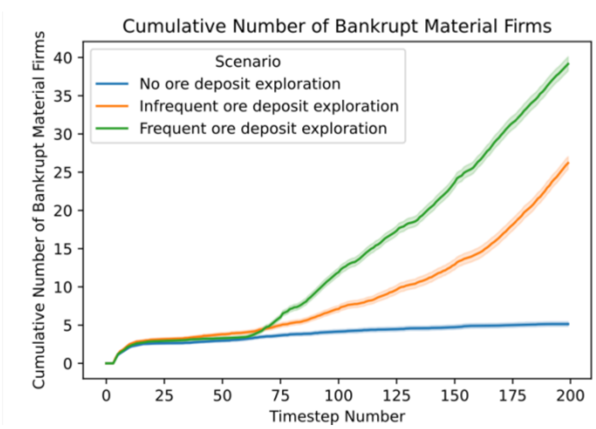
(g)



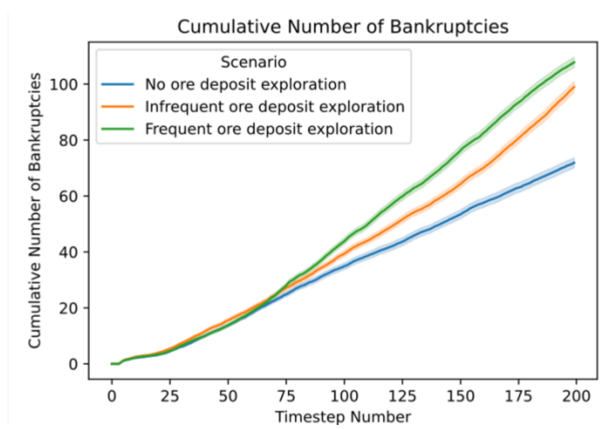
(h)



(i)



(j)



Note: The results in each figure represent the mean of the variable in question from the Monte Carlo repetitions for each experimental condition. The shadow area corresponds to the standard error.

4. Conclusions

Recently, financial climate-related risks have received increasing attention in the literature (Monasterolo et al., 2019; Semieniuk et al., 2021; Campiglio et al., 2022). Physical losses arise from climate shocks that can destroy physical infrastructure (capital stock) and disrupt production networks. In addition, there are concerns that mitigation policies can undermine economic and financial stability, referred to in the literature as transition risks. For instance, the transition to a low-carbon economy entails the devaluation of fossil fuel assets. Such shocks can spread through the network of interconnected financial institutions that hold fossil fuel assets in their portfolios (Battiston et al., 2017). A few studies have examined the impact of metal scarcity on the optimal pathway of the energy transition (Amigues et al., 2015; Fabre et al., 2020; Pommerret et al., 2022). However, to our best knowledge, none of the existing studies looks at the impact of metal scarcity on transition risks and financial stability. With our research, we would like to fill in this gap.

To this end, we develop a macro agent-based model that includes the final goods sector, the capital sector, the banking sector, the energy sector composed of renewable and fossil-fuel power plants, and the commodity sector, which includes material firms and mining sites. In the capital market, capital goods producers constantly engage in R&D activities to improve the productivity of capital goods offered to firms in different sectors. Capital goods differ with respect to the ratio of metal-to-capital, i.e., the material intensity, depending on which sector of the economy they are intended for. For instance, capital goods produced for renewable power plants are more material-intensive than capital goods for fossil fuel producers. The novelty of our approach concerns that material inputs are produced in the commodity market by material firms that extract and process metal ores. The cost of extraction in each site increases with the progressing metal ore scarcity. Our analysis shows that the commodity market can contribute to or mitigate the transition risk. For instance, the greater the competition in the commodity market, the lower the price of material goods, which results in less debt in the economy. However, this comes at the cost of a higher rate of firm bankruptcies as more material firms entering the market also entail a higher rate of their failures.

In our model, investments in renewable energy accelerate metal scarcity, increasing ore extraction costs and material prices. Higher metal prices affect the ability of firms to repay the loans and increase the average loan size. As a result, the larger the share of renewable energy, the more financially unstable the economy, i.e., characterized by a higher number of non-performing loans, the rate of firms' bankruptcies, and the loan-to-deposit ratio, than the fossil-fuel depended economy. One possible solution to this problem is to reduce the material intensity of the economy in sectors other than energy, e.g., by investing in improving resource efficiency. This would slow down the depletion of metal ores and significantly reduce the number of non-performing loans due to progressing metal scarcity in the low-carbon transition.

Our study offers the first step for studying transition risks related to the commodity markets. In future studies, it is important to model the dual role of metals as production inputs and financial assets. Until recently, the metal trade occurred mainly on a bilateral basis. In the last decade, metal futures have become a popular asset class for portfolio investors, just like stocks and bonds, referred to in the literature as the financialization of commodity markets (Cheng and Xiong, 2014). Excessive trade of commodity futures has increased the risk of extreme events and made commodity futures markets vulnerable to bubbles and high price volatility (Li and Su, 2020). To fully capture transition risks emerging from the commodity markets, new models are needed that would account for the role of metals as financial assets to study under which conditions there is a high risk of transmission of shocks from financial (futures) markets to spot markets.

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