CHAPTER 14

A macro-evolutionary approach to energy policy

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CONTENTS

1. Introduction

The literature on climate policy has been dominated by the integrated assessment models (IAMs), with the dynamic integrated climate-economy (DICE) by the recent Nobel prize laureate Nordhaus or The climate framework for uncertainty, negotiation and distribution FUND and policy analysis of the greenhouse effect (PAGE) being the most influential examples of them. These models describe how the accumulation of carbon emissions due to production activities in various sectors affects the global temperature, which in turn causes the reductions in GDP and consumption (Nordhaus, 1994; Tol, 2001; Nordhaus, 2011). IAMs are used to derive optimal policies to bring the economy back to the equilibrium in case unforeseen events disturb the market, for instance shocks to oil prices. Also, they are employed in the assessment of the social cost of carbon and energy taxes (Nordhaus, 2017). Formally, the social cost of carbon (SCC) can be measured either by the discounted present value of the damages imposed on the economy by the emission of one tonne of carbon or by the marginal cost of mitigating that emission. Typically, a model of the global economy is used to derive the 'optimal' trajectory of the future growth path that minimises damages from global greenhouse emissions. The social cost of carbon takes a form of a tax imposed on energy use that ensures that the optimal path is achieved. In its absence, firms and consumers ignore the negative impacts of their activities on the emissions. As a result, the economy follows a sub-optimal 'business-as-usual' path that is prone to climate catastrophes, characterised by extended periods of the negative growth of consumption (Foley et al., 2013).

These models however are too abstract to deal with a changing structure of the economy in the context of low-carbon transitions. This relates to the fact that they focus on the equilibrium conditions and rationality of market participants. In particular, industries are represented by a single firm, which maximizes profits, and one representative consumer maximizing his/her utility. This ensures that over time, all decisions are optimized in the equilibrium. It is

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increasingly recognized that new models are needed for the analysis of energy and climate policies that integrate social processes with technological dynamics in the energy sector, which account for heterogeneity and bounded rationality of consumers and producers (Farmer et al., 2015; Stern, 2016). This is motivated by the fact that transitions to a low-carbon economy require changes in preferences of consumers as well as in the composition of inputs for production, in particular a shift towards less energy-intensive and less polluting energy technologies. These processes are affected by bounded rationality and social interactions of consumers and producers. 'Bounded or limited rationality' describes behaviours not complying with the assumption of perfect rationality. These include behaviours such as loss aversion, myopia, habits and social preferences (Camerer et al., 2004). For instance, present and status quo biases cause people to undervalue energy costs when they buy energy-using durables, such as vehicles, refrigerators or air conditioners. Myopic investors may be reluctant to invest in promising novel energy technologies even if they are likely to be cost-competitive in the long run.

Realistic behaviours have been so far largely ignored in the climate policy assessment (exceptions include the studies by Karp, 2005; Howarth, 2006). In fact, they are difficult to be incorporated into existing economy-climate models. This relates to the fact that behavioural models introduce psychological components into utility functions, which may cause the equilibrium not to exist. As a result, IAMs use relatively simple utility functions, where all complexity of human behaviour is captured by one parameter, the discount rate, which describes how a representative consumer trades current against future consumption.[1] This is surprising as empirical evidence has shown that the discounted utility is an invalid description of how people actually behave (Frederick et al., 2002). Against this background, in this chapter, I will discuss how macro-evolutionary models can improve energy policy advice by allowing one to model an array of different realistic behaviours on the side of consumers, producers and investors.

Macro-evolutionary models use an agent-based modelling technique (see Chapter 18 of this handbook). They offer a realistic representation of socio-economic processes, where macroeconomic outcomes emerge from interactions between large numbers of distinct agents in distinct networks. Such models have been suggested by prominent scholars as a new way of modelling the economics of climate change (Farmer et al., 2015; Stern, 2016). In agent-based models (ABMs), agents are modelled as independent entities having their individual objectives, preferences and knowledge, who perceive

[1] The impact of changes in the value of a discount rate on the social cost of carbon has achieved much scrutiny in the literature, see for instance the study by Pindyck (2013).

and adapt to changes in the environment. They are often described by rules that can accommodate a variety of bounded rational behaviours. Agents' interactions, as well as feedback from aggregate (macro) to disaggregate (micro) phenomena, are the sources of non-linear dynamics and of emergent phenomena.

Macro-evolutionary models address complex interactions between many consumers and producers in different sectors, which allows studying effects of multiple policies beyond other methods. So far, ABMs have been widely adopted in modelling industrial dynamics and technological change (Janssen and Jager, 2002; Windrum and Birchenhall, 1998, 2005; Windrum et al., 2009a,b; Malerba et al., 1999, 2001, 2009; Safarzynska and van den Bergh, 2010) or dynamics of capital growth, labour markets and arising inequalities (Dosi et al., 2015; Fagiolo and Roventini, 2012, 2016). Other models combine financial markets with the real economy to study how the cascades of bankruptcies can propagate between networks of heterogeneous firms and banks (Acemoglu et al., 2013; Henriet et al., 2012; Tedeschi et al., 2012; Thurner and Poledna, 2013). Recently, macro-evolutionary models have introduced energy markets to study micro- and macro-consequences of energy policies (Gerst et al., 2013; Wolf et al., 2013; Ponta et al., 2016; Lamperti et al., 2018; Safarzynska and van den Bergh, 2017a,b see for an overview Balint et al., 2017).

Macro-evolutionary models have proved capable of modelling feedback mechanisms, underlying consumer-producers interactions, between different sectors of the economy as well as between micro- and macro-phenomena. The future challenge ahead lies in modelling complex interactions between energy and financial sectors. This is important in the context of energy policies as transitions to a low-carbon economy require a transformation of the electricity system, which creates a problem of financing investments in the still-expensive renewable energy sector (see Chapter 14 by Jolink and Niesten in this handbook). In particular, the burden of re-paying loans by energy companies that invest in renewable energy can create risk for the financial system. Such risks can spread to other sectors of the economy, causing cascades of bankruptcies of banks and firms in related industries (Safarzynska and van den Bergh, 2017a,b). In addition, too rapid investments in renewable energy may cause a sudden devaluation of assets of fossil-dependent companies, affecting negatively investors holding them, having economy-wide consequences (Campiglio et al., 2017). These issues are complex, dynamic and characterised by non-linear feedback. Modelling them requires different techniques than optimization models currently used in the climate policy assessment. In this chapter, I describe essential building blocks of macro-evolutionary models in Section 2. In Sections 3 and 4, macro-evolutionary models used for energy and climate policies are discussed. Section 5 concludes and formulates suggestions for future research.

2. A macro-evolutionary approach

In macro-evolutionary models, technological change, growth and material input use including energy follow from decentralized social and market interactions. The key notions of the evolutionary macroeconomic agenda are: (1) diversity, selection and innovation; (2) bounded rationality and social interactions; (3) increasing returns and path dependence; (4) and co-evolutionary dynamics between supply and demand, which are discussed below in relation to energy policy (see Witt, 1993; Dosi and Nelson, 1994; van den Bergh, 2018, for an overview of evolutionary economics and Safarzynska and van den Bergh, 2010, for a more technical overview of modelling building blocks in evolutionary economics).

From the evolutionary perspective, changes in the system (economic, social or natural) are driven by the interplay of diversity, selection and innovation. Maintaining diversity of behaviours, strategies or technologies is the basic material for selection to act upon. Selection reduces diversity over time, while innovation introduces new varieties to the population. Diversity of options leaves options open for an uncertain future and encourages innovations that take the form of recombining existing technologies. Yet, it reduces the benefits obtained from increasing returns due to specialization in one or a few technologies. In this context, much attention has been paid in evolutionary economics models to the trade-offs between the benefits from investing in diversity of options in the long run, i.e. possibilities for future innovations from experimentation with existing solutions, and short-term costs (Zeppini and van den Bergh, 2011). As a result, such models can help assessing the optimal mix of energy technologies. So far, policy debates have focused on finding the optimal energy mix, which would reduce the total cost of electricity generation and would allow for better responding to fluctuations in demand (Awerbuch, 2006; Joskow, 2006; Stirling, 2007). Far less attention has been devoted to the costs of forgone innovations, the emergence of which is conditional on maintaining the diversity of options (Weitzman, 1998).

Diversity is essential for selection to act upon. However, it is simultaneously reduced by selection, which limits the variety of options available on the market. Here, heurists of investors such as imitation of successful incumbents, risk aversion and short-sightedness can cause underinvestment in diversity of technological options. For instance, myopic investors prefer to wait until investments by others to reduce the cost of novel technologies. If everyone thinks this way, new technologies may never emerge. In addition, social imitation within networks can be a factor limiting diversity of technological options. Imitation allows saving on costs of individual learning, experimentation or searching by exploiting information already acquired by others. In evolutionary models, it often takes the form of consumers imitating choices of the

'the majority', which has been referred to as 'conformist transmission' (Boyd and Richardson, 1985). This implies that consumers often choose products because others have already adopted it, regardless of their intrinsic preferences. Once the technology becomes dominant, subsequent adoptions only enforce its leading position (Arthur, 1989; Unruh, 2000). Evolutionary models have been used to study policies for unlocking the system, which has become dominated by a single technology (interrelated technologies), when inertia on the side of consumers have created barriers to entry for new firms (Windrum and Birchenhall, 1998).

On the supply side, firms imitate technologies by the best performing companies so as to capture some of their market shares. In macro-evolutionary models, firms engage in imitation and invention, following the seminal model of industry dynamics by Nelson and Winter (1982). In particular, firms do not optimize their output as in mainstream growth models, but instead their behaviour is described by simple routines. To illustrate with an example, in Nelson and Winter (1982) model, each firm devotes a certain fraction of its profits to R&D activities, with the aim of looking for novel technological solutions so as to capture new markets or to improve the quality of their products. However, this approach ignores the role of consumers in the innovation process (emergence and diffusion), as well as in later phases of product development. Moreover, multiple feedback mechanisms and increasing returns underlying interactions between consumers and producers, such as economies of scale, learning by doing or informational returns, contribute to the emergence of monopoly and may lock in the market. To capture demand-supply interactions, Dosi et al. (2010) propose a macro-evolutionary growth model, which bridges Keynesian theories of demand generation and Schumpeterian theories of technology-fuelled economic growth. The model has proved capable of generating business cycles together with a sustained long-term growth. It has been used to study Schumpeterian policies to promote technological innovation at the micro level of firms, as well as macro-Keynesian policies.

3. The interactions of energy sector with manufacturing

Mainstream macroeconomic models used for the assessment of energy policies rely usually on a simplified representation of the energy sector. In such models, a technological change is either imposed exogenously or it is modelled as a substitution between different energy sources depending on stochastic changes in fuel prices. This approach is insufficient to capture risks involved in the transitions to a low-carbon economy as it ignores many aspects of energy markets. In turn, the equilibrium models of the electricity sector study how interactions between competing firms on the wholesale electricity markets affect prices (Powell, 1993; Newbery, 1998; Green, 1999, 2003; Wolak, 2000). Nevertheless, even such models have been criticized for failing to account for: constraints of grid transmission; learning by firms; investments in capacity expansion and interactions between firms and consumers in multiple markets, e.g. fuel (gas), wholesale and retail markets. In this context, agent-based models have become increasingly popular as they allowed to model explicitly: active demand bidding, grid constraints (e.g. Koesrindartoto et al., 2005), multiple markets and different time horizons (e.g. Sensfuss et al., 2007; Micola et al., 2008).

Macro-evolutionary models combine complex interactions in the electricity sector with other industries so as to study the economy-wide effects of multiple policies, including energy taxes. Macro-evolutionary models that account for energy as an input in production of manufacturing products are few but on a rise (Gerst et al., 2013; Wolf et al., 2013; Ponta et al., 2016; Lamperti et al., 2018). For instance, Gerst et al. (2013) extends Dosi et al. (2010) macro-evolutionary model by the energy sector so as to study the short-term and long-term effects of carbon taxes and technology subsidies. In turn, in Wolf et al. (2013) model, CO_2 emissions are calculated for each sector and region, depending on how much energy is used in production in, and carbon intensity of, different sectors. These models have not yet allowed to fully capture how energy policies affect interrelated industries. This relates to the fact that in such models, energy sector is modelled as independent of other industries.

In the study by Safarzynska and van den Bergh (2011), we propose a model of the electricity market, where energy transition occurs through installation of new power plants and exist of obsolete power generators. We later combined it with the manufacturing sector in the study by Safarzynska (2012) and with manufacturing and financial sectors in the study by Safarzynska and van den Bergh (2017a,b) to capture interactions between intertwined industries. In these models, the electricity market is composed of heterogeneous plants producing electricity using different energy technologies. We considered three energy technologies: coal, nuclear and combined combustion gas turbine, for which data were calibrated using the historical data from the British electricity market. Each technology is characterized by different factor substitutions of inputs, fuel prices, operation costs and installation costs. Formally, in the beginning of each period, a firm decides whether to invest in a new power plant. The size or capacity of new plants and the type of fuel to be used are based on the discounted value of future investments. As a result, energy mix in the electricity production evolves over time because of investments decisions. In particular, the type of technology j and the optimal installed capacity k_{ij} are determined by a two-step procedure. First, an owner of the firm evaluates the capacity k_{ij} maximizing expected profits V_{ij} over the plant lifetime T for each energy technology j:

$$V_{ij} = E\left[\left(\sum_{t=t_{sj}}^{T+t_{sj}} e^{-rt}(p_t(\lambda 8760 k_{ij}) - m_j)8760\lambda k_{ij} - e^{-rt_s} I_j k_{ij}\right)\right]$$

Here, I_j is a fixed cost per KW of installed capacity k_{ij} capturing initial investment costs and maintenance expenses that needs to be covered from the revenues over the entire life of the plant $(T-t_{sj})$; t_{sj} indicates the number of years before the plant (of technology j) can be operationalized and r is an interest rate, and where is the expected price of electricity after the installation of new power plant of size k_{ij} embodying energy j. In the model, plants improve their thermal efficiency over time, which measures plants' productivity. This captures learning by doing: the longer the plant exists on the market, the more efficiently it transforms basic energy inputs into electricity. In addition, electricity production by each plant is described by the Cobb–Douglas function with capital, labour and fuel inputs. Plants decide how many inputs to use for production so as to minimize total input costs. This allows us to study adjustments in input use to transitions in the electricity sector.

The model has been combined in the study by Safarzynska (2012) with the manufacturing sector to examine micro-channels through which improvements in energy efficiency may fail to bring about a proportional reduction in the amount of electricity used for the production of consumer products, vehicles and computers, depending on the strength of the network effect in these industries. In the model, energy efficiency of incumbent plants in manufacturing sectors does not change over time, but new firms entering the market adopt more energy-efficient technologies than incumbents. This assumption is motivated by empirical evidence, suggesting that changes in energy efficiency at the plant level are negligible compared with improvements at the industry level.

The results from model simulation indicate that the network effect in consumption may be an important source of the rebound effect. The rebound effect describes the phenomena when policy measures, implemented with the aim of encouraging energy savings in production and consumption, generate results opposite to those expected. The effect goes back to the study by Jevons (1865), who suggests that improvements in the efficiency of coal-fired steam engines would result in more coal consumption, ultimately offsetting the benefits from increased efficiency. Direct and indirect rebound effects can be distinguished (Gillingham et al., 2016). The 'direct rebound effect' describes an increase in energy use as a result of consumers using energy-efficient products more often than their less efficient counterparts, simply because using energy-efficient appliances is cheaper. The indirect effect occurs if incomes saved due to consumers purchasing energy-efficient products are spent on other energy-intensive goods.

In the study by Safarzynska (2012), the rebound effect occurs in industries, where brand recognition is important such as automobile sector as the network effect on the side of consumers prevents diffusion of energy-efficient technologies. The stronger the network effect, the lower the energy saving as a result of policies promoting energy efficiency. Such a rebound effect can be prevented with policies that focus on creating a critical mass of adopters of products (e.g. through advertising or public procurement), whose production is less energy-intensive than production of dominant firms. The model has been also used to study the effectiveness of energy policies, namely, a tax on electricity and renewable obligations. Here, model simulations have revealed a dark side of renewable obligation policies, which requires investing in a new renewable power plant whenever production of electricity with renewable energy falls below a certain threshold. It turned out that such policies may, instead of replacing fossil fuels in electricity generation, create an additional supply of electricity.

The main channel through which energy and electricity markets affect other sectors in macro-evolutionary models is via prices of energy. In the context of transitions to a low-carbon economy, a question arises on how investments in renewable energy affect the price of electricity. Economic theory predicts that the increase of the share of renewable energy in electricity production may reduce the price of electricity in the short run, which is also known as the merit-order effect (Jensen and Skytte, 2002). However, in most countries, the diffusion of renewable energy has been driven by public renewable support schemes, financed by increasing the final electricity price paid by consumers (Moreno et al., 2012). Our model captures these two opposing effects of investments in renewable energy on the electricity price: in the short run, increasing the share of renewable energy lowers the electricity price because more electricity is produced with technologies characterized by lower marginal costs. However, as a result of lower electricity prices, the newly installed power plants become smaller in size as the size of newly installed power plants is determined by their future expected profits given the current price of electricity. Less installed capacity translates into less electricity produced and thus a higher electricity price. A different approach to model energy price can be found in the macro-evolutionary model by Lamperti et al. (2018). Here, the total production cost depends on which power plants are used first to produce electricity. The renewable energy plants are characterized by zero marginal costs of electricity production and thus they are used first, afterwards electricity is produced by the dirty plants. Formally, the authors extend the model by Dosi et al. (2010) to the energy sector and climate module. In the model, energy is produced with two energy technologies: green and dirty technologies. If the maximum electricity production falls short of the demand, an owner of energy companies invest in expansion of capital stock of existing power plants. In particular, he/she invests in a new green capacity if the costs of the cheapest vintage power plant embodying green energy is less than the discount production cost of the cheapest dirty plant. The model has been used to assess climate change damages. In particular, production of energy and manufacturing firms generate CO_2 emissions, which increase surface temperature, just as in conventional climate models. On the contrary to IAMs, which have been criticised for unrealistic modelling of climate change, the authors model impacts of firms on climate change at the micro level. In particular, they introduce stochastic climate damages, which affect labour productivity and energy efficiency of manufacturing firms, as well as their capital stocks and inventories. In this context, it has shown that the model generates much larger climate change damages than those estimated using IAMs.

4. The interactions of energy industry and financial sector

Transitions to a low-carbon economy require a shift from using fossil fuels in production to renewable energy sources. There are concerns that too rapid investments in renewable energy can render substantial losses for the investors holding assets of fossil fuel companies (Campiglio et al., 2017). Although the direct exposure of assets held by companies in various sectors to the fossil fuel industry is small, it can reach almost 40% if indirect effects via financial counterparties are taken into account (Battiston et al., 2017). Moreover, there are concerns that a low-carbon transition will have non-trivial impacts not only on financial systems but also on income distribution. Recent evidence shows that inequality and energy prices can affect financial stability in a non-linear way (Russo et al., 2013; Cardaci and Saraceno, 2015; ESRB, 2016). These examples illustrate that transitions in the energy sectors can have serious impacts beyond transformation of the energy sector. However, these effects have been largely ignored in the climate change assessment using IAMs.

Although some ABMs include both energy and financial sectors, so far interactions between the two has not been modelled explicitly (e.g. Lamperti et al., 2018). To address this gap, in the study by Safarzynska and van den Bergh (2017a,b), we have developed an agent-based model that captures interactions between investments in renewable energy and stability of the financial sector. In the model, the electricity market is composed of energy companies with heterogeneous plants producing electricity from diverse energy sources as described in Section 3. An important novelty here concerns that each new plant entering the market receives a loan, which it has to re-pay by the end of its lifecycle. If banks have insufficient liquidity, they ask other banks for loans in the interbank lending network. As a result, credit connections between banks and firms, as well as power plants, are endogenous, i.e. evolve as a result of activities in the real economy, following the reports of Thurner and Poledna (2013). The bankruptcy of a bank can arise due to failures of loan re-payments triggered by bankruptcy of firms, power plants or other banks.

In the model, there are three main channels through which energy markets affect financial stability and inequality. First, the degree of concentration of loans to energy companies determines the probability of the cascades of bank failures. In particular, if large loans are concentrated in few banks, this is conducive to bankruptcies of banks as risk becomes unevenly spread in the financial sector. Second, energy prices affect the distribution of wealth among owners of different sectors of production (workers, capital owners and owners of energy companies), which generates inequalities. Third, an increase in the price of energy drives the prices of final products up. As a result, wages of workers may become insufficient to buy manufacturing products every period, undermining demand. This in turn reduces firms' profits, increasing the probability of their bankruptcies. In addition, an increase in energy prices may cause firms to be unable to re-pay their loans, further contributing to the likelihood of their bankruptcies. In the study by Safarzynska and van den Bergh (2017a,b), we studies how investments in renewable energy affect interbank connectivity, i.e. a number of links between banks, and distributions of loans in the financial sector. A link between banks is established as follows: in case one, bank borrows money from another bank. This can happen if a bank is asked for a loan by an energy company, but the size of such loan exceeds bank's liquidity. We show that increasing the share of renewable energy in electricity production initially increases the price of electricity and thus improves profits and the ability to re-pay debts of incumbent power plants. However, when the share of renewable energy increases too quickly, financial stability may be at stake as the burden of financing investments in renewable energy offsets the improved profitability of existing power stations. This effect depends on the concentration of loans in the banking sector, i.e. interbank connectivity.

As another example of a framework that combines energy and financial sectors, Dafermos et al. (2017) developed a stock-flow consistent model to study the effects of climate change on financial stability. A stock-flow consistent approach to macroeconomic modelling requires integrating the real and financial sides of the economy, by making sure that changes in liabilities and deposits in banks match firms' and consumers spending. Using such an approach, Dafermos et al. (2017) examined the impact of climate change damages on the price of financial assets and the financial position of firms and banks. In the model, climate shocks destroy the capital of firms, reducing their profitability, which increases the probability of firms' bankruptcies. On the demand side, climate change makes households revise their financial portfolios and shift investments towards more risky assets. Both effects can undermine financial stability. The model, although interesting, relies on the aggregate analysis of financial flows and balance sheets and does not model agents and their interactions explicitly. As a result, it is not capable of addressing technological changes in the energy industry as well as consumers' and products' adjustments to climate policies at the micro level in a way agent-based models can be discussed.

5. Conclusions and policy discussions

Macro-evolutionary models allow for modelling complex interactions between heterogeneous consumers and producers in different sectors. They can accommodate a variety of realistic behaviours, which have been shown to affect consumption and investment but have been ignored in conventional macroeconomic models. As a result, macro-evolutionary models have provided insights on how to unlock a market dominated by an unsustainable technology and how to effectively stimulate diffusion of energy-efficient innovations and renewable energy. It has been shown using such models that ignoring social interactions and bounded rationality in the assessment of energy polices may lead to underestimation of climate damages (Lamperti et al., 2018); rebound effect (Safarzynska, 2016) and a lock-in to unsustainable technology (Windrum et al. 2009a,b) and revealed the conditions under which energy policies may undermine financial stability (Safarzynska and van den Bergh, 2017a,b).

A number of issues has been unresolved and requires attention before deriving future policy lessons for energy transitions. In particular, macro-evolutionary models have failed to incorporate recent empirical evidence on the potential for cost reductions of renewable energy technologies. The costs of many technologies have been shown to decrease along learning curves and can be predicted from the past trends (Farmer and Lafond, 2016). In IAMs, the future costs of energy technologies are often modelled with a one-factor learning curve, according to which technology costs fall as a function of cumulative installed capacity (Messner, 1997; Gritsevsky and Nakicenovic, 2000). In macro-evolutionary models, technology learning occurs through stochastic outcomes of R&D, whereas learning proportional to cumulative installed capacity has been neglected. Integrating learning potential of renewable technologies into macro-evolutionary models is important if such models are to fully capture risks involved in the low-carbon transitions.

In addition, macro-evolutionary models pay much attention to the diffusion of innovations and how to support the process with appropriate policies. Far less attention has been devoted to the topic on how such innovations are financed. However, a key challenge for guiding transitions towards a low-carbon economy lies in mobilizing finance for investments and innovation in renewable energy (Grubb, 2014; Stern, 2015). In this context, studying interactions between firms in financial and manufacturing sectors using macro-evolutionary models is important as finance flows always towards concrete projects and firms. A recent analysis of deal-level global renewable energy assets between 2004 and 14 reveals that the financial flows between different types of actors influence the directions of innovations as well as risk exposure of firms (Mazzucato and Semieniuk, 2018). In particular, public investments typically support a subset of energy technologies, while private firms spread investments more evenly over a wider portfolio of competing technological options. Moreover, private firms invest in far riskier projects than public sector, which can put the financial sector at risk. These effects have not been yet modelled in macro-evolutionary models but constitute an important topic for future research.

Test questions

- How do bounded rationality and social interactions affect the effectiveness of energy policies?
- How does systemic risk spread between and within networks of the energy, manufacturing and financial sectors?
- How can energy policies affect financial stability?
- How do macro-evolutionary models differ from integrated assessment models?
- How do the costs of energy technologies change over time?

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