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Eurace@unibi-eco:

A model of technology transitions

v1.1

Model documentation

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Purpose of this paper is the self-contained description of the green technology extension of the macroeconomic agent-based model Eurace@unibi. The original model is extended in mainly five dimensions: (1) There are two types of production technology, i.e. a green and a conventional. Technology is embodied in capital goods and in the technological capabilities of firms. (2) Employees are endowed with two types of evolving technology-specific skills that are needed to work effectively with specific capital goods. (3) Based on their technological capabilities and the market environment, consumption goods (CG) firms decide whether to invest in green or conventional capital. (4) An environmental accounting keeps track of the environmental impact of CG sector. (5) A policy module allows to investigate the impact of different diffusion policies. Main research areas covered by the model extension are directed technological change, innovation diffusion and technology substitution processes. A key feature of the model is endogenous, technology-specific absorptive capacity of heterogeneous technology adopters that evolves through learning. It is a comprehensive, macroeconomic model that allows to study the macroeconomic and distributional consequences of transition processes. The technical description of the model is complemented by a short summary and discussion of technology transition dynamics in a baseline simulation.

*This work uses a modified version of the Eurace@Unibi model, developed by Herbert Dawid, Simon Gemkow, Philipp Harting, Sander van der Hoog and Michael Neugart, as an extension of the research within the EU 6th Framework Project Eurace. Thanks to Herbert Dawid and Philipp Harting whose support made this model extension possible.

Contents

1. Motivation and overview

Eurace@unibi-eco was developed to study the transition from brown to green technology. It can be generalized to non-environmental technologies and technological change with multiple competing alternatives.

The underlying baseline model is the agent-based macroeconomic model Eurace@unibi that is comprehensively described in Dawid et al. [2018b]. Throughout the paper, many explicit references to the descriptive article of the baseline model are made for readers who are interested in technical details of specific modules. This paper is aimed to be self-contained and the description provided here should be sufficient to understand the functioning of the model. Routines that are newly added to the baseline model are explained in more detail.

Processes of technological change are subject to uncertainty, heterogeneous capacities to adapt, path dependence and non-linear self-enforcing dynamics [Arthur, 1988, cf.]. Agent-based models allow to study the implications of agent heterogeneity, interaction and learning for the technological evolution and its economic and distributional consequences.

The Eurace@unibi modeling paradigm can be characterized as *constructive* approach, i.e. constructing a virtual economy from the bottom up [Tesfatsion, 2006]. In the simulated economy, agents' behavior and interaction are represented by functions of a computer program that are stepwise executed. One step is called "iteration" and represents a working day. Agents interact in discrete time on different markets and exchange physical and financial flows and information. Agents adapt to changes in their environment. Adaptation and the response to interaction is reflected in changes of agents' state variables which can be saved at a given frequency as micro-level time series data. The time series of individual agents can be aggregated and interpreted as macroeconomic time series. Some processes in the model are stochastic. The model is simulated multiple times and the set of multiple simulated time series can be statistically analyzed.

The model's suitability for economic analysis is justified by a two-way validation procedure. First, the underlying assumptions of behavioral routines and interaction patterns at the microeconomic level should be plausible and justified by theoretical and empirical evidence. Second, the emerging macro- and microeconomic patterns should match with empirical stylized facts [see Fagiolo et al., 2019]. The richness of behavioral detail in agents' behavior is constrained by the computational tractability and the desired number of degrees of freedom in the parameter calibration. The Eurace@unibi-eco model is designed according to these guidelines and a summary of the design and validation criteria and their references to the literature is provided in appendix A of Hötte [2019a].

Until now, the model has been used to study how drivers and barriers of green technology diffusion influence the pace and disruptiveness of a large scale technological transformation. In policy experiments, it was analyzed how market based policies may speed up the diffusion of green technologies and their implications for distribution and macroeconomic performance were studied [Hötte, 2019a]. It was analyzed how similarities of competing technologies and spillovers in the process of technological learning may have ambiguous effects for the success and stability of a transformation process. The model was used to illustrate the concept of technological uncertainty and its implications for the economic performance. The representation of technology was used to derive a taxonomy that allows the systematic comparison of different classes of competing technologies [Hötte, 2019b].

Core of the underlying theory of technological substitution is the assumption of technology-specific absorptive capacity. Final goods firms are the potential adopters of green technology and may incrementally replace conventional production capital by a green alternative. The effective utilization of a specific technology requires the adequate skill set which is built up by technological learning. Hence, not only the properties of supplied capital are important, but also the capabilities of technology adopting firms.

Methodologically, this approach differs from the majority of other macroeconomic models of directed technological change in mainly three regards:

1. Agents are heterogeneous. Their behavior and interaction is described by adaptive functions.

2. Decision making is asynchronous which is a source of frictions and uncleared markets.

3. Processes are subject to stochasticity and non-determinacy arising from non-linear, self-enforcing dynamics.

These features have been insightful to build theories of macroeconomic technological transitions driven by interaction and adaptation at the microeconomic level.

The remainder of this documentation paper is structured as follows. In the next section, the paper continues with a short general overview of the model, its macroeconomic structure and a detailed description of the most important parts of the model. In section 3, the transition dynamics and mechanisms of the model are illustrated along a set of exemplary simulation results. This paper concludes with a short outlook on possible extensions and generalizations of the model.

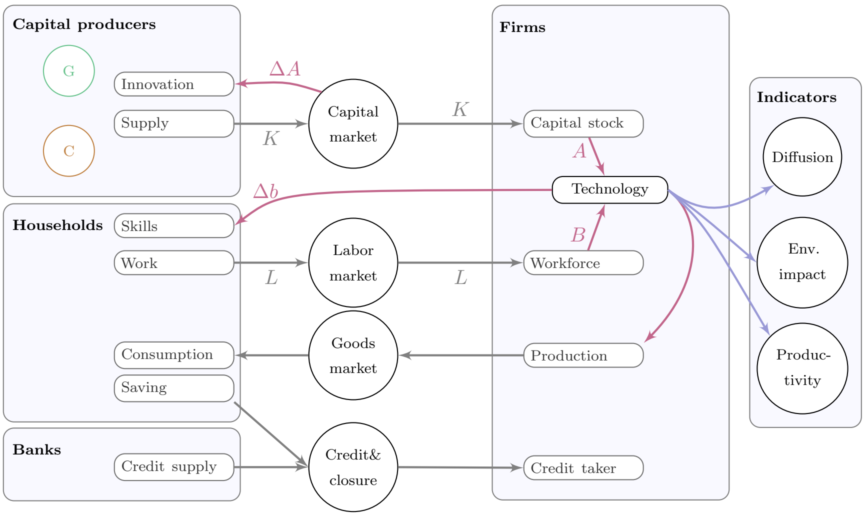
Readers who are interested in the technical implementation of model are invited to have a look on the programming code available in a data publication [Hötte, 2019c].[1]

2. The model

The Eurace@unibi model is a macroeconomic agent-based model that simulates an economy composed of various groups of individual agents that are linked by economic trans- and interactions. The most important links and groups of agents are sketched in figure 1. The main activities of the agents that are relevant for the technological evolution are summarized in table 1. The structure of the simulated economy resembles the structure of other macroeconomic models. Households (HH) supply labor and earn wages. Households' income is either spend for consumption or can be saved. Households are heterogeneous. They differ by skill level and wealth which has implications for their consumption and saving behavior. Skill and wealth differences may be the source

[1]Updates of the model code and software for analysis can be found online in the resources that are referenced in the data publication.

Figure 1: Flowchart of main agents and markets



The large blocks represent the group of agents and their role in the economy. Circles in the middle between represent markets as places where agents interact. Gray (magenta) arrays indicate monetary or physical (immaterial) flows. The block on the right-hand-side contains the main macroeconomic indicators that have been studied. This flowchart is taken from Hötte [2019a] and based on Dawid et al. [2011].

of emerging inequality if relative wages for different skill groups or the ratio between financial and wage income diverge. Households' consumption choice is not deterministic and has probabilistic elements, but it is influenced by relative supply prices.

Firms produce a homogeneous final consumption good (CG) using labor and capital. They are households' employers. Capital is accumulated in a capital stock that depreciates over time and can be expanded or maintained by investment. To finance current production and new investment, firms may borrow money from banks. If firms' are unable to repay their loans they run into bankruptcy. Firms differ by their endowment with capital, labor and financial means. The capital stock is composed of possibly differently productive vintages of capital and the labor force is composed of possibly differently skilled employees. This is the source of heterogeneity of firms' productivity.

Capital or investment goods (IG) are supplied by an investment goods sector that is composed of firms that produce different types of capital. In the eco-technology version, the IG sector is composed of two representative producers. One of them is incumbent in the market and offers a conventional type of capital goods. The other firm is a market entrant and offers a green alternative.[2] The two technologies are qualitatively different by technology type. It is assumed that the entrant technology is superior because it allows its adopters to save variable input costs. In the case of green technologies, this is interpreted

[2]Note that this setting is implemented by a particular parameter setting. The number of heterogeneous types of capital producers and the timing of market entry is only constrained by the computational tractability of the model.

Table 1: Overview of groups of agents and their main activities.

Agent		Main activities	Stocks*
Households	h	Supply labor l_h and acquire technology-specific skills during work $b^{ig}_{h,t}$, consumption, investment and saving.	$b^{ig}_{h,t}$
CG firms	i	Produce consumption goods, demand labor $L_{i,t}$ and invest in new capital goods k^v with properties $(A^v, \mathbb{1}(ig))$, demand credit if necessary. Capital is accumulated as stock $K_{i,t}$ consisting of a mixture of different types of capital goods v. Labor $L_{i,t}$ is a stock that evolves by discrete hiring and dismissal.	$K^{ig}_{i,t}$, $L_{i,t}$, $A^{ig}_{i,t}$, $B^{ig}_{i,t}$
IG firms	ig	Supply capital goods differing by productivity level A^v and technology type ig, invest in R&D to increase maximal supplied productivity $A^V_{ig,t}$.	$A^V_{ig,t}$
Banks		Supply credit, maintain agents' bank accounts, ensure financial closure of the model (stock-flow consistence).	
Government		Collects taxes and pay unemployment benefits, imposes policies.	

* The stock variables shown here do only refer to the technology part of the model. Stocks are tangible (labor force and capital) and intangible (skills and frontier productivity) assets that are accumulated through physical (investment, hiring) or non-physical (learning) activities.

as costly natural resource input. In other contexts, it can be interpreted differently, for example as labor that is replaceable by machines [Goldin and Katz, 1998]. Even though the entrant technology is superior in terms of variable input cost savings, it does not necessarily diffuse because it is subject to entry barriers. Diffusion barriers are measured as lower supplied productivity and lower technology-specific skills of employees that are needed to work effectively with green machinery. Skills B and supplied productivity A are stock variables that are accumulated over time in a process of learning and innovation.

Innovation occurs in terms of discrete productivity enhancements ΔA of supplied capital goods. IG firms offer a range of vintages that differ by productivity. Probabilistic innovation enables IG firms to shift their individual technological frontier upwards and to offer more productive capital goods. The success of innovative activity is endogenous and depends positively on R&D expenditures. IG firms invest a fix share of profits in R&D. Consequently, R&D investments in the more profitable IG sector are higher which has a positive effect on the probability of successful innovation.

Technology-specific skills are accumulated by learning Δb. Households learn during work when working with specific machinery. Skills are technology-specific and the pace of relative learning depends on the intensity to which a technology type is used. For example, if employees only work with green machinery, green skills are accumulated relatively faster.

The Eurace@unibi economy has a financial system. Every agent has a bank account. This accounting module can be used to control the stock-flow consistency of the model. Banks supply credit to CG firms if CG firms' financial means are insufficient to finance current production and investment.

Households' financial wealth consists of safe deposits at private banks and risky assets represented by an index fonds. Firms issue equity which is traded on a stylized financial market. The financial market is kept simple and comprises only an index fonds. The financial market is also used for "revenue recycling" purposes for processes that are not explicitly modeled. This ensures the financial closure of the model.

The model contains a policy module, called Government. It has a redistribution and regulatory function. It collects taxes and pays unemployment benefits. It may also impose economic policies to achieve specific targets, for example diffusion policies to stimulate the transition towards green technologies.

The activities of agents are implemented as behavioral routines like functions in a computer program that are executed stepwise. One iteration step in the model represents a working day, 20 days make up a month and 240 represent a year. Some routines are executed in a daily, monthly or yearly frequency or event-based. The execution of routines is asynchronous. For example, firms' pricing decision is made at another day than households' purchasing decision and not every household or firm is active at the same day. Routines that require interaction are matched across time via a so-called "message board" that stores the information that is exchanged between agents. Asynchronous decision making, incomplete information and bounded rationality of agents are sources of price and wage stickiness. This has the consequence that markets do not necessarily clear. Firms build up inventory stocks (consumers may be rationed) if demand falls below (exceeds) the supplied quantity.

In its *technical* features that concern the execution of routines, the Eurace@unibi-eco model coincides with the baseline model. A detailed description of the technical features of the model and issues of implementation can be found in section 2-3.1 of Dawid et al. [2018b].

CG firms, IG firms and households are the main agents that are involved in the technological transformation. Further, the government may intervene and implement policies to stimulate the diffusion of (green) technology. Their behavioral routines and the policy module are explained in the subsequent sections. Banks have an intermediary function managing the supply of credit. Their behavior is only briefly sketched in this article and the reader is referred to section 3.4 in Dawid et al. [2018b] for more detail.[3]

2.1. Consumption goods sector

CG firms are the key agents involved in technology diffusion. Technological knowledge is developed by innovation in the IG sector and embodied in the productive properties of available capital goods. To have an economic impact, technological knowledge does not only need to be invented, it also needs to be used. In this model, CG firms decide whether to adopt a specific technology when making their investment decisions. Skills of households and the quality of supplied capital goods of IG firms are complementary factors that facilitate or impede the adoption of new technology, but are exogenous

[3]For reasons of simplification and differently from the model discussed in Dawid et al. [2018b], only 2 not 20 private banks are active in the Eurace@unibi-eco economy.

from the firm perspective. Households' technology-specific skills are needed at work. IG firms supply capital goods of different productivity levels and technology type. An incumbent (entrant) IG producer supplies capital goods of the conventional (green) type. Productivity embodied in physical capital and skills of employees are aggregated as firm specific stocks of codified and tacit technological knowledge as a consequence to firms' investment and production decisions. In their investment decision, CG firms decide upon the technology type that is used and have an influence on the skills that are learned by employees. The investment decision influences indirectly the allocation of profit-oriented R&D investments and the direction of research in the IG sector. Conditional on the type of capital that is used by a firm, employees learn during work. The type of machinery that is used at their workplace determines the type of know-how that is accumulated over time. Technological change manifests in the way how final consumption goods are produced. At the same time, the way how goods are produced influences which type of technological knowledge is accumulated throughout the economy.

CG firms make their production decision once a month. They decide upon the production quantity on the basis of estimated demand. This has an influence on their input demand, i.e. the hiring or dismissal of labor and possibly, their credit demand if own financial means are insufficient. If firms are credit constrained, they revise their production decision and input demand is adapted. In the hiring process of labor, firms are not always able to fill all vacancies and they can only dismiss a maximum fraction of employees. Firms produce and deliver goods to the CG market ("mall"), a module that manages the inventory holding.[4]

2.1.1. Production

Consumption good (CG) firms produce homogeneous consumption goods using a Leontief technology combining labor and capital with constant returns to scale. The idea behind the Leontief assumption is that one unit of capital requires one unit of labor. Labor can only replaced in the aggregate sense if more productive capital allows to produce the same amount of output using less labor.

Labor is hired on the labor market and firms invest to replace depreciated capital or to expand their production capacity. Capital goods are accumulated in a stock which can be expanded by investment and depreciates over time. The capital stock is composed of various capital good items that may differ by productivity A^v and technology type $ig = c, g$. The index v can be thought as a pointer to a specific class of capital items in the firm's capital stock with the properties $(A^v, \mathbb{1}(v))$. $\mathbb{1}(v)$ is an indicator for the technology type. It takes the value one (zero) if the vintage v is of type c (g).[5]

[4]The mall represents a regional market and allows to introduce a spatial dimension of the model. Households and firms may have a regional identity and households are assumed to purchase goods only locally [cf. Dawid et al., 2018b, section 4.3].

[5]Throughout this documentation, superscript indices indicate a property of an item, e.g. the vintage or technology type. Subscript indices indicate whether the variable "belongs" to an agent. For example, $K^{ig}_{i,t}$ is capital of type ig owned by CG firm i. In contrast, $K^{v}_{ig,t}$ is the sold quantity of vintage type v sold by IG firm ig.

The variable $K^v_{i,t}$ indicates the amount of capital of vintage v that is in the firm's current capital stock $K_{i,t}$. Formally, $K^v_{i,t}$ represents the number of elements in the firms capital stock with the properties $(A^v, \mathbb{1}(v))$, i.e. $K^v_{i,t} := \{k \in K_{i,t} | A^v(k) = A^v, \mathbb{1}(k) = \mathbb{1}(v)\} \subseteq K_{i,t}$.

Moreover, the notation $K^{ig}_{i,t} \subseteq K_{i,t}$ is used when referring to the part of the capital stock that consists only of items of type ig.

Vintages of different technology types are perfect substitutes in terms of their *theoretical* productivity A^v. But the exploitation of the theoretical productivity at the firm level is constrained by employees' skill level. The theoretical productivity can be interpreted as *codified knowledge* that can be bought on the market [cf. Dosi and Nelson, 2010]. The theoretical productivity differs from the *effective* productivity of a given vintage $A^{Eff_v}_{i,t}$. The effective productivity $A^{Eff_v}_{i,t}$ of a capital good v is given by

$$A^{Eff_v}_{i,t} = \min\left[A^v, B^{ig}_{i,t}\right] \tag{1}$$

where $B^{ig}_{i,t} = \frac{1}{L_{i,t}}(\sum_{h \in L_{i,t}} b^{ig}_{h,t})$ is the average technology-specific skill level of firm i's employees $L_{i,t}$. Specific skills represent technology-specific know-how about the effective utilization of capital of a certain technology type ig. The stock variable $B^{ig}_{i,t}$, called *tacit knowledge*, determines the firm's absorptive capacity for capital of type ig [cf. Cohen and Levinthal, 1990, Edmondson et al., 2003]. Technology-specific skills of employees are imperfectly transferable across technologies, i.e. workers with a high endowment with skills in using conventional capital can not necessarily transfer these skills to the use of green capital. Skills are accumulated over time, hence the effective productivity $A^{Eff_v}_{i,t}$ of a given capital item v may change over time and varies across firms dependent on the firm's stocks of tacit knowledge. In contrast, the theoretical productivity of a given vintage is static and uniform to all firms. The skill-dependent exploitation of productivity imposes a barrier to the adoption of new and more productive vintages or capital vintages of another type ig because it takes time until workers have learned how to use the new machinery. Though their skills may be sufficient to exploit the productivity of older vintages or vintages of the other technology type.

Total feasible output $Q_{i,t}$ of firm i in t is given by the production function

$$Q_{i,t} = \sum_{v=1}^{V_{i,t}} \left(\min\Big[K^v_{i,t}, \max\big[0, L_{i,t} - \sum_{k=v+1}^{V_{i,t}} K^k_{i,t}\big]\Big] \cdot A^{Eff_v}_{i,t} \right) \tag{2}$$

where $L_{i,t}$ is the number of employees, and $\sum_{v=1}^{V_{i,t}} K^v_{i,t}$ is the firm's *ordered* capital stock composed of $V_{i,t}$ different capital stock items. *Ordered* refers to the running order of capital that is determined by the cost-effectiveness of capital goods. Feasible output does not necessarily coincide with the output that is actually produced. It can happen, that firms do not utilize their full capacity. This may occur because of an insufficient availability of labor, insufficient expected demand or because of prohibitively high using costs of capital goods. In such case, most cost-effective capital goods are used first. Firms can use only as much capital as workers are available in the firm to operate the machines.

This is captured by the term $\max\left[0, L_{i,t} - \sum_{k=v+1}^{V} K_{i,t}^{k}\right]$. An additional capital stock item is only used as long as there are workers in the firm who are not intended to work with more productive machines summed up in $\sum_{k=v+1}^{V} K_{i,t}^{k}$. Therefore, the running order of machines is decisive whether a capital stock item is used or not. The cost effectiveness determines the running order and is given by the amount of output per capital unit $A_{i,t}^{Eff_v}$ divided by vintage using costs. Using costs are given by the average wage payment for a worker $w_{i,t}$ and, if it is a conventional capital good, costs for the environmental resource input c_t^{eco}. Formally, this is written as

$$\zeta_{i,t}^{v} = \frac{A_{i,t}^{Eff_v}}{w_{i,t} + \mathbb{1}(v) \cdot c_t^{eco}} \tag{3}$$

where $\mathbb{1}(v)$ is the indicator for conventional capital, i.e. $\mathbb{1}(v) = 1$ if v is of type c, and zero otherwise.[6] The running order is determined such, that those capital stock items $K_{i,t}^{v}$ with the highest cost-effectiveness $\zeta_{i,t}^{v}$ for firm i are utilized first.

Production costs of a firm are composed of wage payments and the expenditures for resource inputs required for each conventional vintage that is used. Total resource costs are given by the unit costs for the resource input c_t^{eco} multiplied with the total number of units of conventional capital $\sum_{v=1}^{V_{i,t}^*} \mathbb{1}(v) \cdot K_{i,t}^{v}$ that are used in current production, i.e.

$$C_{i,t}^{eco} = c_t^{eco} \cdot \sum_{v=1}^{V_{i,t}^*} \mathbb{1}(v) \cdot K_{i,t}^{v}. \tag{4}$$

The $*$ is a marker that indicates that the capital stock items are used for production in t. The resource input costs $c_t^{eco} = e \cdot \tilde{p}_t^{eco}$ are composed of the user price $\tilde{p}_t^{eco}$ for the input multiplied with an efficiency parameter e. The price for the environmental resource $\tilde{p}_t^{eco}$ grows at the same rate as the average wage in the economy. Hence, the cost share for the resource in variable using costs of conventional capital is held constant for an average firm. The user price includes potential environmental taxes (see 2.5.1). The parameter e is fix. Efficiency improvements in the conventional sector occur only indirectly through productivity enhancements.

The decision of firms about the quantity to produce is based on their demand estimations and their inventory stocks. Once a year, firms apply a market research routine to estimate their demand potential for the coming year. In monthly frequency, based on these estimated demand curves and taking account of current inventory stocks at the "shopping mall", they determine the profit maximizing price-quantity combination to make their production decision. Newly produced goods are delivered to the mall where households purchase goods in a weekly frequency. Delivery of goods to the market and purchasing decisions are asynchronous in time. Because the estimated demand and resulting production decision do not necessarily coincide with the real demand and prices can not be immediately adjusted, the consumption goods market does not necessarily

[6] In case of equality of a vintage's cost-effectiveness the vintages are ordered by productivity and in case of further equality the green vintage is used first.

clear. Firms' hold inventory stocks at the mall being composed of a buffer for the case of unpredicted demand overshoot and goods that are remaining at the end of the month if the demand potential was overestimated. These routines are explained in more detail in Dawid et al. [2018b, section 3.2.1-2].

Firms' adjustments of labor and capital stock are sluggish and occur in discrete steps. Firms buy units of capital and hire single employees. The wage paid for an employee is firm-specific. If the workforce of the firm is not sufficient to produce the desired quantity, firms post vacancies with an offered wage at the labor market. Unemployed households send applications if the posted wage satisfies their expectations. If the firm accepts the application, the matching occurs. If the vacancies are not filled, firms adjust their wage upwards. It may occur that even after the wage adjustment the job is left vacant. In such case, firms have to adjust their production decision and produce with reduced capacity. If more than one household apply for a vacancy, the firm's hiring decision is probabilistic but positively influenced by the educational attainment of the applicant. It is assumed that technology-specific skills $b^{ig}_{h,t}$ are not observable for the firm during the application process. In contrast, general skills of applicants interpreted as educational attainment as proxy for ability are observable. Further information about the households' endowment with general and technology-specific skills is provided below in section 2.3. More detailed information about the labor market and the matching process can be found in section 4.2 in Dawid et al. [2018b].

2.1.2. Investment decision

Periodically, firms decide upon investment to replace depreciated and/or obsolete capital and to expand their capacity. Capital goods are obsolete when their using costs per unit of output are prohibitively high.

When firms invest they are faced with the decision which vintage and how many units to buy. Hence, they have to determine the quantity $I^v_{i,t}$, the productivity A^v and the technology type ig of the capital good they want to buy. In line with the empirical literature on firms' investment [Bacon, 1992], the decision is based on the estimated net present value (NPV) of an investment option. Firms chose the option out of possible investments that is expected to have the highest NPV. The net present value (NPV) is given by expected, cumulated and discounted financial in- and outflows of a particular investment option computed along a given time horizon T^{inv} and given discount rate ρ. The time horizon and the discount rate are homogeneous across firms and reflect time preferences and risk attitudes of firms.

The NPV is given by the expected, discounted profit $\hat{\pi}^v$ conditional on an investment in $I^v_{i,t}$ less investment costs, i.e.

$$NPV^v_{i,t} = -\tilde{p}^v_t \cdot I^v_t + \sum_{\tau=0}^{T^{inv}} \left(\tfrac{1}{1+\rho}\right)^{\tau} \cdot \hat{\pi}^v_{i,t+\tau} \tag{5}$$

where $\tilde{p}^v_t$ is the unit price of a certain vintage and I^v_t the amount of capital items to be bought. It may include subsidies if subsidies are used by the government (see

2.5.1). $\hat{\pi}^v_{i,t+\tau}$ is the expected net of revenue and costs in period $t + \tau$ conditional on the investment quantity I^v_t in investment option v. Different investment options have different implication for the expected feasible production quantity, labor and resource input requirements and financial costs. Financial costs are interest payments, dividends and annuities of outstanding and, possibly, interest and annuities of new loans if own financial means are insufficient to finance investment. Firms form expectations about the development of wages and the skills of newly hired employees, prices, inflation, future interest rates and the market size on the basis of past observations. Own potential prices in the NPV calculation are computed on the basis of estimated demand curves in search for the profit maximizing price-quantity combination [cf. Harting, 2019, Dawid et al., 2018b, section 3.2.10]. Firms do also anticipate learning of employees based on past observations.

The investment quantity is chosen in discrete steps and different price-quantity-technology type combinations are compared with each other including an no-investment option. The firm chooses the option with the highest expected NPV. The set of investment possibilities composed of different vintage-quantity combinations that are taken into consideration is restricted to reduce the computational complexity keeping the mixture of conventional and green options in the choice set balanced.

Investment and production expenditures have to be financed in advance. If the firm's own financial means on the bank account are insufficient, it applies for a credit from private banks [cf. Dawid et al., 2018b, section 3.2.8].

2.1.3. Environmental impact

Natural resource inputs required for the utilization of conventional capital cause an environmental damage. The environmental damage $\mathcal{D}_{i,t}$ is modeled in a very stylized way, assuming it to be proportional to the amount of resources required for the utilization of conventional vintages, i.e.

$$\mathcal{D}_{i,t} = e \cdot \sum_{v=1}^{V_i^*} \mathbb{1}(v) \cdot K^v_{i,t}. \tag{6}$$

The economy wide environmental impact is obtained by aggregation of firm level environmental damages, i.e. $\mathcal{D}_t = \sum_i \mathcal{D}_{i,t}$. For reasons of simplification, environmental feedbacks on the economy are assumed away because the focus here is the study of technology diffusion and stylized representation of technology and the economic activity prevents reasonable assumptions about potential climate feedbacks.

Adoption at the firm level is measured by the share of green capital used in current production that is given by

$$\nu^g_{i,t} = \frac{K^{g*}_{i,t}}{K^*_{i,t}} \tag{7}$$

where the asterisk $*$ again indicates that a capital stock item is actually used. The share of green capital used in current production determines the environmental quality of a consumption good which is not observable for consumers. In the policy experiments, the government can pay a price support for environmentally sound products which allows firms to achieve a higher profit margin on green product sales (see 2.5.1). The share ν_t^g aggregated across firms is used to evaluate green technology diffusion at the macroeconomic level at the intensive margin, i.e. it measures the intensity of green technology utilization in current production.

Another indicator determining the environmental performance of production is the so-called eco-efficiency $\epsilon_{i,t}$ which is given by the environmental impact per unit of output, i.e. it corresponds to the environmental damage caused by firm i divided by its output $Q_{i,t}$ in t

$$\epsilon_{i,t} = \frac{\mathcal{D}_{i,t}}{Q_{i,t}}. \tag{8}$$

On the economy-wide level, the eco-efficiency corresponds to $\epsilon_t = \frac{\mathcal{D}_t}{Q_t}$. The eco-efficiency serves as indicator taking the economic activity into consideration.

Note that this indicator is a relative indicator, and does not account for the aggregate environmental impact. It measures the *eco-efficiency*, but does not capture potential rebound effects that may arise when reductions in the material consumption through an improved efficiency are overcompensated by an increase of aggregate output. The eco-efficiency performance may also improve by productivity enhancements in the conventional sector. The absolute environmental performance $\mathcal{D}_{i,t}$ is also referred to as *eco-effectiveness*.

For simplification, it is assumed that resource inputs are exogenously provided with an inelastic supply. Hence, the price for material inputs is independent of the demanded quantity, but may be manipulated by policy.[7]

To ensure the closure of the model, paid resource costs need to be recycled back as income to the economy. For simplification, the costs for natural resources are paid as a lump-sum transfer to households. One may think of a separate labor market in the resource sector. If the resource sector becomes obsolete in consequence of a green transition, households loose part of their monthly income. At the same time, CG producing firms save input costs.

2.2. Investment goods sector

The technological evolution in the simulated economy is embodied in the evolution of the stocks of codified A and tacit technological knowledge B. Codified knowledge is developed in the investment goods (IG) sector. If IG firms successfully innovate, they shift the productivity frontier $A^V_{ig,t}$ upwards which is a measure for the available stock of codified technological knowledge in sector ig in t. The investment goods sector is

[7] This is a strong assumption that is mainly made for simplification reasons. It implies that scarcity in the supply of resources is assumed away. It can be justified through the very aggregate interpretation of resource inputs where a large number of substitutes is available. This deviates from other resource economic models in which scarcity plays an important part and price induced substitution between different types of resource inputs is key mechanism for the reduction of carbon emissions [Gerst et al., 2013, Nijkamp et al., 2005]. In such models, price interactions across different resources represent a decisive mechanism to achieve emission reductions. Here, a shift between two technologies and learning dynamics are studied but not incremental adjustments in the composite of intermediate inputs.

composed of two IG firms $ig \in \{c, g\}$ that offer different types of capital goods.[8] The firm c produces a conventional, the other firm g produces green capital goods. Each IG firm offers a range of vintages that are indexed by $v = \{1, ..., V\}$ that differ by productivity. The parameter V indicates the fix maximal number of vintages that can be supplied by a capital goods producer. The index $v = 1$ refers to the least productive vintage supplied by IG firm ig and $v = V$ to the most productive. If a producer invents a new vintage, the least productive vintage is assumed to be technologically obsolete and is removed from the supply array.[9]

The properties of a vintage v can be summarized by the tuple $(A^v, \mathbb{1}(v))$ where $\mathbb{1}(v) \in \{1, 0\}$ is a binary indicator that is associated with the technology type. It takes the value $\mathbb{1}(v) = 1$ if the vintage v was produced by the conventional IG firm and zero otherwise.

How to interpret "green" and "conventional" capital goods? The distinction between green and conventional capital follows the eco-innovation concept [Arundel and Kemp, 2009]. Eco-innovations are defined in relation to the incumbent and refer to any production practices that are environmentally more benign than the incumbent solution and save material and energy input costs. For example, these technologies can be different kinds of renewable energy and energy efficiency measures, but also re-using and recycling technologies and organizational methods and systems that allow to produce any final good or service without the dependency on material or fossil fuel energy inputs. In short, green capital is interpreted as productive capacity of the firm that enables employees to produce a final consumption good using relatively less (natural) resource inputs compared the incumbent, conventional production technique. The model may be extended to a multi-technology case where the indicator $\mathbb{1}(v)$ is not binary but ranges in the interval $\mathbb{1}(v) \in [0, 1]$. In such case it represents different degrees of eco-performance. Technology-specific skills of both types are proportionally applicable.

Inventions allow IG firms to produce a new and more productive vintages of capital goods. These inventions are interpreted as instructions or blueprints how to develop and produce a new and more productive capital good.

Generally, capital (or investment) goods are any kind of tradable asset which is used by CG firms in production and can be bought on the market and accumulated in a stock. Its lifetime is a matter of the depreciation rate. With a hundred percent depreciation rate capital goods could also be interpreted as intermediates. Here, it is interpreted as machinery or other tangible input that enables employees at the firm to work productively. Though, the interpretation can be straightforwardly expanded to tradable services and tradable intangibles.

[8] The number of IG firms is restricted to two representative IG firms for reasons of simplification. Technically, the number can be increased and also a larger number of technology types is feasible whose technical characteristic $\mathbb{1}(v)$ range in the interval $[0, 1]$.

[9] Technically, that means that vintages are re-indexed but the order is maintained. The second-least productive vintage $v = 2$ becomes the least productive $v = 1$ and so forth, i.e. $v \leftarrow (v + 1) \forall v > 1$. Principally, the obsolescence assumption is not necessary, but in practice it enormously reduces the computational complexity of CG firms' investment decision.

2.2.1. Production

Capital goods are produced with labor as the only input. For reasons of simplification, IG firms are not integrated in the labor market and use only so-called *virtual* labor. Capital is produced with constant returns to scale, i.e.

$$k^v_{ig,t} = (\alpha^v_t)^{-1} \cdot l_{ig,t} \tag{9}$$

where α^v_t is a scaling factor determining the amount of labor $l_{ig,t}$ needed to produce one unit of capital. The scaling factor $\alpha^v_t = \alpha \cdot (\frac{A^v}{A^1})$ depends on the ratio of the productivity of the least productive vintage $v = 1$ in the current supply array to the vintage v. Hence, more productive vintages are more labor intensive and as a consequence more expensive to produce (see 2.2.3). The indexation of vintages v is time dependent. Successful innovation shifts the ratio. Production costs per supplied productivity unit decrease because the least productive vintage becomes obsolete and all supplied vintages are re-indexed (see 2.2.2). The parameter α is homogeneous across different vintages and IG firms.

The total amount of labor used by ig is given by $L_{ig,t} = \sum_{v=1}^{V} K^v_{ig,t} \cdot \alpha^v_t$ where $K^v_{ig,t}$ is the total, demanded quantity of vintage v in t. To ensure the model's closure, the costs for labor inputs $C^{lab}_{ig,t} = p^{lab}_t \cdot L_{ig,t}$ are recycled back to the economy as a transfer to households. Unit labor costs in the IG sector p^{lab}_t co-evolve with average wages in the economy. This assumption can be interpreted as a separated labor market. Hence, there are some invisible households who work in the capital goods sector and consume in the same proportions as households working in the CG sector. The use of *virtual* labor as input implies that capacity constraints are assumed away.

2.2.2. Innovation

The productivity of vintages supplied by IG firm ig in t depends on its current technological frontier $A^V_{ig,t}$. The frontier corresponds to the productivity level $A^V_{ig,t}$ of the most productive vintage indexed with V. If an IG firm ig successfully innovates, its technological frontier is shifted upwards and firm ig is able to offer a new and more productive vintage in $t+1$, i.e.

$$A^V_{ig,t+1} = (1 + \Delta A) \cdot A^V_{ig,t}. \tag{10}$$

Productivity enhancements are discrete steps and the step size ΔA is fix. The success of innovation is probabilistic, but IG firms are able to influence the probability of success by investment in R&D. The probability of success $\mathbb{P}_{ig,t}$ is given by

$$\mathbb{P}_{ig,t}[\text{success}] = \bar{p} \cdot (1 + \widehat{R\&D}_{ig,t})^{\eta} \tag{11}$$

where $\bar{p}$ is a fix minimum probability of innovation success and $\widehat{R\&D}_{ig,t}$ is ig's R&D intensity in the current month. The R&D intensity is computed as monthly R&D spendings in relation to current monthly macroeconomic activity proxied by scaled monthly GDP. The parameter $\eta \in (0, 1]$ gives the returns to R&D. After successful innovation, a more productive vintage is added to the supply array and vintages are re-indexed as explained above. The parameters $\bar{p}$, ΔA and η are set in a way that overall productivity progress resembles empirically documented patterns of productivity and GDP growth rates.

2.2.3. Pricing

IG firms impose an adaptive mark-up over unit production costs captured by the wage proxy mentioned above (2.2.1). Adaptive pricing rules are a common approach for heuristic pricing rules in agent-based models [e.g. Assenza et al., 2015]. The price $p^v_{ig,t}$ of vintage v is given by

$$p^v_{ig,t} = p^{lab}_t \cdot \alpha^v_t \cdot (1 + \mu_{ig,t}) \tag{12}$$

where $p^{lab}_t \cdot \alpha^v_t$ are labor unit costs and $\mu_{ig,t}$ is an adaptive mark-up over production costs that is imposed by firm ig. Labor unit costs are vintage-specific and proportional to the relative productivity of a vintage currently offered by firm ig. More productive vintages require more labor inputs and are more costly to produce. Higher production costs are reflected in the final vintage price.

The firm-specific mark-up $\mu_{ig,t}$ follows an updating rule that depends on trends of firms' pricing behavior, market shares and profits in a given horizon of past periods. The adaption rule is given by

$$\mu_{ig,t} = \begin{cases} \mu_{ig,t-1} \cdot (1 + \delta^\mu) & \text{if case A} \\ \max[\bar{\mu}, (\mu_{ig,t-1} \cdot (1 - \delta^\mu))] & \text{if case B} \\ \mu_{ig,t-1} & \text{else} \end{cases} \tag{13}$$

where $\bar{\mu}$ is a fix minimum mark-up level and δ^μ the size of the updating step. Different cases for the updating routine have to be distinguished:

(A) Firms increase the mark-up in three cases:

- i) They have increased the mark-up in past periods but did not lose market share $\omega_{ig,t}$ measured in relative sales, i.e. $\left[\Delta\mu_{ig,t} \geq 0 \wedge \Delta\omega_{ig,t} \geq 0\right]$ where Δ indicates the deviation from the average computed across a given number of past periods.
- ii) They have increased the mark-up and lost market share, but profits $\pi_{ig,t}$ were rising, i.e. $\left[\Delta\mu_{ig,t} > 0 \wedge \Delta\omega_{ig,t} < 0 \wedge \Delta\pi_{ig,t} > 0\right]$.
- iii) They have decreased the mark-up and the market share increased, but profits decreased, formally $\left[\Delta\mu_{ig,t} < 0 \wedge \Delta\omega_{ig,t} > 0 \wedge \Delta\pi_{ig,t} \leq 0\right]$. From this observation firms conclude that the mark-up was too low to be profit maximizing even though they gained market share.

(B) Firms decrease the mark-up in two cases:

- i) They have increased the mark-up in past periods, lost market share and made lower profits, i.e. $\left[\Delta\mu_{ig,t} > 0 \wedge \Delta\omega_{ig,t} < 0 \wedge \Delta\pi_{ig,t} \leq 0\right]$. Controlling for the market share is a test on the association of the decrease of profits with lost competitiveness. Decreasing profits can be also due to cyclical volatility of investment, and do not necessarily imply that mark-ups were too high.

ii) Firms decreased the mark-up, gained market share and made higher profits, i.e. $\left[\Delta\mu_{ig,t} < 0 \wedge \Delta\omega_{ig,t} > 0 \wedge \Delta\pi_{ig,t} > 0\right]$. Theoretically, a firm can make higher profits even though it has decreased prices and lost market share. This can happen if the market size has increased sufficiently. The combined condition of $[\Delta\omega_{ig,t} > 0 \wedge \Delta\pi_{ig,t} > 0]$ indicates that the increase in profits is not (only) due to changes in the demand on the IG market but likely also a consequence of a higher market share.

The minimum threshold $\bar{\mu}$ ensures that the mark-up never falls below a given minimum value.

In the remaining cases, e.g. when a firm decreased prices, lost market share but made higher profits, the firm is uncertain about the strategy and keeps the price constant.

2.2.4. Revenue allocation

IG firms' revenue is composed of two parts. The first part accounts for *virtual* wage payments for labor inputs to IG production. The amount is channeled back into the economy as a lump-sum transfer that is uniformly allocated across households (see 2.2.1). The remaining part of IG firms' revenue accounts for profits $\pi_{ig,t}$ stemming from the mark-up pricing. A given fraction $\lambda \in (0,1)$ is reinvested in R&D. The remaining share $(1-\lambda)$ of profits is paid as dividends to shareholders. They invest part of their income in a risky index fonds. IG firms are part of the index fonds. This is a simplifying assumption to ensure the financial closure of the model. The financial market is explained briefly in 2.3.2 and more detailed in Dawid et al. [2018b, section 3.6.4 and 4.4.1-2].

To capture the long term nature of R&D planning and budget setting, R&D expenditures are smoothed to ignore the short term volatility of CG firms investment activity. Monthly R&D expenditures are computed as running average of past profits $\pi_{ig,t}$ over the R&D budgeting horizon T^{rd}, i.e.

$$R\&D^{ig}_t = \frac{1}{T^{rd}} \sum_{\tau=1}^{T^{rd}} \lambda \pi_{ig,t-\tau}. \tag{14}$$

R&D expenditures are spent for wages of researchers. This assumption coincides with many other macroeconomic models of technological change [cf. Romer, 1990]. Though in this model version, the labor market for researchers is not explicitly modeled. This assumption implies that trade-offs in the cross-sectoral allocation of researchers and crowding out of production as studied by other authors are assumed away [Popp, 2006, Wolff and Reinthaler, 2008]. R&D expenses are transferred back to the economy to ensure model closure. This is done by treating R&D expenditures as dividends that are paid to shareholders, i.e. to households who have invested in risky assets. A similar smoothing mechanism is applied to the labor cost dummy such that transfer payments do not reflect the same volatility as investments do.

2.2.5. Technological competition

Technological competition is a race between the incumbent conventional and entering green technology. It is assumed that the incumbent conventional technology is established on the market. Hence, the capital stock of CG firms is composed of merely conventional capital. At a given time, the eco-IG firm enters the market. At this point of time, the entrant firm suffers from different entry barriers. These barriers are explained below (2.6).

2.3. Households

Households (HH) act as consumers, savers and investors, and employees in the CG sector. Most important for this model extension is the role of households as employees and how employees learn at work. The other activities of households are only briefly sketched in this paper. Additional detail is available in Dawid et al. [2018b, section 3.6].

2.3.1. Learning employees

Next to codified knowledge developed in the IG sector, technology-specific know-how B_t^{ig} is the second decisive determinant for the macroeconomic technological evolution. Households in their role as employees are the carrier of technology-specific skills (know-how) and accumulate these skills by learning at work. Aggregated at the firm level, technology specific skills represent the stock of tacit knowledge of a firm i, i.e. $B_{i,t}^{ig} = \frac{1}{L_{i,t}} \sum_{h \in L_{i,t}} b_{h,t}^{ig}$. Employees $h \in L_{i,t}$ are characterized by their learning ability and two types of *technology-specific* skills. Workers ability to learn is captured by a time-invariant general skill level b_h^{gen} of employees and moderates the speed of learning.

The two types of technology-specific skills $b_{h,t}^{ig}$ represent the employee's capability to work productively with a specific type of capital $ig \in \{c, g\}$. These skills are stock variables that are growing by stepwise updates that represent a learning process. The learning process is dependent on the household's learning ability $\chi_h^{gen} = \chi(b_h^{gen})$ and the technological properties of the capital stock used in firm i where the employee is working, i.e. $h \in L_{i,t}$. There are two sources of learning. Employees are learning by doing when working with a specific technology type and they can learn via cross-technology spillovers.

Skills are updated from period to period in discrete steps. The size of the updating step $\Delta b_{h,t+1}^{ig} = b_{h,t+1}^{ig} - b_{h,t}^{ig}$ is given by

$$\Delta b_{h,t+1}^{ig} = \chi_h^{gen} \cdot \left(\left[\left(\psi_{h,t}^{ig}\right)^{(1+\chi^{dist})} \left(\psi_{h,t}^{-ig}\right)^{(1-\chi^{dist})} \right]^{1/2} - 1 \right) \tag{15}$$

where $\psi_{h,t}^{ig}$ is the "amount" of knowledge learned during one period through the utilization of a specific technology type ig with $\psi_{h,t}^{ig} \geq 1$. It is normalized to ≥ 1 to ensure spillovers can not be negative and subtraction by 1 ensures that the skill update is zero if there is no learning progress.

Part of the learned knowledge $\psi^{ig}_{h,t}$ is transferable across technology types. It contributes to the accumulation of the endowment with the alternative skill type $-ig$ with $ig \neq -ig$ and $ig, -ig \in \{c, g\}$. The parameter $\chi^{dist} \in [0, 1]$ describes the technological distance between the two technologies which is a source of state dependence.[10] The functional form is inspired by models on state dependent technological change.[11]

The skill update through learning by doing $\psi^{ig}_{h,t}$ is dependent on the technical difficulty of the technologies and the relative amount of effort invested in learning. More complex technologies are more difficult to learn and require a higher amount of effort, also called *intensity of learning.* The size of the updating step also depends on the learning potential $\tilde{b}^{ig}_{h,t}$ which reflects the relative technical novelty of capital ig. Taken together, the amount of knowledge learned by doing is given by

$$\psi^{ig}_{h,t} = 1 + \left(\nu^{ig}_{i,t}\right)^{\chi^{int}} \cdot \tilde{b}^{ig}_{h,t} \tag{16}$$

with $h \in L_{i,t}$. The relative intensity of learning in a specific technology category ig is dependent on the relative amount of technology ig that is used $\nu^{ig}_{i,t} = \frac{K^{ig}_{i,t}}{K_{i,t}}$ at h's workplace $i : h \in L_{i,t}$. This can be understood as proxy for the amount of time that invested in the learning to use a specific type of machinery [cf. Cohen and Levinthal, 1990]. Learning in category ig is faster if the relative amount of used capital of type ig is higher. The parameter χ^{int} captures returns to scale in the learning process. Decreasing marginal returns in the learning process imply that the first hours of learning are more effective than the last. An alternative interpretation of χ^{int} is the *technical difficulty.* If χ^{int} is close to zero, employees learn how to use the machinery irrespectively of the time invested in working with the machine. More difficult technologies are more sensitive to the amount of time invested in learning.

$\tilde{b}^{ig}_{h,t} = \max[0, (A^{ig}_{i,t} - b^{ig}_{h,t})]$ is a measure for the *technical novelty* and represents the learning potential of employee $h \in L_{i,t}$. It is given by the gap between the codified technological knowledge of the employer $A^{ig}_{i,t}$ and the employee's current skill level $b^{ig}_{h,t}$. The larger the gap is, the larger is the potential technological knowledge the employee can learn and the faster is the pace of learning. This accounts for the fact that employees only learn if they are exposed to (codified) technological knowledge they that is new to them, i.e. employees learn only if there is something new to learn.

[10] For simplification, it is assumed that restrictions in the transferability only affect the speed of learning, but skills are not perfectly disjoint. Differences in the levels of technology-specific skills between ig and $-ig$ can be principally fully closed by spillovers even if employees never have worked with one of the technology types.

[11] These models are used to investigate the implications of scarce time and R&D resources that can be invested in the production of technological knowledge and an associated allocation trade-off [cf. Acemoglu, 2002]. The Acemoglu version of state dependence builds on two main assumptions, i.e. (1) the resources that can be invested in R&D are scarce (in terms of a limited amount of researchers that can be allocated across technological sectors), and (2) there may be spillovers in the creation of knowledge, i.e. one sector may be able to use the knowledge that is created in the alternative sector. Both aspects can be plausibly transferred to the process of learning of employees who have (1) a limited amount of time to learn specific tasks, and (2) knowledge about specific tasks might be useful for both technology types. In the version here, spillovers are not stock, but only flow dependent.

Firms can not observe the skill endowment of individual employees, but observe the effectiveness of the production process. Hence, they know the amount of inputs and the amount of output. From this observation they can draw conclusions about their aggregate stock of tacit knowledge $B^{ig}_{i,t}$. This information is used in the investment, pricing and production decision of the firm.

Households are matched to CG firms on the labor market as it was mentioned above (2.1.1). An employed households h works at the same firm until she is dismissed or leaves the firm deliberately. Unemployed household receive an unemployment benefit from the government. If a household does not find a job for a longer duration, she incrementally revises its reservation wage downwards. Further detail is provided in section 4.2 in Dawid et al. [2018b].

2.3.2. Consumption and saving

Beyond their involvement in the labor market and production process, households consume and save. Before households make their consumption decision and after receiving their monthly income, they compute the planned consumption budget for each week of a month. Households' income is composed of wage and financial income from savings and investments. After the payment of taxes, households allocate the disposable income on saving and consumption taking account of current income, current and desired financial wealth [cf. Dawid et al., 2018b, section 3.6.2].

Households purchase goods in a weekly frequency at the mall which serves as intermediary between CG firms and households and as inventory holder. The decision which good to buy is computed by a multinomial logit function where the probability to buy goods produced by firm i depends on the price of the good $\tilde{p}_{i,t}$ and the prices of other goods available at the mall G_t. Goods available G_t are equally valued by consumers, but are produced by different firms and offered at different prices. The supply price of CG firms is subsidy inclusive if a consumption subsidy is paid by the government (see 2.5.1). The probability that household h selects the product of firm i is given by

$$\mathbb{P}[h \text{ buys } i] = \frac{\exp\left(-\gamma^C \log(\tilde{p}_{i,t})\right)}{\sum_{j \in G_t} \exp\left(-\gamma^C \log(\tilde{p}_{j,t})\right)}. \tag{17}$$

The parameter γ^C is a constant that measures the consumers' price responsiveness and is a proxy for the degree of competition on the market. The consumption quantity is determined by the weekly consumption budget of the household, i.e. the full budget is spent if a sufficient amount of goods of the selected producer is available. If the quantity is not available, the household makes a second choice. If it is again not sufficient, the household is rationed. The remaining budget is added to the consumption budget for the subsequent week. More detail is available in Dawid et al. [2018b, section 4.3].

Households' total wealth consists of deposits at their bank account and financial assets invested in a risky index fonds. Once a month and after the subtraction of planned consumption expenditures and taxes, households make a revision of financial asset allocation. For reasons of simplification, there is only one risky asset available that consists of an index of shares issued by CG firms and "virtual shares" of the IG firm and its R&D activities. The portfolio revision consists of the decision whether to buy or sell shares of the risky index fonds [cf. Dawid et al., 2018b, section 6.4.2]. The decision is modeled in a very stylized way and is not responsive to changes in the interest rate. This might be a severe restriction, but facilitates the tractability of the model. Economic effects channeled through portfolio revisions on the financial market are beyond the scope of the current model. Changes in the interest rate affect firms' investment decision through the accessibility and affordability of loans at private banks.

2.4. Banks

Banks serve as financial intermediaries and bookkeepers keeping track of all financial flows and stocks of agents' deposits and liabilities. Agents receive interest income paid for their deposits. Banks do also supply credit to the CG production sector. The supplied interest rate $r^b_{i,t}$ is firm-specific and depends on the volume of the requested credit, its probability of default and the interest rate of money supplied by the central bank. The default probability is computed on the basis of the firm's debt-equity ratio and the credit volume. Banks have to fulfill reserve requirements. This may constrain their capability to grant credit. This module is explained in more detail in Dawid et al. [2018b, section 3.4.2-7]

2.5. Government

In the model, the government has two important roles. First, it reallocates revenue via the payment of transfers and the collection of taxes, e.g. in terms of an unemployment benefit and income taxes. Second, the government may use taxes, subsidies and regulation to achieve particular political targets. In the Eurace@unibi-eco version, policies are studied that may stimulate the diffusion of green technologies. The diffusion process is associated with increasing returns of adoption and, in the long run, typically only one of the two competing technologies survives on the market [cf. Hötte, 2019a]. Policies that stimulate the diffusion process are equivalent to policies that increase the probability that the green technology wins the technology race. The replacement of the incumbent by the green entrant is interpreted as sustainability transition [Safarzyńska et al., 2012].

2.5.1. Policies

In preceding studies [Hötte, 2019a,b], three different market based instruments were analyzed with regard to their diffusion impact and macroeconomic performance. These instruments are a tax on the natural resource input and two different subsidies.

- The **eco-tax** θ is imposed as a value added tax on material inputs. This increases relative costs of conventional capital utilization for CG firms,

$$\tilde{p}^{eco}_t = (1 + \theta) \cdot p^{eco}_t. \tag{18}$$

In this model, the environmental impact of production is proportional to the amount of resource inputs that is used. Hence, the tax can also be interpreted as a tax on the environmental externality.

- The government can use an **investment subsidy** ς^i that reduces the price for green capital goods,
$$\tilde{p}^v_{g,t} = (1 - \varsigma^i) \cdot p^v_{g,t}. \tag{19}$$

- The government may also pay a **green consumption price support** ς^c for environmentally sound produced CGs, i.e.
$$\tilde{p}_{i,t} = \Big(1 - \nu^g_{i,t} \cdot \varsigma^c\Big) \cdot p_{i,t} \tag{20}$$

  This subsidy is directly paid to firms and is proportional to the share of green capital used in current production $\nu^g_{i,t} = (K^{g*}_{i,t}/K^*_{i,t})$. The price support allows CG firms to achieve a higher margin when producing environmentally friendly.

Taxes and subsidies can be alternatively interpreted as technical characteristics when ignoring the fiscal implications of policy. A tax on the environmental resource is the same as a higher degree of technical superiority of the entrant technology in terms of input cost savings. The investment subsidy reflects the production costs of green capital and a consumption subsidy paid as price support is analogue to a higher willingness to pay for green goods. This is discussed in more detail in [Hötte, 2019b].

The tax and the subsidy rates are initialized at a given level at the beginning of the policy horizon and remain constant during the whole horizon. Before the horizon ends, taxes and subsidies are phased out to avoid disruption.[12] The government may freely combine taxes and subsidies and the assumptions about the fix or adaptive rates are a matter of the policy experiment of interest.

2.5.2. Budget balancing

The government is budget constrained and seeks to balance its budget in the long run. Budget balancing occurs via the adaption of a base tax rate that is levied on households' income and firms' profits. The base tax rate is increased if the net of tax income and transfer payments is negative and decreased otherwise. The net inflow is computed as running average over the government's budgeting horizon to obtain smoothness in the evolution of the tax rate.

2.6. Market entry & barriers to diffusion

At the day of market entry t_0, the green technology becomes available as investment possibility for CG firms. At this time, the incumbent technology is established on the

[12] Note that in this version, agents do not adapt expectation with respect to the behavior of policy makers. An analysis of the role of expectation formation about political decisions would require further adjustments in the simulation code.

market. All firms produce only with conventional technology and workers have only worked with conventional capital. Market entering (green) technologies may suffer from different types of barriers to diffusion. Barriers emphasized in the literature are for example technological disadvantages, infrastructural and network effects in favor of the incumbent technology, or labor related factors that concern the insufficient availability of sufficiently skilled employees. Other barriers to technology adoption are effective at the microeconomic firm level such as financial constraints or the vintage structure of the capital stock [Arundel and Kemp, 2009, Triguero et al., 2013, Carlsson and Stankiewicz, 1991]. This analysis focuses on the two broad categories of labor and technology related barriers. Many of the adoption barriers mentioned in the (eco-)innovation literature can be subsumed within the two categories concerning the availability of technology-specific skills and the technological performance of capital supplied by the entrant. The market entry conditions of the green IG firm are given by households' relative endowment with technology-specific skills required to use the entrant technology type and by the relative productivity of supplied green capital goods.

The market entry of the green IG firm is assumed to be enabled by radical innovation. At the day of market entry t_0, the green IG firm starts supplying the first vintage, least productive of green capital $v = 1$. The radical innovation is assumed to enable a surge of follow-up innovations. In the first years after market entry, every 6th month a new and more productive version is brought to market until the maximal number of supplied vintages is reached.[13] After that time, further innovation is probabilistic and dependent on R&D expenditures.

The initial supply array of the entrant firm is initialized proportionally to supplied vintages of the incumbent firm. The frontier productivity of the entrant is given by

$$A^V_{g,t_0} = (1 - \beta^A) \cdot A^V_{c,t_0} \tag{21}$$

where $\beta^A \in [0, 1)$ is a measure for the technological disadvantage of green technology at the day of market entry. The array of supplied vintages is composed of other vintages of lower productivity while the productivity difference between these vintages is proportional to the step size of incremental innovation.

Firms need employees with a sufficiently high level of technology-specific skills to exploit the full productivity of capital. In analogy to the initialization of the entrant's technological frontier, the specific green skill level of households in t_0 is initialized proportionally to the specific skill level for conventional technologies, i.e.

$$b^g_{h,t_0} = (1 - \beta^b) \cdot b^c_{h,t_0}. \tag{22}$$

[13] This assumption matches with an empirical stylized fact of technology transitions elaborated by Grübler [1991]. He interprets basis innovations as shifts in the feasibility frontier that are followed by incremental improvements. Basis innovations are the root of large scale system changes. An alternative interpretation can be found in the transition literature [Geels and Schot, 2007]. Disruptive change in the market environment challenges the incumbent technology. It opens a window of opportunity for a technology established in a niche market to replace the incumbent technological regime. It is incrementally adapted to the needs of a broader group of users.

The parameter $\beta^b \in [0, 1)$ describes a gap in the technological know-how, in particular it determines to which extent workers are less able to use the new, green technology in relation to the technology they are used to. For example, if $\beta^A = \beta^b = 0.05$, supplied vintages of the green firm have a 5% lower productivity and workers have a 5% lower level of green skills.

The parameters β^A and β^b represent different types of barriers to technology diffusion. This way of initialization allows to control the conditions of market entry and to make sensitivity tests about the effectiveness of different types of barriers to diffusion.

2.7. Simulation settings and calibration

The simulation model is run for a given number of simulation runs R and for a given number of iterations T. The model is run multiple times because it has stochastic elements, for example in the innovation process, the labor market matching and consumption decision. The outcome of a single run is not necessarily representative. The number of R is set such that a sufficiently large sample of simulated time series data is generated that can be studied with statistical tools. A typical number of R ranges between 50 and 200. Its choice is dependent on the variation across runs and whether additional randomness, for example as Monte Carlo analysis on initial conditions, is introduced.

A basic setting for the time horizon in diffusion studies is $T = 15000$ which corresponds to a horizon of roughly 60 years, i.e. 240 working days per year. After a given number of iterations t_0, the green technology producer enters the market. An exemplary day of market entry is $t_0 = 600$. The range of barriers that produces a sufficiently large fraction of non-trivial patterns of diffusion ranges between $[0, 0.1]$. The price of the natural resource is initialized at the day of market entry such that resource input costs roughly correspond to 10 percent of the average wage paid in the economy.

In each iteration, agents are sequentially activated and execute their behavioral routines in a given order. A selection of routines that are executed during one iteration and the sequential and conditional activation of agents is illustrated in figure 2 as pseudocode.

The simulation model can be thought as computer program that executes stepwise the behavioral functions described above. Initial endowments and parameter settings are used as input to the model. The initial conditions were largely taken from the baseline Eurace@unibi model. Information on determination of initial conditions and parameter settings is available in Dawid et al. [2018b, appendix A]. The extensions of the model made a re-calibration of some of the parameters necessary. This was done following an indirect calibration approach [cf. Fagiolo et al., 2019]. Hence, parameters were set in a way that the simulated time series data reproduces empirical micro- and macroeconomic regularities. Whenever parameters have a direct natural interpretation as e.g. time horizons or discount rates, empirical analogues were directly used.

Other parameters were set in a way that the model reproduces empirical stylized facts. More information on the procedure and the calibration results is available in Hötte [2019a, appendix A].

Figure 2: Stylized routine executed during each iteration

```
Data: Initial population
Result: Time series of population
begin
  Initialize
  for t in SimulationHorizon do
    if t = MarketEntry then                           /* Set entry barriers etc. */
      Initialize green skills b^g_{h,t} ∀ h ∈ HH
      Initialize market entrant A^V_{g,t}
    for a in ListofAgents do
      if t = a.TimeToAct then                         /* asymmetric activation */
        if (a = IG.conv) ∨ ( a = IG.green ∧ t > MarketEntry) then
          if InnovationSuccess then                   /* monthly */
            Increase techn. frontier A^V_{ig,t}
            Replace oldest vintage by new one
          Adapt supply prices
          Send supply info to CG firms
          if CG buys capital good then                /* event based */
            Deliver capital & receive revenue
          if t = LastDayOfMonth then
            Compute revenue & set R&D budget
        if a = CG then
          if t = TimeToInvest then                    /* periodically */
            Read capital supply info
            Estimate NPV for different investments
            Choose most profitable option k*
            if k* > 0 then
              Financial means sufficient?
              if Yes then
                Buy k* and add to K_{i,t}
          if t = TimeForPriceUpdate then              /* periodically */
            Update supply prices
          Execute production                          /* monthly */
          Update technology (B^{ig}_{i,t}, A^{ig}_{i,t}) ∀ ig ∈ {c, g}
        if a = h ∈ HH then                            /* monthly */
          Receive income & set consumption budget
          Update skill level b^{ig}_{h,t} ∀ ig ∈ {c, g}
        if a ∈ { Government, financial intermediaries } then
          Execute agent's routines
```

This pseudocode sketches a selection of routines executed during each iteration. The routines executed by the government and financial intermediaries are not shown here. Interaction between agents is organized via a so-called “message board” that stores information sent by an active agent until the addressee is activated again and can update its memory.

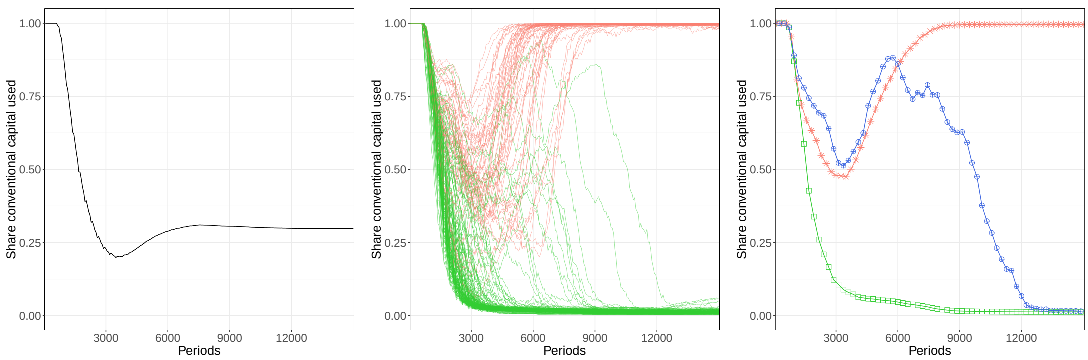
3. Illustrative simulation results

This model provides a framework for the study of transition processes. Here, a technology transition is defined as a large scale technology substitution process. The conventional, incumbent technology is possibly substituted by the entrant green technology. This substitution process can be illustrated by diffusion curves. Macro- and microeconomic side effects can be studied with the simulated time series of economic indicator variables.

In this section, a short overview of the properties of the model are illustrated using a set of 200 simulation runs à $T = 15000$ iterations with a parameter setting that generates non-trivial diffusion dynamics. In $t_0 = 600$, the green technology enters the market and suffers from moderate diffusion barriers captured by 3% lower knowledge stocks, i.e. $\beta^A = \beta^b = 0.03$. There are moderate spillovers in the learning process, i.e. $\chi^{dist} = 0.5$, and decreasing returns to learning, $\chi^{int} = 0.5$. This set of simulations was used as baseline scenario in Hötte [2019b]. The model and simulated data are available in Hötte [2019c]. Diffusion patterns are trivial if the entry conditions are sufficiently favorable (prohibitively unfavorable) that the entrant technology immediately and permanently diffuses (does not diffuse at all). Non-trivial diffusion patterns are characterized by technological competition among the two technology types. It is ex-ante not clear whether the green technology will permanently replace the incumbent, conventional alternative.

The model's suitability for economic analysis is justified by an empirical validation procedure that is explained in more detail in Hötte [2019a]. A short summary of the validation criteria applied to this set of simulations is provided in the appendix A.

Figure 3: Simulated diffusion curves



(a) Aggregate across runs (b) Single runs (c) Aggregate by regime

One core indicator to study diffusion processes is the share of conventional capital ν_t^c that is used for production in time t. In figure 3, the time series of this diffusion measure is shown in three different representations. Figure 3a shows an aggregate diffusion curve given by the average computed across 200 simulation runs. The average share of conventional technology use at the end of the simulation horizon accounts for roughly 30% corresponding to a green technology diffusion rate of 70%. Though, the aggregate curve hides an important pattern. In figure 3b, the diffusion curves of each single simulation run are shown. Within a single simulation run, the economy converges typically to one of two possible technological states with roughly 100% or 0% conventional technology utilization. The diffusion process in the model is subject to increasing returns that arise from learning dynamics and endogenous innovation. Relative R&D investments in technology type ig are positively dependent on relative profit made in sector ig. Employees learn relatively faster skills of type ig if they are working relatively more with capital goods of technology type ig. Increasing returns lead to the convergence to one of the two states. The dominance of the green (conventional) technology is interpreted as green (conventional) technological regime [cf. Dosi, 1982]. A heuristic definition of a technological regime of type ig is given by a share of technology use ν_T^{ig} at the end of the simulation horizon T that is larger than 50%.

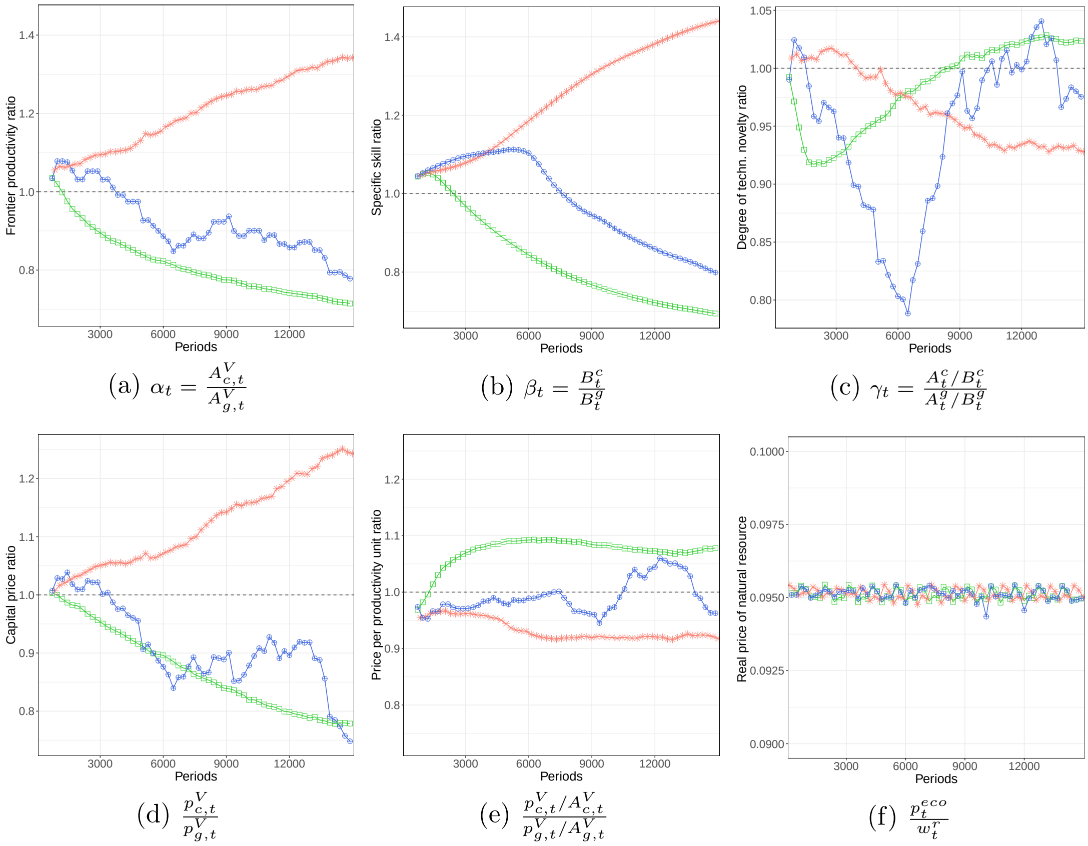
The relative frequency of green regimes in T is interpreted as transition probability for a given set of initial conditions. In the example shown in figure 3, in 142 out of 200 simulation runs a transition is observed which corresponds to a transition probability of 71%. This roughly coincides with the average share of green technology use shown in figure 3a. Though, it should be noted that the pace of convergence and the stability of the regime depends on the characteristics of the two technologies and initial conditions. Initial conditions and technology characteristics are for example initial diffusion barriers (β^A, β^b), the properties of the learning function (χ^{int}, χ^{dist}), policies ($\theta, \varsigma^i, \varsigma^c$) and the macroeconomic environment.[14] In a forthcoming study it is shown that the stability of the diffusion process is sensitive to knowledge spillovers in technological learning [Hötte, 2019b]. If the technological distance χ^{dist} is small, knowledge is easily transferable across technology types. Hence, for firms it is easy to switch to the green technology but it is also easy to switch back to the incumbent type. In such case, the divergence of ν_t^c is less pronounced and ν_t^c may range well between 0 and 100%.

Figure 3b reveals another important property of the diffusion process. In some of the simulation runs, the transition to one of the two regimes is clear cut. The initial surge of green technology diffusion is triggered by the technical superiority of the entrant. Though, initial diffusion is not necessarily permanent. In some of the runs path dependence in the process of knowledge accumulation outweighs the technical advantage and the economy quickly relapses into the conventional regime. In other cases, path dependence is overcome and the economy rapidly converges to the green state. Most interesting, some of the diffusion curves are characterized by multiple local extrema. This is an indicator for long enduring technological uncertainty, i.e. firms switch between two different technology types. It is uncertain which technology will dominate at the end of the simulation time.

To illustrate the drivers of technological convergence and the macroeconomic effects of technological uncertainty, the set of simulation runs is split into three subsets that are illustrated by three different lines in the time series plots shown in 3c. The green (red)

[14] Note that there is an alternative interpretation of the policy parameters. The tax scales the technical superiority of the entrant technology in terms of input cost savings. The investment subsidy is related to the supply price of green capital and can be associated with the production costs of green capital goods. The consumption subsidy is an analogue to a higher willingness to pay for green products. This is discussed in more detail in Hötte [2019b].

Figure 4: Technological indicators



(a) $\alpha_t = \frac{A^V_{c,t}}{A^V_{g,t}}$ (b) $\beta_t = \frac{B^c_t}{B^g_t}$ (c) $\gamma_t = \frac{A^c_t/B^c_t}{A^g_t/B^g_t}$

(d) $\frac{p^V_{c,t}}{p^V_{g,t}}$ (e) $\frac{p^V_{c,t}/A^V_{c,t}}{p^V_{g,t}/A^V_{g,t}}$ (f) $\frac{p^{eco}_t}{w^r_t}$

curves represent the green (conventional) the subset of runs whose technological evolution was relatively stable. The blue curve represents the subset of so-called *switching regimes* that are characterized by a long lasting technological uncertainty.[15]

This differentiation helps identifying the core mechanisms that drive the technological divergence. In figure 4a and 4b, increasing returns to diffusion are illustrated in terms of relative knowledge stocks. Figure 4a and 4b show the ratio of the frontier productivity

[15]The formal definition is the same as used in Hötte [2019a]. A technological regime is defined by the set of runs that exceed the 50% threshold, i.e. $r^{eco} = \{r \in R/\{r^{switch}\}|\nu^c_{T,r} < .5\}$ and $r^{conv} = \{r \in R/\{r^{switch}\}|\nu^c_{T,r} \geq .5\}$ where r is a single run out of the set of runs R excluding the switching regimes. A switching regime r^{switch} is characterized by two criteria: (a) The level of conventional (green) technology utilization in T is less than 90%: $a := (\nu^{ig}_{T,r} < 90\%), ig \in \{c, g\}$. (b) The final level of conventional (green) capital utilization is higher than 50%, but the minimum level of conventional (green) technology utilization within the second half of simulation time had been fallen below 25%, i.e. $b := (\nu^{ig}_{T,r} > .5 \wedge \min_{t\in[t_{half},T]} \nu^{ig}_{t,r} < .25), ig \in \{c, g\}$. Criterion (b) indicates large fluctuations at a relatively late point in time. In this exemplary set of simulation runs, only 2 out of 200 runs are classified as switching regimes. Note that this is a heuristic definition without any formal justification, but serves well for the purpose of illustration.

supplied in the two IG sectors $\alpha_t = (A^V_{c,t}/A^V_{g,t})$ and the ratio of technology-specific skill endowments $\beta_t = (B^c_t/B^g_t)$. A level > 1 (< 1) indicates an advantage for the conventional (green) technology. These figures illustrate path dependence of the diffusion process. The relative advantage of the conventional (green) technology becomes stronger in the conventional (green) regime. A shift to the alternative technology type becomes increasingly difficult.

The delayed divergence of the skill ratio (figure 4b) is a result of technological legacy path dependence in the learning process during the early diffusion phase. In the early phase after market entry, firms still have a large share of conventional capital in their capital stock. The relative pace of learning is dependent on the relative amount of capital that is used in a firm. This explains why the skill related disadvantage of the entrant β_t initially increases, independently of the emerging technological regime.

The divergence of knowledge stocks is least pronounced in the switching regimes. This is a result of uncertainty about the allocation of learning and R&D resources. If firms switch between the two technologies and both types of technology are used, learning and R&D resources are invested in both types and both knowledge stocks grow, i.e. the stocks do not diverge.[16]

Figure 4c illustrates the relative degree of technological novelty. The degree of novelty of a technology is given by the ratio of supplied productivity and the level of the corresponding skill level. If this ratio is high, the technology is relatively new to employees and the know-how is not yet sufficiently high to exploit the full productivity. This has a positive effect on the pace of learning, but only if firms invest in the corresponding technology type.

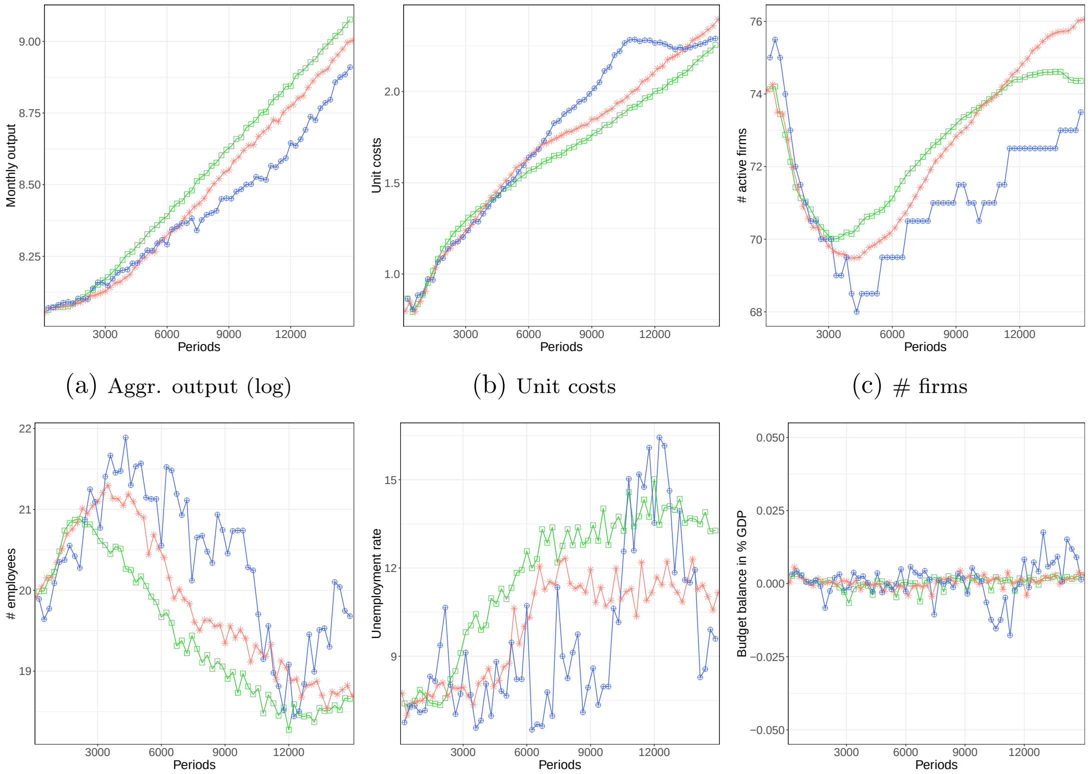
Figure 4d confirms the functioning of the adaptive capital pricing mechanism. It shows the price ratio for the most productive vintage offered by the IG producers. In the subset of green (conventional) regimes, the green (conventional) technology is relatively more expensive in nominal terms. The relative price of the relatively more demanded capital type increases. Though, in real terms defined by the IG price per supplied productivity unit, the dominant technology is relatively cheaper. Hence, improvements in the productive quality of the dominant technology outweigh the relative increase in nominal prices.

The green entrant technology is interpreted as technically superior because it allows its users to save material input costs. By the design of the model, this relative advantage is stable over time. Hence, the price of the natural resource is assumed to grow by the same rate as wages. Wages and the natural resource are variable input costs in production. The share of variable input costs to be paid for the natural resource is constant as shown in figure 4f. Small fluctuations are due to delayed smoothing routines in the model.

Uncertainty about the allocation of R&D and learning resources in the switching regime has macroeconomic side effects in the long run. In figure 5 a selection of macroeconomic time series is shown. In the long run, aggregate output (figure 5a) is significantly

[16] The jumpy behavior of the blue curve is due to the small number (2) of simulation runs classified as *switching regimes*. Discrete adjustments as e.g. in the innovation or market entry function (see below 5c) are not smoothed by aggregation over a larger number of runs.

Figure 5: Macroeconomic patterns



(a) Aggr. output (log) (b) Unit costs (c) # firms

(d) # employees (e) Unemployment (f) Gov. budget balance

lower in the switching regimes and unit costs (figure 5b) are higher. Technological uncertainty is associated with a waste of R&D and learning resources. These resources are partly invested in a technology type that is obsolete in the long run. This undermines productivity improvements compared to a regime where the economy specializes in only one technology type. If the divergence between both possible technological trajectories is clear-cut, all resources are invested in learning and R&D to improve only one technology type.

The other figures in 5 illustrate some general properties of the simulation model. Figure 5c shows the evolution of the number of active firms. The initial surge of green technology adoption is associated with an increase in competition among CG firms. Some firms are not able to sustain and leave the market. Note that the subsequent growth of the number of active firms is mechanically driven by the design of the model. The probability that a new firm is founded is given and only the number of market exits is fully endogenized.[17]

[17] With a given probability, an insolvent and inactive firm agent is re-founded and endowed with a stock of seed capital. This is interpreted as entry of a new CG producer. Note that the maximal number of firms is limited (here 120).

Similarly, the evolution of the average number of employees as measure for the firm size reflects partly the evolution of the number of firms. The market exits in the early diffusion phase lead to an expansion of capacity of surviving firms and the average number of employees increases.

The unemployment rate increases on average some years after the market entry at the time when the technological specialization begins and stabilizes after some time. Figure 5f confirms the balancing of the governmental budget. The differences between the green and conventional regime that are visible in the figures are significant for the later phases of the diffusion process tested by a Wilcoxon signed rank test available [cf. supplementary material of Hötte, 2019b]. Note that these differences should not be over-interpreted. Monthly output in the green regimes is higher because the conventional regimes are characterized by a higher technological uncertainty than green runs. The green technology is initially taken up independently of the resulting technology type. Learning and R&D invested in the green technology during the initial uptake are wasted if the economy is transition is permanently reversed. This would be different in a situation with prohibitively high barriers in comparison to the technical superiority of the entrant such that diffusion does effectively not take place.

A more comprehensive discussion of the properties of the simulated data is available in Hötte [2019a,b] and the associated appendices and supplementary material. In these articles, also a set of model validation criteria is discussed.

4. Outlook

In this paper, a self-contained, concise description of the Eurace@unibi-eco model is provided. Along an illustrative example, the main features of the transition dynamics that can be generated with the model are discussed.

The model provides a framework for studies of diffusion and technology transitions at the macroeconomic and industry level. Until now, it had been applied to the study of green technology diffusion, though its scope is not limited to this case.

The framework of the model leaves room for numerous extensions which might be relevant in the context of diffusion and transition. Potential fields for the future application of the model are an extension to a multi-technology case, R&D spillovers in the accumulation of codified knowledge, the role of regulation and non-market based political instruments, green finance, heterogeneous and evolving consumer preferences, the responsiveness of labor demand for specific skills and the spatial dimension of technological change.

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A. Model validation

This section summarizes some of the macroeconomic patterns that were used for model validation. The selection of these validation criteria is motivated in Dawid et al. [2018a]. These criteria and the computation of the indicators in the application to the Eurace@unibi-eco model are explained in more detail in Hötte [2019a].

Average growth rates and the size of business cycle variation are summarized in table 2. The average growth rate of aggregate output accounts for 1.6% and the business cylcle volatility for 0.13%.

Table 2: Growth rate and business cycle

	Avg. growth rate		Business cycle size	
Mean (Std)	.0163	(.0010)	.0013	(.0017)
Within-run var.	.0010	(.0010)	.0004	(.0005)

The mean (standard deviation) of the growth rate is the arithmetic mean of the geometric means of the within-run growth rate. The size of the business cycle (BC) is evaluated as percentage deviation of time series data from the bandpass filtered trend. The within-run variation is the mean of the within run standard deviation of the growth rate (BC size). Its standard deviation is shown in parentheses.

Cross- and autocorrelation patterns of macro- and microeconomic time series data are shown in table 3. The cross correlation is the correlation between business cycle dynamics and lagged macroeconomic indicators as e.g. consumption, unemployment, prices or investment. Business cylce dynamics are measured as cyclical deviation of aggregate output from its long term trend. The correlation patterns confirm procyclical patterns of consumption, prices and investment and a countercyclical pattern of unemployment.

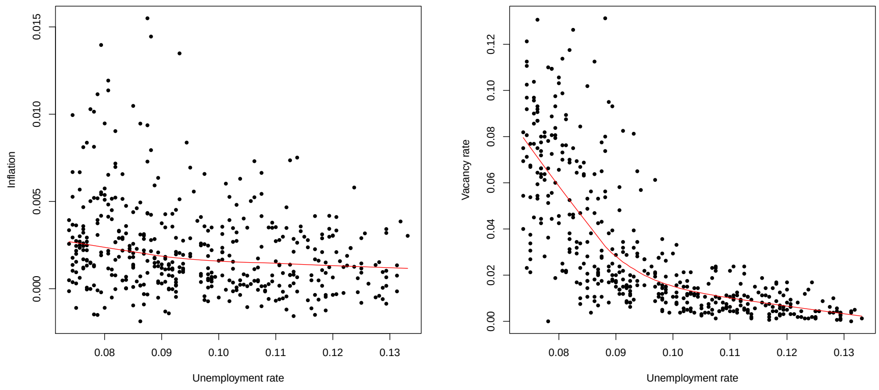
In figure 6 plots of a Phillips and Beveridge curve using the simulated data are shown. The Phillips curve exhibits a slightly negative relationship between inflation and unemployment. The Bereridge curve illustrates the negative association between the unemployment rate and the vacancy rate. Figure 7 shows the relative volatility of output, consumption and investment and output, vacancies and unemployment. It confirms that investment is more volatile than consumption and output.

Table 3: Cross correlation patterns

	t-4	t-3	t-2	t-1	0	t+1	t+2	t+3	t+4
Output	-.119	.238	.612	.895	1	.895	.612	.238	-.119
	(.097)	(.077)	(.043)	(.012)	(0)	(.012)	(.043)	(.077)	(.097)
Consumption	-.474	-.473	-.332	-.069	.253	.541	.71	.713	.557
	(.056)	(.067)	(.078)	(.075)	(.063)	(.056)	(.055)	(.052)	(.054)
Unemployment	.145	-.209	-.586	-.878	-.995	-.899	-.623	-.252	.107
	(.096)	(.077)	(.045)	(.015)	(.008)	(.014)	(.043)	(.077)	(.097)
Vacancies	-.148	.014	.207	.382	.490	.500	.411	.254	.076
	(.079)	(.075)	(.092)	(.120)	(.139)	(.137)	(.116)	(.087)	(.072)
Price	.021	.153	.274	.351	.362	.305	.198	.071	-.042
	(.112)	(.120)	(.131)	(.136)	(.130)	(.113)	(.096)	(.092)	(.102)
Debt	-.126	-.011	.124	.241	.309	.311	.250	.149	.041
	(.126)	(.131)	(.128)	(.117)	(.103)	(.09)	(.085)	(.088)	(.094)
Inflation	-.364	-.333	-.212	-.031	.157	.295	.35	.316	.218
	(.081)	(.078)	(.079)	(.087)	(.099)	(.105)	(.101)	(.091)	(.086)
Productivity	.116	-.022	-.176	-.302	-.363	-.341	-.245	-.108	.028
	(.113)	(.087)	(.102)	(.145)	(.173)	(.169)	(.137)	(.098)	(.087)
Investment	-.234	-.164	-.054	.070	.179	.246	.258	.219	.147
	(.091)	(.088)	(.098)	(.113)	(.120)	(.114)	(.097)	(.086)	(.091)
Price eco	-.130	-.262	-.335	-.327	-.240	-.106	.032	.134	.178
	(.113)	(.128)	(.135)	(.127)	(.112)	(.106)	(.116)	(.125)	(.124)
Avg. wage	.019	-.129	-.261	-.334	-.326	-.240	-.107	.031	.133
	(.103)	(.112)	(.127)	(.135)	(.127)	(.112)	(.106)	(.116)	(.125)
Mark up	-.164	.068	.313	.505	.588	.542	.386	.173	-.033
	(.121)	(.11)	(.131)	(.168)	(.187)	(.174)	(.134)	(.096)	(.094)

This table shows cross correlation patterns in the volatility of macroeconomic time series with (lagged) business cycle dynamics, i.e. variation in aggregate output. All variables are measured as cyclical argument of the underlying time series. The first row corresponds to the autocorrelation of a business cycle. The presented values are averages of the run-wise correlations. In parentheses, the standard deviation across simulation runs is shown.

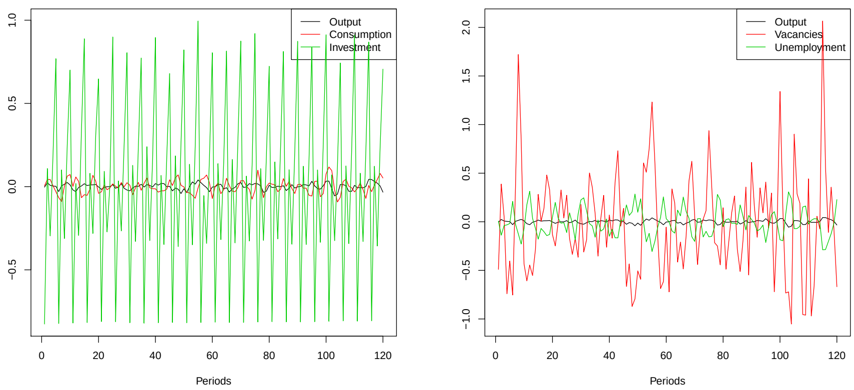
Figure 6: Beveridge and Phillips curve.



(a) Phillips (b) Beveridge

These figures show a Phillips and Beveridge curve for a randomly drawn simulation run. The data accounts for non-smoothed time series data covering the whole simulation period of roughly 60 years. Outliers are removed from the data.

Figure 7: Relative volatility plots



(a) Output, consumption, investment (b) Output, vacancies, unemployment

These plots show the relative magnitude of fluctuations captured by the cyclical argument of macroeconomic bandpass filtered time series and measured as percentage. The shown series cover a 10 year period at the end of the simulation horizon of a randomly drawn single run out of the set of 210 simulation runs.