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How to accelerate green technology diffusion? Directed technological change in the presence of coevolving absorptive capacity

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Learning costs of a green transition depend on the stability of the diffusion path.

Technological uncertainty is costly. It leads to a misallocation of resources.

Increasing returns in learning stabilize a technological regime (green or lock-in).

Sufficiently strict policy facilitates coordination and reduces uncertainty.

Subsidies and taxes perform differently conditional on type of diffusion barriers.

How to accelerate green technology diffusion? Directed technological change in the presence of coevolving absorptive capacity

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Abstract

The time window for effective climate change mitigation is closing. Technological change needs to be accelerated to limit global warming to a manageable level. Path dependence of technological change is one explanation for sluggish diffusion of green technologies. Firms acquire capital that differs by technology type and build up type-specific technological know-how needed to use capital efficiently. Path dependence emerges from cumulative knowledge stocks manifested in the productivity of supplied capital and firms' capabilities. Increasing returns arise from induced innovation feedbacks and learning by doing. Relatively lower endowments with technological knowledge are a barrier to diffusion for new technologies. This paper shows how the evolution of relative stocks of technological knowledge explains different shapes of diffusion curves. Using an eco-technology extension of the macroeconomic agent-based model Eurace@unibi, it is shown how the effectiveness of different climate policies depends on the type and strength of diffusion barriers. Environmental taxes can outweigh lower productivity and subsidies perform better if lacking capabilities hinder firms to adopt a sufficiently mature technology.

Keywords: Directed technological change, technology diffusion, climate policy, absorptive capacity, agent-based model.
JEL: O11, O33, Q55, Q58, C63

1. Introduction

Climate change is an existential threat to human conditions of living. The time window to limit global warming to a manageable level is closing. If a certain temperature threshold is crossed, an irreversible cascade of tipping points in the climate system may be triggered that drives the warming dynamics out of human control. Steffen et al. (2018) have shown that this threshold may be two degrees or even lower. The Paris Agreement implies a median warming of 2.6-3.1 degrees (Rogelj et al., 2016). To reduce the risk of triggering catastrophic irreversibilities, the development and diffusion of climate-friendly technologies need to be accelerated (cf. IPCC, 2018; Steffen et al., 2018; Hagedorn et al., 2019).

Many of the technological solutions are known and available on the market (IPCC, 2018; Hagedorn et al., 2019). Some of these technologies are even superior, e.g. if they improve energy efficiency or save material input costs. But diffusion is sluggish. In some cases, an initial diffusion is even reversed, although the technology is superior in the long run. Path dependence is an explanation for sluggish diffusion and technological lock-in in inferior technologies (David, 1985; Cowan, 1990; Unruh, 2000; Geels & Schot, 2007; Høyer, 2008). A microeconomic source of path dependence is the dependency of R&D activity and adoption decisions on current endowments with technological knowledge (Dosi, 1982; Allan et al., 2014; Sarr & Noailly, 2017).

In this paper, path dependence at the microeconomic level is integrated into a macroeconomic model of directed technological change. This systematic approach helps to understand how green transitions can be accelerated. Based on empirical and theoretical insights of the evolutionary innovation and macroeconomic directed technological change literature, a microeconomic model of technological learning is developed. Capabilities of firms are accumulated over time during production. The model is implemented as an eco-technology extension of the macroeconomic agent-based model (ABM) Eurace@unibi (Dawid et al., 2019; Hötte, 2019b). Evolving capabilities of heterogeneous firms determine whether firms can profitably adopt clean technologies.

Path dependence is decomposed into supply- and demand-side diffusion barriers embodied in the productivity of supplied capital goods and absorptive capacity of heterogeneous adopters. Absorptive capacity is the capability to make effective use of a specific technology. Technology is heterogeneous by type (green or brown). Firms choose between types when acquiring capital goods and build up type-specific technological know-how needed to exploit the productive potential of capital. Path dependence arises from cumulative knowledge stocks manifested in the productivity of supplied capital and firms' capabilities. Increasing returns in knowledge accumulation arise from positive feedback loops of market-induced innovation and learning by doing.

The extended model is used to simulate a technology race between a conventional incumbent and a green entrant technology. The utilization of the incumbent technology requires costly inputs of a natural resource. The green technology is superior because it allows adopters to save input costs, but it suffers from barriers to diffusion embodied in lower productivity of supplied capital and lacking technology-specific capabilities of adopters.

Lower productivity of the entrant is a *supply-side* barrier to diffusion because *codified* technological knowledge embodied in the productivity of the capital goods can be bought on the market. Lacking capabilities are *demand-side* diffusion barriers. Capabilities, interpreted as *tacit knowledge*, can not be bought on the market but are learned during technology utilization (cf. Cowan et al., 2000).

In the simulations, the entry conditions for the green technology are sufficiently favorable that the green technology initially diffuses. Initial diffusion is not necessarily stable and depends on the dynamics of competition, innovation and learning. Whether a green transition occurs is probabilistic. In an experiment, it is shown how the two types of diffusion barriers influence the probability and pattern of diffusion. Four key results are derived from this first analysis:

1. The convergence to a stable technological state is driven by endogenous innovation and technological learning. Both weaken or strengthen the firm-specific profitability of green technology adoption. This is a mechanism of *"endogenous recreation"* of a technological regime (cf. Geels & Schot, 2007).

2. Despite the initial superiority, the success of diffusion is not certain. In the presence of increasing returns to diffusion, *small events* at the micro-level do not necessarily average out and may have a lasting impact on the technological trajectory (Arthur, 1989).

3. Path dependence may cause a lock-in in an inferior technology. In the beginning, the incumbent technology dominates the market. Scale effects in learning and innovation may dominate and the initial superiority of the green, entrant is offset.

4. The macroeconomic performance is sensitive to the stability of the diffusion process. Technological uncertainty is macroeconomically costly. Potential adopters and technology developers possibly waste learning and R&D resources in a technology that is obsolete in the long run.

The analysis does also show that relative prices and the relative performance of technology types matter. This is a starting point for market-based climate policies. In a policy experiment, it is shown that the performance of different policy instruments is conditional on the type and strength of diffusion barriers.

If barriers are supply-sided, taxes on the natural resource input compensate for the disadvantage of lower productivity. If barriers are demand-sided and adopters' have a lower absorptive capacity for green capital, subsidies perform well. Subsidies paid as a price support for green products strengthen increasing returns and contribute to the stabilization of the emergent technological regime. This may be associated with a market concentration process because the technological catch-up of late adopters is impeded by the policy. Investment subsidies effectively stimulate green technology uptake but may increase technological uncertainty if path dependence is strong.

The optimal stringency and instrument-mix of policy are sensitive to the type and strength of diffusion barriers. Policies that are not sufficiently strict to trigger a permanent transition increase technological uncertainty. This leads to a misallocation of learning and R&D resources and undermines the technological specialization. Sufficiently strict policies can facilitate the coordination among economic agents and accelerate the specialization in the new technology. This can reduce the costs of technological learning significantly.

A novelty of this study is the coevolutionary approach to endogenous innovation and coevolving, heterogeneous absorptive capacity. Previous studies have focused on diffusion barriers at the supply side and policy-induced innovation (cf. Löschel, 2002; Popp et al., 2010; Balint et al., 2017). In this paper, it is shown that the distinction between the types of adoption barriers can be important to understand the differential effectiveness of different political instruments.

In the majority of previous macroeconomic studies, directed technological change is considered as an allocation problem with a focus on the allocation of R&D resources (cf. Haas & Jaeger, 2005; Acemoglu et al., 2012; Balint et al., 2017; Lemoine, 2018). Here, the incorporation of heterogeneous agents re-frames the study of directed technological change and sustainability transitions as coordination problems. Coordinated adoption behavior in the presence of self-reinforcing learning and innovation dynamics contributes to the stabilization of transition pathways. This feature is enabled by the modeling approach based on heterogeneous interacting agents.

The remainder of the paper is structured as follows: In section 2, the paper is motivated by a survey of the related literature. In section 3, the main features of the eco-technology extension of the Eurace@unibi model and the design of experiments are introduced. The results of the baseline simulation and a series of experiments on the technological starting conditions of the entrant technology are presented in section 4. It is discussed how the mechanisms underlying the simulated diffusion curves can explain diverse empirically observed patterns of diffusion. Section 5 is dedicated to the policy experiments. Section 6 concludes.

2. Background

On the theoretical level, this paper links the macroeconomic literature on endogenous and directed technological change with evolutionary, microeconomic studies of technological learning. It focuses on the interplay between technological change and the effectiveness of climate policy. Methodologically, the paper belongs to the field of evolutionary, agent-based macroeconomic analyses of climate policy.

2.1. Directed technological change as evolutionary process

Two aspects are important for the understanding of directed technological change. First, technological change is endogenous, i.e. it is driven by goal-oriented R&D and adoption decisions. Second, technological change is non-neutral and the choice between different technology types depends on their relative performance (Löschel, 2002; Pizer & Popp, 2008; Popp et al., 2010; Balint et al., 2017).

In the evolutionary literature of innovation and technological change, adaptive behavior and interactions at the microeconomic level are a source of emerging patterns of innovation, diffusion and technological change at the macro level (Farmer et al., 2015; Balint et al., 2017). Technological change is driven by the coevolution technological development and learning of interacting agents subject to bounded rationality and group dynamics. Path dependence and lock-in effects may occur (Safarzyńska et al., 2012).

The economic environment influences the decisions of investors whether an invention is introduced on the market (Dosi, 1991; Foxon & Andersen, 2009) and captures regulatory, infrastructural, technological and behavioral aspects (Safarzyńska et al., 2012). In this study, the economic environment is understood as all factors that enable or hinder firms to adopt climate-friendly production techniques. Potential adopters are faced with firm-, industry- or region-specific challenges that arise from accumulated infrastructures, technological capabilities and behavioral routines (Arundel & Kemp, 2009). *Absorptive capacity* describes firms' ability to make use of specific technological novelties (Cohen & Levinthal, 1990). It influences the perception and value of a technological solution, and may be a source of heterogeneous adoption patterns (Allan et al., 2014).

Here, absorptive capacity is interpreted as firms' *tacit* knowledge required to use a specific technology effectively. These capabilities are tacit because they can not be traded on the market (Cowan et al., 2000). Tacit knowledge is heterogeneous across firms. Insufficient capabilities and limited transferability of capabilities across technology types can be a barrier to adoption (Arundel & Kemp, 2009). The decisive property of absorptive capacity and addoption barriers is the cumulative nature, not the conceptual coverage. The accumulation of technology-specific capabilities depends on the extent to which a specific technology type is used. This is a microeconomic source of increasing returns to adoption (Arthur, 1989; Dosi & Nelson, 2010).

2.2. Technological change in macroeconomic models of climate change

The dynamics of technological change are critical for the effectiveness and costs of climate policy. A comprehensive overview of early approaches to incorporate directed technological change into climate economics and simulation models is provided by Grübler et al. (2002) and Löschel (2002). In early approaches, directed technological change is quasi-autonomous and explanations about the origins of green technology development was lacking. Acemoglu (2002) closed this gap and integrated a microeconomically founded theory of the R&D market into an analytical, macroeconomic general equilibrium framework. This work built the basis for a subsequent climate-economic applications and studies of innovation-led transitions to green technology (Acemoglu et al., 2012; Lemoine, 2018; Lamperti et al., n.d.).

This study uses an ABM and focuses on the role of a heterogeneous population of green technology adopters with evolving absorptive capacity. Uncertainty, interactions of boundedly rational, heterogeneous agents and the emergence of multiple equilibria are critical for the analysis of technological change in the long run (Pindyck, 2013; Farmer et al., 2015). ABMs offer a tool to account for these aspects.

Seminal approaches in macroeconomic agent-based climate policy modeling were made by Gerst et al. (2013); Wolf et al. (2013); Rengs et al. (2015); Lamperti et al. (2018b). Their models focus on different aspects related to the nexus of climate, the economy and policy. Haas & Jaeger (2005) and Wolf et al. (2013) modeled technological change as a process of imitation and mutation which is interpreted as innovation, and endogenous dynamics of differential R&D investments. The ENGAGE model, proposed by Gerst et al. (2013), focuses on the energy sector. Technological change from learning by doing and accumulated R&D efforts is manifested in energy efficiency and productivity improvements of capital goods. Rengs et al. (2015) focuses on the evolution of consumer behavior and the interplay of Veblen- and snob-effects steering the development of consumers' preferences for sustainable products.

A very recent contribution is the integrated assessment approach introduced by Lamperti et al. (2018a). It captures coevolutionary features of the economy and potential feedbacks from climate change. Endogenous growth emerges from different types of incremental innovation. The authors analyzed how different policies affect the probability of a green transition (Lamperti et al., 2018b). Monasterolo & Raberto (2019) extended a behavioral Stock-Flow consistent model by an energy module to study the effect of phasing out of fossil fuel subsidies on energy transition dynamics.

In contrast to the existing (agent-based) climate economic modeling approaches, the model used in this paper focuses on the demand side of technology and the evolution of absorptive capacity of heterogeneous adopters.

3. The model

The model is an extension of the ABM Eurace@unibi (cf. Dawid et al., 2019). The Eurace@unibi model simulates an artificial, stock-flow consistent macroeconomy with heterogeneous interacting agents. It is able to reproduce a series of micro- and macroeconomic stylized facts. In previous studies, the model was used to study the impacts of different macroeconomic policy interventions (e.g. Dawid & Gemkow, 2013; Dawid et al., 2014, 2018b,c).

In the following subsections, I sketch the main structure of Eurace@unibi and introduce the eco-technology extension of the model schematically. A concise technical introduction to the model extension including the relevant equations is available in the appendix A. The Eurace@unibi baseline model is extensively documented in Dawid et al. (2019). A self-contained description of the eco-technology extension and its linkage to the baseline model is available in Hötte (2019b). The full code of the model is available in a data publication (Hötte, 2019a).

3.1. Overview of the macroeconomic structure

The Eurace@unibi model represents a macroeconomy composed of different groups of heterogeneous agents that are linked by their trans- and interactions on different markets and by mutual flows of information. The most relevant agents are depicted in figure 1. Heterogeneous households supply labor on the labor market to consumption goods (CG) producing firms. They spend their income for consumption and savings. Households differ by income and skill endowment b. CG firms use labor L and capital K to produce a homogeneous consumption good. Employees of a firm need to know-how to use capital goods for production. This know-how is captured by employees' specific skill level. The average skill level of a firm's workforce is a proxy for the technological capabilities B of the firm. Capital or investment goods (IG) are supplied by two heterogeneous IG firms, each representing a specific technology type. Each of them supplies a range of vintages with different productivity levels A. Probabilistic, incremental innovation enables IG firms to bring more productive capital goods to the market.

[Figure 1 about here.]

Capital goods differ by productivity and technology type. One of the two IG producers supplies a climate-friendly, *green* technology, the other supplies an environmentally harmful, *conventional* alternative. Both IG producers invest part of their revenue in R&D activities. Monthly R&D spendings positively affect the probability of innovation success. Successful innovation is associated with an upwards shift of the IG producer-specific technological frontier. If an IG producer successfully innovates, the productivity of supplied capital is multiplied by a factor of $(1 + \Delta A)$.

Dependent on the productive properties of capital and firms' technological capabilities, CG firms make investment decisions and buy capital goods on the capital market. Technology in the model is interpreted as the bundle of the productivity characteristics of capital, firms' technological capabilities and the type of capital (green or conventional). Firms' production technology is decisive for their productivity and environmental performance. On the aggregate level, technology is a core indicator to study diffusion patterns and the economic and environmental performance.

Firms can apply for credit from banks to cover current expenditures and to finance investment if their own financial means are insufficient. The financial market is used as a technical tool to ensure the macroeconomic and financial closure of the model. A government (not shown in figure 1) has a re-distributive and regulatory function. It collects income from taxes and pays unemployment benefits. The government may also impose different (climate) policies.

Firms' market exit is endogenous. Firms that are unable to repay loans go bankrupt and exit the market. New firms are founded at random and build up production capacities out of an initial monetary budget (see Harting (2019)). The transactions between the agents are stock-flow consistent. Agents behave boundedly rational, have limited foresight and incomplete information. Decision making, information updating processes and routines are asynchronous. This is a source of stickiness of prices, wages and production decisions.

Asynchrony means that some routines are executed in a daily, monthly or yearly frequency, other routines are event-based. For example, firms' credit demand routine is only executed if own financial means are insufficient. The asynchrony of production and consumption routines implies that there is no instantaneous market clearing.

3.2. The eco-technology extension of Eurace@unibi

The model extension focuses on endogenous innovation dynamics of competing technologies supplied by two representative capital good producers. Competitive innovation dynamics are modeled as a technology race between an incumbent, *conventional* technology c and an entrant, *green* technology g. The use of the conventional technology is environmentally harmful and requires costly material and energy inputs. The green technology is environmentally neutral and allows adopters to reduce material input costs. It is potentially technologically superior in the long run. More generally, technological superiority is a reduction in unit production costs. This reduction is enabled by radical innovation and not achievable by the incumbent technology.[1]

In this study, the radical innovation of the market entrant is interpreted as a stylized version of input-saving eco-innovation defined as a change in (production) routines that is less environmentally harmful than the incumbent alternative and input cost saving (Arundel & Kemp, 2009).

[1] In a more general interpretation, this can be any type of technology or machine that complements one unit of labor, but its use is cheaper than the use of the pre-existing alternative. It can be a reduction of material or energy input requirements or regulatory compliance costs. In another context, the reduction could also be understood as the replacement of certain occupations or tasks that are complementary to other, non-machine-replaceable tasks. It may also apply to shifts in consumer preferences if certain product characteristics can only be satisfied by the incumbent technology if costly technical "add-ons" are implemented.

Technology. The most decisive part of the model is the representation of firms' production technology. Firms use labor and capital as physical inputs. At the firm level, technology is presented as a two-dimensional bundle of intangible knowledge stocks embodied in these two inputs.

Codified knowledge is represented by the aggregate, average productivity $A^{ig}_{i,t} = \frac{1}{K^{ig}_{i,t}} \sum_{v \in K^{ig}_{i,t}} k^v_{i,t} A^v$ of a firm's technology-specific capital stock $K^{ig}_{i,t}$ composed of single capital stock items $k^v_{i,t}$ of technology type $ig = c, g$.[2] The productivity A^v of a capital good k^v is fix, but the composition of the capital stock at the firm level may change as a result of investment and depreciation.[3] The index v indicates a specific vintage with the properties $(A^v, \mathbb{1}(v))$ where $\mathbb{1}(v)$ is the indicator for technology type ig. It takes the value one if the vintage is conventional, and zero otherwise. v simultaneously indicates the theoretical productivity and the technology type.

Tacit knowledge is represented by technological capabilities $B^{ig}_{i,t} = \sum_{h \in L_{i,t}} b^{ig}_{h,t}$ of CG firm i where $b^{ig}_{h,t}$ are the technology-specific skills of employees $h \in L_{i,t}$ in time t. Technology-specific skills are needed to make effective use of the productivity embodied in a capital good A^v. Employees need to know-how to use a specific type of capital efficiently.

Codified and tacit knowledge are technology-specific. An employee who knows how to use conventional capital does not necessarily know how to use the green alternative, but she can learn it if she accumulates experience when working with it. Employees are *learning by doing.*

[2]If not explicitly defined differently, throughout the paper superscript indices indicate qualitative information about the type of a variable, e.g. the vintage v or technology type ig. Subscript indices refer to the agent or time dimension t associated with the variable. For example, ig in the superscript refers to the technology type. If it is used in the subscript, it indicates that this variable is associated with the capital producer ig.

[3]$K^{ig}_{i,t}$ is the *used* capital stock of type ig. The total used capital stock $K_{i,t} = \sum_v k^v_{i,t}$ is composed of different vintages and different technology types $ig = c, g$. Firms do not necessarily produce at full capacity. If estimated demand is insufficient, firms use only the most cost-effective capital stock items. Learning and the environmental impact are dependent on the *used* capital stock. More technical detail is available in the appendix A.

The codified knowledge embodied in a capital vintage is uniform for all firms, but the tacit knowledge is firm-specific. It is interpreted as a firm's absorptive capacity for a specific technology. Henceforth, the bundle of codified and tacit technological knowledge of firms is referred as to *effective* productivity $A_{i,t}^{Eff_v}$. The effective productivity is bounded above by the availability of matching technological capabilities, hence $A_{i,t}^{Eff_v} = \min[A^v, B_{i,t}^{ig}]$ with index v as pointer to a specific vintage in the firm's capital stock.

The theoretical productivity A^v of a capital good is a static property and uniform for all firms. In contrast, effective productivity is firm-specific and the source of heterogeneous benefits of adoption. The effective productivity of a given vintage v may change over time due to learning.

Barriers to diffusion. Barriers to diffusion are embedded in the two dimensions of technology. Lacking capabilities $B_{i,t}^{ig}$ can be a demand-sided barrier to green technology adoption even if the technology is superior in terms of input costs. A supply-sided diffusion barriers is associated with technical performance of the capital good itself. If such a barrier is present, green capital goods are technologically less mature and have a relatively lower productivity A^v.

These barriers are stylized aggregates of different types of diffusion barriers documented in the empirical literature on eco-innovation (cf. Carlsson & Stankiewicz, 1991; Arundel & Kemp, 2009; Triguero et al., 2013). Diffusion barriers can be the source of a *technological lock-in* in the conventional technology.

Two types of learning dynamics influence the evolution of diffusion barriers. First, employees are *learning by doing.* CG firms buy capital goods from IG firms and add the newly bought capital goods to their capital stock $K_{i,t} = \sum_v k_{i,t}^v$. Employees learn dependent on the type of production machinery they use at work. The more time they spend on working with technology type ig and the better the productive quality of the capital equipment of type ig at the firm level, the faster employees accumulate the corresponding skills $b_{h,t}^{ig}$.

[Figure 2 about here.]

Second, IG firms are *learning by searching*. Endogenous innovation in the IG sector affects the codified part of technological knowledge embodied in the productivity level of supplied capital. IG firms invest a fraction of monthly profits in R&D. Monthly R&D spendings positively affect the probability to innovate successfully and launch a new, more productive capital vintage on the market. Higher profits in sector ig are associated with a faster pace of technological progress in this sector. A stylized representation of technology, the learning mechanism and the role of technology for the macroeconomic outcome is shown in figure 2. The formal implementation including equations is explained in more detail in the appendix A.

Green technology producer's market entry. On the day of market entry t_0, the green technology becomes available as investment option for CG firms. At this time, the capital stocks of all CG firms consist only of conventional capital. Workers have only worked with conventional capital.

The entrant technology is subject to diffusion barriers. These barriers are effective in two ways. At the day of market entry t_0, the entrant IG firm g produces at a lower technological frontier A^V_{g,t_0} where V indicates the most productive vintage supplied by an IG firm. Vintages supplied by the green entrant have lower productivity than those supplied by the incumbent. Further, the green technology is new to firms and employees have not yet learned how to use the new technology. They have a relatively lower endowment with technology-specific know-how b^g_{h,t_0} for green capital utilization.

To ensure comparability across simulation runs, the market entry conditions of the green technology are normalized in relation to the incumbent c in t_0. Supplied productivity of the green producer is initialized by

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

where $\beta^A \in [0, 1)$ is the percentage technological disadvantage of green technology at the day of market entry. It is assumed, that the market entry of the green technology was associated with a technological breakthrough that enables the rapid development of a full range of varieties of green capital that differ by productivity (cf. appendix A.4).

Using the terminology of the transition literature, the entering technology is a radical innovation that was developed in the "protected space" of a market niche. A technological breakthrough or external pressure on the incumbent enables the new technology to enter the market at the "regime level" (Geels & Schot, 2007).[4]

The green capital is supplied at the same prices as incumbent capital in t_0, but the price *per productivity unit* is higher due to the assumed technological disadvantage. The initialization of technology-specific skills for green capital utilization is similar. Households' endowment with green skills is scaled in relation to its skills for conventional technology use, i.e.

$$b^g_{h,t_0} = (1 - \beta^b) \cdot b^c_{h,t_0}. \tag{2}$$

The parameter $\beta^b \in [0, 1)$ describes a technological knowledge gap. It determines the extent to which workers' skills for green technology use are lower compared to their conventional skills.

3.3. Simulation settings and experiments

The simulations are run with $H = 1600$ households, two IG firms, two private banks and up to $I = 120$ CG firms. Because CG firms can enter or exit the market, the number of CG firms can vary over time. At the initialization period, the number of active CG firms was determined by the calibration process and is 74.[5] The simulations are run for $T = 15000$ iterations corresponding to

[4]Empirical historical examples for niche markets that were the source of radical innovations are for example the army, NASA, organic farming or early developments for renewable energy technologies. The forces that govern the technological development in market niches differ from the market forces at the regime level. Pressure on the regime technology may be caused by e.g. regulation, environmental consequences, changing consumer values or oil price shocks (Geels, 2002; Geels & Schot, 2007; Safarzyńska et al., 2012).

[5]The number 74 is a result of the calibration procedure of the initial population. The model is run for a given number of periods until a snapshot of the population is used as initial

approximately 62.5 years interpreting one iteration as a working day and a year to consist of 240 working days. The runs were repeated 210 times to generate a sufficiently large sample of simulated economic data that can be analyzed.

At the beginning of the simulations, the conventional technology is incumbent. After $t_0 = 600$ iterations, the green capital supplier enters the market. On the day of market entry, the green technology is assumed to be technically less mature. The green IG firm produces at a $\beta^A = 5\%$ lower frontier productivity A^V_{g,t_0}. Additionally, the employees of adopting CG firms have a $\beta^b = 5\%$ lower level of green technology-specific skills b^g_{h,t_0}.

Later, these assumptions are relaxed in a series of experiments about drivers and barriers to diffusion, and their interplay with innovation oriented climate policy. In this analysis, it is assumed that there are moderate cross-technology spillovers in the learning process. Part of the knowledge that is learned by the utilization of a technology type is transferable to the use of other technology. Transferable skills are those that coevolve with technological progress, but are independent of the technology type, for example, computer skills. An in-depth analysis of the role of learning spillovers for technology choice and the evolution of market structure is subject to a forthcoming study (Hötte, 2019d).

To justify the model's suitability as a tool for economic analysis, the model's link to the observed economic reality needs to be demonstrated. This is done by an indirect calibration approach (cf. Fagiolo et al., 2017). The model is calibrated such that it reproduces empirical stylized facts as for example growth rates, auto- and cross-correlation patterns of GDP, output, unemployment, investment and consumption aggregates.

An overview of the macroeconomic patterns that are matched by the model is provided in table 1. A more detailed explanation of these criteria, technical details and test results is provided in the supplementary material II. Most of the parameter values are taken from the original Eurace@unibi model. More detail on the calibration of the original model can be found in Dawid et al. (2018b).

population for the simulation exercise.

Table 1 also provides an overview of stylized facts of innovation that have been used for the *technological* conceptualization of the model. It is briefly mentioned how the model satisfies these criteria. More comprehensive information can be found in Hötte (2019c,b).

[Table 1 about here.]

4. Results

In a series of experiments, the coevolution of diffusion, knowledge stocks and the relative technological superiority of the green and brown technology is studied. The coevolutionary process has an impact on the pathway of transition and its macroeconomic side effects.

In this section, I describe the core features of the baseline scenario. Subsequently, I present the results of an experiment on the strength of barriers and explain how the observed patterns coincide with empirical observations. In the next section, it is analyzed how market-based policies can accelerate the process of a green transition.

4.1. The baseline scenario: Two possible technological regimes

In the simulations, entry barriers are sufficiently low such that the green technology outperforms the conventional in terms of effective using costs. Initial adoption rates are high and the green technology incrementally diffuses. Technology diffusion is measured by the aggregate share of conventional capital that is used in t. It is given by $\nu_t^c = \frac{\sum_i K_{i,t}^c}{\sum_i K_{i,t}}$ with $K_{i,t}^{ig}$ as amount of capital of type $ig = c, g$ that *used* by firm i in t and $K_{i,t} = K_{i,t}^c + K_{i,t}^g$.

Figure 3 illustrates the evolution ν_t^c. On the left-hand side, ν_t^c is shown as an average across runs. On the right-hand side, it is shown for single simulation runs. It can be seen that the average across runs hides a pattern of divergence and uncertainty in the technology choice. The disaggregated plot illustrates that the phase of initial green technology uptake is not necessarily sustainable. In the beginning, in almost all runs, the ν_t^c decreases, but in roughly half (49%)

of the considered cases initial diffusion reverses after some time and ν_t^c converges to a lock-in state with roughly 100% utilization of conventional capital.

In some of the runs, the direction of the diffusion process changes several times. The model has stochastic elements. For example, innovation success is probabilistically dependent on past R&D spendings. Households' consumption choice is influenced by prices, but based on a probabilistic multinomial logit function (cf. Hötte, 2019b). The same holds for the matching process on the labor market. These stochastic elements have an influence on technology supply, the economic performance of CG firms and, as a consequence, on their investment activity and adoption behavior.

[Figure 3 about here.]

The final technological state is interpreted as "technological regime" defined by the dominance of a technology type measured at the *intensive margin.*

Definition. *A* ***technological regime*** *is defined as set of runs that match the threshold condition of* 50%, *i.e.* $r^{eco} = \{r \in R/\{r^{switch}\}|\nu^c_{T,r} < .5\}$ *and* $r^{conv} = \{r \in R/\{r^{switch}\}|\nu^c_{T,r} \geq .5\}$. r *is a single run out of the full set of runs* R *and* r^{switch} *is a special case introduced below.*

A ***regime shift*** *or* green transition *is defined as situation where the incumbent conventional technology is replaced by the entrant green until the end of simulation time, i.e.* $\nu^g_T = \frac{\sum_i K^g_{i,T}}{\sum_i K_{i,T}} > .5$.

The diffusion curves reveal that the divergence is even stronger and a more rigorous definition could be applied since the technology share converges to one of the extreme values of 100% or 0%. Using these definitions, 98 (107) out of 210 runs are defined as *eco* (*conv*) regimes. The remaining 5 runs are classified as *switch* scenarios that are discussed in further detail below.

The disaggregated diffusion curves (3) reveal that initial adoption is not necessarily stable. In some cases, the fallback towards conventional technology is subject to a second reversal towards green technology. Four questions arise from these observations:

1. What are the drivers for the convergence to stable states?
2. Why is the technological regime shift probabilistic?
3. Why is an ongoing diffusion process reversed in some cases?
4. What are the macroeconomic implications of different diffusion patterns?

To address the third and fourth question, an additional technological regime type is introduced. It is called *switch* regime characterized by a diffusion pattern that exhibits high volatility during the simulation.

Definition. ***Switch regimes*** *are identified by two criteria: (a) The level of conventional (green) technology utilization did not converge, i.e. it is less than 90% in* T*, i.e.* $a := (\nu^{ig}_{T,r} < 90\%), ig \in \{c, g\}$*. (b) The final level of* $\nu^{ig}_{T,r}$ *is higher or equal 90%, but its minimum level within the second half of simulation time fell below 25%, i.e.* $b := (\nu^{ig}_{T,r} \geq .9 \wedge \min_{t\in[t_{half},T]} \nu^{ig}_{t,r} < .25), ig \in \{c, g\}$*. In these scenarios, the variation of* ν^c_t *is high for a long time which is an indication for late or lack of technological convergence.*

The selection criteria identify those runs that are characterized by a long lasting uncertainty about the final technological state. Henceforth, this phenomenon is referred to as *technological uncertainty.* The switch scenarios occur relatively rarely. In the this set of simulations it happened only in 5 out of 210 runs. Insights that are drawn about r^{switch} should be interpreted as hints to interesting aspects rather than generally valid regularities. In the subsequent section, the results are represented as aggregates within a technological regime.

The technological evolution. The stabilization of final states is reflected in the bifurcation-like pattern that is observable in the diffusion curve and in the evolution of relative knowledge shown in figure 4. Relative knowledge stocks are measured as ratio of the average level of green over conventional technology-specific skills $\beta_t = b^g_t/b^c_t$ and the ratio of the frontier productivity of the two technologies $\alpha_t = A^V_{g,t}/A^V_{c,t}$. The divergence is driven by endogenous learning dynamics.

In the initial phase, the skill related disadvantage is increasing in *all* regimes. The vintage structure of firms' capital stock consists entirely of conventional machinery on the day of market entry. Employees pace of green learning depends on the technology that is used in production. The high initial share of conventional machinery retards the accumulation of green skills even if the green technology is incrementally taken up. In contrast, the difference in the frontier productivity exhibits an immediate divergence between the two regimes.

[Figure 4 about here.]

The role of relative knowledge stocks dominates the evolution of relative nominal capital prices. The relative, nominal price for capital of the dominant technology increases which is a result of adaptive mark-up pricing. More demanded technology becomes nominally more expensive. However, technical progress in the dominant sector is relatively faster as a result of endogenous R&D investments. The relative price per productivity unit decreases for the dominant technology. Faster progress offsets the increase in relative nominal prices (see figure in the appendix 8).

Macroeconomic side effects. Comparing the different technological regimes, allows to draw conclusions about macroeconomic side effects of the transition.

[Figure 5 about here.]

A comparison time series of macroeconomic indicators exhibit differences across technological regimes. In figure 5, the time series of log aggregate output and the number of active firms are shown. The significance of differences across scenario types is confirmed by series of Wilcoxon rank sum tests comparing the outcome within subsets for different phases of the diffusion process (cf. table 6 and Hötte (2019c)).

As illustrated in figure 5(a), the green and conventional regimes do not exhibit remarkable differences in aggregate output in the long run. This does not hold in the initial phase, defined as the first 10 years after market entry. The green regimes are characterized by significantly lower output, which is not visible in the time series plot but indicated by the Wilcoxon test (available in Hötte, 2019c). This is interpreted as *learning costs*. Firms have a lower productivity when they have to learn how to use new technology. This is only a temporary effect that diminishes by the end of the simulation time. Learning costs are an evolutionary interpretation of abatement costs. These costs arise during the switch to an alternative, less mature and less routinized technology.

Remarkable is the significantly worse performance of the *switch* regime. Aggregate output is significantly lower during the whole simulation horizon. This observation illustrates the costs of technological uncertainty. Uncertainty retards technological specialization. R&D and learning resources are invested in a technology that is obsolete in the long run. The negative effect of technological uncertainty is confirmed by a regression analysis of the growth rate g_t^{output} in percentage points on the volatility of the diffusion process σ_t^{ν} measured as variance of ν_t^c across a time window of 2.5 years. The result is shown in equation (3). Time clustered standard errors are shown in parentheses.

$$g_t^{output} = \underset{(.0397)}{1.7614^{***}} \quad - \underset{(.0066)}{.0640^{***}} \cdot \sigma_t^{\nu} \quad + \epsilon_t \tag{3}$$

The volatility is associated with lower economic growth. This finding is robust across different model configurations including different sets of control variables. Additional analyses are available in the data publication. In a forthcoming study, it is shown that the volatility of the diffusion process depends on the characteristics of the competing technology (Hötte, 2019d). The macroeconomic side effects depend on the types of technologies that compete.

The time series of the number of active firms indicates intensified competition after the green technology entered the market (cf. figure 5(b)). This leads to a series of market exits. After some time, the situation stabilizes and new firms incrementally enter the market. The market entries are a probabilistic process with an exogenously determined entry probability and should not be over-interpreted. But the exit dynamics are fully endogenized and informative about firms' ability to adapt (cf. Hötte, 2019b). In the green regimes, a second surge of market exits is observable. When the economy stabilizes at the green regime, those firms that were not able to adapt to the changing technological environment are not any longer competitive and exit the market.

The lack of specialization in the switch regimes allows a larger variety of firms to co-exits. Additional macroeconomic indicators and a short discussion of these indicators can be found in figure 10 in the appendix. Further discussion and additional test statistics and figures can found in the accompanying working paper Hötte (2019c).

Discussion. The four questions outlined above can be answered as follows:

1. Endogenous accumulation of tacit and codified technological knowledge leads to an increasing divergence in the relative performance of technologies. This stabilizes the transition process and leads to the convergence towards the final technological state.

2. Some of the economic processes in the model are probabilistic. This affects firms' investment behavior and the productivity of supplied technology. In the presence of increasing returns to diffusion, "small events" do not necessarily average out and have a lasting impact on the technological trajectory (cf. Arthur, 1989).

3. Increasing returns in learning are a source of path dependence. In the initial phase, the capital stock of CG firms is entirely composed of conventional capital. This slows down the accumulation of skills that are required to make use of the green technology even if it is incrementally adopted. Dependent on the interplay with the stochastic elements, this may lead to a technological lock-in.

4. Both stable regimes perform similarly in the long run. This is partly due to the parametrization. In the early diffusion phase, the green regimes are subject to learning costs in terms of lower productivity and output. This difference vanishes in the long run if the regime converges to a stable state.

Learning costs are more pronounced if the technological pathway is uncertain and producers enduringly switch between technology types. Technological uncertainty is costly because learning resources are misallocated and the specialization is retarded. The initial surge of green technology diffusion is associated with stronger competition among CG firms. This leads to a series of market exits. The exit dynamics are stronger if the economy converges to the green regime because a second market cleansing occurs. Firms that failed to adopt the new technology go bankrupt.

Is the transition to green technology costly? The answer developed in this study is: It depends on the pathway of transition and the type of technology. A controversy in studies on green directed technological change is the existence and extent of macroeconomic abatement costs. The arguments range from distortions in the technology choice (Popp et al., 2010), the incorporation of damage functions (Stern, 2008) to innovative dynamics triggered by environmental regulation (Ambec et al., 2013). This study does *not* address the question whether the transition to green technologies is economically superior in the long run.[6]

Instead, it focuses on the pathway of transition. In these simulations, both technologies perform similarly in the long run if the pathway of diffusion is stable. The shape of the transition curve is decisive for the macroeconomic outcome. If the pathway of diffusion is associated with high uncertainty, a misallocation of learning resources in a technology that is obsolete in the long run undermines the specialization and the pace of productivity growth. This also reduces the competitive pressure on firms. It may protect jobs at large incumbents, but is costly in terms of long term growth.

[6]Recent studies on climate change sufficiently indicate that the switch to green technologies is an *existential* question (IPCC, 2018; Steffen et al., 2018). That should be sufficient as motivation to foster a green transition.

4.2. Barriers to diffusion

What is *marginal* impact of barriers on the transition probability? To address this question, a series of Monte Carlo (MC) experiments with randomly drawn levels of β^A and β^b is run.

4.2.1. The strength of diffusion barriers

Barriers can be prohibitively high that green transitions do effectively not occur. To obtain a balanced sample of both regimes, β^A and β^b are drawn uniformly at random from an interval $[0, .15]$ that is sufficiently low.

The distribution of the random draws in t_0 is shown in figure 6 on the left-hand side. In the middle figure, it is shown how the endogenously evolving difference in technological knowledge has emerged until the end of the simulation time T. Two clusters in the opposite corners of the plot have formed.

[Figure 6 about here.]

Compared to the baseline scenario, the diffusion barriers are higher on average. This reduces the frequency of observed transitions to 37%. A Wilcoxon test confirms that the transition occurs more frequently if initial diffusion barriers are low (cf. 7). Observations about the macroeconomic and technological time series patterns are qualitatively similar to those of the baseline scenario. The divergence of relative technological knowledge stabilizes the transition process and technological uncertainty is costly. Time series plots and a short discussion can be found in the supplementary material III.3.

The MC setting allows studying the role of entry barriers by a regression analysis. The results of an OLS and binary Probit model are shown in table 2. The aggregate ν^c_T is regressed on initial conditions and a set of controls.[7]

[7]The binary specification captures the binary nature of the response variable. The share of conventional capital that is used in the last period is roughly 100% or 0%, but there is little variation between them. The variation in the control variables beyond the randomized entry conditions arises from the period until the day of market entry $t \in [0, 600]$. The initial population in $t = 0$ is identical in all 210 simulation runs. In all specifications, smoothed

[Table 2 about here.]

The barriers β^A and β^b both enter with positive coefficients and are economically and statistically significant across different model specifications. Positive coefficients indicate a higher share of conventional capital in T and a negative association with the transition probability. Robustness tests using the percentage difference in skill and productivity levels measured at later snapshots in time and more disaggregated firm data confirm that these relationships hold at different aggregations and across time.

What can be said about the magnitude of effects?. In columns (1)-(5), the results of different OLS models are shown. Column (6) presents the results of a binary Probit model. It is consistently found that the supply-side barrier β^A enters with a larger coefficient and exhibits a stronger association with the transition dynamics than the demand-side barrier β^b. Also, its explanatory power measured by the R^2 is higher. Including both barriers in simple linear terms helps to explain roughly half of the variation.

The coefficients of the linear OLS model can be interpreted as marginal effect on the probability of technological lock-in. In the linear model, a change by one percentage point in β^A (β^b) is associated with a 5% (3.8%) higher share of conventional capital utilization. But the relationship between the barriers and the transition likelihood is non-linear. The value range used in this experiment is truncated and barriers can be prohibitively high to prevent a transition. In columns (4) and (5), the results of a regression model that includes quadratic and interaction terms of β^A and β^b.[8]

values of the dependent variables are used, i.e. one-year averages.

[8] I refrain from an in-depth study of the functional form of the relationship between different barriers and diffusion for mainly two reasons. First, the effect of the barriers on the pattern of diffusion is sensitive to the assumptions on the shape of the endogenous innovation and learning function. These functions are set in a plausible, but stylized way and the outcome should not be over-interpreted in quantitative terms. In economic reality, the underlying mechanisms of learning and innovation vary across different technological fields. Second, the

The effectiveness of β^A as a barrier to diffusion is diminishing. The opposite is found for β^b.[9] The macroeconomic controls are not significant. This is not surprising because the variation between the simulation runs is low. The simulations are initialized with identical populations and the variation in the controls stems from the first 600 iterations until the day of market entry.

4.2.2. Which firms are early adopters?

This question is addressed by a regression of the share of ν^c_{i,t_1} of individual firms i in $t_1 = 1800$, i.e. 5 years after market entry. At this time, diffusion at the intensive margin is low and the variation is high. The aggregate ν^c_{i,t_1} is 81.26%. The median firm uses 100% conventional capital. But there are also firms that use only green capital. The standard deviation of $\nu^c_{i,t}$ is 29.22%.

The results reveal insights into the macroeconomic diffusion process and into the relationship between firm characteristics and early green technology uptake at the micro level. The regression results are shown in table 3.

[Table 3 about here.]

Both barriers hinder green technology uptake. The coefficients of β^A and β^b are statistically significant and enter with positive coefficients. Quantitatively, the barriers are less significant compared to the analysis above. Both barriers have a diminishing effect reflected by the negative coefficients of the squared terms in columns (4) and (5).

Compared to the previous regression on the emerging regime, lacking skills have higher relative explanatory power for early green technology uptake. In relation to β^A, the economic significance of β^b and its explanatory power captured by the R^2 in column (1) is higher compared to the previous regression.

better fit of more complex functional forms comes at the cost of lower ease of interpretation and expected lower generalizability, also referred as to *bias-variance trade-off* (cf. Bishop, 2006). The regressions should underline the qualitative insights derived of this study.

[9] A more comprehensive discussion of these results and interactions between β^A and β^b is available in Hötte (2019c).

This is reflected in the relative coefficients compared to β^A and the higher R^2 in column (2). The interaction term ($\beta^A\beta^b$) is statistically significant and has a negative coefficient.

Firms with a high general endowment of tacit knowledge B^c_{i,t_0} on the day of market entry, tend to adopt earlier. Above average B^c_{i,t_0} is an indicator for a high-skilled workforce at the firm. High skilled employees are assumed to have higher ability and to learn faster in the Eurace@unibi economy irrespective of the type of skills that needs to be learned.[10]

The stock variables reflect the general, but not technology-specific endowment of a firm with human capital and technology. The stock of codified knowledge is negatively associated with the likelihood to be an early adopter. On the day of market entry, firms do only have conventional capital and a high level of $A^c_{i,t}$ indicates that a firm is operating at a high productivity level. It may also indicate investments in new machines shortly before the green technology becomes available. Both are impediments to early green technology uptake. The negative association with diffusion suggests that firms with more productive capital stock are less likely to be early adopters.

Firms with high adoption rates in t_1 charge significantly higher prices ($Price_{i,t_0}$) in t_0, but are not characterized by significant differences in firm size ($\#employees_{i,t_0}$, $output_{i,t_0}$) and production efficiency ($UnitCosts_{i,t_0}$). Price setting in the Eurace@unibi is based on estimated demand functions and a profit maximization rationale taking account of production efficiency and desired output. Price differences that are not due to differences in efficiency or firm size arise from heterogeneous expectations. If prices are too low, firms possibly underestimate their demand potential. Excess demand may be an incentive to expand capacity by investments in new machinery. Firms with too high prices have overestimated their demand potential and are more likely to reduce capacity.

[10]By design of the model, skills are symmetrically scaled down by β^b, i.e. each firm has a similar *skill ratio* in the beginning. But firms are heterogeneous in absolute levels skill and productivity endowment.

Higher investment activity triggers green technology adoption during the early surge of diffusion.

4.3. The empirical content of the model

The simulation results provide an explanation for two empirical patterns that are central in diffusion studies, s-shapes and path dependence. Many studies refer to an s-shaped pattern that is explained by different potential reasons such as the spread of information and heterogeneous benefits from technology adoption (Nelson & Winter, 1977; Pizer & Popp, 2008; Kemp & Volpi, 2008; Rogers, 2010; Allan et al., 2014).

But the s-shaped pattern does not hold in general. It is often observed when *successful* diffusion is measured at the *extensive* margin, i.e. the binary entry whether the technology was adopted or not. In a comprehensive, empirical historical study, Comin et al. (2006) measured diffusion at the *intensive* margin and found very heterogeneous patterns of diffusion curves. In some cases, the authors confirmed the s-shape, in other cases, they observed concave or even inverted u-shaped patterns.

The authors argue the different patterns to be (partly) explainable by the types of technologies under consideration and by the circumstances of adoption. Inverted U-forms are observed when a technology initially diffuses but is driven out of the market by a competing alternative in the long run (Geels & Schot, 2007). The proposed model sheds light on the dynamic interplay of learning and endogenous innovation of two competing alternatives. Learning and innovation are key to understand the evolution of substitutability and superiority of competing technologies.

A second central pattern in the diffusion literature is path dependence. Possible sources of path dependence are learning and network externalities, the institutional environment, habits, search and information frictions (e.g. Dosi, 1982; Arthur, 1988; Dosi, 1991; Safarzyńska et al., 2012; Unruh, 2000). Here, path dependence of technological change is reflected in two stocks of technological knowledge, i.e. technology-specific skills and productivity.

The perceived, relative profitability of a technology determines whether it is chosen by adopters. The relative difference in the endowment with *tacit* and *codified* technological knowledge is informative about the relative profitability. The bifurcation-like patterns of relative knowledge stocks $\alpha_t = \frac{A^V_{c,t}}{A^V_{g,t}}$ and $\beta_t = \frac{B^c_t}{B^g_t}$ coincide with the convergence towards the final technological regime and explain path dependence of diffusion.

An important observation is the inverted u-shape in those runs that (1) end up in the conventional regime but experienced a short period of diffusion, and (2) the switching regimes that exhibit wave-like patterns with two or more substantial peaks in the diffusion curve. In these cases, the green technology initially diffuses. After some time, competitive pricing dynamics become active and the green and conventional technology compete for market share. Additionally, endogenous learning dependent on the pre-existing capital infrastructure is working against green technology.

Endogenous learning is only one type of path dependence, but the simulations show that path dependence may be sufficiently strong that even after initial diffusion of an initially superior technology the diffusion process is reverted. In such a case, the diffusion curve is u-shaped. Comin et al. (2006) argue that inverted u-shapes may occur in those cases where the diffusing technology is replaced by a superior substitute. Empirical examples for races between technologies to become the dominant design are the competition between different propulsion engines for cars in the early 20th-century (Høyer, 2008), different types of nuclear power reactors (Cowan, 1990) or the QWERTY keyboard (David, 1985). The diffusion curve of the "losing" technology exhibits an inverted u-shaped pattern.

Learning costs during the early phase of technological transition can be an explanation for the *"Modern Productivity Paradox"* discussed by David (1990). The author argues that one source of delay in the transmission of productivity gains from new technologies to aggregate factor productivity growth arises from path dependence in the ability to exploit the full productive potential of new technologies.

5. What is the scope for green technology diffusion policies?

Above, the dynamic interplay between long- and short-term technological performance is discussed as driver of diffusion dynamics. The entrant technology is only superior in the long run if initial disadvantages of lower technological knowledge are overcome. Can policy help to overcome diffusion barriers and is the effectiveness sensitive to the strength and type of diffusion barriers?

To answer these questions, an experiment on different market-based policies is run. The considered policy instruments are a tax on the resource input and two types of subsidies. The tax θ is imposed as value added tax on material inputs making the use of conventional capital more costly. An investment subsidy σ^i reduces the price for green capital goods by a fixed factor. A consumption subsidy σ^c is implemented as firm-specific price support for eco-friendly produced final goods. The level of support is linearly scaled by the relative amount of green capital goods $\nu^g_{i,t}$ that is used by the firm. The government seeks to balance its budget. If expenditures for subsidies exceed the tax revenue, other taxes e.g. on income are increased such that the budget is balanced in the long run. The formal implementation of policies is documented in the appendix A.5.

5.1. *The impact of policies on the technological evolution*

To explore the interplay of policy and barriers, a set of MC simulations is run with randomly drawn levels of β^A, β^b, and policies. The diffusion barriers are drawn from the same interval ($\beta^A, \beta^b \in [0, .15]$) as above (see 4.2). The intervals for the subsidies and the eco-tax had been set such that the average levels of the different subsidies are similarly effective as diffusion stimulus.[11] The intervals are $\theta \in [0, 1]$, $\varsigma^i \in [0, 1]$ and $\varsigma^c \in [0, .025]$. The initial conditions are summarized in table 9 in the appendix B.3.1. 210 simulations are run 15000 iterations. The simulation results of the MC experiment above (4.2.1) serve as no-policy baseline. In figure 9, time series of technological and macroeconomic core indicators

[11] Note that the diffusion effectiveness does not necessarily coincide with the environmental effectiveness which is also responsive to output and productivity growth (cf. Hötte, 2019c).

are shown. The colored (gray) lines represent the policy experiment (baseline scenario). The time series are disaggregated by the type of technological regime without the additional distinction of switch-regimes.

[Figure 9 about here.]

Measuring diffusion at the extensive margin the presence of policy exhibits a strong effect. The relative frequency of observed technological transitions is increased from 27% to 59%, i.e. 123 out of 210 simulation runs. The effect of the policy on diffusion appears to be strongest in the beginning. Even if path dependence leads to a reversal to conventional technology, the share of green technology utilization is significantly higher in an early phase of diffusion (cf. figure 9(a-b) and appendix B.3.2). The time series of relative productivity α_t and relative skill endowments β_t are shown in figure 9(d) and (e). In comparison to the benchmark scenario, the divergence between different regimes is less pronounced. Moreover, a descriptive comparison of the average initial diffusion barriers computed within green (conventional) runs shows that, on average, the diffusion barriers in the policy scenario are higher (lower) (cf. 9). This can be interpreted as an upwards shift of the threshold level of diffusion barriers that is prohibitively high and prevents green transitions. Diffusion barriers and policies operate in opposite directions. Barriers inhibit and policies stimulate the diffusion of green technology. The diffusion policy increases the intensity of competition in situations where the green technology is only competitive with policy support. This might result in increased technological uncertainty with negative effects on productivity growth in the short run.[12]

5.2. Is the effectiveness of policy conditional on the strength and type of diffusion barriers?

To shed light on the relationship between the transition probability and the interplay of barriers and policy, a regression analysis of $\nu^c_{i,T}$ is run. The

[12] A longer discussion can be found in Hötte (2019c).

explanatory variables are β^A, β^b, the policies θ, ς^i, ς^c and firm-specific controls. The results are shown in table 4. Columns (1)-(5) show the coefficients of different model specifications in an OLS model. Column (6) shows additionally the results of a binary Probit model.[13]

[Table 4 about here.]

Columns (1)-(3) show the results of different regressions of $\nu^c_{i,T}$ on the policy instruments and barriers in isolation, ignoring the potential interaction of both. The coefficients of the variables deviate from those where interaction terms of policy and barrier strength had been included. This finding motivates to consider the interaction in more detail. The observations can be summarized as follows.

The eco-tax θ is only effective as a diffusion stimulus in the presence of supply-side barriers β^A. The coefficients of θ and the interaction term $\beta^b\theta$ are not significant or have an only weakly significant negative association with the transition probability.

The consumption subsidy ς^c has a strong positive association with the transition probability indicated by the negative coefficients of ς^c in all model specifications. Its effectiveness is increasing in the strength of both types of diffusion barriers. The interaction with the supply-side barrier β^A is statistically and economically less significant.

The investment subsidy ς^i has an ambiguous effect on the transition probability. In the absence of diffusion barriers, i.e. when the interaction terms $\beta^A\varsigma^i = \beta^b\varsigma^i = 0$, the association of ς^i with the transition probability is negative (cf. column (4)-(6)). Its overall effect on the transition probability can only be positive if β^A and β^b are sufficiently large. The interaction with β^A is quantitatively stronger and statistically more significant.

[13] Explanatory notes can be found in B.4.

Summing up, all policy instruments may stimulate a green transition. Their effectiveness is conditional on the type and strength of diffusion barriers.

5.3. How can the differential effectiveness of policies be explained?

The effects of the political instruments on the relative superiority of a technology type and on the investment decision of firms differ over time. The tax θ imposes an additional cost burden on firms that are using conventional capital. It is proportional to the price of the environmental resource. Early after market entry, it increases marginal production costs because the share of conventional capital use is high. Firms that incrementally switch to green technology reduce the tax burden and costs for the natural resource input. This effectively compensates for the incurred disadvantage if firms adopt less productive green capital. This type of production-cost balancing is permanent.

In contrast, the investment subsidy ς^i operates through the channel of one-time investment costs. It reduces the price for green capital but does not provide a permanent compensation for higher production costs that arise from an inferior productivity performance. Its effectiveness is not sensitive to the composition of the capital stock. The other two instruments (relatively) reward firms that switch to green technology with lower input costs or higher mark-ups. In another study, it was shown that this can be associated with delayed technological convergence and higher technological uncertainty (Hötte, 2019d).

The level of support by ς^c is most sensitive to the composition of ν_t^c. It is paid as price support for green products which is proportional to the amount of green capital that was used in production. The level of support is low in the beginning but becomes stronger if firms incrementally adopt. If the green technology does not diffuse, its effect diminishes. This has a stabilizing effect on the diffusion pattern. If initial green technology uptake is sufficiently high to trigger the transition, the support by ς^c becomes stronger. This reinforces the ongoing diffusion process.

From the perspective of a firm, the two types of barriers have different dynamic implications for the investment decision. The skill barrier β^b is dynamic.

In their investment decision, firms anticipate the effect of incremental learning. Firms also anticipate the increasing level of support by ς^c when incrementally replacing conventional by green capital. The consumption subsidy is most effective in the long run. In contrast, the productivity barrier β^A is static. Less productive capital goods that are adopted remain in the capital stock until being depreciated. The tax is static, too. It permanently compensates for the disadvantage of lower productivity. The investment subsidy is least sensitive to the dynamic effects of the diffusion process. In this study, it had not been tested how expectations, time preferences and depreciation rates interact with the different types of policies. This is left for future work.

5.4. How do different policies affect the firm population?

The policies operate through different channels that are differently important at different stages of the diffusion process. This does not only affect the diffusion process but may also have an impact for the characteristics of the firm population. Figure 9(i)-(l) shows the time series of the number of active firms, monthly aggregate output, firm size and unit costs.

The first years after t_0 are characterized by a surge of market exits (cf. figure 9(i)). The policies cause a downward shift in the threshold level of diffusion barriers that prevent a transition. Hence, in the presence of policy, a transition may occur even if the conditions are unfavorable. This is associated with technological uncertainty, learning costs and slow down in output growth during the first $5-10$ years (cf. figure 9(j)).

After some time, the technological regime stabilizes and the surge of market exits stops. This effect is stronger in the policy experiment. The exits are followed by an increase in the firm size (cf. 9(h)). Hence, the market becomes more concentrated with fewer, but larger firms. In the benchmark scenario and in the lock-in regime, the growth of the average firm size is stopped. In the policy experiment, the concentration process continues.

Additional regression analyses of the firm size as a measure for firm size and unit costs as a proxy for production efficiency reveal that the effects of policy differ across instruments, time and indicator variables. The results and additional explanations are provided in the appendix B.3.2.

In the long run, ς^i is associated with a larger average firm size measured by the number of employees. Firms produce with Leontief technology. This implies that the number of used capital stock items is one-to-one proportional to the number of employees. It provides an incentive to build up additional capacity. Firms that invest more take relatively more advantage of the subsidy. The capacity expansion effect triggered by ς^i is independent of the emerging technological regime but stronger in the transition regimes.

In the lock-in regimes, θ has a weak positive effect on the firm size. In a preceding analysis, it was observed that θ contributes to the surge of market exits in the early phase after market entry. It imposes an additional cost burden on firms and makes it more difficult to survive. The lower number of firms is one driver of the evolution of the firm size. Firms estimate their demand potential in consideration of the number of competitors. A larger number of competitors is associated with smaller firms ceteris paribus.

If the economy converges to the green regime, ς^c provides a competitive advantage for firms that have early invested in green capital. Two effects make it difficult for late adopters to catch up. First, they still have a high share of conventional capital which undermines the pace of learning when switching to green technology. Second, the price support ς^c is dependent on the share of green capital. Early adopters with a higher share of green capital benefit more. The consumption goods market is characterized by price competition. Firms that receive higher price support can charge lower profit-maximizing prices. Part of their profit margin is paid as a subsidy. This makes it difficult for late adopters with a lower $\nu^g_{i,t}$ to sustain on the market. In the lock-in regimes, the effect of the consumption subsidy vanishes. It becomes neutral because it is proportional to $\nu^g_{i,t}$ which converges to zero.

5.5. Summary and discussion

Three core insights can be derived from the policy experiment:

1. The policy can increase the transition probability. Policies stimulate the initial green technology uptake. If initial uptake is sufficiently high, path dependence embodied in relative technological knowledge is overcome and the green technology permanent diffuses. The effect of the policy as diffusion stimulus may come with the cost of higher technological uncertainty. If policies are not sufficiently strict to trigger a permanent transition, it retards specialization effects in conventional technology when the economy relapses to the conventional regime. Retarded specialization has a negative effect on productivity and economic performance. When using relative indicators for the environmental performance measure, an insufficiently strict policy may be detrimental because lower production efficiency is associated with a worse environmental performance per unit of output.[14]

2. The effectiveness of different instruments is conditional on the type and strength of diffusion barriers. A tax imposed on the natural resource input required for the use of conventional machinery may offset the disadvantage if firms adopt technically less mature and less productive green technology. It is not effective if lacking skills hinder firms to adopt. If barriers are sufficiently low, it might be even detrimental because it imposes a cost burden on firms when the penetration of conventional capital is still high. This undermines the financial capacities and slows down investment activities in superior green technology. The effectiveness of the consumption subsidy is increasing in the strength of both types of barriers. This effect is stronger if the barrier is demand-sided, i.e. when lacking skills hinder firms to adopt green technology. It is an instrument that stabilizes an

[14] The environmental effect in absolute terms compared to the baseline is a matter of calibration. The worse economic performance in uncertain environments may offset the efficiency effect. Here, the calibration is chosen such that the economic performance across different regimes in the policy and benchmark scenario does not substantially differ but this is also a matter of the choice of other characteristics of the competing technologies (Hötte, 2019d).

ongoing diffusion process and is not distorting if the economy is locked in. An investment subsidy operates via an instantaneous price mechanism in firms' investment decisions. Its effectiveness is independent of the type of barriers.

3. Policies affect firms asymmetrically. The initial phase after the market entry of the green capital producer is characterized by strengthened competition and a surge of market exits. This effect is more pronounced in the policy experiment. The policy countervails the effect of diffusion barriers which intensifies the technology race in situations where the green technology would not sustain without policy support. If the green technology wins the race, firms that successfully adopt green capital benefit most from the subsidies. If a transition occurs late adopters have difficulties to survive on the market. They do not only technologically have to catch up, but also take less advantage of the consumption subsidy. The investment subsidy provides an incentive to build up capacity. This effect is independent of the success of a technological regime shift.

Many approaches in the existing literature on economic climate policy are based on equilibrium models with homogeneous agents and focus on direct and indirect price mechanisms that stimulate the substitution of conventional by green capital. The nexus of climate policy and directed technological change is represented as an allocation problem. The introduction of heterogeneous and interacting agents in the presence of increasing returns to adoption re-frames directed technological change as a problem of coordination in the process of learning and specialization (cf. Jaeger, 2013).

This different setting has implications for the design of policy. Policymakers can provide incentives to strengthen the coordination in technological development and learning. Policies are most effective if they are sufficiently strict given a specific set of diffusion barriers. The Eurace@unibi provides a macroeconomic test environment for policies and to control for the economic side effects. It was shown that the entry of the green technology is associated with intensified competition, a series of market exits, increased unemployment and a phase of low growth. The policy has reinforced this effect.

It was also shown that the performance of different market-based climate policies is conditional on the type and strength of barriers. Taxes help to overcome supply-sided diffusion barriers that are embodied in the productivity of capital goods. Tradable, innovation-induced knowledge embedded in productivity is typically the way how directed technological change is modeled in innovation and climate economics (cf. Löschel, 2002; Popp et al., 2010).[15]

In the model in this paper, productivity embedded in capital goods is only one side of the coin. Diffusion barriers may also take the form of lacking tacit knowledge that is required to make use of the technology. Endogenous innovation and the accumulation of codified knowledge is a "by-product" of increased adoption. The coevolution strengthens and stabilizes the convergence to the final technological state.

The economic outcome of the transition process is conditional on the evolution of the two types of knowledge stocks. The resulting pace of technological specialization is higher if agents behave coordinately and all learning and R&D resources are allocated to only one of the two technology types. An effective and economically viable design of policy in terms of strength and instrument-mix is sensitive to the type of diffusion barriers.

6. Concluding remarks

In this article, a microeconomic model of technological learning of heterogeneous firms as a driver of directed technological change is introduced. The microfoundations of the model base on insights of the empirical and theoretical literature on technological knowledge, learning and absorptive capacity. This microeconomic model implemented in an eco-technology extension of the

[15] Approaches based on learning curves typically focus less on the causal mechanisms that drive the accumulation of knowledge and are of main interest in the directed technological change literature.

macroeconomic ABM Eurace@unibi that is used to study transition pathways in a technology race between an incumbent, conventional technology and a market-entering climate-friendly alternative. The market entrant is superior because it allows saving resource input costs, but suffers from diffusion barriers embodied in lower productivity and lacking capabilities of heterogeneous firms. In a policy experiment, the implications of different types of diffusion barriers for the design of market-based climate policy are derived. The analyses have shown that technological superiority in terms of permanent variable cost reductions is not sufficient to ensure long term diffusion. If diffusion barriers are high, path dependence in technological learning and endogenous innovation may dominate and the process of initial green technology uptake can be even reversed.

Directed technological change is represented as a coordination problem among heterogeneous agents. The economic outcome and the transition probability is dependent on the coevolution of supplied technology and absorptive capacity of adopting firms. A key insight from this perspective is that technological uncertainty is costly.

Market-based policies can help to overcome diffusion barriers but, dependent on the type of diffusion barriers, different instruments perform differently well. Taxes effectively compensate disadvantages related to the productivity of the green alternative. Subsidies help if lacking non-tradable capabilities at the firm level impede the diffusion process. For the design of policy, the heterogeneous nature of diffusion barriers is important. Conditional on the strength of barriers, policies need to be sufficiently strict to provide an effective mechanism of coordination. Lack of coordination causes technological uncertainty. This is economically unfavorable because learning and R&D resources are possibly wasted for the development of a technology type that is obsolete in the long run.

One core limitation of the model are the assumptions about cross-sectoral knowledge spillovers in the learning process. The assumptions about learning spillovers are justified by qualitative insights from the literature. Here, spillovers only exist in the learning by doing process, but spillovers may be also relevant in the R&D sector. Empirical studies on innovation networks and spillovers confirm the importance of technological similarity for diffusion (cf. Carvalho & Voigtländer, 2014; Acemoglu et al., 2016). Spillovers may affect the process of relative knowledge accumulation. In a forthcoming study, this topic is addressed in more detail (Hötte, 2019d).

Qualitative case studies and sector-based quantitative insights (cf. 4.3) support the model's validity. It is challenging to find robust quantitative and cross-technology sector consistent measures for the concepts of technological knowledge introduced in this paper, and for the clear distinction between different types of technologies. These measures would be required for a general empirical validation of this model. This work is left for future research.

Acknowledgements

This work was enabled by the support of a wide range of people. Particular thanks to Herbert Dawid and Philipp Harting for practical help and fruitful discussions. Thanks to Mattias Endres, Robert Wilms and two anonymous reviewers for helpful comments. Further thanks to Wolfgang Britz, Sander van der Hoog, Antoine Mandel, Angelo Secchi and many others who have facilitated this project. Particular gratitude is owed to the Studienstiftung des Deutschen Volkes who have granted me the (not only) financial independence to pursue this project. 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.

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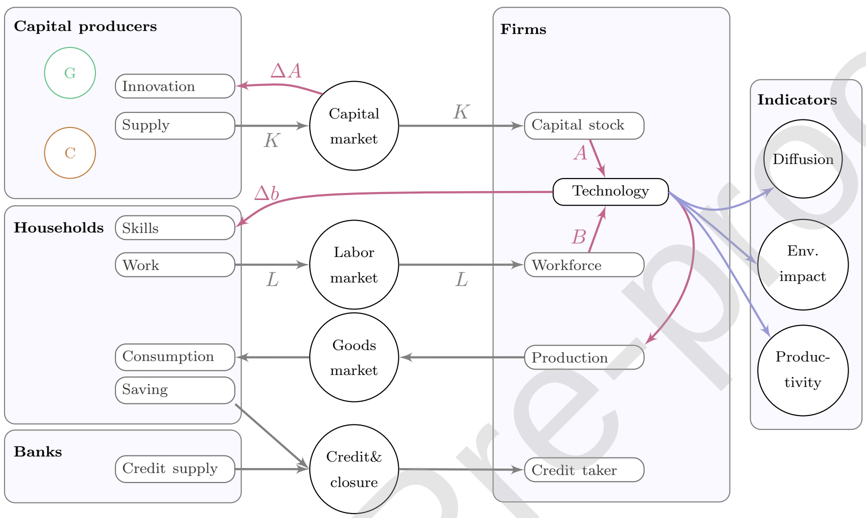
Figures and tables

Figures

Figure 1: Macroeconomic structure of Eurace@unibi-eco



Sketch of the most important model elements, i.e. agents and markets. G: green (C: conventional) capital goods producer. A: productivity of capital K, B: firms capabilities embodied in labor L. Arrows indicate market transactions and direction of influence.

Figure 2: Schematic representation of the innovation, learning and diffusion.

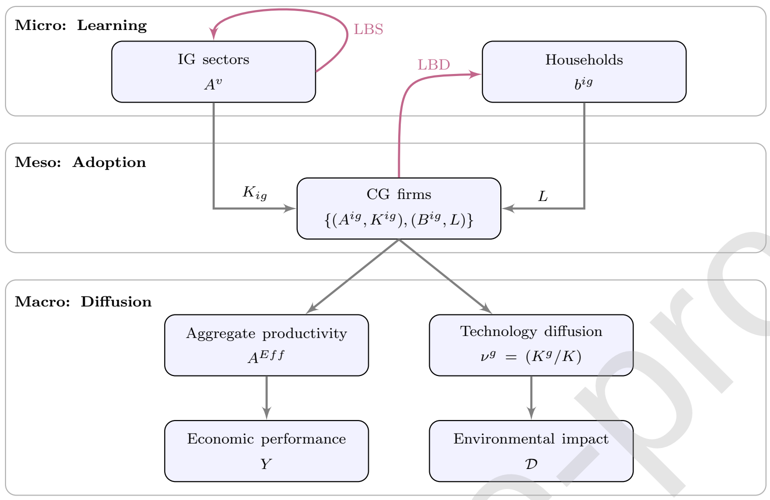
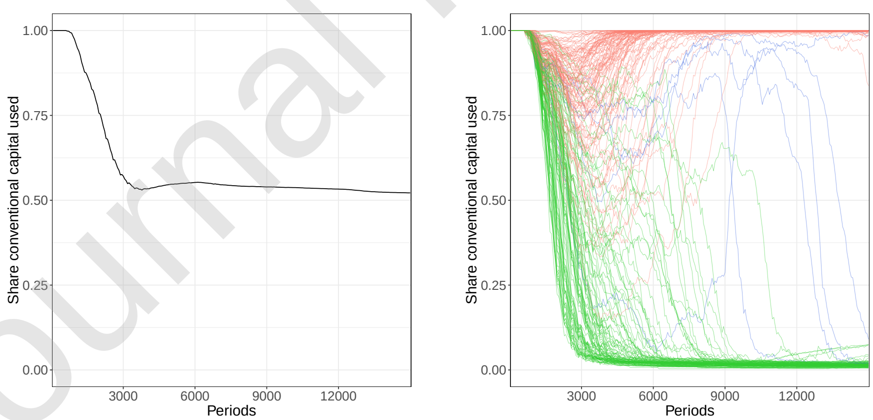


Figure 3: Evolution of the share conventional capital used ν_t^c.

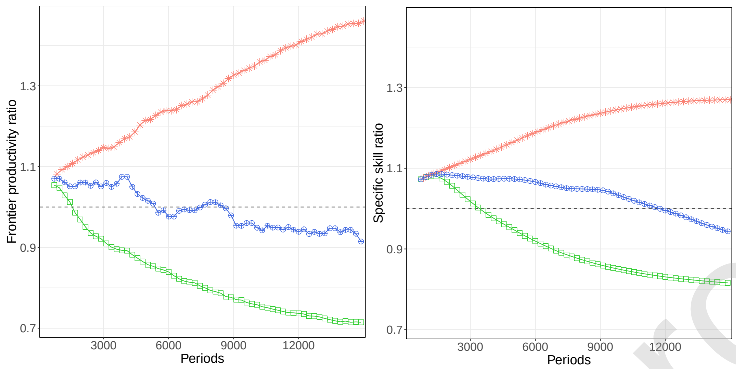


(a) Batch

(b) Disaggregation

3(a) shows the average ν_t^c of all simulation runs, (b) shows $\nu_{r,t}^c$ for each single run r.

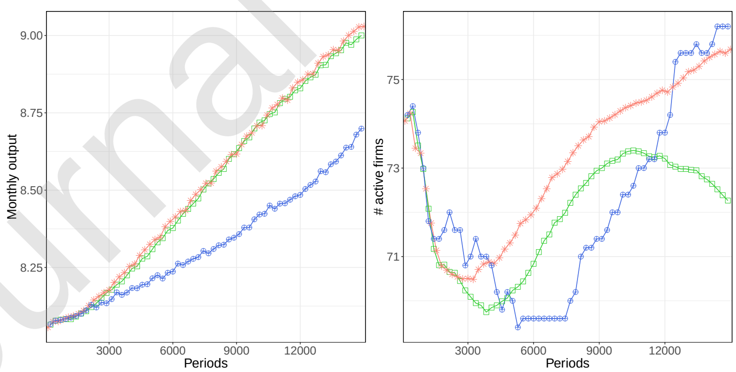
Figure 4: Relative knowledge stocks over time



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

Evolution of relative stocks of codified (α_t) and tacit knowledge (β_t) measured as average across $r \in \{r^{eco}, r^{conv}, r^{switch}\}$. The different regimes are indicated by different line shapes (□: eco, $*$: conv, $\oplus$: switch).

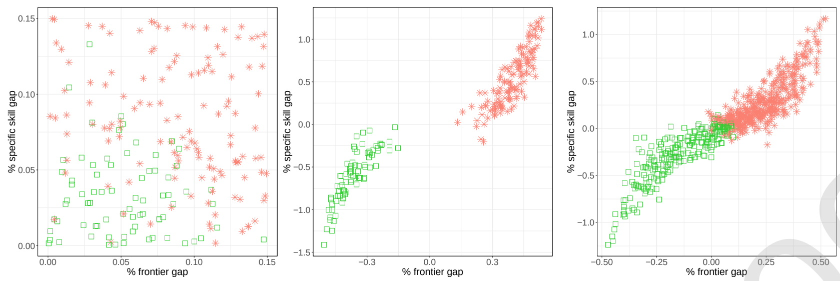
Figure 5: Output and number of firms.



(a) Monthly output (b) #active firms

These figures show the evolution of output and the number of active firms. The different shapes indicate different regime types (□: eco, $*$: conv, $\oplus$: switch).

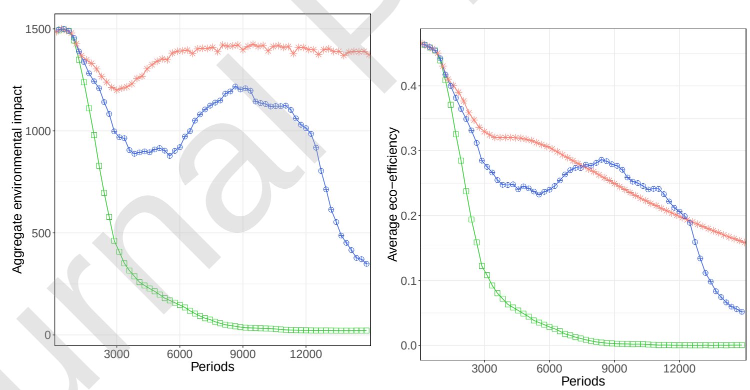
Figure 6: Distribution of β^A and β^b at different times.



(a) $t_0 = 600$ (b) $T = 15000$ (c) All periods

□ ($*$) indicates that the final technological regime is eco (conv).

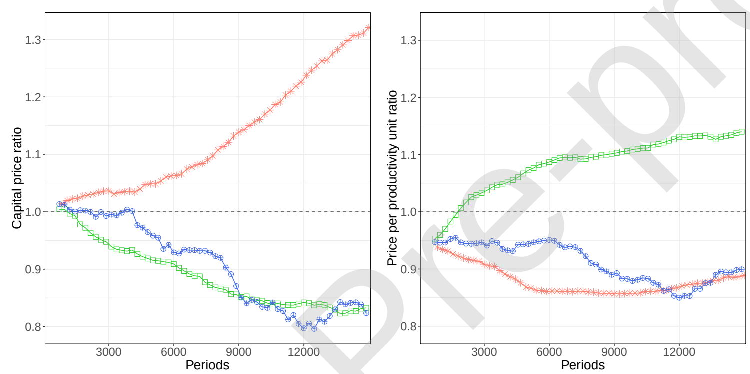
Figure 7: Environmental absolute and relative performance



(a) Aggregate environmental impact (b) Average ecoefficiency

These figures show the evolution of the aggregate environmental impact and ecoefficiency as environmental impact per unit of output. The line types indicate different scenario types (□: eco, $*$: conv, $\oplus$: switch).

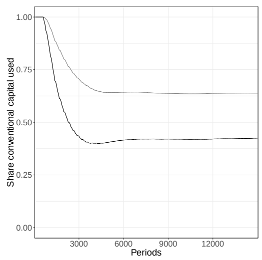
Figure 8: Capital price indicators



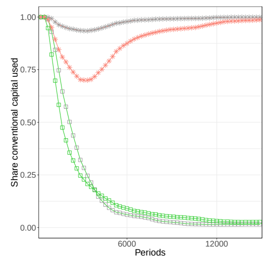
(a) $\frac{p_t^c}{p_t^g}$ (b) $\frac{p_t^c/A_t^c}{p_t^g/A_t^g}$

The different line shapes indicate the scenario type (i.e. □: eco, ∗: conv, ⊕: switch). Figure (a) shows the evolution of the ratio of prices paid for the most productive vintages supplied by the conventional and green producer. Figure (b) shows the evolution of the price-per-productivity-unit ratio.

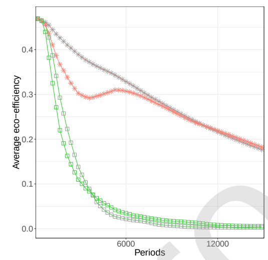
Figure 9: Technological and macroeconomic time series



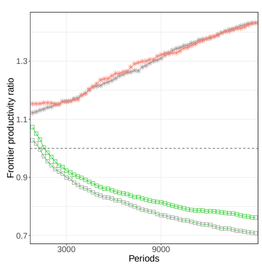
(a) ν_t^c batch



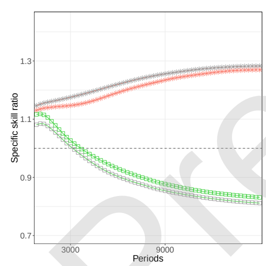
(b) ν_t^c by regime type



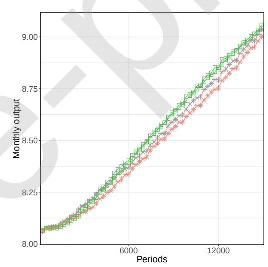
(c) Eco-efficiency



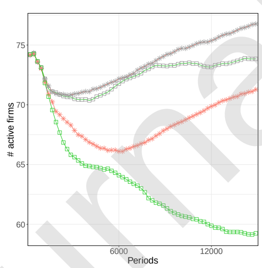
(d) $\alpha_t = \frac{A^V_{c,t}}{A^V_{g,t}}$



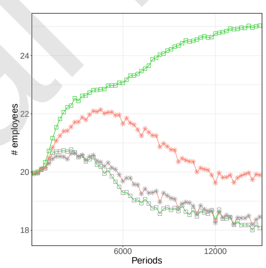
(e) $\beta_t = \frac{b^c_t}{b^g_t}$



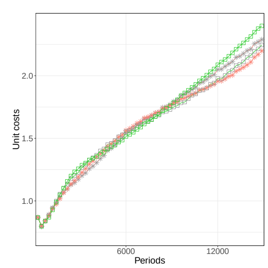
(f) Aggr. output



(g) # active firms



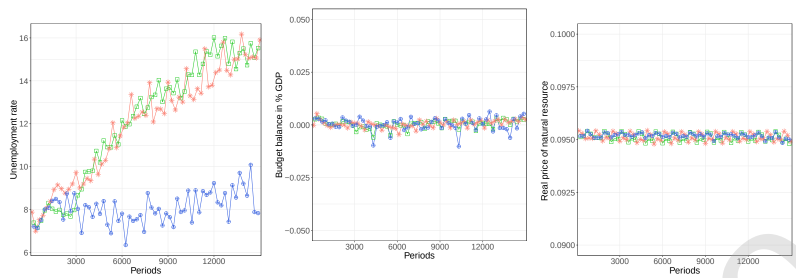
(h) # employees



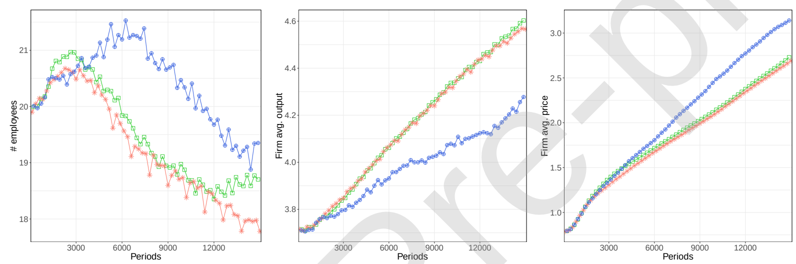
(i) Unit costs

Technological and macroeconomic characteristics of the policy experiment with random barriers in comparison to the baseline scenario without policy but randomly drawn barriers (gray). Different line types represent different regimes (□: eco, $*$: conv).

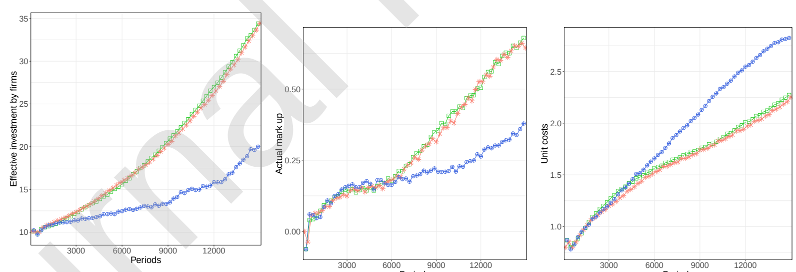
Figure 10: Time series of macroeconomic and technological indicators



(a) Unemployment rate (b) Gov. budget balance (% GDP) (c) $c^{eco_t}/\bar{w}_t$



(d) Avg. # employees (e) Avg. output (f) Avg. price by firms



(g) Avg. effective investment (h) Avg. mark up (i) Avg. unit costs

These figures show the evolution of macroeconomic and firm-level key indicators. The different shapes indidicate the technological regime type (□: eco, ∗: conv, ⊕: switch). The jumpy behavior (esp. for the number of active firms) of the switch curve is due to the small number of runs within the set).

Tables

Table 1: Stylized facts as design and validation criteria

Macroeconomic stylized facts:
Growth rates: Quantitative matching of aggregate output growth rate.
Business cycle volatility: Evaluated by the variance of cyclical component of band-pass filtered time series data of aggregate output.
Persistence of fluctuations: Autocorrelation of output fluctuations.
Cross-correlation of economic key indicators with output fluctuations: Pro-cyclical consumption, investment, employment and vacancies. Anti-cyclical wages, mark-ups and unemployment.
Relative magnitude of fluctuations: Investment is more volatile than output, output is more volatile than consumption. Vacancies are more volatile than unemployment, unemployment is more volatile than output.
Phillips curve: Negative relationship between unemployment and inflation.
Beveridge curve: Negative relationship between unemployment and vacancies.
Stylized facts of innovation:
Uncertainty: Probabilistic technological progress and uncertain market success (cf. Nelson & Winter, 1977; Dosi, 1988; Windrum, 1999).
Incremental nature of innovation: Incremental upwards shift in the technological frontier within a technological trajectory (cf. Dosi, 1988).
Embodied technology: Technology is intangible, but embodied in physical capital goods and skill sets of labor (cf. Romer, 1990; Windrum, 1999).
Tacit knowledge: Technology has a tacit dimension that is not tradable and determines the absorptive capacity of firms (cf. Dosi, 1991; Windrum, 1999; Dawid, 2006; Di Stefano et al., 2012).
Heterogeneous benefits of adoption: Firms are heterogeneous in their capability to make productive use of new technology (cf. Nelson & Winter, 1977; Allan et al., 2014).
Knowledge spillovers: Learning spillovers from accumulated knowledge ("standing on the shoulders of giants") and spillovers across technology types in learning (transferable skills) (cf. Gillingham et al., 2008; Pizer & Popp, 2008; Allan et al., 2014).
Creative destruction and obsolescence: Technology-specific knowledge of the long-term inferior technology is obsolete and worthless (cf. Köhler et al., 2006; Klimek et al., 2012).
Vintage structure as adoption barrier: Pre-existing capital inhibits the adoption of radical innovation (cf. Metcalfe, 1988; Kemp & Volpi, 2008; Ambec et al., 2013).

The macroeconomic validation scenario are a selection of criteria used and described in more detail in Dawid et al. (2018b). More information about the validation procedure and a demonstration how the criteria are matched by the model is provided in the supplementary material II.

Table 2: Technological regime shift and initial conditions

Dependent variable: ν_T^c.						
	OLS					Probit
	(1)	(2)	(3)	(4)	(5)	(6)
(Intercept)	.2754***	.2676***	-.0103	-.1351	-36.47	-2.6088***
	(.0605)	(.0437)	(.0550)	(.0884)	(45.16)	(.3805)
β^b	.0448***		.0377***	.0188	.0202	.1896***
	(.0065)		(.0052)	(.0200)	(.0202)	(.0317)
β^A		.0548***	.0507***	.1136***	.1167***	.2716***
		(.0052)	(.0047)	(.0152)	(.0153)	(.0382)
$(\beta^b)^2$				.0026*	.0025*	
				(.0012)	(.0012)	
$(\beta^A)^2$				-.0023**	-.0024**	
				(.0009)	(.0009)	
$\beta^b \cdot \beta^A$				-.0035***	-.0035***	
				(.0010)	(.0010)	
+controls						
Adj./ps.R^2	.1814	.3492	.4769	.5316	.5316	.4761
AIC	237.67	197.02	125.15	131.88	136.64	142.61
Significance codes: 0 *** .001 ** .01 * .05 . .1 1.						

Share of conventional capital ν_T^c regressed on the macroeconomic level on diffusion barriers β^A, β^b, measured in percentage points, and initial macroeconomic conditions. Columns (1)-(5): OLS, column (6): binary Probit model.

Table 3: Early adopters

Dependent variable: ν^c_{i,t_1}						
	OLS					Probit
	(1)	(2)	(3)	(4)	(5)	(6)
(Intercept)	.5461***	.6054***	.3921***	.1027***	-.8139***	-11.48***
	(.0042)	(.0033)	(.0040)	(.0057)	(.1539))	(2.005)
β^b	.0329***		.0291***	.0684***	.0685***	.2171***
	(.0005)		(.0004)	(.0013)	(.0013)	(.0231)
β^A		.0307***	.0274***	.0875***	.0881***	.3882***
		(.0004)	(.0003)	(.0010)	(.0010)	(.0181)
$(\beta^b)^2$				-.0009***	-.0009***	.0070***
				(.0001)	(.0001)	(.0018)
$(\beta^A)^2$				-.0020***	-.0020***	-.0053***
				(.0001)	(.0001)	(.0012)
$\beta^b \cdot \beta^A$				-.0038***	-.0038***	-.0148***
				(.0001)	(.0001)	(.0021)
B^c_{i,t_0}					-.7317***	-6.898**
					(.1647)	(2.151)
A^c_{i,t_0}					1.448***	12.67***
					(.0883)	(1.167)
$\#employees_{i,t_0}$					.0006	-.0038
					(.0014)	(.0173)
$Output_{i,t_0}$					-.0251	.2390
					(.0264)	(.3180)
Age_{i,t_0}					.0003*	.0015
					(.0001)	(.0014)
$Price_{i,t_0}$					.3637***	4.201**
					(.0983)	(1.329)
$UnitCosts_{i,t_0}$					-.0203	-.2407
					(.0148)	(.1807)
Adj./ps.R^2	.2634	.2893	.4911	.6371	.6480	.5451
AIC	5349	541.00	-4454.08	-9509.46	-9972.83	6049.5
Significance codes: 0 *** .001 ** .01 * .05 . .1 1.						

Share conventional capital utilization at firms $\nu^c_{i,t}$ in $t_1 = 1800$ on barriers and initial firm characteristics. Columns: (1)-(5) OLS, (6) binary probit.

Table 4: Technological regime shift and initial conditions

Dependent variable: $\nu^c_{i,T}$ at firm level in $T = 15000$						
			OLS			Probit
	(1)	(2)	(3)	(4)	(5)	(6)
(Intercept)	.7522***	.0025	.2553***	-.0463	1.572***	2.496
	(.01490)	(.0181)	(.0198)	(.0298)	(.4231)	(1.6710)
θ	-.0019***		-0.0027***	-.0005	-.0006	.0027.
	(.0002)		(.0001)	(.0004)	(.0004)	(.0015)
σ^c	-0.1426***		-0.1337***	-.0498***	-.0533***	-.1592**
	(.0063)		(.0054)	(.0140)	(.0140)	(.0582)
σ^i	.0006		-0.0041**	.0262***	.0259***	.1753***
	(.0017)		(.0014)	(.0039)	(.0039)	(.0160)
β^A		.0224***	.0228***	.0478***	.0507***	.1797***
		(.0028)	(.0027)	(.0035)	(.0036)	(.0142)
$(\beta^A)^2$		.0010***	.0015***	.0015***	.0014***	.0067***
		(.0002)	(.0002)	(.0002)	(.0002)	(.0007)
β^b		.0371***	.0524***	.0592***	.0598***	.1879***
		(.0037)	(.0035)	(.0042)	(.0042)	(.0162)
$(\beta^b)^2$		-.0026***	-0.0030***	-.0031***	-.0031***	-.0098***
		(.0002)	(.0002)	(.0002)	(.0002)	(.0008)
$(\beta^b\beta^A)$		.0015***	.0006***	.0013***	.0012***	.0097***
		(.0002)	(.0002)	(.0002)	(.0002)	(.0008)
$(\beta^b\theta)$				7e-05*	7e-05*	.0001
				(3e-05)	(3e-05)	(.0001)
$(\beta^b\sigma^c)$				-.0090***	-.0086***	-.0462***
				(.0012)	(.0012)	(.0049)
$(\beta^b\sigma^i)$				-.0007*	-.0008*	-.0061***
				(.0003)	(.0003)	(.0012)
$(\beta^A\theta)$				-.0003***	-.0003***	-.0017***
				(3e-05)	(3e-05)	(.0001)
$(\beta^A\sigma^c)$				-.0017	-.0023*	-.0084.
				(.0010)	(.0010)	(.0047)
$(\beta^A\sigma^i)$				-.0026***	-.0027***	-.0184***
				(.0003)	(.0003)	(.0013)
Adj./ps.R^2	.0568	.2994	.3596	.3828	.3851	.3433
AIC	15172	11896	10907	10506	10470	10020
Significance codes: 0 *** .001 ** .01 * .05 . .1 1.						

$\nu^c_{i,T}$ on diffusion barriers, policy parameters and initial conditions. Columns: (1)-(5) OLS, (6) binary probit. The policy parameters and barriers are measured in percentage *points*. The coefficients of firm level control variables are not significant except from the stock of skills $B^c_{i,t}$ which is diffusion inhibiting but not very dominant.

Table 5: Overview of the eco-technology extension added to the original Eurace@unibi.

Extensions of the Eurac@unibi model	
Static properties	
Technology	
IG firms	Price competition among two IG firms, each representing a different technology type $ig = \{c, g\}$ with c as conventional and g as green type.
CG firms	Environmental impact and resource use associated with utilization of non-green capital and type-specific technological capabilities B_i^{ig} of CG firms $i \in I$.
Households	Type-specific capabilities b_h^{ig} of household $h \in H$ to work effectively with production capital of her employer.
Dynamics	
Innovation	
IG firms	Endogenous, probabilistic technological improvements in IG sectors dependent on sectoral R&D investments.
Diffusion	
CG firms	Technology adoption decision based on relative expected profitability which is dependent on firms' technology type-specific capabilities.
Learning	
Households	Learning is dependent on the type of technology they are using at work. Employees as "carrier" of tacit part of evolving technological knowledge of firms.
Policy	
Government	Innovation and climate policy measures: Material input taxes, subsidies for eco-innovation adoption and clean production.

Table 6: In this table the results of a Wilcoxon test on equality of means are shown.

t	Mean (Std)			p-value		
	eco	*conv*	*switch*	*eco*, *conv*	*eco*, *switch*	*conv*, *switch*
Share conv. capital use						
$[0, 600]$	1.00 (0.00)	1.00 (0.00)	1.00 (0.00)	NA	NA	NA
$[0, 15000]$	.1991 (.0777)	.9583 (.0463)	.6720 (.1195)	<2.2e-16	.00018	.00020
Monthly output						
$[0, 600]$	8.067 (.0023)	8.067 (.0022)	8.068 (.0024)	.7334	.9084	.9326
$[0, 15000]$	8.509 (.1035)	8.522 (.0868)	8.322 (.0640)	.3981	.0006	.0003
Unemployment rate						
$[0, 600]$	7.472 (.2187)	7.456 (.2024)	7.397 (.2138)	.8357	.6730	.6120
$[0, 15000]$	12.18 (6.611)	11.95 (5.604)	8.089 (.4756)	.4430	.0009	.0006
Eco-price-wage-ratio						
$[0, 600]$	.0952 (2.5e-5)	.0952 (3.6e-5)	.0952 (1.8e-5)	.6930	.9939	.7353
$[0, 15000]$	.0951 (5.6e-5)	.0951 (4.6e-5)	.0952 (1.8e-5)	.5549	.0054	.0063

The means are computed as average over the subset of periods for each single simulation run. The time interval $t \in [0, 600]$ corresponds to the time before market entry, the interval $t \in [0, 150000]$ for the sample average. Test on other time intervals are not presented here, but are available in the accompanying data publication.

Table 7: Initial conditions

t	Mean (Std)	Mean (Std)	Mean (Std)	p-value*
Frontier gap		*conv*	*eco*	
600	.064 (.043)	.082 (.041)	.032 (.027)	2.3e-16
15000	.117 (.373)	.531 (.322)	-.594 (.304)	<2e-16
Skill gap		*conv*	*eco*	
600	.077 (.046)	.089 (.042)	.052 (.032)	4.8e-10
15000	.117 (.373)	.393 (.085)	-.360 (.084)	<2.3e-16

Initial mean and standard deviation of randomized entry barriers differentiated by regime type. The p-value in the last column indicates the significance of difference between the two scenarios derived from a two-sided Wilcoxon test on equality of means.

Table 8: Results of a Wilcoxon test on equality of means.

t	Mean (Std)		p-value	Mean (Std)		p-value
	eco	*conv*	*eco*, *conv*	*eco*	*conv*	*eco*, *conv*
	Share conventional capital used			Eco-price-wage-ratio		
[601, 3000]	.6337 (.1830)	.9595 (.0844)	<2.2e-16	.0951 (6.8e-5)	.0952 (5.0e-5)	.3544
[3001, 5400]	.1549 (.1903)	.9486 (.1371)	<2.2e-16	.0951 (8.7e-5)	.0951 (6.6e-5)	.0011
[5401, 15000]	.0278 (.0455)	.9922 (.0520)	<2.2e-16	.0951 (4.9e-5)	.0951 (4.7e-5)	.1846
[0, 15000]	.1840 (.0763)	.9803 (.0616)	<2.2e-16	.0951 (4.3e-5)	.0951 (3.8e-5)	.0137
	% frontier gap			% skill gap		
[601, 3000]	-.0414 (.0586)	.1142 (.0677)	<2.2e-16	.0425 (.0338)	.1147 (.0454)	<2.2e-16
[3001, 5400]	-.1702 (.1209)	.1740 (.1154)	<2.2e-16	-.0485 (.0550)	.1590 (.0596)	<2.2e-16
[5401, 15000]	-.4132 (.2310)	.3731 (.2208)	<2.2e-16	-.2408 (.0780)	.2964 (.0764)	<2.2e-16
[0, 15000]	-.2970 (.1677)	.2881 (.1608)	<2.2e-16	-.1530 (.0595)	.2371 (.0617)	<2.2e-16
	Monthly output			Unemployment rate		
[601, 3000]	8.118 (.0203)	8.120 (.0177)	.2065	8.089 (.6501)	8.608 (.7857)	2.9e-8
[3001, 5400]	8.272 (.0664)	8.263 (.0572)	.3618	10.59 (3.292)	9.121 (1.825)	.0002
[5401, 15000]	8.722 (.1306)	8.681 (.1340)	.0335	14.71 (9.688)	11.78 (4.641)	.0525
[0, 15000]	8.527 (.0916)	8.500 (.0933)	.04593	12.70 (6.597)	10.67 (3.191)	.0420
	# active firms					
[601, 3000]	71.52 (1.298)	71.56 (1.150)	.5416			
[3001, 5400]	70.62 (2.035)	71.26 (2.000)	.02798			
[5401, 15000]	73.11 (4.209)	74.52 (2.910)	.0427			
[0, 15000]	72.50 (2.788)	73.51 (2.095)	.0192			

Means are computed as average over the subset of periods and disaggregated by run. The time interval $[601, 3000]$ ($[3001, 5400]$, $[5401, 15000]$) corresponds to the first ten ($10 - 20$, > 20) years after market entry. The interval $[0, 150000]$ accounts for the sample average.

Table 9: Overview of parameter and variable initialization.

		conv	*eco*	
	Mean (Std)	Mean (Std)	Mean (Std)	p-value
β^A	.077 (.043)	.102 (.035)	.059 (.039)	1.3e-12
β^b	.076 (.044)	.081 (.042)	.072 (.045)	.194
θ	.515 (.291)	.476 (.276)	.543 (.297)	.090
σ^c	.013 (.007)	.011 (.007)	.014 (.007)	.002
σ^i	.052 (.028)	.050 (.029)	.053 (.027)	.443

The four columns on the right-hand side show the initialization by regime type, i.e. *eco* and *conv*.

Table 10: Dynamic and conditional effects of policy

Dep. var: $\nu^c_{i,t}$, $\#employees_{i,t}$, $UnitCosts_{i,t}$									
	$\nu^c_{i,t}$			$\#employees_{i,t}$			$UnitCosts_{i,t}$		
t	1,800	3,000	9,000	1,800	3,000	9,000	1,800	3,000	9,000
$\mathbb{1}^{eco}$	-.0281*	-.3125***	-.8967***	1.483***	2.400***	-.2193	-.0483***	.0486***	.1709***
	(.0136)	(.0157)	(.0106)	(.2982)	(.3836)	(.4530)	(.0050)	(.0059)	(.0147)
θ	-.0010***	-.0015***	.0003**	.0004	.0058.	.0111**	-2e-5	-3e-5	5e-5
	(.0001)	(.00012)	(8e-5)	(.0023)	(.0030)	(.0035)	(4e-5)	(5e-5)	(.0001)
σ^i	-.0093***	-.0165***	-.0056***	.0153	.0037	.1083***	-.0015***	.0019***	-.0071***
	(.0010)	(.0011)	(.0008)	(.0215)	(.0277)	(.0327)	(.0004)	(.0004)	(.0011)
σ^c	-.0477***	-.0743***	.0054	.2661	.3676	-.0536	-.0027.	.0270***	-.0112*
	(.0041)	(.0047)	(.0032)	(.0897)	(.1153)	(.1362)	(.0015)	(.0018)	(.0044)
$\mathbb{1}^{eco}\theta$	-.0014***	-.0011***	-.0005***	-.0027	-.0104**	-.0055	.0004***	.0003***	-.0002
	(.0001)	(.0002)	(.0001)	(.0030)	(.0039)	(.0046)	(5e-5)	(6e-5)	(.0002)
$\mathbb{1}^{eco}\sigma^i$	-.0063***	.0069***	.0089***	-.1445***	-.2515***	.4090***	.0011*	-.0048***	-.0307***
	(.0014)	(.0017)	(.0011)	(.0316)	(.0406)	(.0479)	(.0005)	(.0006)	(.0016)
$\mathbb{1}^{eco}\sigma^c$	-.0012	.0468***	.0106*	-.3515**	-.4362**	.9063***	.0228***	-.0154***	.0121*
	(.0056)	(.0065)	(.0044)	(.1222)	(.1572)	(.1857)	(.0020)	(.0024)	(.0060)
R^2	.6795	.6738	.8987	.6413	.5316	.2039	.4137	.3664	.1757
AIC	-4124	-961.3	-9609	63870	69421	73091	-26497	-22569	-2478
Mean	.6011	.4582	.4722	22.98	23.25	23.04	1.075	1.252	1.785
Std.	(.0034)	(.0039)	(.0047)	(.0695)	(.0783)	(.0709)	(.0009)	(.0010)	(.0023)
Significance codes: 0 *** .001 ** .01 * .05 . .1 1. R^2: for OLS heterosked. adjusted.									

OLS regression of $\nu^c_{i,t}$, $\#employees_{i,t}$, $UnitCosts_{i,t}$ measured at firm level in $t \in \{1800, 3000, 9000\}$ on firm level controls and the different political instruments and its interaction terms with a dummy $\mathbb{1}^{eco}$ that indicates whether a green transition occurred until T. $\mathbb{1}^{eco}$ captures systematic differences across technological regimes. The coefficients of the firm level controls are not shown here, but are available in an accompanying data publication.

Appendix

A. Model documentation

In this section, the formal implementation of the eco-technology extension of the Eurace@unibi model is introduced. For an introduction to the baseline model itself, its calibration and applications in economic policy analysis, the interested reader is referred to articles of the original developers of the model (e.g. Dawid et al., 2019; Harting, 2019). A concise but self-contained introduction to the eco-technology extension of the model is available in Hötte (2019b). The most relevant changes and extensions compared to the baseline model are summarized in table 5.

[Table 5 about here.]

In the subsequent subsections, I introduce the relevant parts of the model extension in technical detail. These are the CG firms' production technology highlighting the difference between the theoretical and effective productivity of capital, and employees' learning function.

A.1. Consumption goods firms' production technology

CG firms produce homogeneous consumption goods with a constant returns to scale Leontief technology combining labor, capital and natural resource inputs if conventional capital is used. Labor is hired on the labor market. Capital goods are accumulated in a stock that can be expanded by investment and depreciates over time. The capital stock is composed of various items that can differ by productivity and technology type. It is important to note the *vintage* approach. Newer machines are in tendency more productive, and capital stock items can be either green or conventional.

The variable $K^v_{i,t}$ indicates the quantity of capital goods of type v with the characteristics $(A^v, \mathbb{1}(v))$ within the firm's current capital stock $K_{i,t}$. Formally, the amount of capital of type v is given by $K^v_{i,t} := \{k \in K_{i,t} | A^v(k) = A^v, \mathbb{1}(k) =$

$\mathbb{1}(v)\}$. Further, I use the notation $K^{ig}_{i,t}$ when referring to the part of the capital stock that is composed of vintages of technology type ig, i.e. $K^{c}_{i,t} = \sum_v \mathbb{1}(v) \cdot K^{v}_{i,t}$ and $K^{g}_{i,t} = \sum_v (1 - \mathbb{1}(v)) \cdot K^{v}_{i,t} = K_{i,t} - K^{c}_{i,t}$ where $\mathbb{1}(v)$ is the technology type identifier taking the value one (zero) if the vintage v is of conventional (green) type.

The exploitation of the productivity of a given vintage at the firm level is constrained by the firm's technological capabilities $B^{ig}_{i,t}$. This capability may differ across technology types. The effective productivity $A^{Eff_v}_{i,t}$ of a capital good v in time t is given by

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

where A^v is the theoretical productivity and $B^{ig}_{i,t}$ is the average specific skill level of firm i's employees.

Technology-specific skills are accumulated over time, hence the effective productivity of a capital stock item $A^{Eff_v}_{i,t}$ changes over time and varies across firms. The skill-dependent exploitation of productivity imposes a barrier to the adoption of new technology. It takes time until workers have learned how to use new machinery while their skills may be sufficient to exploit the productivity of older vintages.

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

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

where $L_{i,t}$ is the number of employees, and $\sum_{v=1}^{V} K^{v}_{i,t}$ is the firm's *ordered* capital stock composed of V different capital stock items. *Ordered* refers to the running order of capital that is determined by the cost-effectiveness of capital goods. It may occur that firms do not utilize their full capacity. For example when the available amount of labor or demand for consumption goods are insufficient and using costs of capital goods exceed the expected marginal revenue it is not profitable to produce with full capacity. In such case, most cost-effective capital goods are used first.

Firms can only use as much capital as workers are available in the firm to operate the machines. This is captured by the term $\max\left[0, L_{i,t} - \sum_{k=v+1}^{V} K_{i,t}^{k}\right]$.[16]

The cost effectiveness $\zeta_{i,t}^{v}$ is given by the marginal product $A_{i,t}^{Eff_v}$ divided by using costs. Variable using costs consist of wage $w_{i,t}$ and, if it is a conventional capital good, unit costs of the natural resource input c_t^{eco}. The cost-effectiveness is given by

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

where $\mathbb{1}(v)$ indicates the capital type.[17]

The decision about the production quantity is based on demand estimations and inventory stocks. Based on estimated demand curves, firms determine the profit-maximizing price-quantity combination. Because the estimation can be imperfect and prices cannot be immediately adjusted, the consumption goods market does not necessarily clear (see for additional detail Dawid et al., 2019).

Production costs of a firm are composed of wage payments and expenditures for natural resource inputs required for each conventional vintage that is used. Total resource costs are given by the resource unit price c_t^{eco} multiplied with the total amount of conventional capital that is used in current production, i.e.

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

with V as the set of vintages that are actually utilized for production in t. The natural 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.[18]

The utilization of conventional capital is associated with the degradation of an environmental resource. The damage is proportional to the number of

[16] The process of hiring new employees is explained in the references of the original model.

[17] 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.

[18] The *real* price of the natural resource is assumed to be constant, i.e. it is exogenously given and grows at the same rate as the average wage in the economy. Hence, on average, the ratio between variable labor and resource input costs is held constant. Note that this does only hold on average because wages may be different across firms.

conventional capital units that are used in production. If conventional capital becomes more productive, a relative decoupling takes place. The environmental damage per unit of output decreases.

The composition of firms' capital stock changes by depreciation and investment. In their investment decision, firms have to decide about the technology type, productivity level and the number of capital goods to buy. This decision is based on the estimated net present value. In the computation, firms take account of the expected price and wage developments and anticipate technology-specific learning of their employees.

Investment and production expenditures have to be financed in advance. If the firm's own financial means on the bank account are not sufficient, it applies for credit from private banks. A formal explanation of the firms' investment decision and the environmental impact is available in the supplementary material I.1.

A.2. Employees' technological learning

Households act as consumers, savers, and employees. The consumption decision is based on a multinomial logit function in which the purchasing probability negatively depends on the price of the good (see Dawid et al., 2019).

Technological learning is embedded in the evolution of households' technology-specific skills. Technology-specific skills $b^{ig}_{h,t}$ of employee h are learned during work. The speed of learning depends on the technological properties of the capital stock that is used by the employer and h's learning ability. The ability depends on the household's (fix) general skills χ_h. It moderates the speed of learning (cf. Hötte, 2019b).

There are two ways of how technology-specific skills are accumulated. Households *learn by using* a specific technology type $\psi^{ig}_{h,t}$. Part of the technological knowledge learned is transferable across types and contributes to the stock of technology-specific skills of the alternative technology type indexed by $-ig$ with $ig \neq -ig$ and $ig, -ig \in \{c, g\}$.

The evolution of the technology-specific skill level $b^{ig}_{h,t}$ is given by

$$b^{ig}_{h,t+1} = b^{ig}_{h,t} + \chi_h \cdot \max\left[(\chi^{spill} \cdot \psi^{-ig}_{h,t}), \psi^{ig}_{h,t}\right] \tag{A.5}$$

with $\chi^{spill} \in [0,1]$ as spillover intensity or degree of transferability of technological knowledge.

The pace of learning $\psi^{ig}_{h,t}$ is dependent on the *intensity of learning* $\nu^{ig}_{h,t}$ and the *degree of technological novelty* $\Delta b^{ig}_{h,t}$. It is given by

$$\psi^{ig}_{h,t} = \max\left[\chi^{int}, \nu^{ig}_{h,t}\right] \cdot \Delta b^{ig}_{h,t}. \tag{A.6}$$

with $\chi^{int} \in [0,1]$ as lower bound. The intensity of learning in a specific technology category ig is dependent on the relative amount of technology ig that is used $\nu^{ig}_{h,t} = \frac{K^{ig}_{h,t}}{K_{h,t}}$.

This is interpreted as *intensity of effort* or time invested in learning a specific type of skills (cf. Cohen & Levinthal, 1990). Learning skills of technology type ig is faster if the relative amount of this type in the used capital stock is higher. The relative amount is assumed to reflect which relative time the employee is working with a technology type and learning by doing. The fixed parameter $\chi^{int} \in [0,1]$ imposes a minimum level on the sensitivity of learning progress to the intensity of effort.[19]

Employees learn only if “there is something new to learn”. $\Delta b^{ig}_{h,t} = \max[0, (A^{ig}_{h,t} - b^{ig}_{h,t})]$ represents the learning potential. The learning potential is given by the gap between the average productivity level $A^{ig}_{h,t}$ of h's employer and its current skill level. The larger the gap is, the larger is the “amount” of technological knowledge the employee may learn and the faster is the pace of learning. This assumption reflects a notion from the learning curve literature that employees learn faster if they are exposed to novel technological environments (Thompson, 2012).

$A^{ig}_{h,t}$ is the average productivity of vintages of type ig in the capital stock of h's employer. $A^{ig}_{h,t}$ imposes an upper bound on learning by doing. However, the

[19]Note that this representation slightly differs from the model version introduced in Hötte (2019b).

skill level $b^{ig}_{h,t}$ may exceed $A^{ig}_{h,}$ if $\chi^{spill} \cdot \phi^{-ig}_{h,t}$ is sufficiently high and the employee learns from spillovers.

A.3. Capital goods and innovation

Each IG firm $ig \in \{c, g\}$ offers a range of capital vintages indexed by $v = \{1, ..., V\}$ that differ by productivity. The index $v = 1$ refers to the least productive vintage supplied by firm ig and $v = V$ to the most productive. The incumbent firm c produces conventional, the entrant firm g produces green capital goods.

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

$$A^V_{ig,t+1} = (1 + \Delta A) \cdot A^V_{ig,t}. \tag{A.7}$$

Productivity enhancements are discrete steps given by $\Delta A \cdot A^V_{ig,t}$ where the factor ΔA is uniform across IG sectors, but the productivity enhancement in absolute terms depends on the current level of the frontier. Hence, there is a positive externality from existing technological knowledge.

The success of innovation is probabilistic and 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

$$\mathbb{P}_{ig,t}[\text{success}] = \bar{p} \cdot (1 + \widehat{R\&D}_{ig,t})^{\eta} \tag{A.8}$$

where $\bar{p}$ is a fix minimum probability of innovation success. It can be interpreted as technological knowledge that is generated independently of the market for example in public research institutions or by inventors that are independent of the market. $\widehat{R\&D}_{ig,t}$ is ig's R&D intensity in the current month.

The parameter $\eta \in (0, 1]$ determines the returns to R&D.

Capital goods are produced with a constant returns linear production function using labor as the only input. For reasons of simplification, their labor demand is not integrated into the labor market. Hence, capacity constraints are assumed away.

IG firms use an adaptive mark-up pricing based on observations about past market shares and profits and their previous pricing behavior. IG firms' revenue is used to cover labor costs for IG production. Remaining profits are partly invested in R&D and partly paid as dividends to shareholders. These routines are formally explained in the supplementary material I.2.

A.4. Green technology producer's market entry

On the day of market entry t_0, the green IG firm g starts supplying the first, least productive vintage with the productivity $A^1_{g,t_0} = (1 - \beta^A) \cdot A^1_{c,t_0}$. $\beta^A \in [0, 1)$ is the percentage technological disadvantage of green technology on the day of market entry.

The market entry was associated with a technological breakthrough that enables the rapid development of further varieties of green capital. A whole supply array becomes successively available. Half a year after the day of market entry, the next and incrementally more productive vintage is added to the array of available vintages. It has the productivity level $A^2_{g,t} = (1 + \Delta A) \cdot A^1_{g,t} = (1 - \beta^A) \cdot A^2_{c,t_0}$.[20]

This procedure repeats every sixth month until the maximum number of the supplied vintages is reached. Thereafter, additional technological progress happens through the innovation procedure as introduced above (see A.3).

Note that the initial supply array is proportional to the supply array of the conventional producer in t_0. The green vintages are supplied at the same prices as vintages of the incumbent in t_0, but the *price per productivity unit* is higher due to the assumed technological disadvantage.

[20]Six months can be referred as to "rapid" in comparison to the innovation probability that ranges typically around 3% (endogenous) which corresponds to approximately one innovation every five years.

A.5. Policy

The government can use a tax on natural resource inputs and two different subsidies to stimulate the diffusion of green technologies.

The policy instruments are implemented as follows:

- An **environmental tax** θ^{eco} is imposed as a value added tax on material inputs. This makes the use of conventional capital relatively more costly for CGfirms,

$$\tilde{p}^{eco}_{i,t} = (1 + \theta^{eco}) \cdot p^{eco}_t. \tag{A.9}$$

  Because the environmental impact of production is proportional to the use of material inputs, this tax can also be seen as a tax on the environmental externality. Alternatively, different levels of the tax can interpreted as different degrees of technological superiority of the entrant technology.

- An **investment subsidy** σ^i reduces the the price for green capital goods,

$$\tilde{p}^v_t = (1 - \sigma^i) \cdot p^v_t. \tag{A.10}$$

- The government may also pay a **green consumption price support** σ^c for environmentally sound produced CG, i.e.

$$\tilde{p}_{i,t} = \left(1 - \nu^g_{i,t} \cdot \sigma^c\right) \cdot p_{i,t} \tag{A.11}$$

  This subsidy is directly paid to firms and is proportional to the share of green capital used in current production $\nu^g_{i,t} = \frac{K^g_{i,t}}{K_{i,t}}$. The price support allows CG firms to achieve a higher mark-ups when producing in an environmentally friendly way.[21]

The tax and the subsidy rates are initialized at a fix level at the day of market entry. The government seeks to balance its budget and adjusts other taxes accordingly, i.e. if the budget balance is negative, non-environmental taxes are increased and vice versa if the balance is positive.

[21] Note that the consumption subsidy is analogous to a higher willingness to pay of consumers for green products.

A.6. Additional notes on the parameter settings

In these simulations, moderate spillovers in the learning process are assumed captured by $\chi^{int} = \chi^{spill} = .5$. The technological knowledge required for the effective use of a certain technology is often partly transferable (cf. Cohen & Levinthal, 1990). For example, skills such as programming or basic engineering knowledge are usable independently of the *type* of capital that is used, but technological knowledge about the technical details of a combustion machine has little use in the production of wind energy.

Studies on corporate learning suggest employees being exposed to changes in their working environment to learn faster which justifies the assumption that the speed of learning is positively dependent on the degree to which a technology is new to employees with a fix minimum pace of learning captured by $\chi^{int} > 0$ (Thompson, 2012). Further, these parameters are sector and technology dependent, but sectoral heterogeneity is not within the scope of the present analysis. The choice of the values for barriers and learning parameters is based on a series of sensitivity tests. These values are set such that the probability of a green transition is roughly 50%.

Initial conditions are determined in a series of *training simulations*. The model is based on a calibrated version of the Eurace@unibi model and an initial population is taken from previous applications. The initial population reflects the initial distribution of skills and wealth across households and firms and the firm size distribution. However, the introduction of the additional module made a partial recalibration of the model necessary. Starting with an initial population, the model was run for different parameter settings until stable economic processes have emerged. At that time, the population was saved and used as initial input to the model. This explains, for example, the arbitrarily seeming number of 74 firms.[22]

[22]The number of periods until the day of market entry was set such that the economy is on a stable path of development, but sufficiently small that the divergence across runs is not too large. The deviations across different runs that emerge during this time are of minor

B. Simulation results

B.1. Baseline scenario

[Figure 7 about here.]

The figures on the aggregate environmental impact and eco-efficiency reveal that there is a relative decoupling of environmental damage and production activities. The level in figure 7(a) stabilizes even if no transition to the green technology takes place. This is due to improved production efficiency and in consequence a reduction of emissions per unit of output (cf. figure 7(b)). However, the improvement in terms of eco-efficiency is fully outweighed by an increase in the total quantity of output. This phenomenon is also known as *rebound effect* (cf. Arundel & Kemp, 2009).

[Figure 8 about here.]

Figure 8 shows the evolution of relative nominal prices for capital goods and prices that are normalized by the supplied productivity level. Nominal prices evolve as expected, i.e. the more demanded technology becomes relatively more expensive which is a result of the adaptive pricing mechanism in the capital goods market. When considering not nominal prices normalized by the offered productivity level the pattern is reversed. In this setting the growth in the productivity performance outweighs the demand induced price increase of the more demanded technology. These plots confirm that the endogenous technological evolution dominates the market demand induced scarcity effect that underlies the upward trend of the nominal price ratio in favor of the more demanded technology.

The divergence between green and conventional technological regimes is not only reflected in technology utilization, but also in capital prices, skills and technological development. The endogenous nature of technological innovation

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importance. The number of 210 simulation runs was chosen such that it factorizes with the number of available cores of the computer that was used for the simulations.

is the dominating force that governs the process of divergence of the two technological regimes. A more detailed discussion of price indicators and the relative pace of learning and technological innovation is provided in the accompanying working paper Hötte (2019c).

[Figure 10 about here.]

The Wilcoxon test confirm the significance of differences between the switch and the other two scenarios. In the beginning, before the green capital producer enters the market, the differences are not significant but a considerable divergence is observable in later periods. Even though there are learning costs in terms of lower aggregate output in the switch scenario, the unemployment rate is lower which is due to lower average productivity. Unit costs are higher, firms charge higher prices but lower mark-ups. This additionally lowers the opportunities of investments and higher prices are reflected in lower real wages. In the switch scenario, firms have more employees on average but produce a lower quantity of output.

[Table 6 about here.]

B.2. Random barrier experiment

[Table 7 about here.]

[Table 8 about here.]

B.3. Policy experiment

B.3.1. Initialization

The initializations of the random parameters are summarized in table 9. On the left-hand side, the initial conditions for the full set of simulations are shown. The remaining columns represent the initializations of the runs within the subsets of ex-post classified technological regimes. The p-value in the last column indicates whether the difference in initial conditions between conventional and green regimes is significant tested by a two-sided Wilcoxon test. On average, β^A (ς^c) is significantly lower (higher) in the subset of green regimes. This is an indication that the interactions among policies and barriers might be important to understand the effectiveness of the other political instruments.

[Table 9 about here.]

Additional test statistics on the significance of differences between the policy and the benchmark scenario disaggregated by type of the emerging regime is available in the accompanying data publication.

B.3.2. Additional information about the evolution of policy effects over time

An evaluation of policy effects over time is made by a regression analysis of the diffusion measure and other firm-level variables on policy instruments, barriers and firm-level controls. To capture systematic differences across different technological regimes, a dummy variable $\mathbb{1}^{eco}$ and its policy interaction terms are included in the regression.[23]

[23] Additional technical information and a short discussion about the choice of this regression model is provided below.

[Table 10 about here.]

Table 10 shows the results of a regression analysis of the $\nu^c_{i,t}$ measured 5, 10 and 35 years after market entry ($t \in \{1800, 3000, 9000\}$) on the different policies, barriers and firm-level controls. The table has to be read as follows. The coefficient of $\mathbb{1}^{eco}$ shows fix differences between the different technological regimes. To get the marginal impact of a tax on $\nu^c_{i,t}$ in the transition regime, the coefficient of θ and $\mathbb{1}^{eco}\theta$ have to be added. Five years after market entry, all instruments are associated with a significantly lower share of conventional capital utilization.

The different instruments have different impacts on the shape of the diffusion curve and the impact differs depending on the type of the emerging regime. Ten years after market entry in $t = 3000$, all instruments still have a net negative association with $\nu^c_{i,t}$. In the transition regimes, the effect of θ is stronger, but the effect of the subsidies is weaker. 35 years after market entry, the θ has a net positive coefficient in the conventional, and negative in the green regimes. More conventional (green) capital is used in the conventional (green) regimes. Hence, both instruments have contributed to the technological divergence. The opposite is true for ς^i.

In another series of regressions, it is analyzed how the different policy instruments affect the firm size measured as the number of employees and production efficiency of firms captured by unit costs. The same model configuration is used as introduced above. The dependent variable is evaluated 5, 10 and 35 years after the day of market entry. The coefficients of the policy instruments and their interaction with the type dummy $\mathbb{1}^{eco}$ are summarized in table 10.

The regressions of $\#employees_{i,t}$ in $t = 3000$ and $t = 9000$ reveal that the increase in the average firm size that occurs in the transition regimes is alleviated by subsidies. At this early phase, the policy instruments have no significant relationship with the firm size if the economy is locked in. Unit costs are differently affected, dependent on the type of emerging regime. All policy instruments increase unit costs in the transition regime in $t = 3000$. This is largely explainable by increased learning costs.

In $t = 3000$, i.e. ten years after market entry, this situation has stabilized. In the lock-in regimes, a positive association between both subsidies and unit production costs is observed (cf. 10). The subsidies have stimulated the initial uptake of green technology. If firms switch back to conventional capital, they have the burden of green capital that undermines their speed of specialization in the conventional technology. The opposite effect is observed in the eco-regimes where the higher green capital penetration, in the beginning, accelerates the technological specialization.

B.4. Technical remarks on the regression analysis

B.4.1. Data preprocessing and controls

The simulated time series data is monthly data. The data that is used for the regression analyses is one-year average data averaging across the 12 monthly observations in the intervals $[600, 720]$, $[1800, 1920]$ and $[14780, 15000]$ for initial conditions, early adopters and the final state. For reasons of simplification, the firm data is treated as pooled cross-sectional data ignoring firm entries and exits.

The firm level controls that are included in the regression analyses, but are not explicitly shown in table 4 and 10 are the level of skills and productivity of the conventional technology, firm output, age and the price. ν^c_{i,t_0}, $\#employees_{i,t_0}$ and $UnitCosts_{i,t_0}$. In table 10 also barriers to diffusion are included in the model but not shown. Further, the number of employees and unit costs are also used as dependent variables. In this case, all controls are used except the dependent variable itself. All controls are measured in t_0. For all variables in the regression model, one-year average data is used.

B.4.2. Model selection

The main model selection criterion for the regressions presented in the article is *ease of interpretation*. Multiple other model configurations with different types of interaction and squared terms of barriers and policies had been tested and also different types of link functions. Some of these experiments are available in the accompanying data publication. The simple OLS version was found to deliver robust results and is easy to interpret.

Moreover, it should be kept in mind that this is a simulation model with many degrees of freedom. The exact shape of the non-linear relationship between diffusion barriers, policies and the transition probability is of little explanatory value because the empirical analogue is lacking. The chosen versions are sufficient to retrieve the most important structural relationships in the model and to illustrate the story of this paper.

B.4.3. Effectiveness of policies over time

In section 5.1 and 5.4, the results of a regression of $\nu^c_{i,t}$, $\#employees_{i,t}$ and $UnitCosts_{i,t}$ at different snapshot in time are introduced.

There might be concern about the inclusion of the dummy variable. The dummy variable is aimed to capture systematic differences between different types of technological regimes. One might be concerned about the endogeneity of the dummy variable and reverse causality in the regression model of $\nu^c_{i,t}$. In fact, these concerns cannot be ruled out. Alternative modeling approaches (instrumental variable and finite mixture models) had been tested, but these models suffer from other pitfalls. For example, it is not easy to find an instrument that is correlated with $\mathbb{1}^{eco}$ but not with the error term in the second stage regression. Mixture models are subject to a high number of degrees of freedom in the exact modeling choice. This makes it difficult to identify a robust functional form that is sufficiently general for the different data sets and allows the comparison over time.

The OLS model is mainly chosen for reasons of simplification, ease of comparison, interpretation and communication. Tests with other models did not yield substantially different results. Hence, for the purpose of underlining the theoretical findings that are derived in this study, the model seems to be sufficient even if the author is aware of the weakness of the statistical method.