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How to accelerate green technology diffusion? An agent-based approach to directed technological change with coevolving absorptive capacity

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How to accelerate green technology diffusion? An agent-based approach to directed technological change with coevolving absorptive capacity

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The window of opportunity for effective climate change mitigation is closing. Hence, it is decisive to understand how to accelerate the diffusion of climate friendly technologies. Path dependence of technological change is an explanation for sluggish diffusion even if a technology is superior in the long run. This paper studies the determinants of diffusion, learning and the coevolution of innovation and heterogeneous absorptive capacity. I show how the effectiveness of different market based climate policies depends on the type and strength of diffusion barriers.

I introduce a macroeconomic agent-based model that is an eco-technology extended version Eurace@unibi model. Technology is heterogeneous by type (green or brown). Firms choose between types when acquiring capital goods and build up type-specific technological know-how that is needed to exploit the productive potential of capital. Path dependence is operationalized as accumulated diffusion barriers taking the form of inferior technical performance of supplied green capital and type-specific know-how of adopters. The barriers interrelate with positive feedback loops from market induced innovation dynamics and learning by doing, and analyze how these mechanisms explain path dependence and the emerging macroeconomic patterns of technology diffusion. Environmental taxes can outweigh a lower technical performance and subsidies perform better if lacking capabilities hinder firms to adopt a sufficiently mature technology.

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Contents

1. Introduction

Climate change is an existential threat for human conditions of living. In its 2018 Special Report, the IPCC has highlighted that there is a window of opportunity to limit Global Warming to a manageable level, but the window is closing. The effective mitigation of climate change and the avoidance of its potentially disastrous consequences is critically dependent on a profound technological transformation from current fossil-fuel and resource-intensive techniques of production to climate friendly alternatives. Such technological transformation requires the development and fast diffusion of environmentally sound technologies (cf. European Commission 2011; IPCC 2015). Aim of innovation oriented climate policies is to overcome barriers and to strengthen drivers of green technology diffusion to accelerate the process of technological transformation. To design effective policies, it is important to understand the determinants of technology diffusion. The objective of this paper is to contribute to the understanding of these determinants and to link microeconomic insights on barriers to green technology adoption decisions of individual firms with the macroeconomic study of directed technological change. In a policy experiment, I show that the effectiveness of diffusion policies is sensitive to the type and strength of barriers, i.e. whether barriers relate to the side of technology supply or demand.

In this paper, green technologies are interpreted as eco-innovations. Eco-innovations are defined comprehensively as any type innovation across the whole economic system that are environmentally more benign than the incumbent technological solution. These innovations contribute to the achievement of climate targets and to overcome resource scarcity, and should simultaneously establish a path of sustainable economic growth (O'Brien et al. 2014). Innovation and climate targets are combined, and the complementary nature of environmental targets and economic development emphasized (Foxon and Andersen 2009). This contrasts with the trade-off conception that is suggested by numerous theoretical approaches in the economics of climate change that interpret any climate policy intervention as distortion to otherwise optimally allocated production and research resources (cf. Jaeger 2013; Stern 2008). Eco-innovation policies abandon the idea of directional neutrality of technological progress, and are aimed to steer the direction of technological development to establish a technological paradigm of sustainability.

These considerations shift the focus from aggregate welfare considerations towards an understanding of economic conditions that influence the direction of technological change. Dosi (1982) introduced the concept of technological paradigms embedded in the mindsets of technological practitioners, i.e. those who are in charge for the utilization, deployment and development of technical solutions. Their mindsets are built upon the prevalent technological environment, and are critical for the nature of technological solutions that are selected and technologically further developed. Cohen and Levinthal (1990) emphasize that firm specific technological capabilities determine firms' perception and ability to commercially adopt technological novelties.

The contingency of technology choice and innovation on the economic status-quo represents a source of *path dependence*. Path dependence is empirically well documented for the choice between the green and brown technologies (cf. Aghion et al. 2014, 2016;

Allan et al. 2014; Kemp and Volpi 2008; Safarzyńska et al. 2012; Sarr and Noailly 2017). This contingency represents an impediment for the diffusion of clean technologies if there is an incumbent alternative. Breaking path dependence in technological change is critical for the long-term effectiveness of climate policy, and the conditions how to overcome it are an important field of study for climate-economists working on directed technological change.

Existing macroeconomic studies on endogenous directed technological change identify the relative profitability of using and developing a particular technology to be decisive for the technology choice. Other approaches focusing on diffusion investigate the role of technological learning in terms of unit costs that are decreasing in cumulative production experiences. Gillingham et al. (2008) and Popp et al. (2010) provide comprehensive overview studies. Common to these studies is their aggregate nature and the abstraction from heterogeneity of technology types and its users. Though other studies found heterogeneity to be critical for the speed and shape of diffusion patterns (Allan et al. 2014; Comin et al. 2006).

In this study, I enrich the macroeconomic perspective on directed endogenous technological change by a microeconomic framework with an emphasis on evolving heterogeneity of firms in terms of capabilities to profitably adopt clean technologies. Technological capabilities of firms are accumulated over time during the process of production and represent a form of organizational learning (Thompson 2012). I show that these capabilities represent a decisive factor of green technology diffusion. Capabilities are technology specific and hint to the nature of the technological paradigm.

Green technologies interpreted as eco-innovations encompass the organizational and infrastructural environment that affects the effective productive usability of capital goods (Arundel and Kemp 2009). The two technologies are interpreted as competing technological regimes (Kemp 1994). Brown capital is assumed to be incumbent and green to be a market entering technology that can possibly replace the incumbent. Endogenous innovation and technological learning weaken or strengthen the firm specific profitability of technology adoption resulting in a bifurcation-like pattern of technology choice. Hence, the economy converges either to a green or brown technological state while the probability of a technological regime shift in favor of green technologies is dependent on initial conditions, endogenous technological advances and learning. Innovation oriented climate policies aim to alter the market conditions in favor of green technologies.

This study differs from equilibrium based approaches in one fundamental dimension. Equilibrium models rely on the assumption of socially optimal environmental-economic pathways representing climate policy as allocation problem (cf. Balint et al. 2017; Haas and Jaeger 2005). In contrast, this study frames the choice of the technological pathway as coordination problem with self-reinforcing dynamics. Welfare judgments about policy outcomes are made by the evaluation of macroeconomic variables of interest such as aggregate output, environmental effectiveness, unemployment or distributional patterns.

This simulation study is based on an eco-technology extension of the macroeconomic agent-based model (ABM) Eurace@unibi (Dawid et al. 2011, 2018d). The Eurace@unibi model is able to reproduce macro- and microeconomic stylized facts and was formerly used in different policy studies (e.g. Dawid and Gemkow 2013; Dawid et al. 2014, 2018b,c). The structure of the model resembles traditional macroeconomic models. In contrast to representative agent approaches, it is characterized by agent-heterogeneity, a high degree of behavioral resolution in agents' decision making routines that are subject to bounded rationality and limited foresight, and the focus on the dynamics of interaction. The eco-technology extended version of the model allows to investigate the dynamic interplay between technological characteristics, learning and innovation, its implications for green technology diffusion and the (long-term) effectiveness innovation-oriented climate policy. In this paper, I introduce the eco-technology extension of the model and show how the model reproduces stylized patterns of green technology diffusion. In a baseline simulation, the model exhibits a probabilistic technological regime shift. This shift is not necessarily stable but depends on the dynamics of competition, innovation and learning. These dynamics are partly probabilistic and partly a result from market interactions. In a series of experiments, I analyze how the market entry conditions interrelate with the emergent pattern of diffusion. I find that not only the performance of supplied technology important, but also the capabilities of technology users. The simulation results helps understanding diverse and partly opposite observations in empirical studies of technology diffusion. Two results from the study of barriers are worth being emphasized. First, technological uncertainty is costly. If the technological regime is unclear, potential adopters do not know in which technology to invest and possibly waste learning and R&D resources in the technology that is obsolete in the long run. Second, the analysis shows that relative prices and the relative performance of technology types matter. This could be a potential starting point for policies that steer the technological development in a sustainable direction.

In a policy experiment, I show that different policy instruments perform differently well conditional on the type and strength of diffusion barriers. If barriers are related to the technical performance of green capital goods, environmental taxes compensate for the disadvantage for the lower productivity. This barrier type is a *supply-side* barrier because the technological knowledge embedded in the productivity of the capital good can be bought on the market.

Barriers in terms of lacking capabilities of firms to make effective use of the green technology are *demand-side* barriers. Capabilities can not be bought on the market, but are learned during technology utilization. If barriers are demand-sided, subsidies can be a trigger of technological transition. Further, if the green technology is sufficiently competitive by its technological properties, a tax imposed on the utilization of brown capital in the pre-existing capital stock may work in an unintended direction because it hampers firms' financial capabilities to invest in green technologies.

Previous studies climate economic studies have focused on diffusion barriers at the supply side taking account of policy induced directed technical change. In this study, I show that the distinction between the two barrier types and their coevolution is essential to understand the differential effectiveness of different political instruments.

The remainder of the paper is structured as follows: In section 2, I motivate the objective and methodological approach of the paper by a survey of the related literature. In section 3 and 4, I introduce the main features of the eco-technology extension of the Eurace@unibi model and the design of experiments. The results of the baseline simulation and a series of experiments on the technological starting conditions of the entrant technology are discussed in section 5 and section 6 is dedicated to the policy experiments. Section 7 concludes with a discussion of the empirical interpretation and core insights of the analysis for diffusion policies.[1]

2. Related literature

This study is most closely linked to three branches in the literature. On the theoretical side, it bridges the macroeconomic literature on endogenous and directed technological change with evolutionary, microeconomic studies of technological learning, and highlights the implications for the effectiveness of climate policy. On the methodological side, the paper belongs to the young branch of evolutionary, agent-based macroeconomic analyses of climate policy.

2.1. Directed technological change as evolutionary process

Two aspects are in focus of macroeconomic studies of green technologies diffusion belonging to the field of directed technological change. First, technological change is endogenous, i.e. it is driven by goal oriented decisions about R&D investments and adoption. Second, technological change is non-neutral and the choice between different technology types is dependent on the relative performance of types. Climate policies aim to influence the relative profitability in favor of green technologies (Acemoglu et al. 2012).

Two branches of literature on endogenous directed technological change can be distinguished. The first branch is rooted in the neoclassical equilibrium tradition, and the second is based on evolutionary theory (see for an overview Balint et al. 2017; Gillingham et al. 2008; Löschel 2002; Popp et al. 2010; Sarr and Noailly 2017). The former has a relatively long modeling tradition and related studies build on (computable) general equilibrium and optimal growth models that have achieved a high degree of empirical coverage and complexity (Gillingham et al. 2008; Löschel 2002; Pizer and Popp 2008; Sarr and Noailly 2017).

Evolutionary approaches on macroeconomic green technological change represents a rather young field of research and climate policy analyses at the macro-level are scarce. Such studies are based on agent-based computational methods and allow the simulation of complex, nonlinear interactions of heterogeneous agents (Balint et al. 2017; Farmer et al. 2015; Gerst et al. 2013; Lamperti et al. 2018; Sarr and Noailly 2017). This project belongs to the second branch of literature.

In the evolutionary tradition, much emphasis is put on adaptive behavior and interactions at the microeconomic level as source of emerging macroeconomic stylized patterns of innovation, diffusion and technological change. The emphasis on interactions

[1] All results that are presented and discussed in this paper are available online in a separate data publication. The data publication does also contain the code of the simulation model and the software that was used for the statistical evaluation of the simulated data, and should enable the user to reproduce the results (see Hötte 2019).

is shared by many scholars on eco-innovation who emphasize the (yet) underexploited potential of evolutionary approaches to study the complex interactive processes that underly green technology development and diffusion (e.g. Rennings 2000; Safarzyńska et al. 2012).

Eco-innovations are defined as any technology for economic activity that is environmentally less detrimental than the incumbent alternative. The concept serves as interpretative framework for climate friendly technologies that compete with incumbent, conventional alternatives. In a macroeconomic framework, this is captured by the binary distinction between green and brown technologies. Eco-innovation is not linked to specific technical applications, but rather reflects a broader technological paradigm in terms of defining and achieving economic targets. Rennings (2000) argues eco-innovation diffusion to be an evolutionary process, and emphasizes the long-term transitory nature of eco-innovation.

Transition processes are subject to multi-level interactions of individuals and their socio-economic and structural environment. Challenges for sustainable transition policies are path dependence and lock-in effects that result from scale effects in technological learning and development, group dynamics, bounded rationality, and the coevolution of structures and behavior (Safarzyńska et al. 2012). Technological path dependence and lock-in effects in technology choice and the resulting modeling challenges have been extensively discussed by numerous authors (Arthur 1988; Dosi 1991; Gillingham et al. 2008; Löschel 2002; Sarr and Noailly 2017; Unruh 2000).

The evolutionary concept builds on an analogy between biological evolution and the three stage concept of innovation, i.e. invention, innovation in terms of commercialization of an invention, and diffusion (Dawid 2006). Emphasis is put on the interaction with the environment. The economic environment influences the decisions of firms and investors whether an invention is selected to be introduced on the market (Dosi 1991; Foxon and Andersen 2009).

The economic environment is a broad concept 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 routines in their production processes. It is closely linked to the idea of *absorptive capacity* (Cohen and Levinthal 1990). Here, I subsume the economic environment within firms' capabilities to effectively exploit the productive value of a specific technology. Potential adopters are faced with firm, industry or region specific challenges that arising from evolved infrastructures, technological capabilities and behavioral routines (Arundel and Kemp 2009). Firms are heterogeneous in terms of absorptive capacity. This capacity influences the perception and the productive value of a technological solution, and was highlighted a source of heterogeneous adoption patterns (Allan et al. 2014). I extend the interpretation of absorptive capacity to cover both, firm's capabilities but also firm specific external conditions such as complementary infrastructures that result from a coevolutionary process of using a specific production technology.

The decisive property of absorptive capacity and barriers to adoption is the cumulative nature, not the conceptual coverage. The accumulation of technology specific capabilities is dependent on the extent to which a specific technology type is used and can be interpreted as a microeconomic source of dynamic increasing returns that may result in path dependence (Arthur 1989; Dosi and Nelson). Absorptive capacity can be interpreted as technology specific capabilities of the adopter. The cumulative nature of technology specific capabilities can cause path-dependence of technological development and the sectoral composition of the economy. Path-dependence of technological progress is a widely recognized stylized fact of technological change (Arthur 1988; Dosi 1982, 1991; Hanusch and Pyka 2007; Huang et al. 2017), and is particularly important for climate policy design and the green transformation of the economy (Aghion et al. 2014, 2016; Kemp and Volpi 2008; Safarzyńska et al. 2012).

These findings underline the notion of technological paradigms by Dosi (1982), and highlight technological learning and limits to the transferability of capabilities across technology types to be an important determinant of successful diffusion. This is in line with the empirical investigations on barriers of eco-innovation diffusion (Arundel and Kemp 2009). In the present study, I take up the idea of technology specific capabilities as ability to make productively use of technical equipment of a certain type and study the interplay of knowledge accumulation, diffusion and policy. This investigation is based on an evolutionary, agent-based macroeconomic model. The model builds a bridge between the macroeconomic literature on directed technological change and the microeconomic (evolutionary) literature on the determinants of technology adoption. I propose a consistent modeling framework to embed the evolution of firm specific technological capabilities of firms and its interdependence with macroeconomic technological progress and innovation diffusion.

2.2. Evolutionary, agent-based macroeconomic models and climate change

Aspects such as the accounting for 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 (Farmer et al. 2015). Agent-based evolutionary models offer a tool to account for these aspects, though the number of these models is small.

Many existing approaches on eco-friendly technologies focus on the diffusion of specific technologies in spatially bounded areas (e.g. Cantono and Silverberg 2009; Karakaya et al. 2014; Schwarz and Ernst 2009; Sopha et al. 2011; Zhang et al. 2011), but are highly detailed with regard to the individual and regional adoption circumstances and technological characteristics. These models provide insights into the micro-level dynamics of innovation and diffusion processes, but lack important macroeconomic feedbacks.

The number of macroeconomic studies on green directed technological change is much scarcer. Seminal approaches in *macroeconomic* agent-based climate policy modeling were made by Gerst et al. (2013); Lamperti et al. (2018); Rengs et al. (2015); Wolf et al. (2013).

The existing macroeconomic agent-based models focus on different aspects related to the nexus of climate, the economy and policy. Similar to climate economic modeling in Computable General Equilibrium and Integrated Assessment Models, the ENGAGE model, proposed by Gerst et al. (2013) offers a detailed representation of the energy sector. The model is dedicated to serve as tool for scenario and policy discovery. It is calibrated on US data and captures different types of endogenous innovation improving labor or energy efficiency in the capital or consumption goods producing sector. Technological change from learning by doing and accumulated R&D efforts is manifested in energy efficiency and productivity improvements of capital goods.

The *Lagom* models developed by Haas and Jaeger (2005) and Wolf et al. (2013) present an early attempt to large-scale agent-based climate economic modeling. Much emphasis is put on the role of heuristically behaving agents with heterogeneous, adaptive expectations. Agents learn over time which implemented in the updating of structural characteristics represented by technology and consumption coefficients, mark-up rules and reference wages. Technological change occurs via imitation of successful behavioral routines and technological characteristics, and mutation which is interpreted as innovation. This process is independent of endogenous dynamics associated with differential R&D investments. A remarkable feature of the *Lagom* model is the possibility to use empirical input-output data and the possibility of a regional disaggregation.

Rengs et al. (2015) focus on the evolution of consumption behavior and the interplay of Veblen- and snob-effects steering the development of consumers' preferences for sustainable products. Diffusion among consumers arises through conspicuous consumption and herding behavior. The authors investigate how an interplay of different endogenous consumption dynamics interrelates with different types of climate policy.

The most recent approach in macroeconomic climate ABM is, to the best of my knowledge, the agent-based integrated assessment model (ABIAM) developed by Lamperti et al. (2018). It captures not only coevolutionary features of the economy, but also potential feedbacks from climate change. The model is based on the K+S macroeconomic ABM (Dosi et al. 2017) that is extended with a climate-economy module. Endogenous growth emerges from different types of incremental innovation that is improving labor productivity, energy efficiency or environmental friendliness. The directedness of technological change enters via the substitution possibilities and different types of renewable and fossil fuel energy and energy efficiency improvements.

It remains to be emphasized that agent-based climate economic models are at relatively early stage of development, and are hardly comparable in terms of empirical and sectoral disaggregation as achieved by popular equilibrium based climate-economic models. Therefore, these models should be seen, at least in the short term, as valuable methodological complement being able to shed light on aspects in climate-economic studies that are difficult or infeasible to capture by aggregate equilibrium based methods (Balint et al. 2017; Farmer et al. 2015; Pindyck 2013). In contrast to the agent-based climate economic modeling approaches discussed above, the model presented in this paper focuses on the demand side of technology in terms of evolving absorptive capacity of heterogeneous of firms that are potential adopters of green technology. Firms differ in their abilities to learn to make effectively use of specific technologies. This is a source of initial, but also emergent heterogeneity, and may have important implications for the success of green technology diffusion.

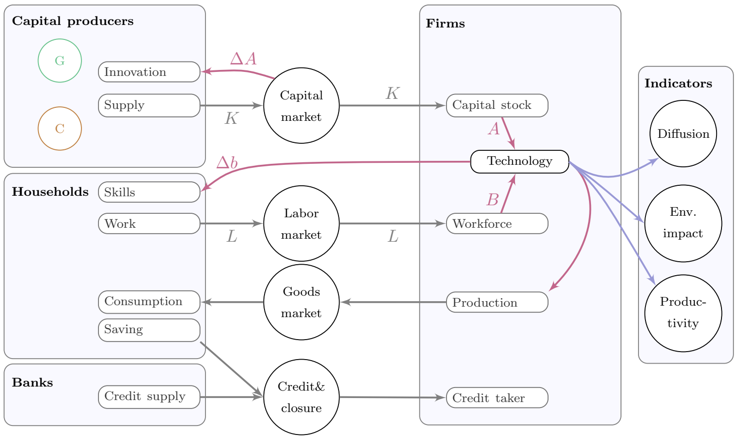


Figure 1: This figure gives an overview of the structure of the macroeconomic framework and shows how technology is embedded in this framework. It shows the main agents (two capital producers (G for green, C for conventional), firms, households), their main activities and the markets as places of their interaction. Gray (magenta) arrows indicate interactions on the market (flows of knowledge). A is the productivity of capital goods K, and B are technological capabilities of firms that are embedded in the technology specific skills b of employees L. Productivity of capital goods increases via endogenous innovation ΔA, households' skills increase by learning Δb. The financial module manages the settlement of monetary transfers and credit supply and serves as mechanism of macroeconomic closure (not shown here, see verbal explanations in the text and (Dawid et al. 2018d)). Blue arrows indicate the link of production technology to the main indicators for macroeconomic evaluation.

3. The model

The model is an extension of the macroeconomic, agent-based model Eurace@unibi (cf. Dawid et al. 2018d). In previous studies, the Eurace@unibi model was shown to be able to reproduce a number of macro- and microeconomic stylized facts.

In the following subsections, I briefly sketch the macroeconomic structure of Eurace@unibi. Subsequently, I explain the most relevant parts of the eco-technology extension in more detail. A more comprehensive technical documentation of the model extension can be found in the appendix (B).

3.1. Overview

The Eurace@unibi model represents a macroeconomy composed of groups of heterogeneous agents that are linked by their trans- and interactions. The most relevant agents are depicted in the flowchart in figure 1. Households supply labor on the labor market to consumption goods (CG) firms and spend their income for consumption and savings. Households are heterogeneous with regard to income and specific 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 captured by employees' specific skill level and the average skill level of the workforce is a proxy for technological capabilities B of the firm. This determines how productively the firm can make use of its capital stock K. 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 of different productivity levels A. By probabilistic, incremental innovation, IG firms are enabled to supply more productive capital goods.

In the eco-technology extension of the model, capital goods do not only differ in terms of productivity, but also by 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 from selling capital goods in R&D which positively affects the probability of innovation success, i.e. the likelihood to incrementally increase the supplied productivity by a factor of $(1 + \Delta A)$. Dependent on the productive properties of capital and firms' technological capabilities, CG firms make their investment decisions and buy capital goods on the capital market. Technology in the model is interpreted as the aggregate of the productivity characteristics of capital, firms' technological capabilities and the type of capital (green or conventional). The production technology of firms is decisive for their competitiveness in terms of production efficiency and for its environmental performance. On the aggregate level, technology is a core indicator to study diffusion patterns, and the economic and environmental performance.

Every agent has a bank account. Banks pay interest on agents' deposits and give credits to CG firms in case that a firm's financial means are insufficient to cover current expenditures and to finance investment. The financial market is also used as a technical tool to ensure the macroeconomic and financial closure of the model. A government which is not shown in the flowchart in figure 1 has a re-distributive and regulatory function. It collects income from taxes, pays unemployment benefits. The government is able to set specific innovation-oriented climate policies.

The model features endogenous firm entry and exit. Firms that are unable to repay loans run into bankruptcy and exit the market. New firms are founded randomly and start building up production capacities out of an initial monetary budget (see Harting (2015)).

The transactions between the agents are stock-flow consistent. Agents behave boundedly rational and have limited foresight, respectively incomplete information. Decision making and information updating processes and routines are asynchronous which is a source of stickiness of prices, wages and production decisions. Asynchrony means that some routines are executed on a daily, other on a monthly or yearly basis, or event based. For example, firms' credit demand routine is only executed if own financial means are insufficient. The asynchrony of production and consumption routines allows the modeling of inventory holdings on the CG market instead of instantaneous market clearing. Rather than being perfectly rational profit and utility maximizers, households and firms underly incomplete information and execute adaptive behavioral routines based on expectations.

For an extensive and formal 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. 2018b,d; Harting 2015). A very detailed technical overview of the baseline model is given in Dawid et al. (2011).

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

3.2. The eco-technology extension of Eurace@unibi

The most relevant changes and extensions compared to the baseline model are listed in table 1. The full code of the extended model is available in an accompanying data publication Hötte (2019).

The focus of this model extension are endogenous innovation dynamics of competing technologies supplied by two representative capital good producers. These are modeled as a technology race between an incumbent, *conventional* technology c and an entrant, environmentally sound *green* technology g. The use of the conventional technology is not only environmentally harmful, it also requires material and energy inputs that are costly. The green technology is environmentally neutral and allows adopters to reduce material input costs, i.e. it is potentially technologically superior in the long run. More generally, technological superiority is interpreted as unit production costs reduction that is enabled by radical innovation and not achievable by the incumbent technology. This may concern any type of variable input costs to production that is used in a bundle with production labor. It can be a material input but also another type of labor that can be replaced by a machine or any type of regulatory compliance costs. Examples are energy saving, computer and automation technologies, open source software and digital payment systems. In the climate context, input costs savings can also be regulatory compliance costs, often named as Pollution Abatement Costs Expenditures. In this study, the radical innovation is interpreted as a stylized version of input-saving eco-innovation defined as *any* change in (production) routines that is less environmentally harmful than the incumbent alternative (Arundel and Kemp 2009), but note that it may also be a regulatory shock that makes the use of the conventional technology more costly.

The most decisive part of the model is the representation of firms' production technology. Firms use labor and capital as inputs. Technology is interpreted as a bundle of immaterial properties embodied the these two inputs. It is composed of two dimensions. A *codified* dimension of technology is represented by the productivity A^v of a capital good k^v. The index v indicates a specific vintage of capital that is supplied by an IG producer $ig = c, g$. If not explicitly defined differently, throughout the paper superscript indices are used to indicate qualitative information about the type of a variable, i.e. the vintage or technology type. Subscript indices refer to the agent or time dimension t associated with the variable. If ig is used in the superscript, it refers to the characteristic of the technology item, if it is used in the subscript, it indicates that this variable is associated the capital good producer ig.

The second, *tacit* dimension of technology are technological capabilities B^{ig} of a CG firm that are embodied in the technological skills of the firm's workforce L. These capabilities are needed to make effective use of the productive properties of a capital good A^v. In other words, employees need to know how to use a specific type of capital productively. This knowledge is technology specific. An employee who knows how to use a conventional capital good does not necessarily know how to use the green alternative, but she can learn it if she accumulates experience when working with it. That means, employees, and consequently firms, are *learning by doing.* The codified part of technology is available on the market and uniform to all firms, but the tacit part is firm specific and introduces adopter heterogeneity. It can also be interpreted as a firm's absorptive capacity for a specific technology.

Henceforth, I will refer to the productivity of capital as *theoretical* productivity when referring to A^v and as *effective* productivity A^{Eff} when referring to the bundle of codified and tacit technological knowledge of firms. The effective productivity is bounded 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. Vintages are characterized by the tuple $(A^v, \mathbb{1}(v))$ where $\mathbb{1}(v)$ is the indicator for technology type ig. It takes the value one if the vintage is conventional, and zero otherwise. Hence, v simultaneously indicates the theoretical productivity and the technology type. The theoretical productivity of a capital good is a static property and uniform for all firms, but the 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 are embedded in the two dimensions of technology. Lacking capabilities can represent a barrier to green technology diffusion even if green capital is superior in terms of input cost savings.

Next to lacking capabilities, a second type of diffusion barriers can exist that is associated with technological characteristics of the capital good itself, i.e. green capital goods could be technologically less mature and have a relatively lower productivity A^v. These barriers represent a stylized aggregate of different types of diffusion barriers that had been documented in the empirical literature on eco-innovation (cf. Arundel and Kemp 2009). Diffusion barriers can be the source of a technological lock-in in the

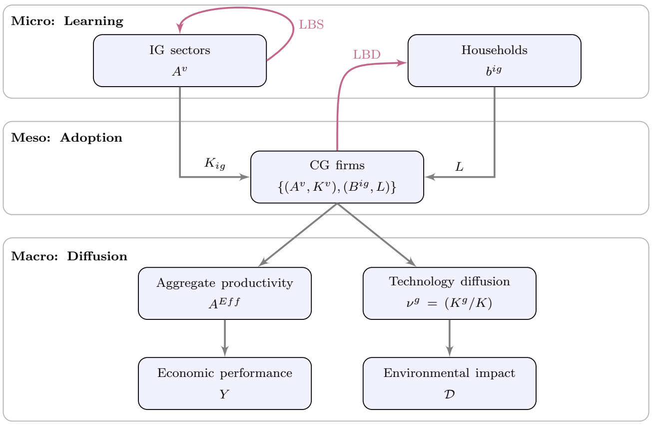


Figure 2: Schematic representation of the innovation, learning and diffusion module within the Eurace@unibi model. (1) Micro-level: Innovation and learning, i.e. IG sectors are *learning by searching* (LBS) via the re-investment of profits from selling capital goods K_{ig} in R&D and incrementally shift the technological frontier A^v upwards. Households are *learning by doing* (LBD) when working at firms with specific production capital. (2) Meso-level: Technology adoption by CG firms. CG firms acquire labor L and capital K^v to produce. Firms' tacit technological knowledge is embedded in the skills of their employees B^{ig}. CG firms decide which technology type $ig \in \{c, g\}$ is bought. (3) Macroeconomic level: Diffusion and economic performance. At the macroeconomic level the emergent properties of micro- and meso-level interaction become observable in terms of technology diffusion patterns measured by the share of green capital used ν^g and in terms of economic indicators such as aggregate productivity A^{Eff} and aggregate output Y.

conventional technology. Innovation oriented climate policies are aimed to overcome such barriers and to prevent a technological lock-in in the incumbent technology.

Two types of learning dynamics influence the evolution of the two dimensions of technology, i.e. the evolution of 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. A firm's capital stock is composed of vintages that may differ by productivity and technology type. Employees learn dependent on the type of the production machinery they use at work. The higher the relative intensity of working with a technology type and the better quality of the capital equipment of a certain technology type at the firm level, the faster employees accumulate the corresponding skills.

Second, endogenous innovation in the IG sector affects the codified part of technology represented by the level of labor productivity of supplied capital. IG firms invest a fraction of profits in R&D that positively affect the probability to successfully innovate and launch a new, more productive capital good on the market. Hence, IG firms are *learning by searching*. Higher profits of an IG firm are associated with a faster pace of technological progress in the corresponding sector. A stylized representation of technology, the learning mechanism and the role of technology for the macroeconomic outcome is shown in figure 2.

In the subsequent subsections, I introduce the relevant parts of the model extension in technical detail. These parts are the CG firms' production technology highlighting the difference between the theoretical and effective productivity of capital, and employees' learning function. A more comprehensive description of other relevant parts of the model, such as the investment decision rule of CG firms and the pricing, production and innovation routines of the capital good producers can be found in the appendix (B). To understand the findings of the simulation analysis, it is not required to know the technical implementation of the model introduced in the following subsections. An impatient reader may feel free to skip it and continue with section 4.

3.2.1. Consumption goods firms' production technology

CG firms produce homogeneous consumption goods with a constant returns to scale Leontief technology combining labor, capital and, in case of conventional capital, natural resource inputs. Labor is hired on the labor market. Capital goods are accumulated in a stock which 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 $K_{i,t}^{v}$ 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 $K_{i,t}^{v} := \{k \in K_{i,t} | A^v(k) = A^v, \mathbb{1}(k) = \mathbb{1}(v)\}$. Further, I use the notation $K_{i,t}^{ig}$ when referring to the part of the capital stock that is composed of vintages of technology type ig, i.e. $K_{i,t}^{c} = \sum_v \mathbb{1}(v) \cdot K_{i,t}^{v}$ and $K_{i,t}^{g} = \sum_v (1 - \mathbb{1}(v)) \cdot K_{i,t}^{v} = K_{i,t} - K_{i,t}^{c}$ where $\mathbb{1}(v)$ is the technology type identifier taking the value one (zero) if the vintage v is of conventional (green) type.

In absence of technology specific skills, different vintages are perfect substitutes, but in their presence the exploitation of the productivity of a given vintage at the firm level is constrained by the firm's technological capabilities. The effective productivity $A_{i,t}^{Eff_v}$ of a capital good v is given by

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

where A^v is the theoretical productivity and $B_{i,t}^{ig}$ 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 $A_{i,t}^{Eff_v}$ changes over time and varies across firms. The skill-dependent exploitation of productivity imposes a barrier to the adoption of new technology because 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

$$Q_{i,t} = \sum_{v=1}^{V} \left(\min\Big[K_{i,t}^{v}, \max\big[0, L_{i,t} - \sum_{k=v+1}^{V} K_{i,t}^{k}\big]\Big] \cdot A_{i,t}^{Eff_v} \right) \tag{2}$$

where $L_{i,t}$ is the number of employees, and $\sum_{v=1}^{V} K_{i,t}^{v}$ 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. 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 $\max\left[0, L_{i,t} - \sum_{k=v+1}^{V} K_{i,t}^{k}\right]$.[2] The cost effectiveness $\zeta_{i,t}^{v}$ is given by the marginal product $A_{i,t}^{Eff_v}$ divided by using costs, i.e. wage $w_{i,t}$ and, if it is a conventional capital good, unit costs of the natural resource input c_t^{eco}, i.e.

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

where $\mathbb{1}(v)$ indicates the capital type.[3]

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 can not be immediately adjusted, the consumption goods market does not necessarily clear (see for additional detail Dawid et al. 2018d).

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.

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

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. 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.[4]

The utilization of capital causes an environmental damage that is for simplification reasons assumed to be linear in the amount of conventional vintages used,

$$\mathcal{D}_{i,t} = e \cdot \sum_{v=1}^{V} \mathbb{1}(v) \cdot K_{i,t}^{v} \tag{5}$$

with e as fix environmental efficiency parameter. The share of conventional capital goods used by a firm in current production determines the environmental quality

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

[3]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.

[4]Note that this does only hold on average because wages may be different across firms.

of a consumption good. The quality is assumed to be not observable to consumers. The economy wide environmental impact is obtained by aggregating the firm level environmental damage over firms, i.e. $\mathcal{D}_t = \sum_i \mathcal{D}_{i,t}$. For reasons of simplification, environmental feedbacks on the economy are assumed away, since the focus of the present modeling approach is the study of technology diffusion.

Periodically, firms decide whether to invest in new capital items either for reasons of capacity expansion or to replace depreciated or obsolete units. This decision is based on the expectations about the relative profitability of different investment options. On the capital goods market, each capital producer supplies a range of vintages of different productivity. Hence, the available capital goods differ not only by technology type, but also by productivity within the same technology category. Using the estimated net present value, firms try to identify the best combination of quantity, productivity and technology type, and invest if sufficient financial means are available. These routines are explained in more detail in the appendix (B.2).

3.2.2. Capital goods and innovation

Two IG firms $ig \in \{c, g\}$ offer 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 it its technological frontier is shifted upwards and the firm is able to offer a new and more productive vintage with the productivity

$$A^V_{ig,t+1} = (1 + \Delta A) \cdot A^V_{ig,t}. \tag{6}$$

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

$$\mathbb{P}_{ig,t}[\text{success}] = \bar{p} \cdot (1 + \widehat{R\&D}_{ig,t})^{\eta} \tag{7}$$

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. When IG firms successfully innovate, they add a new and more productive vintage to the array of supplied vintages.

IG firms can only offer a limited number of vintages given by V. If this number is exceeded, the least productive vintage $v = 1$ becomes obsolete and is removed from the supply array. After the removal, vintages are re-indexed such that the index $v = 1$ corresponds again the the least, and V to the most productive vintage.

Innovation is associated with a learning process that has a positive side effect on the production costs of the whole range of supplied vintages. Labor costs for the production of a vintage v are proportional to its relative productivity in comparison to the least productive vintage $v = 1$. This proportion remains constant, but the least productive vintage is a more productive version after successful innovation. Hence, innovation allows the IG sector to produce more *productivity units* with given inputs.

IG firms use labor to produce capital goods and use adaptive mark-up pricing in response to the developments of their market share, profit and past pricing decisions. Profits are partly re-invested in R&D and partly recycled back to households as dividends. These and other routines such as production and pricing are explained in the appendix (see B.1).

3.2.3. Employees' technological learning

Households act as consumers, savers, and employees. The consumption decision is based on a multinomial logit function where the purchasing probability negatively depends on the price of the good (see Dawid et al. 2018d). CGs are assumed to be homogeneous from the consumer perspective even though products may differ by the environmental performance in production.

Technological learning is embedded in households' technology specific skills. Technology specific skills $b^{ig}_{h,t}$ are learned during work. The speed of learning depends on the technological properties of the capital stock that is used by the employer and the household's learning ability that depends on its (fix) general skills b^{gen}_{h} and moderates the speed of learning (cf. Dawid et al. 2018c).

There are two ways 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 accumulation 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

$$b^{ig}_{h,t+1} = b^{ig}_{h,t} + \chi_h \cdot \max\left[(\chi^{spill} \cdot \psi^{-ig}_{h,t}), \psi^{ig}_{h,t}\right] \tag{8}$$

with $\chi^{spill} \in [0, 1]$ as spillover intensity or degree of transferability of technological knowledge. Technology spillovers represent the part of technology specific skills that is transferable.[5]

[5] Skills are assumed to be not perfectly disjoint and limitations affect only the speed of learning. In principle, the difference in skills across technology types $\Delta b_{h,t} = b^{ig}_{h,t} - b^{-ig}_{h,t}$ can be completely closed via spillovers even if workers were never exposed to technology type $-ig$ with $ig, -ig \in \{c, g\}, -ig \neq ig$, but the pace of learning in skill category $-ig$ is lower.

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

$$\psi^{ig}_{h,t} = \max\left[\chi^{int}, \nu^{ig}_{h,t}\right] \cdot \Delta b^{ig}_{h,t}. \tag{9}$$

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 as *intensity of effort* or time invested in learning a specific type of skills (cf. Cohen and Levinthal 1990). Learning of a certain technology type ig is faster, if the relative amount of this type in the used capital stock is higher assuming that the relative amount reflects how intensely a worker is applying his technological knowledge and learns by doing. The fix parameter $\chi^{int} \in [0, 1]$ imposes a minimum level on the sensitivity of learning to the exposure of the employees to a certain technological environment.

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 with $A^{ig}_{h,t}$ as average productivity of capital of type ig that is used at the firm where the household is working. The learning potential is given by the gap between the average productivity level $A^{ig}_{h,t}$ and the households current skill level $b^{ig}_{h,t}$. 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).

3.2.4. Green technology producer's market entry and barriers to diffusion

At the day of market entry t_0, the eco-technology becomes available as investment possibility for CG firms. At that time, the capital stocks of all CG firms consist of merely conventional capital, and workers have only worked with conventional capital. In the literature on eco-innovation diffusion, it is extensively discussed how (green) entrant technologies may suffer from different types of adoption barriers, such as technological disadvantages, infrastructural and network effects in favor of the incumbent technology, skill and learning related barriers, and/ or financial constraints of the adopter or the vintage structure of the adopter's capital stock (Arundel and Kemp 2009; Carlsson and Stankiewicz 1991; Triguero et al. 2013).

I focus on those barriers that undermine the effective productivity of capital and result from lower relative knowledge stocks stemming from less cumulated R&D efforts and less experience in technology utilization. Barriers to diffusion are effective in two ways. At the day of market entry t_0, the entrant green technology sector has a lower technological frontier A^V_{g,t_0}. Hence, supplied vintages have a 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 knowledge 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 conventional technology.

At the day of market entry t_0, the green IG firm starts supplying a first vintage of green capital. This green vintage is initialized proportionally to the least productive vintage offered by the conventional firm, i.e.

$$A^1_{g,t_0} = (1 - \beta^A) \cdot A^1_{c,t_0} \tag{10}$$

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 further varieties of green capital. In particular, a whole array becomes successively available. Half a year after the day of market entry, the next and incrementally more productive vintage is added with the productivity level $A^2_{g,t} = (1 + \Delta A) \cdot A^1_{g,t} = (1 - \beta^A) \cdot A^2_{c,t_0}$.[6] This procedure repeats every sixth month until the array of supplied vintages has reached the maximum supply number. Further technological progress happens through the innovation procedure as introduced above (see 3.2.2). 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.

Similarly is the initialization of technology specific skills for green capital utilization. Households' endowment with green technology specific skills is scaled in relation to its specific skill level for conventional technology use, i.e.

$$b^g_{h,t_0} = (1 - \beta^b) \cdot b^c_{h,t_0}. \tag{11}$$

The parameter $\beta^b \in [0, 1)$ describes a technological knowledge gap, in particular it determines the extent to which households' skill level for green technology utilization is lower in relation to that of the conventional technology. For example, if $\beta^A = \beta^b = .05$, supplied vintages of the green firm have a 5% lower productivity and employees have a 5% lower level of knowledge about the utilization of green technology in comparison to conventional capital.

4. Settings and experiments

4.1. Calibration and initialization of parameters

The simulations are run with $H = 1600$ households, two IG firms, two private banks and $I = 120$ 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 active number of CG firms is set to 74.[7] The simulations are run for $T = 15000$ iterations corresponding to approximately 62.5 years interpreting one iteration as working day and a year to

[6] Six months can be referred as to "rapid" in comparison to the innovation probability that ranges around 3% (not constant) which corresponds to approximately one innovation each five years.

[7] Do not wonder about this apparently arbitrary number. It is due to the calibration via running the model through a transition period before the experiment starts.

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. At the day of market entry, the green technology producer is assumed to suffer from entry barriers corresponding to a $\beta^A = 5\%$ lower frontier productivity A^V_{g,t_0} and $\beta^b = 5\%$ lower technology specific skills b^g_{h,t_0} embodied in employees' capabilities. These assumptions are later relaxed in a series of experiments about drivers and barriers to diffusion, and their interplay with innovation oriented climate policy.

To justify the model's suitability as 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), i.e. 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 stylized facts used for model validation is provided in appendix A. The parameter settings are summarized in the appendix C.1. Most of the parameter values are taken from the original Eurace@unibi model (see for more detail on the model calibration Dawid et al. 2018b, and the references therein). Some of the parameters have been slightly adjusted to iron out distortions caused by the model extension.

Other parameters allow to steer the cyclical volatility of the model for example via the time horizon chosen for the smoothing of dividend payments or the revenue recycling of IG producers. These parameters are set relatively conservative to reduce the influence of business cycle dynamics on technology choice. These dynamics may reveal insights into the industrial dynamics in economically fragile environments and investment cycles, but hamper the isolation of the different determinants of technology choice.[8]

In this analysis, moderate technological spillovers are assumed, i.e. χ^{spill}= .5 and χ^{int}= .5. An in-depth analysis on the role of learning spillovers for technology choice and the evolution of market structure is subject to a forthcoming study. The characterization of eco-technology and associated learning spillovers is highly stylized. It is likely that the technological knowledge required for either technology is partly transferable (cf. Cohen and Levinthal 1990). For example, skills such as programming or basic engineering knowledge are usable independently of the *type* of capital that is

[8]This might be a restrictive assumption because business cycles had been shown to play a decisive role for the investment in new technologies. For example, Anzoategui et al. (2016) have investigated the role of business cycles on a technology adoption and explain the persistence of negative productivity shocks by reduced investments in new technology during crises, but did not distinguish between different types of technology. Purpose of this study is the investigation of factors that hinder the switch between different, substitutive technology types even though the study of the impact of business cycles on directed technological change represents a promising field for further research. Hershbein and Kahn (2018) have provided job posting based indication that the Great Recession was a trigger of routine-biased technological change in severely hit areas in the US. Though, an investigation of the role of business cycles in the presence of different barriers to adoption is beyond the scope of this study.

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 $\chi^{int} > 0$ assumption (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 the 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%.

4.2. Simulations

A series of experiments is run to investigate the coevolution of technology diffusion, the stocks of technological knowledge and relative superiority of a technology type. The initial conditions at the day of market entry can be decisive for the type of the technological regime at the end of simulation time.

The experiments investigated below start with a baseline scenario with fixed entry barriers at a sufficiently low level such that a technological regime shift toward green technologies occurs in approximately 49% of the cases. The analysis of the benchmark helps understanding the dynamics of the model and to characterize two types of possible regimes with either green or conventional technology dominance.

The parameters β^A and β^b represent different types of barriers to green technology diffusion. In simulation experiments, I investigate first the relationship between diffusion and the strength of barriers. In a subsequent experiment, I explore the implications for the design of innovation oriented climate policies comparing different political instruments, namely an environmental tax that makes the use of the incumbent conventional technology more expensive and two subsidies that either stimulate the adoption of green technology at the firm level, i.e. an investment subsidy for green capital, or focus on the creation of "green product markets", i.e. a price support paid for final goods that are produced with green machinery.

5. Results

In this section, I give an overview of the core findings of the simulations. In the first subsection, I discuss the bifurcation like pattern that results as a consequence of the technological regime shift. Thereafter, I present the results of the experiments on the strength of barriers.

The most relevant indicator for technology diffusion is share of conventional capital used in t. The inverse $(1 - \nu_t^c)$ indicates green technology diffusion at the intensive margin, i.e. it indicates how intensively a certain technology is used in t.[9]

[9] An alternative indicator is the productivity weighted share of green capital in production. Which indicator to use is a matter of priority setting in the analysis. The unweighted measure has the advantage that it is more informative about the environmental performance of the economy and about employees exposure to a specific technology type and its consequences for learning. However, the link between these two aspects and the unweighted diffusion measure is a result from the

Insights on the evolution of adoption barriers are derived from the differences in the stocks of codified and tacit technological knowledge which are represented as the ratio of frontier productivity of the conventional to the green technology $\alpha_t := A^V_{c,t}/A^V_{g,t}$ and the ratio of the corresponding skill levels $\beta_t := b^c_t/b^g_t$ where b^{ig}_t is the average technology specific skill level of all households in the economy.

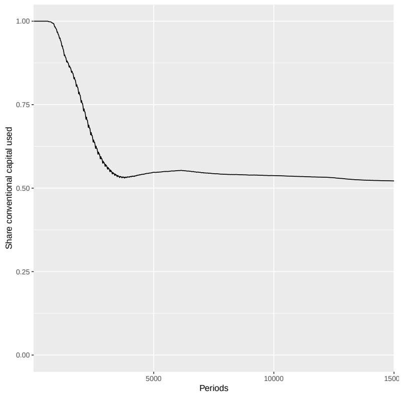
5.1. The baseline scenario: Two possible technological regimes

For this exercise, the entry barriers are set at a sufficiently low level such that the the green technology outperforms the conventional in terms of effective using costs captured by $\zeta^{ig}_{t_0}$ for an average firm. This setting is chosen to illustrate that path dependence in technological learning may outweigh technological superiority in the long run. In a subsequent sensitivity test, this assumption will be relaxed.

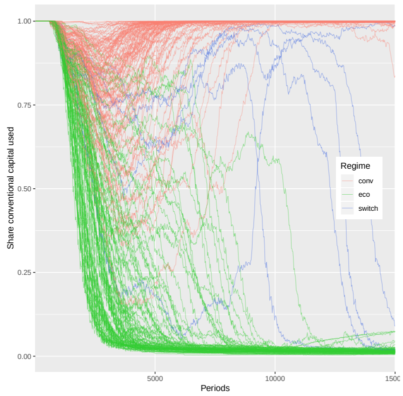
As expected, initial adoption rates are high which is plausible from the fact of lower effective using costs. Figure 3 illustrates the evolution of the share of conventional capital use in the simulation runs. On the left hand side, the share is shown for the average across runs. On the right hand side, it is shown for single runs. It becomes clear that the consideration of the average hides a pattern of divergence in the technology choice. The disaggregated plot indicates that a phase of initial green technology take up is not necessarily sustainable. In the beginning, in almost all simulation runs the share of conventional capital used decreases, but in approximately 51% of the considered cases the initial diffusion reverses after some time and the share converges to a technological state with roughly 100% utilization of conventional capital. Though, the technological regime is not necessarily stable. In some of the simulation runs, the direction of the diffusion process switches several times.

Henceforth, I use the word "technological regime" to describe the dominance of a technology type measured at the *intensive margin*. A technological regime is defined by the 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 $r^{conv} = \{r \in R/\{r^{switch}\}|\nu^c_{T,r} \geq .5\}$ where r represents a single run out of the full set of runs R and r^{switch} is a special case introduced below. I define a *regime shift* or *green transition* by a situation where the incumbent conventional technology is replaced by the entrant green until the end of simulation time, i.e. $\nu^g_T = \frac{\sum_i \sum_g K^g_{i,t}}{\sum_i \sum_v K^v_{i,t}} > .5$. The plotted 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 almost 100% or 0%. Using these definitions, 98 (107) out of 210 runs are defined as *eco* (*conv*) scenarios. The remaining 5 are classified as *switch* scenarios which are discussed in further detail below. The distinction between different technological regimes and a look on the diffusion curves (3) reveals that initial adoption is not necessarily stable. In some cases the fall back towards the conventional technology is subject to a second reversal towards the green technology. Hence, it is important to understand why this happens in the simulations

Leontief assumption made about the production technology with respect to both, labor and natural resource inputs.



(a) Batch



(b) Disaggregation

Figure 3: These plot show the evolution of the share conventional capital used for production from the day of market entry onwards. The lower the share, the higher is the diffusion of green capital in actual production. Figure 3a shows the average across all simulation runs. Figure 3b shows the share for each single run. The colors are an indicator for the type of technological regime. Green (red) can be interpreted as scenarios in which the economy converges to a technological regime with only green (conventional) capital utilization. The color blue indicates those runs, that are characterized profound switches between the two types of technology used. Precise definitions of the regimes are introduced in the text.

and what can be learned from these insights about real world patterns of technological competition and diffusion.

Before addressing questions related to the process of transition, it is worth mentioning the key difference between the green and the conventional regime that is relevant for climate policy analysis. Next to the technological divergence, there is also a divergence in the environmental performance. The use of conventional machinery is associated with a negative environmental externality. This externality can be assessed by considering the evolution of the aggregate environmental impact (C.1a). The model is calibrated such that the environmental impact stabilizes at a given level if a technological transformation does not take place and is reduced to almost zero if there is a transition to green technology. Though, the evolution of environmental impact per unit of output (called *eco-efficiency*) reveals a pattern of *relative decoupling* caused by improvements in productivity (C.1b), hence the reduction of damage per unit of output. Though, for the achievement of climate targets an *absolute decoupling* is needed, i.e. the reduction of the aggregate environmental impact (Arundel and Kemp 2009). In particular, relative improvements in efficiency are not sufficient if the gain in terms of reduced emissions is outweighed by an increase in economic output.[10]

Three questions arise from these observations and guide the following analysis: (1) What are the underlying reasons for the convergence to stable states, (2) for the

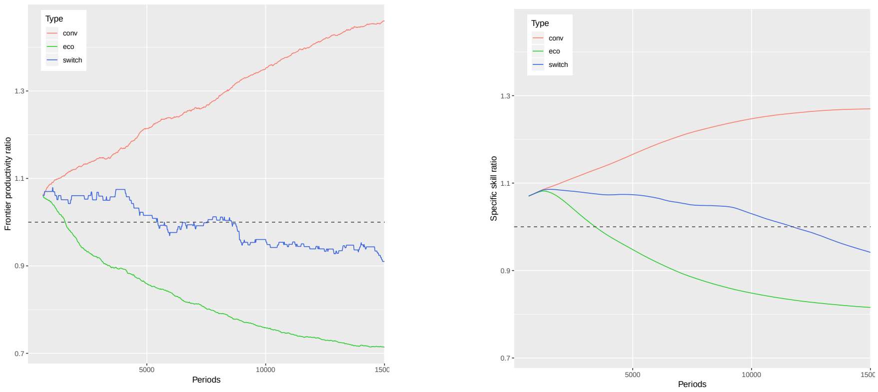
[10]This insight has given rise to the debate related to post-growth economies (e.g. Jackson 2009). Much of the controversy is sensitive to the choice and definition of economic output and empirical issues of measurement, though there is a consensus about the necessity of change in patterns of production and consumption and subject of this study is to gain an understanding of the drivers and barriers of change.

probabilistic nature of the technological regime shift, and (3) why is the regime shift reversed in some cases. Further, I investigate the macroeconomic implications. To address the third question, I define an additional state of technological regimes, called *switch* regimes, where the diffusion pattern exhibits high volatility over the considered simulation period.

These scenarios are identified by two criteria: (a) The level of conventional (green) technology utilization did not converge to a level close to 100% by the end of the simulation horizon, i.e. it is less than 90%: $a := (\nu^{ig}_{T,r} < 90\%), ig \in \{c, g\}$. (b) The final level of conventional (green) capital utilization is higher than 50%, but the minimum level of conventional (green) technology utilization within the second half of simulation time had been fallen below 25%, i.e. $b := (\nu^{ig}_{T,r} > .5 \wedge \min_{t \in [t_{half}, T]} \nu^{ig}_{t,r} < .25), ig \in \{c, g\}$. In these scenarios, the variation in the diffusion dynamics is high for a long time which is an indication for late or lacking technological convergence. The criteria for the selection of the switch scenarios are set arbitrarily and specifically for the given set of simulations, but identify those scenarios that are characterized by a *long* lasting uncertainty about the final technological state. I refer to this phenomenon as *technological uncertainty.*

The switch scenarios occur relatively rarely. In the present set of simulations it happened only in 5 out of 210 runs. A proper statistical analysis of this scenario type would require a larger sample, and the insights drawn about r^{switch} should be interpreted as hints to interesting aspects rather than generally valid regularities. Henceforth, the results are represented as aggregates across runs differentiated by technological regime.

Which are the drivers of technological convergence? A good candidate to explain the stabilization in final states is the endogenous nature of learning. As illustrated by figure 4, the bifurcation like pattern is also observable in the evolution of the ratio of technology specific skills needed for conventional capital utilization over those required for green capital β_t and in the corresponding ratio of frontier productivity α_t. Worth noting is the contrast between the smooth and lagged process of learning by doing captured by the skill ratio in comparison to the jumpy nature of the technological frontier that results from the probabilistic nature of innovation. In consequence, the divergence of the β_t curves is smoother than the divergence of the frontier curve α_t. In the initial phase, the skill related disadvantage is increasing for *all* regime types, while the difference in the frontier productivity exhibits an immediate divergence between the different regimes. Hence, the relatively lower endowment with skills for green capital utilization can be seen as a factor that retards the process of green transformation. In contrast, the difference in the technological frontier diverges early and appears to be an early indicator for the direction of further technological evolution. Alternative explanation for the technological divergence could rely in relative prices for capital goods. In figure 5 two plots of capital price indicators are shown. The plot on the left hand side, 5a shows the ratio of nominal prices for the most productive vintage of the conventional producer and green producer. As expected, the adaptive pricing rule causes a divergence such that the prices for the more demanded technology



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

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

Figure 4: Plots of the evolution of entry barriers from the day of market entry onwards. Figure 4b (4a) show the evolution of the percentage difference of technology specific skills (the technological frontier) for an average run within the corresponding technological regime (as defined in the text) indicated by the colors.

type are higher in nominal terms, i.e. the green technology is nominally more (less) expensive if the green (conventional) technology dominates the market. Though, more important than nominal prices are prices per productivity unit. Here, the opposite is true. Apparently, endogenous technical progress that shifts the technological frontier upwards dominates the price dynamics of adaptive pricing in response to market demand.

It becomes clear from all these plots that the divergence between green and conventional technological regimes is not only reflected in technology utilization, but also in capital prices, skills and technological development. It seems that the endogenous nature of technological innovation is an important force that governs the process of divergence of the two technological regimes.

The evaluation of the price per productivity ratio, points to an aspect that may help answering the questions about the stability of diffusion. The curve for of the *switch* scenarios remains relatively close to the initial level during the first half of the simulation horizon and later rather co-moves with the curve of the *conventional* regimes while the nominal price ratio, but also the α_t and β_t curves rather co-move with the curve that represents the *eco* regimes. Another interesting question is how firms' ability to make effective use of a technology develops. In figure 6a the evolution of the ratio of the average effective productivity $A_t^{Eff(ig)}$ of firms is shown. This pattern very well coincides with the observations made about the evolution of the frontier and technology specific skill ratio.

The degree of technological novelty of a capital good is a measure for difference between employees technology specific skills and the technological frontier of a technology type and is decisive for the pace of learning (see above 3.2.3). It is here defined as the ratio of the frontier productivity and employees' corresponding skill level, i.e.

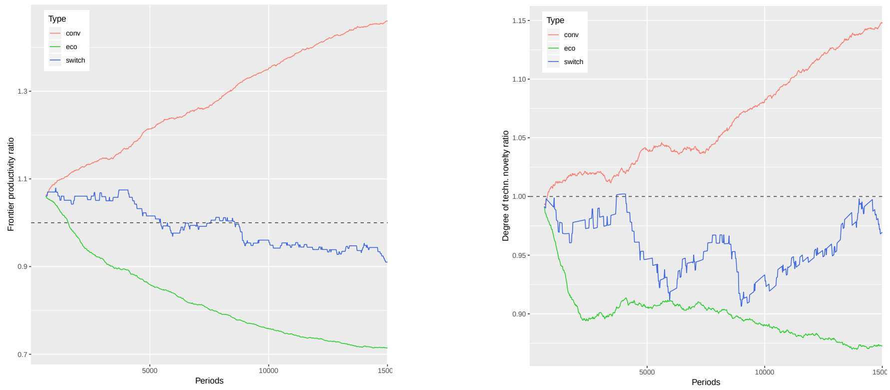
(a) $\frac{p_t^c}{p_t^g}$ (b) $\frac{p_t^c/A_t^c}{p_t^g/A_t^g}$

Figure 5: The colors indicate the scenario type as defined in the text (green for r^{eco}, red for r^{conv}, blue for r^{switch}). Figure 5a the evolution of the ration of prices paid for the most productive vintages supplied by the conventional and green producer. Figure 5b shows the evolution of the price-per-productivity-unit ratio.

$(A^V_{ig,t}/b^{ig}_t)$.Employees learn only if they are exposed to technological novelties. Roughly spoken, they learn only if there is something new to learn. The evolution of the relative degree of technological novelty, i.e. the ratio of novelty of the two technology types, is shown in figure 6b. In the green scenarios, at the early phase of technology uptake the degree of technological novelty of the green technology increases rapidly but stabilizes after some time. Worth mentioning is one observation. The relative degree of technological novelty is higher for the dominating technology.The divergence in the relative degree of novelty across technological regimes indicates further, that the dominating technology grows faster in productivity than the corresponding skill level. The pace of technological improvement by innovation is relatively larger for the dominating technology. Learning in the dominated technology is to a higher extend driven by spillovers than by learning by doing.

It is not only interesting to study the patterns of technological development, but also to have a look on the macroeconomic outcome in general. A relevant issue in studies on directed technological change are the costs of learning during the transformation towards green or technologies that replace an incumbent conventional technology type. Costs of learning can be interpreted as a type of *abatement costs*. Traditionally, abatement costs are a concept in climate policy analysis and understood as production inefficiencies in terms of distorted allocations of production resources when environmental regulations are imposed (cf. Pizer and Popp 2008). Though, the concept of abatement costs relies on the assumption of efficient production with unique equilibrium in the business-as-usual (when no policy is applied), an assumption that does obviously not hold in this study.

The model gives an evolutionary interpretation of abatement costs, namely those costs that result from the switch to an alternative, less mature and routinized technology.



(a) $\frac{A_t^{Eff_c}}{A_t^{Eff_g}}$ (b) $\frac{A^V_{c,t}/b^c_t}{A^V_{g,t}/b^g_t}$

Figure 6: The colors indicate the scenario type as defined in the text. Figure 6a shows the evolution of the ratio average effective productivity of firms, and figure 6b shows how the relative degree of novelty develops. A value > 1 indicates that the conventional technology is relatively "more new" to employees than the green technology. The degree of novelty is an indicator for the pace of progress and is relevant for the speed of learning.

The simulation results exhibit multiple (stochastically determined) stable economic pathways that can be compared with each other.

The technology shift is associated with the obsolescence of technological knowledge which is more pronounced if the technological pathway is uncertain and producers enduringly switch between green and conventional capital. Figures 7 illustrate differences in macroeconomic indicators across the different technological regimes, i.e. monthly (log) output and the number of active firms. Additional plots on further macroeconomic indicators such as unemployment, the price for the natural resource and the consumer price index can be found in figure C.2 in the appendix. To check the significance of differences across scenario types, I ran a series of Wilcoxon rank sum tests comparing the averages of different subsets of time accounting for different phases of diffusion (before market entry, initial, medium , and end phase) and with/without control for *switch* scenarios. The tests confirm that the differences across all scenario types in output, unemployment and the natural resource price are not significant before the day of market entry, but become significant if comparing later snapshots in time. The *eco* and *switch* scenario do not exhibit significant differences in monthly output in the initial phase of technology diffusion, i.e. in $t \in [601, 3000]$, but both are associated with significantly lower output than the *conventional* regimes. This could be interpreted as *learning costs* in terms of lower productivity and output. In the long run, learning costs in terms of lower output are not significant when comparing the *eco* and *conventional* regime, but the *switch* scenarios exhibit significantly lower output. A similar observation can be made when considering the unemployment rate, but here, the switch scenarios are associated with lower unemployment. These findings are interpreted as costs of *technological uncertainty* that is reflected in a lower output in absolute terms and in relative terms per unit of labor. Lower unemployment rates can be desirable, but in the present case it represents a waste of resources if invested labor resources are not associated with a gain in total wealth and when neglecting distributional consequences. A summary of the test statistics for the time before market entry and the whole sample is provided in table 15 in the appendix. The Wilcoxon test further confirms that there is no significant difference in the price for the natural resource in relation to the wage when comparing the green and the conventional regime. This is intended by the design of the price adjustment mechanism that determines the price of the natural resource, and confirms the technological divergence in the baseline scenario is driven by other factors than the evolution of input prices.

Apparently, there are no abatement costs in terms of output in the long run if the technological evolution is clear cut, i.e. when comparing green and conventional regimes. But there are learning costs. In the early phase of technology diffusion, i.e. in the first ten years after market entry, aggregate output is significantly lower. But this is only a temporary effect that diminishes by the end of simulation time. The time series of the number of active firms indicates stronger competition that leads to the market exit of firms and, likely as a consequence, higher unemployment. As observable in the plot of the evolution of the number of active firms, figure 7 the market cleansing at the end of the transition time occurs only in the case of a technological regime shift but not when the conventional technology remains dominant. This is in line with the Schumpeterian idea of creative destruction associated with radical innovation. Competitive pressure increases and leads to the market exit of firms that are not able to adapt to the new technological environment.

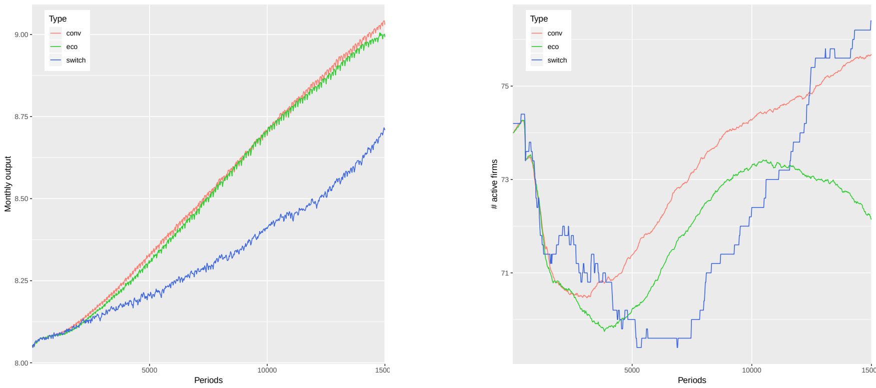
In contrast, if there is high uncertainty about the resulting technological regime and the evolution is characterized by enduring switches between green and conventional technologies, no technological specialization occurs. Costs of learning and the obsolescence of knowledge are high. The plot of monthly output indicates that these costs are reflected in final output.

5.1.1. The model's empirical relevance: Stylized facts of diffusion and technological superiority

The results of these simulation exercises can be linked to two patterns that are central in empirical studies on diffusion and can be used for the validation of the model.[11]

1. **Patterns of diffusion:**
   Many studies in innovation economics refer to an s-shaped pattern of diffusion. It captures the observation that diffusion processes are composed of a phase of early adoption with low adoption rates, a phase of acceleration when the adoption rate reaches its maximum and a phase of saturation. This is explained by different potential reasons such as the spread of information and heterogeneous benefits from technology adoption (Allan et al. 2014; Kemp and Volpi 2008; Nelson and Winter 1977; Pizer and Popp 2008; Rogers 2010).

[11] Further stylized facts that served as guideline for the design of the model are summarized in appendix A.2.



(a) Monthly output

(b) #active firms

Figure 7: These figures show the evolution of output and the number of active firms. The different colors indicate the technological regime type. The jumpy behavior (esp. for the number of active firms) of the blue line (indicating *switch* scenarios is due to the small number of runs within the set).

Though, the s-shaped pattern is a generally observed pattern when considering diffusion at the intensive margin and taking account of replacement dynamics. The intensive margin refers to the intensity of use, and not only to the binary occurrence whether the utilization of a technology was observed or not (named as *extensive margin*). Comin et al. (2006) made a comprehensive study on historical technology adoption data covering 115 different technologies, 150 countries and 200 years. They found that the s-shape does not to hold in general when using the *intensive* margin as diffusion measure. In some cases, the authors confirmed the s-shaped pattern, 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-shapes refer to situations in which a technology initially diffuses until it is replaced by a superior technological alternative. The present study sheds light the dynamic interplay of learning and endogenous innovation in an environment of two competing alternatives. Learning and innovation are key to understand the evolution of substitutability and superiority among competing technologies. Recall that technology specific skills can be interpreted very broadly and may capture *all supporting factors* that facilitate the effective utilization of a technology, are built up over time of use and are not bought by individual users on the market. This can be specific knowledge, but also infrastructure, institutions and supply and demand networks, etc.

2. **Path-dependence of technological change:**
   Path dependence in processes of neutral and (climate friendly) directed technological change is documented in the innovation and endogenous growth literature. Identified sources of path-dependence are learning and network externalities, the institutional environment, habits and search and information frictions (Aghion

et al. 2014, 2016; Arthur 1988; Dosi 1982, 1991; Hanusch and Pyka 2007; Huang et al. 2017; Safarzyńska et al. 2012). In this study, path dependence of technological change is reflected in the two stocks of technological knowledge, i.e. technology specific skills and the productivity of the available technology types. The perceived, relative profitability of a technology type determines whether it is chosen by adopters. The relative difference between green and brown skills, interpreted as *tacit*, and between the corresponding technological frontiers, interpreted as *codified* technological knowledge, are informative about the relative profitability. The main distinction between these two knowledge types from an economic point of view is that, in contrast to codified, tacit knowledge can not be bought on the market. There is a general endowment with tacit knowledge in the economy embedded in the economy's labor force, but its level is heterogeneous across firms.[12]

The bifurcation-like patterns of the two types 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 one of two possible technological regimes.

The Eurace@unibi-eco model is able to reproduce different types of diffusion curves dependent on the settings concerning the entry barriers.

Barriers can also be prohibitively high that either no diffusion at all occurs or only for a very short period in time. A small fraction of firms invests in green capital goods, but the market penetration of green capital does not achieve a sufficiently high level. Technological disadvantages of the green technology become stronger as a result of endogenous learning and innovation. In the long run, the green technology is not any longer used by individual firms.

If barriers are sufficiently low, the model shows an concave diffusion pattern measured by the share of green capital used in current production. Initial diffusion starts immediately because the green technology outperforms the conventional alternative until it slows down. The slow down is caused by two reasons. First, the skill related barrier is increasing. Learning in a category is positively dependent on the share of the technology type that is used and the pre-existing capital stocks are entirely composed of conventional capital. This favors the incumbent technology at the early phase of diffusion. Second, the green technology producer increases prices in response to the positive demand shock.

The most interesting case are intermediate barriers ranging between $5 - 10\%$ productivity and skill related disadvantages. These values are associated with s-shaped and inverted u-shaped patterns with fluctuations if the periodicity of observations is sufficiently small (e.g. monthly, non-smoothed data). In the initial phase, the technology slowly starts diffusing. The slow start is mainly explainable by the relatively smaller supply portfolio of green alternatives. At the day of market entry, only one vintage of green capital is available on the market, but a higher number of conventional

[12] It is also possible to consider cross-regional differences in the endowment with technology specific skills to investigate cross-country differences in technology adoption, but this is not purpose of this study.

alternatives. As a consequence, the probability that the green vintage meets the technological requirements of potential adopters is small.[13]

After some time, the diffusion process accelerates until competitive pricing dynamics and endogenous learning from the pre-existing capital infrastructure cause a slow down in the diffusion process. Endogenous learning conditional on technological legacy leads to the second stylized fact of technology diffusion, namely *path dependence* and the possibility of a *technological lock-in.* Endogenous learning represents only one type of path dependence, but the simulations show that path dependence may be such strong that even after an initial diffusion of an initially superior technology the diffusion process is reverted. In such case, the diffusion curve exhibits a u-shaped pattern.

This matches the argument brought by Comin et al. (2006) that inverted u-shapes may occur when the diffusing technology is replaced by a superior substitute. In the present study, both types of capital are perfect substitutes with regard to the output that is produced. Endogenous learning can undermine the initial superiority of the green technology, represented as permanently reduced material input costs.[14]

5.2. Barriers to diffusion

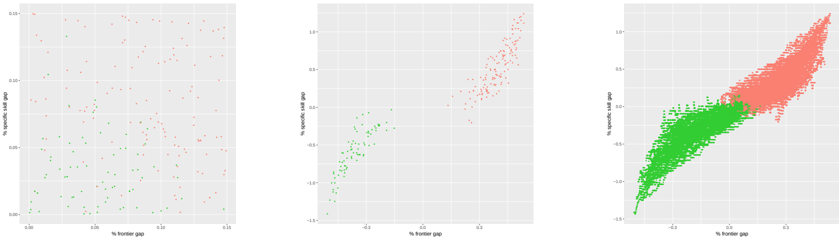
What is *marginal* impact of the strength of barriers on the transition probability? To address this question, I run a series of Monte Carlo experiments randomizing the level of skill β^b and technology related barriers β^A within the critical value range that allows to generate a sufficiently well mixed sample of simulation runs converging to one of the two technological regimes. Preceding analyses have shown that barriers can be prohibitively high that a regime shift does effectively not occur within a tractable amount of simulation runs. These analyses have pointed to a value of approximately $> 20\%$ while it needs to be noted that the stochastic nature of the model it is not possible to analytical derive a definite threshold level. To obtain a balanced sample of green and conventional regimes, the value range is set sufficiently low to generate data within the range of *critical* levels of diffusion barriers, i.e. β^b and β^A are uniformly drawn from the interval $[0, .15]$. The distribution of the initial conditions is plotted in figure 8a. As before, a divergence of barriers is observable. In figure 8b the differences in the barriers are shown at the end of simulation time. Two clusters in the opposite corners of the plot have formed.

5.2.1. The level of entry barriers

Compared to the baseline scenario, the diffusion barriers are higher on average. As expected, this reduces the frequency of simulation runs that exhibit a transition towards

[13] This insight is derived from counter-factual simulations, the supply restriction was assumed away and an immediate market penetration was observed even though this penetration was not necessarily permanent.

[14] An important difference to the patterns of diffusion studied by Comin et al. is the type of data that is used. The simulation model represents an experimental tool that allows the collection of data at the desired resolution in time, at well defined definition of technology and without any problem of missing data. These conditions are difficult to meet by research in economic history, though the parallels in the observed patterns are striking.



(a) $t = 600$ (b) $t = 15000$ (c) All periods

Figure 8: Figure 8a illustrates the distribution of the settings of the barriers at the day of market entry. The colors of the points indicate the scenario type (green for r^{eco}, red for r^{conv}, blue for r^{switch}). In figure 8c the distribution of barriers is shown across the whole simulation time. Note that the scaling across axes differs, i.e. the absolute dispersion in 8b and 8c is higher than in $t = 600$. The colors indicate the share of conventional (red) or green (green) capital used.

t	Mean (Std)	[min,max]	Mean (Std)	[min,max]	Mean (Std)	[min,max]	p-value*
Frontier gap			*conv*		*eco*		
600	.064 (.043)	[.001,.150]	.082 (.041)	[.002,.150]	.032 (.027)	[.001,.133]	2.3e-16
15000	.117 (.373)	[-.506,.535]	.531 (.322)	[-.204,1.24]	-.594 (.304)	[-1.41,-.033]	<2e-16
Skill gap			*conv*		*eco*		
600	.077 (.046)	[.001,.149]	.089 (.042)	[.001,.149]	.052 (.032)	[.001,.148]	4.8e-10
15000	.117 (.373)	[-.506,.535]	.393 (.085)	[.133,.535]	-.360 (.084)	[-.506,-.152]	<2.3e-16

Table 2: This table show the initialization of entry barriers. In the columns *eco* and *conv*, the properties of the corresponding subsets are shown, i.e. those initializations that result in an eco (conv) regime and the lower part of table shows how the barriers have evolved until the end of simulation time. *The p-value in the last column indicates the significance of difference between the green and conventional scenario derived from a two-sided Wilcoxon test on equality of means.

green technology, i.e. 77 out of 210 runs which corresponds to 37%. The corresponding plots of the time series of the diffusion measure ν_t^c can be found in the appendix C.2.2.

The descriptive analysis of the barrier settings that are associated with a green transition indicates that a transition is more likely if barriers are low. This is illustrated by the time series plots of the skill and productivity ratios, but also visible at the degree of technological novelty and the price-per-productivity ratio (see C.2.2). The time series are disaggregated by scenario type and exhibit a significant difference in the mean values at the day of market entry in favor the of the resulting regime. Barriers and prices per productivity unit for green capital are on average higher in the subset of runs that exhibit a lock in in the technological regime. This observation is summarized in table 2 showing the means and value ranges of the initialization for the full set of runs and the subset of green and conventional regimes. A two sided Wilcoxon test confirms the significance of the differences in the mean.

Comparing the average outcome of green and lock-in regimes, weak support for a better macroeconomic performance of the green regime in terms of aggregate output can be found during the late phase of diffusion and when considering the average across all periods (C.3j). This is confirmed by a Wilcoxon test at a 5% significance level (table 16). Though, the permanence of this effect is not clear since the differences are no longer significant in the last period of simulation. A further observation is the amount of firm exits at the late phase of technology diffusion which is significantly higher when a green transition occurs (cf. C.3i). A possible explanation is that those firms that miss the opportunity to switch to green technology are no longer competitive if the green technology permanently establishes on the market. Note that the model only has a very stylized, stochastic firm entry rule such that only firm exits can be studied, but entry dynamics are insufficiently captured. The green scenarios are further associated with a significantly higher unemployment rate at the early phases of technology diffusion.

What is the impact of the level of barriers on the transition probability? The random initialization of barriers allows to study the role of entry barriers by a simple regression of the final state on initial technological conditions and a set of controls.[15] Next to an analysis on the macroeconomic level, I test how initial conditions at the firm level help explaining the transition probability. Because the share of conventional capital utilization of individual firms at the end of simulation can be almost perfectly explained by the technological regime, i.e. all firms use almost 0 or 100% capital of a specific type, this does not allow to study adopter heterogeneity, but rather contributes to the understanding of the transition at the macro level. In addition to these analyses, I investigate the role of firm heterogeneity at an early phase of diffusion, i.e. I seek to identify the characteristics of early adopters.

[15] The variation in the control variables beyond the randomized entry conditions arise from the period until the day of market entry $t \in [0, 600]$. The initial population in $t = 0$ is identical in all simulation runs. In all specifications, I used smoothed values, i.e. one year averages, of the time dependent explanatory variables.

Initial conditions and techn. regime shift					Dependent variable: Aggregate share conventional capital used.					
	OLS					Probit				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
(Intercept)	.2754***	.2676***	-.0103	-0.1351	-36.47	-.7039***	-.9419***	-2.6088***	-1.1221.	1.95.2
	(.0605)	(.0437)	(.0550)	(.0884)	(45.16)	(.1901)	(.1794)	(.3805)	(.6059)	(257.0)
β^b	.0448***		.0377***	.0188	.0202	.1387***		.1896***	-.3162*	-3.098.
	(.0065)		(.0052)	(.0200)	(.0202)	(.0226)		(.0317)	(.1552)	(.1626)
β^A		.0548***	.0507***	.1136***	.1167***		.2285***	.2716***	.1842	.2101
		(.0052)	(.0047)	(.0152)	(.0153)		(.0307)	(.0382)	(.1498)	(.1658)
$(\beta^b)^2$				.0026*	.0025*				.0286**	.0284**
				(.0012)	(.0012)				(.0091)	(.0010)
$(\beta^A)^2$				-0.0023**	-.0024**				-.0009	-.0004
				(.0009)	(.0009)				(.0089)	(.0010)
$\beta^b \cdot \beta^A$				-.0035***	-.0035***				.0218.	.0232
				(.0010)	(.0010)				(.0129)	(.0138)
B_t^c					15.71					120.0.
					(11.41)					(70.87)
$A_{c,t}^V$					-.6661					-7.601
					(.9565)					(6.358)
Output					3.509					16.11
					(5.886)					(32.87)
#firms					-.0246					-.1550
					(.0304)					(.1721)
w_t^r					-2.430					-13.51
					(1.764)					(10.18)
Adj./ps.R^2	.1814	.3492	.4769	.5316	.5316	.1316	.3157	.4761	.4954	.4824
F-statistic	47.31	96.25	113.1	48.44	24.72					
AIC	237.67	197.02	125.15	131.88	136.64	237.67	186.86	142.61	137.26	140.85

Significance codes: 0 '***' .001 '**' .01 '*' .05 '.' .1 ' ' 1. R^2: for OLS heterosked. adjusted; for Probit adjusted McFadden pseudo.

Table 3: Technological regime shift and initial conditions: Share conventional capital ν_t^c on the macroeconomic level in $T = 15000$ on diffusion barriers β^A, β^b, measured in percentage points, and initial macroeconomic conditions ($t = 600$). The diffusion barriers are defined as percentage difference between the technological frontier and technology specific skill levels (see 4.2). Columns: (1)-(5) OLS, (6)-(10) binary Probit.

For all these model specifications, I ran a simple OLS and a binary Probit regression. The binary specification is appropriate due to the binary nature of the response variable, i.e. the share of conventional capital that is used in the last period is roughly 100% or 0%, but there is little variation in between. Though, these coefficients are less straightforward to interpret because the marginal influence of an explanatory variable depends on the other explanatory variables. The OLS version allows a straightforward interpretation of the coefficients.

The results of the regression analysis at the macroeconomic level are summarized in table 3.

As expected, the barriers β^A and β^b both enter with positive coefficients, and are economically and statistically significant at the $< .1\%$ level across different linear model specifications. Positive coefficients indicate a higher share of conventional capital utilization in $t = 15000$, i.e. a negative association with the likelihood of a technological regime shift. I repeated these regression exercises for different snapshots in time, i.e. in ten-year steps after the day of market entry using no longer the initial, but contemporaneous barrier level. The results (not shown here) confirm the relationships to hold across time and can be interpreted as indication of path dependence.

What can be said about the magnitude of effects? Comparing the results of the OLS and the binary Probit regressions, it is consistently found that the frontier related barrier β^A enters with a larger coefficient. Hence, the supply-sided barrier exhibits a stronger association with the transition dynamics than the demand-sided barrier. The adjusted R^2 of the OLS (Probit) suggest that approximately 18% (13%) of the variation can be explained by the skill barrier alone compared to 35% (32%) when considering only the frontier barrier. Including both barriers in simple linear terms helps explaining roughly half of the variation. The coefficients of the linear OLS model can be roughly interpreted as marginal effect probability of a technological lock-in in the conventional regime (or inverse of the transition probability). Considering the regression specification without the interaction term, a change by one percentage point in β^A (β^b) is associated with a 5% (3.8%) higher share of conventional capital utilization. Though, the effects are non-linear. The value range of the target variable is truncated and barriers can be prohibitively high, i.e. a transition becomes highly unlikely and does effectively not occur within a reasonable amount of simulation runs.

Techn. regime and initial conditions.					Dependent variable: Share conventional capital used by firms in $t = 15000$					
	OLS					Probit				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
(Intercept)	.2837***	.2642***	-.0120.	-.1478***	-3.036***	-.6569***	-.9277***	-2.574***	-1.093***	-17.90***
	(.0070)	(.0051)	(.0064)	(.0103)	(.2867)	(.0218)	(.0207)	(.0437)	(.0698)	(1.652)
β^b	.0440***		.0372***	.0189***	.0217***	.1353***		.1866***	-.3226***	-.2965***
	(.0008)		(.0006)	(.0023)	(.0024)	(.0026)		(.0036)	(.0178)	(.0191)
β^A		.0554***	.0515***	.1180***	.1172***		.2294***	.2729***	.1920***	.1996***
		(.0006)	(.0005)	(.0018)	(.0018)		(.0035)	(.0044)	(.0171)	(.0189)
$(\beta^b)^2$				.0026***	.0025***				.0287***	.0276***
				(.0001)	(.0001)				(.0011)	(.0011)
$(\beta^A)^2$				-.0026***	-.0025***				-0.0016	-.0010
				(.0001)	(.0001)				(.0010)	(.0011)
$(\beta^b \beta^A)$				-.0035***	-.0036***				.02259***	.0221***
				(.0001)	(.0001)				(.0015)	(.0016)
$B^c_{i,t}$					.3880					2.595
					(.3118)					(1.804)
$A^c_{i,t}$					.0887					-.8045
					(.1666)					(.9816)
#employees					.0036					.0178
					(.0026)					(.0148)
Output					.0599					.4323
					(.0472)					(.2722)
Age					.0003*					.0019.
					(.0002)					(.0010)
Price					2.358***					14.27***
					(.1862)					(1.076)
Unit costs					.0762**					.5090***
					(.0265)					(.1510)
Adj./ps.R^2	.1757	.3503	.4742	.5374	.5448	.1469	.3385	.5015	.5434	.5546
F-statistic	3394	8588	7182	3701	1436					
AIC	18666.85	14874.77	11506.30	9468.82	8393.00	17724	13744	10355	9485.8	8378.8

Significance codes: 0 '***' .001 '**' .01 '*' .05 '.' .1 ' ' 1. R^2: for OLS heterosked. adjusted; for Probit adjusted McFadden pseudo.

Table 4: Firm level regression: Share conventional capital utilization at firms $\nu^c_{i,T}$ at the end of simulation time ($T = 15000$) on barriers and initial firm characteristics ($t = 600$). Columns: (1)-(5) OLS, (6)-(10) binary probit.

The relationship between barriers and the transition probability is not straightforward to identify and specific to the restrictions imposed by the design of the model and the experiment. Here, I restrict the analysis to the incorporation of quadratic and interaction terms of the barriers.[16]

In the OLS specification, the frontier gap β^A exhibits a diminishing negative effect on diffusion and its quadratic term enters with a negative coefficient. The opposite is found for the skill related barrier. Though, these findings are confirmed by the binary Probit model, but are not or only weakly significant when using aggregate data at the macroeconomic level.

This regression exercise is repeated at a higher level of disaggregation considering the responses of individual firms to study whether firm characteristics at the day of market entry play a role.[17] At the end of simulation time, the variation in the diffusion measure $\nu^c_{i,T}$ can be almost perfectly explained by the technological regime type. Hence, the results of this analysis rather reflect the regime than the individual technology choice.[18] The regression results yield similar results as before with regard to the direction, magnitude, significance and explanatory power of entry barriers. Again, I find that the inhibiting effect of the frontier (skill) barrier is diminishing (increasing). Using firm level data, the coefficients of the skill barrier and the interaction term exhibit higher significance in the Probit model. The squared frontier gap is not significant, but this is not surprising and is due to difference in the functional form of the two models and the interdependence of the marginal effects of explanatory variables in the Probit model. This is supported by the finding, that the coefficient of the skill related barrier has a large and significant negative coefficient in the Probit specification with interaction terms, but its squared value enters with a positive one. This indicates that low skill related barriers do not impose a (strong) barrier to diffusion which is in line with the finding of increasing coefficient in the OLS model.

[16] I refrain from an in-depth study of the functional form of the relationship between different types of 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. It should be kept in mind that the mechanisms that determine technological learning and the success of innovation in the economic reality are likely to vary strongly across different technological fields due to different patterns of innovation, learning and spillovers across technology types. Second, the better fit of more complex functional forms comes at the cost of lower ease of interpretation and an expected lower generalizability, also referred as to *bias-variance trade-off* (cf. Bishop 2006). The chosen version is sufficient to underline the core insights derived from this study.

[17] I make a simple static cross sectional analysis even though it would be possible to apply panel methods incorporating run or firm fix effects and to study the dynamics over time. Run fix effects would undermine the explanatory power of barriers which are specific to a given set of runs. Similarly, firm fix effects are not relevant here because a similar distribution of firms is given in each sample of a run. Variation between firms across runs is low stems from the period before the day of market entry. The inclusion of firm controls is expected to capture this variation.

[18] A simple regression of $\nu^c_{i,T}$ on a dummy variable indicating the regime type explains $> 99\%$ of variation. Given the intercept of .9992, the coefficient of a dummy that indicates a green regime accounts for $-.9984$. The R^2 accounts for .9995. Similar findings hold true for a binary Probit specification of the regression, but in such case the interpretation of coefficients is less obvious.

The interaction term of barriers ($\beta^A \beta^b$) is significant at a $< .1\%$ level and enters with a negative coefficient in the OLS models at the macro- and microeconomic level. In the Probit specification it is only significant at the firm level, but enters with the opposite sign. Again, this difference can be explained by the different functional forms of OLS and Probit models and the fact that an OLS model is less precise in the prediction of truncated variables at the boundaries. Even though the functional form of the influence of the barriers is not entirely clear from this analysis, a comparison of the AIC suggests the models with interaction terms to be preferable.

The total marginal effect of an increase in a specific barrier is given by the composite of the linear, the quadratic and the interaction term and is sensitive to the level of the *both* barriers. The coefficients of the interaction term are negative in the OLS specification. Hence, given that a barrier is sufficiently low, the negative effect of a marginal increase in a barrier is decreasing in the level of the other barrier and may diminish if the other barrier is prohibitively high. For example, if the frontier barrier is such high that the green technology does not diffuse at all, the skill barrier is irrelevant. Further, the cumulative marginal effect of both barriers is relatively stronger if barriers are asymmetrically distributed (e.g. high β^A and low β^b, and vice versa).

The observed relationship of the interaction of the two barrier types does not hold true in the Probit model, though an increase of barriers does not necessarily coincide with a lower transition probability. Suppose that barriers are sufficiently low, i.e. such that the negative coefficient of β^b outweighs the positive coefficients of its squared value and the interaction term. In such case, a marginal increase in β^b may be associated with a lower probability of technological lock-in. It is likely that this pattern in the data is captured differently by the two model specifications. Following the Probit model, increasing symmetry of barriers is only associated with a higher transition probability if both barriers are sufficiently low and only a marginal increase in β^b is considered. This points to the importance of *effective* productivity.

Are other macro- and microeconomic conditions systematically related to the transition probability? In the regression analyses at the macroeconomic level, the included macroeconomic control variables are not significant and do not contribute to the explanation of the variation. This is not surprising due to the design of experiments. The variation in the controls only arises from the transition period $t \in [0, 600]$ that is required for technical reasons. The coefficients of variation are low ($< .05$) across all control variables besides the barriers.[19] The irrelevance of the controls slightly changes when repeating the regression with controls taken from later snapshots in time when the variation between different simulation runs is higher. Though it should be kept in mind that this could be partly due to the joint determination of macroeconomic conditions and the technological regime. The Wilcoxon test confirmed the significance of difference between the two regime types.

[19] Other macroeconomic controls such as the price for the material input p_t^{eco} and relative capital prices that are typically included in climate policy and diffusion studies are not relevant in this experiment or implied by other controls. The variation in p_t^{eco} is, by design, linearly bound to the wage. Capital prices are uniform at the time of initialization. The variation in the capital price per productivity unit is captured by β^A.

Using firm level data to explain technology diffusion, I find the stocks of codified $A^c_{i,t}$ and tacit knowledge $B^c_{i,t}$ to be significant in the OLS and Probit version of the model. The stock of tacit knowledge $B^c_{i,t}$ enters with a negative coefficient, hence it is positively associated with the probability of a green transition. The opposite holds true for the stock of codified knowledge. Again, the variation across runs arises from the transition period and due to the cross-sectional nature of the regression analysis, it captures differences in the distribution of firm characteristics between simulation runs. Relatively higher stocks of $A^c_{i,t}$ indicate a c.p. higher productivity of conventional capital that is used by individual firms that survive until the end of the simulation horizon.[20] A higher stock of $A^c_{i,t}$ could indicate recent investment in high-quality conventional capital. This points to the importance of investment cycles, but definite conclusions would require a deeper going analysis. Tacit knowledge $B^c_{i,t}$ is partly transferable across technology types, but $A^c_{i,t}$ is bound to a specific item in the capital stock. This conceptual difference in the two types of technological knowledge may help understanding the opposite signs of their coefficients. Higher endowment with tacit knowledge is an indication for the availability of skilled workers and seems to have a positive association with the probability of a technological regime shift.

Other control variables such as the age, price and unit costs enter with statistically significant positive coefficients, i.e. are positively associated with a technological lock in. Higher unit costs can either reflect inefficiencies in the production process or an additional cost burden from capital investment annuities. Higher prices have a similar association, but may have additionally a negative effect on the demand side. Though, the variation in these control variables is low at the considered snapshot in time and - within this experiment - they are only of minor economic significance as determinant of the probability of a technological transition.

Which firms are early adopters? In a second step, I repeat the regression analysis for an earlier snapshot in time and ask for the role of diffusion barriers and firm characteristics at an early phase of the diffusion process. This is done by regressing the share of conventional capital used on firm level in period 1800, i.e. 5 years after market entry, on barriers and firm characteristics. At this time, the variation in the share of conventional capital utilization across firms is high. The results from this regression give insights for the macroeconomic process of diffusion patterns, but also give insights on the relationship between firm characteristics and individual green technology uptake, i.e. the likelihood of being an early adopter.

Five years after market entry, diffusion at the intensive margin is low, i.e. on average conventional capital utilization accounts for 81.26% on average and the median firm uses 100%, i.e. it has not adopted green technology at all, but the variation is high. Firms exist that use only green capital. The cross-sectional standard deviation of conventional capital utilization accounts for 29.22%. A simple OLS (Probit) regression

[20] There is one theoretical exception. By the design of the simulation program it is possible that the ID of a firm that is exiting the market is re-used for a newly founded firm. I do not control for that. Due to the small number of newly founded firms and the relatively large pool of "available IDs", I expect the influence of these firms to be negligible in quantitative terms. Further, it does not undermine the interpretation with respect to the transition probability.

of $\nu^c_{i,1800}$ on a dummy variable that indicates the resulting technological regime explains 39.57% (28.22%) of variation.

Again, both types of barriers are highly significant across all regression settings and enter always with positive and statistically significant coefficients. Though, the economic significance of barriers is lower than in the analysis before, i.e. interpreting the coefficients of the linear model as marginal effects, a 1% increase in β^A (β^b) is associated with a 2.74% (2.91%) higher share of conventional capital utilization in $t = 1800$. In contrast to the analysis above, the demand-sided barrier appears to be more decisive in the early phase of diffusion when using the OLS model. The inclusion of the squared terms indicates that the marginal negative effect of barriers on the the pace of diffusion is diminishing, i.e. both enter with a negative coefficient in the OLS model specification. In the Probit specification, the squared term of the skill barrier exhibits a positive coefficient indicating an increasing marginal effect.[21]

The barrier interaction term ($\beta^A \beta^b$) is statistically significant and has a positive association with green technology adoption. Hence, symmetric barriers are less inhibiting than asymmetric. This underlines the importance of effective productivity, i.e. the bundle of skills and physical capital, is more decisive than either of these components in isolation.

In addition, also the stocks of tacit and codified knowledge are statistically and economically significant. The stock of tacit knowledge is positively associated with diffusion. By design of the model, skills are symmetrically scaled down by the skill related entry barrier, i.e. each firm has a similar in the beginning *skill ratio*.[22] Hence, the stock variable reflects the general endowment of a firm with human capital and not technology specific knowledge. The stock of codified knowledge is negatively associated with the likelihood to be an early adopter. At the day of market entry, firms do only have conventional capital and a high level of $A^c_{i,t}$ indicates the quality of the firms' capital stock. The negative association with diffusion suggests that firms with more productive capital stock are less likely to be early adopters.

[21] Note that in the early phase of diffusion, the variation within the range of green technology utilization is high. Hence, the binary specification of the Probit model insufficiently accounts for the variation within the value range of $\nu^c_{i,t}$ while the OLS model does not capture the truncated nature and the interdependence of marginal effects with the levels of other explanatory variables, if not explicitly included.

[22] The skill ratio is only approximately identical because the data used for regression is smoothed taking the yearly average and initial technology uptake is differently across firms.

Identify early adopters						Dependent variable: Share conventional capital used at firm level in $t = 1800$.				
	OLS					Probit				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
(Intercept)	.5461***	.6054***	.3921***	.1027***	-.8139***	.2292***	-.0913**	-1.648***	-1.735***	-11.48***
	(.0042)	(.0033)	(.0040)	(.0057)	(.1539))	(.0253)	(.0219)	(.0425)	(.0747)	(2.005)
β^b	.0329		.0291***	.0684***	.0685***	.1915***		.2462***	.2047***	.2171***
	(.0005)		(.0004)	(.0013)	(.0013)	(.0041)		(.0058)	(.0224)	(.0231)
β^A		.0307***	.0274***	.0875***	.0881***		.2536***	.2698***	.3789***	.3882***
		(.0004)	(.0003)	(.0010)	(.0010)		(.0056)	(.0060)	(.0172)	(.0181)
$(\beta^b)^2$				-.0009***	-.0009***				.0077***	.0070***
				(.0001)	(.0001)				(.0018)	(.0018)
$(\beta^A)^2$				-.0020***	-.0020***				-.0047***	-.0053***
				(.0001)	(.0001)				(.0012)	(.0012)
$(\beta^b\beta^A)$				-.0038***	-.0038***				-.0159***	-.0148***
				(.0001)	(.0001)				(.0020)	(.0021)
$B^c_{i,t}$					-.7317***					-6.898**
					(.1647)					(2.151)
$A^c_{i,t}$					1.448***					12.67***
					(.0883)					(1.167)
#employees					.0006					-.0038
					(.0014)					(.0173)
Output					-.0251					.2390
					(.0264)					(.3180)
Age					.0003*					.0015
					(.0001)					(.0014)
Price					.3637***					4.201**
					(.0983)					(1.329)
Unit costs					-.0203					-0.2407
					(.0148)					(.1807)
Adj./ps.R^2	.2634	.2893	.4911	.6371	.6480	.2345	.3125	.5287	.5348	.5451
F-statistic	5349	6089	7218	5253	2276					
AIC	5349	541.00	-4454.08	-9509.46	-9972.83	10292	9243.2	6335.8	6254.1	6049.5

Significance codes: 0 '***' .001 '**' .01 '*' .05 '.' .1 ' ' 1. R^2: for OLS heterosked. adjusted; for Probit adjusted McFadden pseudo.

Table 5: Firm level regression: Share conventional capital utilization at firms $\nu^c_{i,t}$ in an early phase of technology diffusion ($t = 1800$) on barriers and initial firm characteristics ($t = 600$). Columns: (1)-(5) OLS, (6)-(10) binary probit.

6. What is the scope of green technology diffusion policies?

In the analysis above, it was shown that the dynamic interplay between long- and short-term technological performance is decisive to understand processes of technology diffusion. In the short run, taking knowledge stocks as given, the incumbent technology outperforms the entrant if barriers are sufficiently high. The entrant technology is superior in the long run, but only if disadvantages in terms of lower technological knowledge are overcome. Path dependence in technological learning at the firm level countervails the process of initial technology diffusion triggered by the technology's superiority in terms of lower input costs. A relevant question for the design of innovation oriented climate policy design is how different political instruments affect these dynamics, whether policy measures can bridge the costly period of learning and can prevent the relapse into the conventional technological regime.

6.1. Two simple experiments

To investigate this question, I ran two simulation experiments on a set of policies, namely a mixture of a tax on the resource input and one of two subsidies. A green investment subsidy reduces the price of green capital goods and a price support is granted for eco-friendly produced consumption goods.

The policy instruments are implemented as follows:

- An **environmental tax** θ_t^{eco} is imposed as a Value added tax (VAT) on material inputs. This makes the use of conventional capital relatively more costly for CG firms,
$$\tilde{p}_{i,t}^{eco} = (1 + \theta^{eco}) \cdot p_t^{eco}. \tag{12}$$
Because the environmental impact of production is proportional to the use of material inputs, this tax can also be interpreted as a tax on the environmental externality.
- An **investment subsidy** σ_t^{inv} reduces the the price for green capital goods,
$$\tilde{p}_t^v = (1 - \sigma^{inv}) \cdot p_t^v. \tag{13}$$
- The government may also pay a **green consumption price support** σ_t^{cons} for environmentally sound produced CGs, i.e.
$$\tilde{p}_{i,t} = \left(1 - \nu_{i,t}^g \cdot \sigma^{cons}\right) \cdot p_{i,t} \tag{14}$$
This subsidy is directly paid to firms and is proportional to the share of green capital used in current production $\nu_{i,t}^g = \frac{K_{i,t}^g}{K_{i,t}}$. The price support allows CG firms to achieve a higher mark-ups when producing in an environmentally friendly way.[23]

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

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.

The two types of subsidies conceptually reflect the difference between static and dynamic aspects of technological superiority. The investment subsidy decreases the price for green capital goods immediately and all green technology adopters benefit homogeneously. The price support for green consumption goods, in contrast, relates to the dynamic aspect of technological barriers. Whether firms benefit depends on the *relative extent* to which they are using green capital and it has a more permanent effect dependent on the vintage structure of the capital stock. The support by the consumption subsidy becomes stronger if more green capital is adopted. This reinforces the increasing returns of green technology adoption resulting from learning at the firm level and endogenous innovation in the capital goods sector.

Further, the investment subsidy serves as an incentive to expand capacity because it is proportional to the absolute amount of green investments. The consumption subsidy, in contrast, is paid proportionally to the relative amount of green capital utilization.

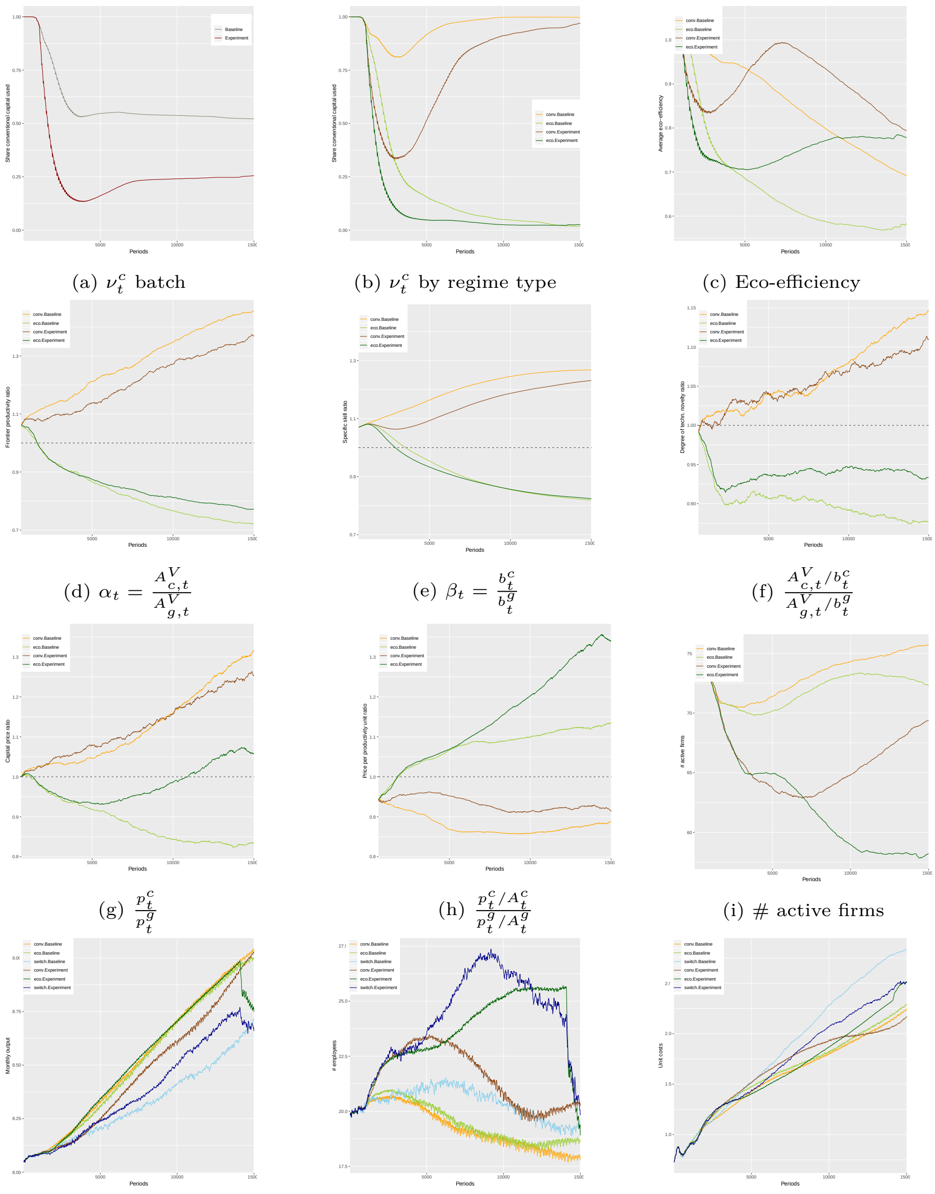
I perform Monte Carlo experiments on these policy instruments within two different settings. First, I make a comparison against the baseline scenario with the 5% fix entry barriers discussed above (see 5.1). Second, to explore the interplay of policy and the strength of barriers, I ran a set of policy simulations with randomized barriers drawn from the interval $[0, .15]$ as done in the sensitivity test above (see 5.2).

The levels of the two subsidies and the eco-tax are drawn at random from a uniform distribution. In preceding exploratory analyses, average levels for the two subsidies were found that generate similar results in terms of diffusion effectiveness. The diffusion effectiveness does not necessarily coincide with the environmental effectiveness which is also responsive to output and productivity growth. This will be discussed in further detail below. For each experiment, I ran 210 simulation runs à 15000 iterations. The policy measures are applied after the green capital goods producer has brought the full range of its vintage supply to the market and terminated abruptly, i.e. without any phasing out, shortly before the end of the simulation horizon.

6.1.1. Green technology diffusion and the strength of policy

In the first experiment, barriers are fixed at a 5% level and the policy parameters are initialized at random values. The random initializations are summarized in table 6. In the first two columns, I show the mean and standard deviation and the value range of the random draws for the whole set of simulation runs. In the latter four columns, these descriptives are disaggregated by regime type. The last column shows the p-value of a Wilcoxon test which confirms that those scenarios that exhibit a green transition were on average initialized with a significantly higher eco-tax and consumption subsidy. Before discussing the effect of the policy parameters on the resulting technological state, it is worth summarizing some descriptive observations of the simulation results.

The diffusion measure represented as aggregate across simulation runs (see figure 9a) suggests that the policy has stimulated the diffusion of green technologies. Transitions



(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) $\frac{A^V_{c,t}/b^c_t}{A^V_{g,t}/b^g_t}$

(g) $\frac{p^c_t}{p^g_t}$

(h) $\frac{p^c_t/A^c_t}{p^g_t/A^g_t}$

(i) # active firms

(j) Monthly output

(k) Avg. # employees per firm

(l) Unit costs

Figure 9: The policy experiment (baseline) is represented by the dark (bright) colored curve (resp. dark-red (gray) in 9a). 9b–9l, the colors (green, red, blue) indicate the type of the technological regime (eco, conventional, switch). Figures 9a and 9b show the evolution of the macroeconomic diffusion measure ν_t^c comparing the policy experiment with the baseline. The aggregated diffusion curve illustrates the total difference in diffusion, while the disaggregation into green and conventional regimes hides the effectiveness of policies on diffusion due to the different sample sizes, i.e. differences in the number of runs classified as green and conventional regimes.

24			*conv*		*eco*		
	Mean(Std)	[min,max]	Mean(Std)	[min,max]	Mean(Std)	[min,max]	p-value
θ^{eco}	.506(.302)	[.000,.991]	.399(.293)	[.000,.959]	.540(.299)	[.002, .991]	.004
σ^{cons}	.013(.007)	[3.3e-5,.025]	.011(.007)	[.001,.025]	.014(.007)	[3.3e-5,.025]	.029
σ^{inv}	.052(.028)	[.000,.010]	.049(.028)	[.000,.099]	.052(.029)	[.003, .010]	.456

Table 6: Overview of parameter and variable initialization, i.e. in $t_0 = 600$. The four columns on the right-hand side show the initialization by regime type, i.e. *eco* and *conv*. The last column shows the p-value of a two-sided Wilcoxon test on the alternative hypothesis of equality of means.

towards a green technological regime are observed at a higher frequency compared to the baseline scenario introduced above (see 5.1). When using the classifications of green and conventional regimes as introduced above, 158 (45) scenarios are classified as *green* (*conventional*) technological regime. The remaining seven fall into the *switch* category. Neglecting the *switch* scenarios, this corresponds to a transition probability of approximately 76% compared to 49% in the baseline. In figure 9, several time series of some of the macroeconomic and technological core indicators are shown in comparison to the baseline scenario focusing only on the difference between green and conventional regimes and referring to the switch scenarios only when the difference to the two relatively "stable" technological regimes is worth noting. The colors of the time series (green, red, blue) indicate the regime type (eco, conventional, switch) and the brightness (dark, bright) of colors the simulation set (experiment, baseline). The qualitative patterns of evolution of macroeconomic and technological indicators during the phase of policy application are similar to those of the baseline scenario discussed above, but the quantitative differences between the experiment and the baseline can be interpreted as expected side effects of the policies.

Using a two-sided Wilcoxon test, I evaluate the significance of differences of the patterns in the time series that are disaggregated by regime type and policy application. I compare the average outcome of the type-disaggregated time series for different phases of diffusion. This helps addressing the question whether policies perform differently at different phases of technological transition and whether the performance is conditional on the technological state at the end of simulation time. The results are summarized in table 7. The findings confirm that the transition to green technologies occurs more rapidly, i.e. the ν_t^c is significantly lower in the subset of green technological regimes in the first 10 years after market entry, but also later. Though, in later phases the difference is less significant. The same finding is observed within the subset of conventional regimes. The mean value of ν_t^c of conventional regimes in the policy scenarios is lower than the mean of green regime in the baseline during the early diffusion phase. This indicates the effectiveness of policy as accelerator of diffusion in the beginning, but this is not always sufficient to trigger a technological regime change.

The technological indicators, i.e. the frontier productivity ratio α_t, the skill ratio β_t, the ratio of technological novelty $\frac{A^V_{c,t}/b^c_t}{A^V_{g,t}/b^g_t}$ and relative capital price indicators exhibit the same divergent behavior as above, but the divergence is slightly less pronounced when the policies are applied. The policies influence the market outcome and only indirectly affect the technological indicators. The Wilcoxon tests (see table 7) confirm these findings, i.e. the less pronounced difference between regime types and that the difference between the policy and the baseline in the technological variables seems to be driven indirectly by developments on the market. In particular, the difference in the frontier ratio α_t is not or only weakly significant when comparing green (conventional) regimes with and without policy. Hence, policies have only a minor influence on the evolution of the relative frontier at the early phase of diffusion which is partly due to the sluggish response of R&D expenditures to changes in revenue.[25] The technology uptake in the early diffusion phase is driven by prices and other determinants and not by an indirectly policy induced increase in innovation. In contrast, the specific skill ratio β_t seems to be sensitive to policy at the early phase of diffusion. This is not surprising due to the significantly higher technology uptake in both regime types if policies are applied. The observation that the technological differences between the two regime types is less pronounced in the presence of policy is an indication for the effectiveness of policy at the margin, i.e. the policy may trigger a transition even though the green technology is not clearly dominating by its technological properties.

Though, the application of the policies is not without costs. Firms have a lower average productivity compared to the baseline and produce at higher unit costs (9l) regardless whether considering green or conventional regimes. This is also reflected in the evolution of the eco-efficiency (9c) which indicates the environmental impact per unit of output produced. This is due to two reasons. First, the environmental tax makes the utilization of conventional capital more expensive causing an increase in unit costs if conventional capital is used. This undermines the financial capacities of firms to invest. Second, if firms use green capital goods, production efficiency is (initially) lower due to the barriers and learning costs. The policies have a distorting impact on the investment decisions of firms and firms may be induced to invest in capital types that are inferior to the alternative that would be chosen in the absence of policy. The application of the policy is associated with a series of market exits of firms. Surviving firms are larger measured by the number of employees per firm (9k). Hence, policy benefits are distributed asymmetrically across firms.

Evaluating the policy outcome in terms of aggregate output (9j), the policy does not exhibit a significant effect if a technological transition occurs. Though, if the economy is locked in in the conventional technology, policy is costly in terms of aggregate output. This finding underlines the notion of costliness of technological uncertainty. Climate policy is costly if it has no effect, i.e. if it does not trigger a transition towards green technology. It increases the technological uncertainty reflected in the less pronounced divergence of the technology indicators, i.e. the frontier productivity α_t and skill ratio β_t, associated with a delayed specialization in the conventional technology. Further, the tax on the environmental resource imposes an additional cost burden for firms and negatively affects firms' financial capacities to invest. On the other hand, if the policy successfully triggers the transition, it might be a supporting factor for firms that adopt green technology but comes at the disadvantage of those that do not adopt.

[25] The R&D budget is computed as a fix fraction of the rolling average profit computed across five years (see B.1). Note that the influence of expectations about future profitability for the R&D budget allocation are neglected in this model. This is justified by the technological uncertainty, but might be taken into consideration in future studies (see also section 7).

		eco			*conv*		
		Mean (Std)		p-value	Mean (Std)		p-value
	t	*Baseline*	*Policy*		*Baseline*	*Policy*	
ν_t^c	Early	.685 (.132)	.463 (.077)	<2.2e-16	.896 (.069)	.588 (.123)	<2.2e-16
	Late	.106 (.169)	.041 (.044)	.0266	.953 (.082)	.730 (.205)	<2.2e-16
α_t	Early	.986 (.055)	.989 (.052)	.9605	1.11 (.065)	1.08 (.045)	.0165
	Late	.817 (.104)	.842 (.083)	.0480	1.28 (.152)	1.20 (.121)	.0060
β_t	Early	1.06 (.020)	1.05 (.015)	3.9e-7	1.10 (.016)	1.07 (.015)	2.1e-13
	Late	.904 (.054)	.896 (.043)	.2947	1.21 (.049)	1.14 (.061)	2.0e-10
Output	Early	8.11 (.016)	8.11 (.021)	.808	8.12 (.021)	8.11 (.017)	2.3e-5
	Late	8.50 (.104)	8.52 (.125)	.1534	8.52 (.096)	8.43 (.089)	5.9e-7
Unit costs	Early	1.04 (.063)	1.05 (.065)	<2.2e-16	1.04 (.063)	1.05 (.067)	<2.2e-16
	Late	1.63 (.151)	1.65 (.185)	<2.2e-16	1.64 (.161)	1.66 (.197)	7.7e-13
# Employees	Early	20.6 (5.13)	21.4 (5.94)	<2.2e-16	20.5 (5.04)	21.3 (6.00)	1.2e-11
	Late	19.5 (4.16)	23.6 (5.30)	<2.2e-16	19.5 (4.00)	23.4 (5.36)	<2.2e-16

Table 7: The early (late) phase of diffusion and policy horizon is defined as $t \in [600, 3000]$ ($[3001, 12000]$). In the two sided Wilcoxon test, averages within these time intervals are compared.

The sharp decline at the end of the policy horizon is eye-catching. A similar kink is observable in the average number of employees per firm (9k) and the unemployment rate (not shown here). This is due to abrupt end of policy measures, i.e. there is no smooth phasing out of policy and firms struggle with the adaptation to the changed economic environment. Preceding analyses using only one of the two subsidies have shown that this sharp effect is only associated with the consumption subsidy. This can be explained by the long-term nature of the consumption subsidy. In the presence of $\sigma^{cons} > 0$, firms investing in green capital anticipate the price support when setting prices, selling goods and making investment decisions. The immediate end of policy renders their pricing behavior inappropriate for the new political environment. The abruptness is not necessarily realistic, but serves as illustration of the possible consequences of unforeseen political shocks. The abrupt end of policy has no effect if the economy is locked-in the conventional technological regime. Particularly the discontinuation of subsidies has an effect firms rather than the eco-tax which is only paid by firms using conventional technology.

The channels of policy transmission and its effectiveness are not entirely clear from this analysis recalling the initial distributions of policy rates summarized in 6. The columns on the right-hand side in table show the initial policy parameters disaggregated by scenario type. As expected, the initialization of the eco-tax is on average significantly higher in those simulation runs that result in the *eco* regime than in those classified as *conventional*. The p-value (.004) of a Wilcoxon test on the equality of means highlights that this difference is statistically significant. Further, *eco* regimes exhibit a higher initialization of the two subsidies, but only the difference in the consumption subsidy σ^{cons} is statistically significant with a p-value of .029. This is surprising because preceding analyses on policy instruments in isolation, *all* policy measures were effective as diffusion stimuli. The design of the policy experiment, i.e. the choice of the value range for subsidies, was made such that the two subsidies perform similarly well in their impact on diffusion.

The analysis in the preceding section (5.2.1) has highlighted the importance of different types of adoption barriers for the diffusion of green technologies, and in

			eco		*conv*		
	Mean(Std)	[min,max]	Mean(Std)	[min,max]	Mean(Std)	[min,max]	p-value
β^A	.071(.041)	[.000,.148]	.054(.035)	[.000,.138]	.097(.036)	[.003,.148]	2.6e-13
β^b	.080(.045)	[.001,.150]	.079(.046)	[.001,.149]	.080(.044)	[.001,.150]	.916
θ^{eco}	.531(.299)	[.006,.999]	.530(.304)	[.006,.995]	.532(.292)	[.007,.999]	.916
σ^{cons}	.012(.007)	[.000,.025]	.012(.007)	[.000,.025]	.012(.007)	[.000,.024]	.692
σ^{inv}	.050(.029)	[.001,.100]	.054(.029)	[.001,.100]	.044(.028)	[.002,.099]	.010

Table 8: Overview of parameter and variable initialization, i.e. in $t_0 = 600$. The four columns on the right hand side show the initialization by regime type, i.e. *eco* and *conv*.

consequence it is expectable that barriers also play a role for the effectiveness of innovation oriented climate policies. The analysis of the interaction of both is subject to the subsequent subsection.

6.1.2. The interplay between barriers and the strength of policy

The interplay between the strength of barriers and policy can be investigated by an experiment with randomized diffusion barriers and randomized tax and subsidy rates. These valued are drawn uniformly from the intervals that were used in the experiments above, i.e. $\beta^A, \beta^b \in [0, .15]$, $\theta^{eco} \in [0, 1]$, $\sigma^{inv} \in [0, .10]$ and $\sigma^{cons} \in [0, .025]$. The qualitative properties of the macroeconomic and technological outcome are similar to those above and are not discussed here to avoid repetition. For the sake of completeness, an overview of the macroeconomic and technological outcome of the simulations is provided in the appendix C.4. The random barrier experiment (see section 5.2.1) serves as baseline scenario without policy. Briefly summing up the diffusion impact, the policy seems to have a positive effect on the transition probability, i.e. approximately 61% of the simulation runs (129 out of 210) exhibit a transition to green technologies compared to 27% in the baseline.

In table 8, I give an overview on the initializations of barriers and policy parameters and make a comparison of means across green and conventional regime types.

On the right-hand side of the table, the initializations are split by regime type, i.e. the mean values and intervals of initializations are shown for the subsets of runs that are ex-post classified as green or conventional regime using the threshold $\nu_T^c \lesseqgtr .5$. Comparing the means of β^A and β^b confirms the finding of section 5.2.1, i.e. that entry barriers are decisive for the transition to green technology. Now, only the productivity related barrier β^A is significant.

Technological regime and the interplay of barriers and policy.							Dependent variable: $\nu^c_{i,t}$ at firm level in $t = 15000$			
	OLS					Probit				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
(Intercept)	.5122***	-.0304	-.1792***	-.0225	-.3018	.0314	-1.7435***	-2.3862***	-1.646***	-2.560.
	(.0131)	(.0185)	(.0244)	(.0302)	(.3899)	(.0337)	(.0795)	(.1029)	(.1326)	(1.4793)
θ^{eco}	.0002		-.1590***	.0827***	.0886***	.0004		-.5839***	.4912***	.5104***
	(.0001)		(.0105)	(.0177)	(.0196)	(.0004)		(.0386)	(.0776)	(.0848)
σ^{cons}	.0125*		-.0068	.0004	.0074	.0339*		.0066	-.0790	-.0503
	(.0061)		(.0050)	(.0132)	(.0136)	(.0156)		(.0185)	(.0565)	(.0586)
σ^{inv}	-.0211***		-.0189***	-.0403***	-.0386**	-.0540***		-.0751***	-.2133***	-.2059***
	(.0015)		(.0012)	(.0034)	(.0034)	(.0039)		(.0046)	(.0158)	(.0162)
β^b_t		.0135***	1.079***	-.4167***	-.4563***		.0306*	3.940***	-2.665***	-2.789***
		(.0034)	(.0704)	(.1125)	(.1258)		(.0126)	(.2578)	(.4900)	(.5386)
$(\beta^b_t)^2$		-.0008***	-.0053***	.1175***	.1180***		-.0008**	-0.0188***	.4861***	.4900***
		(.0002)	(.0003)	(.0081)	(.0084)		(.0002)	(.0013)	(.0325)	(.0337)
β^A_t		.0357***	.0417***	.0275***	.0277***		.1437***	.1745***	.0832***	.0915***
		(.0031)	(.0030)	(.0035)	(.0036)		(.0139)	(.0144)	(.0169)	(.0174)
$(\beta^A_t)^2$		.0015***	.0012***	.0011***	.0011***		.0029***	.0021**	.0022**	.0019*
		(.0002)	(.0002)	(.0002)	(.0002)		(.0007)	(.0008)	(.0008)	(.0008)
$(\beta^b_t\beta^A_t)$		.0002	-.0000	.0681***	.0081***		.0014*	.0001	.3727***	.3706***
		(.0002)	(.0002)	(.0079)	(.0081)		(.0007)	(.0007)	(.0383)	(.0394)
$(\beta^b_t\theta^{eco})$				-.0199***	-.0199***				-.0820***	-.0825***
				(.0013)	(.0014)				(.0053)	(.0054)
$(\beta^b_t\sigma^{cons})$				-.0084***	-.0088***				-.0380***	-.0399***
				(.0011)	(.0011)				(.0043)	(.0044)
$(\beta^b_t\sigma^{inv})$				.0008**	.0007**				.0035***	.0032**
				(.0003)	(.0003)				(.0010)	(.0011)
$(\beta^A_t\theta^{eco})$				-.0110***	-.0111***				-.0603***	-.0600***
				(.0013)	(.0013)				(.0062)	(.0064)
$(\beta^A_t\sigma^{cons})$				.0066***	.0063***				.0415***	.0402***
				(.0011)	(.0011)				(.0050)	(.0052)
$(\beta^A_t\sigma^{inv})$				.0017***	.0016***				.0122***	.0118**
				(.0003)	(.0003)				(.0013)	(.0014)
$B^c_{i,t}$					.9319*					3.420*
					(.4066)					(1.567)
$A^c_{i,t}$					-.0448					.2901
					(.2471)					(.9626)
					+other contr.					+other contr.
Adj./ps.R^2	.0143	.3273	.3509	.3706	.3697	.0101	.2738	.3013	.3317	.3311
F-statistic	65.32	1299	902.4	562.1	354.9					
AIC	18936	13841	13367	12961	12282	18095	13274	12771	12215	11574
BIC	18973	13894	13442	13081	12454	18125	13319	12839	12327	11738
Significance codes: 0 '***' .001 '**' .01 '*' .05 '.' .1 ' ' 1. R^2: for OLS heterosked. adjusted; for Probit adjusted McFadden pseudo.										

Table 9: Technological regime shift and initial conditions: Share conventional capital $\nu^c_{i,T}$ in $T = 15000$ on diffusion barriers, policy parameters and initial conditions ($t = 720$). Columns: (1)-(5) OLS, (6)-(10) binary probit. The policy parameters and barriers are measured in percentage *points*.

Considering the policy parameters, it seems that the mean value of initial taxes and subsidies is not systematically different across the two subsets of green and conventional regimes, except for the investment subsidy which is higher in the green subset, i.e. .054 compared to .044. A Wilcoxon test confirms that only the difference in the investment subsidy is significant at a 1% level. This is at odds with the observation above when the barriers were fixed and only σ^{inv} was *not* significant. Though, this table gives an overview of the parameters in isolation and does not account for potential interactions among policies.[26]

The insignificance of mean shifts of policies and the observation of a profound difference in the transition probability compared to the baseline with random barriers but without policy suggest that it is not sufficient to study barriers and policy instruments in isolation. To shed light on the interrelation between the final technological state and the interplay of barriers and policy, I repeat the regression analysis from above and perform a linear regression of the share of conventional capital used by individual firms at the end of simulations $\nu^c_{i,T}$ on initial conditions, i.e. on the barrier settings and firm specific controls. As before, at the end of simulations, the economy converged to one of the two possible technological states and the variation between the extrema of 0% and 100% is low and $\nu^c_{i,t}$ can directly be associated with the type of the technological regime.

In column (1) and (6), the results of an regression of $\nu^c_{i,T}$ on the set of policy parameters are show. This configuration has only little explanatory power. The R^2 suggests that only 1.4% (1%) of the variation can be explained by the linear (Probit) model. Only the investment subsidy exhibits a positive association with a technological regime shift. It is significant at a $<$ 1% level. The consumption subsidy is slightly less significant (5%) and has, surprisingly, a positive coefficient, hence it is associated with a higher conventional capital utilization in $t = 15000$, i.e. it seems to inhibit diffusion.

In column (2) and (7), the analysis is repeated, but this time on barriers only. The findings are in line with those discussed in more detail above. Barriers inhibit diffusion. Both effects are non-linear. The marginal effect of the productivity (skill) related barrier β^A (β^b) is increasing (decreasing). The interaction term is not significant. The observations on the interaction and squared terms deviate from the findings above (5.2.1) where both barriers and the interaction term exhibited decreasing marginal effects in the linear model. Using the barriers instead of policy parameters as explanatory variables, is more powerful in explaining the variation, i.e. the R^2 accounts for roughly 33% in the OLS, and 27.4% in the Probit model. In the previous analysis, barriers and their interaction and squared terms were able to explain more than 60% of the variation in the OLS model. The much lower R^2 and the differences in the coefficients are an indication for a possible interaction between barriers and policy variables.

When the policy variables are added as simple linear terms to the regression model, the coefficients exhibit the same qualitative association with the transition probability but have a slightly larger coefficients, i.e. are economically more significant. In

[26]The comparison of means is not a comparative static, *ceteris paribus* analysis at the mean. The random parameters are drawn from a uniform distribution. With an increase in sample size, a statistical c.p. analysis could be simulated, but the insights are only point estimates valid at the mean. The given sample of simulation runs is apparently too small to obtain significant results.

this specification, not only the investment subsidy, but also the resource tax have a significantly positive association with the transition probability. Interpreting the coefficients as marginal impacts of policy and barriers on the transition probability, an increase in σ^{inv} by one percentage point corresponds to a 2% increase in the transition probability. An analogous interpretation could, but should not, be applied to the eco-tax. The 15.9% coefficients seems unrealistically high and can only be explained by the presence of barriers, i.e. the skill barrier enters with a very high coefficient which suggests a misspecification of the simple linear model.

In columns (4)-(5) and (9)-(10), I show the result from an analysis with explicit account for interactions between barriers and policy. All interaction terms are statistically highly significant, i.e. most of them at a $< 1\%$ level. The coefficients differ only slightly between the model with and without controls.

How does the effectiveness of different policies depend on the strength of barriers? The main result from this analysis is that the effectiveness of policies is sensitive to the level of barrier, but the direction of their interaction is not uniform across different policy instruments. Subsequently, I discuss the findings instrument by instrument.

1. The **environmental tax** serves only as a diffusion stimulus, if barriers are sufficiently high. Both interaction terms $\beta^b\theta^{eco}$ and $\beta^A\theta^{eco}$ have economically and statistically significant, negative coefficients, but the tax alone has a positive one. Hence, in the absence of barriers the tax exhibits an inhibiting effect on technology diffusion. In a preceding analysis, I have run a simulation experiment on the policy instruments in isolation. The tax performed badly with regard to its macroeconomic and environmental outcome. A tax imposes an additional cost burden on firms which negatively affects their financial capacity to invest. This is associated with lower economic output, productivity, but also less green technology diffusion. By the design of the experiment, the green technology is superior to the conventional in the early phase after market entry which triggers the initial surge of green technology adoption given that barriers are sufficiently low. The tax reduces firms investment activities in general and as a consequence, it also slows down the diffusion of green technologies. Though, if barriers are sufficiently high, the tax outweighs the barrier imposed disadvantage in productivity performance of the green technology and distorts investment incentives accordingly.

2. The inclusion of barrier-policy interaction terms does explain why the **consumption subsidy** did not exhibit a significant effect in the analyses before, although preceding analyses on policy instruments in isolation (not shown and discussed here) have indicated that the consumption subsidy is one of the most economically and environmentally efficient means to stimulate green technology diffusion. The interaction terms reveal the mechanisms that determine effectiveness of the consumption subsidy. The two interaction terms $\beta^b\sigma^{cons}$ and $\beta^A\sigma^{cons}$ enter the regression equation with opposite signs, i.e. the former has a stimulating,

the latter an inhibiting effect on green technology diffusion. The consumption subsidy is a long term oriented policy instrument. It rewards firms that switch permanently and consistently to the green technology and strengthens the effect of increasing returns of learning and endogenous innovation. The consumption subsidy is proportional to the amount of green technology that is used. Hence, firms with a large share of green technology utilization benefit more, but also learn faster to exploit efficiently the green technology because the relative speed of learning is positively dependent on the relative amount of green technology use (cf. 3.2.3). This may be a decisive competitive advantage of green over conventional firms when the technological outcome is uncertain. The effectiveness of the consumption subsidy is undermined if the green technology suffers from low productivity in terms of its technical characteristics. Hence, the subsidy is a good instrument to strengthen and stabilize an ongoing diffusion process of a technology that is sufficiently mature to compete with the incumbent, but whose permanent adoption is uncertain because firms do insufficiently well know how to use it. It is worth emphasizing that consumption subsidy is analogous to a higher willingness to pay of consumers for green products assuming that the environmental performance of the product is perfectly observable. The experiment on different subsidy levels would be reflected in different levels of the willingness to pay.

3. The **investment subsidy** in contrast, does irrespectively of the presence of barriers exhibit a statistically and economically significant effect. This effect is diminishing in the level of barriers. The subsidy decreases the price for green capital goods and distorts the investment decision accordingly.

When including the same firm level control variables as in the analyses above, only the stock of knowledge $B^c_{i,t}$ is significant and exhibits a negative effect on technology diffusion. The explanatory power of the other microeconomic conditions that were significant in the experiment before are outweighed by the policies.

The policies are effective via different channels which are differently important at different stages of the diffusion process. To shed light on these mechanisms, I made another regression analysis on the impact of policy on technology diffusion, firm size measured as number of employees and unit production costs at different snapshots in time, i.e. 5, 10 and 35 years ($t \in \{1800, 3000, 9000\}$) after the green technology has entered the market. The effects of the policies may not only differ across time, but also differ across technological regimes, i.e. the policy outcome might be different in a transition compared to a lock-in. This difference can be studied by the inclusion of interaction terms of policy and dummy variables that indicate a green transition.

The interaction terms allow to answer the question how the policy affects the diffusion process *given that a green transition is successful.* I do further include the same set of firm level control variables as above and barriers to diffusion. In table 10, I do only show the coefficients of the policy variables and regime-type dummy and its interaction terms of an OLS regression. The results can be interpreted as a simple correlation analysis between the outcome and the initial conditions. I chose the OLS version for reasons of simplification and ease of interpretation.

Do effects of policy differ across time and scenario type?							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]	-.1719***	-.4005***	-.9431***	.2868	.7267*	.1325	-.0153*	.0648***	.2640***
	(.0106)	(.0124)	(.0046)	(.2438)	(.3272)	(.3969)	(.0060)	(.0058)	(.0116)
θ^{eco}	.0134**	-.0150**	.0024	.1285	.3450**	.0843	.0030	.0504***	.0966***
	(.0042)	(.0049)	(.0018)	(.0967)	(.1302)	(.1596)	(.0024)	(.0023)	.0047
σ^{inv}	-.0203***	-.0205***	-.0001	.0245	.0033	-.1013**	.0007	.0054***	-.0088***
	(.0010)	(.0011)	(.0004)	(.0221)	(.0296)	(.0354)	(.0005)	(.0005)	(.0010)
σ^{cons}	-.0794***	-.1043***	-.0094***	.1671.	.2625*	.7501***	-.0039.	.0156***	.0363***
	(.0038)	(.0044)	(.0016)	(.0874)	(.1165)	(.1393)	(.0022)	(.0021)	(.0041)
$\mathbb{1}$[eco]θ^{eco}	.0009***	-.0007***	.0004***	.0016	.0030	.0138**	-.0004***	8.3e-5	.0006***
	(.0001)	(.0001)	(4.9e-5)	(.0026)	(.0035)	(.0043)	(6.5e-5)	(6.3e-5)	(.0001)
$\mathbb{1}$[eco]σ^{inv}	-.0021.	.0061***	-.0049***	-.0324	-.0639.	.7212***	.0011	-.0068***	-.0422***
	(.0012)	(.0014)	(.0005)	(.0281)	(.0377)	(.0462)	(.0007)	(.0007)	(.0013)
$\mathbb{1}$[eco]σ^{cons}	-.0243***	.0308***	-.0063**	-.0400	-.3233*	-.5856**	.0280***	-.0008	-.0545***
	(.0048)	(.0056)	(.0021)	(.1102)	(.1477)	(.1794)	(.0027)	(.0026)	(.0052)
Adj./ps.R^2	.6335	.6779	.9729	.6950	.5471	.1910	.1808	.3294	.2852
F-statistic	1148	1348	21250	1514	774.2	140.9	147.4	315.1	237.5
AIC	-6095	-2020	-28704	85363	90115	87703	-22692	-23453	-4488
BIC	-5912	-1838	-28524	85545	90296	87883	-22510	-23272	-4308
Mean	.6010	.4022	.4242	21.26	21.33	22.78	1.071	1.251	1.765
Std.	(.3251)	(.3970)	(.4888)	(8.207)	(8.838)	(7.797)	(.1271)	(.1305)	(.2421)
Significance codes: 0 '***' .001 '**' .01 '*' .05 '.' .1 ' ' 1. R^2: for OLS heterosked. adjusted.									

Table 10: This table shows the coefficients of an OLS regression of the dependent variable $\nu^c_{i,t}$, $\#employees_{i,t}$, $UnitCosts_{i,t}$ measured at firm level in $t \in \{1800, 3000, 9000\}$ on the different policy measures and its interaction terms with a type dummy $\mathbb{1}(eco)$ indicating that a green transition has occurred until the end of the simulation horizon. Not shown are the coefficient of a set of firm level controls evaluated at the begin of simulations, i.e. $B^c_{i,t}$, $A^c_{i,t}$, β^A, β^b, output, price, firm age.

Five years after market entry, firms in the set of eco regimes exhibit on average a share of conventional capital utilization that is by 17% lower compared to firms in the lock in regimes. This indicates path dependence. Dependent on the policies, the difference is even larger. The subsidies have in general a negative association with the share of conventional capital that is used in $t = 1.800$. Conditional on a transition the observed relationship is even stronger. The consumption subsidy exhibits a stronger effect than the investment subsidy. The coefficients can be roughly interpreted as percentage change. An increase in the consumption subsidy by one percentage point is associated with 7.9% lower share of conventional capital utilization and, conditional on a regime shift, the effect is even by 2.4% larger.[27] The two subsidies have in general, i.e. independent of the green transition, a positive effect on diffusion evaluated 5 years after market entry. Surprisingly, the tax enters with an opposite coefficient, i.e. higher tax rates are associated with *less* diffusion in the beginning. Most likely, this is due to the negative impact of the tax on investment in general. Firms' investment decisions are subject to financial constraints. Additional cost burdens hamper firms' capacity to invest. This is very well in line with the findings above. If investments in the green alternative are sufficiently attractive, costs imposed on the pre-existing production capital stock of firms can be associated with an unintended slow down in the transition process.[28] The other firm level variables of interest do, mostly, not exhibit a significant association with the policy variables at this early stage of the diffusion process. Only unit costs have a slightly positive, but highly significant, association with the consumption subsidy and, surprisingly, a negative one with the eco-tax given that a transition occurs. Unit costs do not only reflect variable input costs, but also annuities of past investments and effective productivity. Because the tax hampers firms' financial capabilities to invest, lower investment activities may explain why the tax has a negative association with unit costs in the short run given that a transition occurs. The consumption subsidy reduces the pressure from price competition for firms that produce more environmentally friendly, i.e. it allows less productive firms with higher unit costs to survive on the market because they can charge higher mark-ups.

Ten years after market entry, i.e. in $t = 3000$, the policies, irrespective of the resulting technological regime, exhibit a statistically and economically strong association with technology diffusion. An increase by one percentage point in the consumption (investment) subsidy is associated with a 10% (2.1%) lower share of conventional capital use. Recalling the different value ranges of the two subsidies, i.e. $\sigma^{cons} \in [0, .025]$ and $\sigma^{inv} \in [0, .1]$, qualifies the difference, i.e. the difference suggested by the different scales of coefficients diminishes when considering changes in relative terms such as

[27] Recall the value range of the subsidy, i.e. $\sigma^{cons} \in [0, .025]$. For the regression analysis, the policy parameters were transformed in percentage points, i.e. multiplied by 100. Though, the relative effect of the consumption subsidy has to be deflated if compared to $\sigma^{inv} \in [0, .1]$.

[28] Though, recall the difference in the absolute and relative environmental performance of firms. A lower share of conventional capital used is not necessarily associated with a lower environmental impact because of the distinction between replacement and capacity expansion investments. In reality, capacity expansion investments are often associated with an additional environmental burden when taking account the whole life-cycle of the capital good comparable to the well known rebound effect even if the capital good performs environmentally better during the time of use (cf. Arundel and Kemp 2009).

doubling the subsidy rate. Surprisingly, the interaction terms of the subsidies with the type dummy $\mathbb{1}(eco)$ have positive coefficients, i.e. a negative association with green technology diffusion. The sign of these two variables has flipped compared to $t = 1800$. This confirms that subsidies can have a distorting impact on the transition probability.

The intermediate phase of technology diffusion is characterized by a high degree of technological competition (see e.g. C.4). In the presence of policies, the divergence of the technological variables is on average less pronounced at an early phase of diffusion. This retards the emergence of a clear technological pathway and can explain the counterintuitive observation that the share of conventional capital utilization is increasing in the strength of policy in the intermediate diffusion phase. The stronger the policy is, the less clear is the divergence of technological indicators. The policy shifts the margin. Some of the simulations runs in the subset of eco regimes are policy induced, i.e. in such cases the transition would most likely not have occurred in the absence of policy.

Further, firms that are not able to sustain in the intensified technological competition, increasingly leave the market. Ten years after market entry, it is more obvious which of the two technological regimes emerges. The subsidies have influenced firms to invest in green capital even if this may be an individually non-optimal solution in terms of quantity and productivity. In plot C.4i in the appendix, I show the evolution of the number of active firms comparing the two technological states in the baseline and the policy experiment. The number of market exits is highest in the policy experiment given that a green transition occurs. Hence, the result can be interpreted such that the subsidy has induced some firms to adopt green capital even though the quantity-productivity combination is not a sustainable firm strategy.

The policies do not only show an association with the diffusion measure, but also with the number of employees and unit costs. In transition regimes, firms are on average larger and have higher unit costs in $t = 3000$. Irrespective of the technological regime, unit costs are positively associated with the policy parameters except from the investment subsidy, i.e. the stronger the policy is, the higher unit costs are observed. Only the investment subsidy exhibits, conditional on a green transition, a negative relationship.

At the late phase of the simulation time, i.e. 35 years ($t = 9000$) after the day of market entry, the convergence to one of the two technological states is largely completed. More than 94% of the variation in the share of conventional capital utilization at firm level can be explained by the type dummy. In contrast to the preceding analysis on policies and their interaction with barriers, the investment subsidy and the eco-tax do not any longer exhibit a significant effect if not controlling for the technological regime. When controlling for the regime, both subsidies exhibit a positive impact on diffusion, i.e. are associated with a lower share of conventional capital utilization. At this time, firms that are not any longer able to sustain on the market have exited. The negative coefficients of the interaction terms $\mathbb{1}(eco)\sigma$ indicate that the subsidies have stimulated a *deepening* of the green capital adoption among the surviving firms. Though, the effects of the policy parameters are small. At the late stage of the diffusion process, the variation in the share of conventional capital utilization across different runs is rather a question of the regime and the self-enforcing dynamics than of policy. Only within a regime class, the policies can explain part of the variation.

Regarding the firm size measured as number of employees, the two types of subsidies exhibit different effects. When not controlling for the regime type, the investment subsidy exhibits a negative association with the number of employees. Though, this negative association is overcompensated if a green transition was successful. Also the consumption tax has a net positive association with the number of employees, but its coefficients exhibit opposite coefficients compared to the investment subsidy, i.e. the positive association of the subsidy with firm size is lower if a green transition occurs. The positive association of policy and firm size is due to the higher number of market exits in the presence of policy (cf. C.4i). The investment subsidy distorts instantaneous investment decisions most while the stimulating effect of the consumption subsidy has a long term nature. This can explain the difference between the two measures. The investment subsidy is an incentive for firms to quickly build up green capacity. Those who invest relatively more, take more advantage of the subsidy. In contrast, the consumption subsidy is proportionally paid to firms. Firms benefit independently of their size and the subsidy is not an incentive to increase capacity.

Unit production costs are on average higher in those simulation runs that exhibit a technological transition. Though, the subsidy-type interaction term are negatively associated with unit costs. This supports the hypothesis, that the subsidies have stimulated investment in more productive capital goods.

6.2. Insights from the policy analysis

For effective climate change mitigation policies aim to accelerate a sustainable transformation of the economy. Policy makers have different instruments at disposal. Here, I studied the impact of three types of market based policy instruments, namely a resource tax, a green investment subsidy and a price support for environmentally benign products and evaluated the outcome of the policy measures compared to a business as usual scenario without policy. In an additional experiment, I studied the sensitivity of policy effectiveness to the strength of diffusion barriers.

Four core insights can be derived from the preceding analysis.

1. **Policy can effectively stimulate a green transition.** The analyses have shown that policy measures are effective as diffusion stimulus at the *intensive margin* independently of final technological outcome. Policies stimulate green technology adoption at the margin, i.e. in an environment of technological uncertainty where none of the two technologies clearly dominates by its technological characteristics. Higher green technology utilization during the diffusion process is associated with increasing returns to adoption resulting from learning and endogenous innovation, i.e. it is a path dependent process. The higher intensity of green technology utilization positively affects the probability of a technological regime. This could be also interpreted as *extensive margin* of diffusion referring to the distinction made by Comin et al. (2006).

2. **The effectiveness of policy measures is conditional on the *type* of diffusion barrier that needs to be overcome.** If barriers take the form of insufficient technological capabilities to exploit the productive value of green capital, i.e. if firms do insufficiently know how to use green machinery, it is a question of *learning by using* to make the green technology competitive. A price support for green products stimulates the creation of green markets and serves as a stimulus for green technology take-up, utilization and *learning*. An environmental tax can be detrimental if it reduces firms' financial capacities to invest. But, if the barrier is related to the technological properties of the green capital good, i.e. if it is sufficiently less productive than the conventional alternative, the tax compensates firms *enduringly* for having adopted an inferior technology. The disadvantage at the firm level resulting from the skill related barrier is overcome by learning over time. In contrast,the firm level disadvantage arising from the investment in a less productive machine remains until the capital good is depreciated or taken out of use. Hence, a tax can compensate for this permanent disadvantage.

   An investment subsidy is an instantaneous price mechanism that influences firms' investment decision. In contrast to the consumption subsidy, its effectiveness is independent of the *type* of barriers.

   An alternative view on the different *types* of diffusion barriers can be derived from a technological life-cycle perspective. At early phases of development, new technologies are less mature and exhibit a lower productivity. In such situation, diffusion and further development can be stimulated by environmental taxation. At later stages, when technologies are sufficiently mature and diffusion success is a matter of technological know-how and experience in green technology utilization, it is more effective to support the creation of green consumer markets and not to undermine firms' financial capabilities to invest. Investment subsidies distort the investment choice with regard to the technology choice, but regarding the amount and chosen productivity level. These subsidies should be handled with care because the increase technological uncertainty and can undermine efficiency improving specialization effects.

3. **Policies can be detrimental if the transition does not occur.** Policies increase green technology take up in the early phase of diffusion. This is beneficial if the transition takes place because firms and the innovation sector earlier specialize in the green technology. If the transition does not occur the specialization in the conventional technology is retarded. This has a negative effect on productivity. When using the relative indicator eco-efficiency as environmental performance measure, the presence of policies reduces the environmental performance per unit of output. Though, recall that relative indicators are not sufficient to combat climate change. By the design of the model, the increase in productivity is associated with an increase in output which offsets the positive effect of an improved efficiency of resource utilization if the economy is on a stable technological path (cf. C.1a).

4. **Policies affect firms asymmetrically.** Policies strengthen competition among firms. The introduction of the environmental tax imposes an additional cost burden on firms leading to a series of market exits. Those firms that successfully adopt green capital benefit from the subsidies. If a transition occurs some of the non-adopters are no longer able to survive on the market because they suffer from additional competitive disadvantages associated with the subsidies. In contrast, if the transition does not occur, the number of market exits is lower. Green firms do not benefit any longer from green subsidies when switching back to the conventional technology, but do not suffer from policy induced competitive disadvantages. The consumption and the investment subsidy exhibit opposite effects on firm size. The consumption subsidy is proportional to the amount of green technology utilization, while the investment subsidy is bound to investment activities. Hence, firms that invest more frequently and expand capacity are benefit relatively more than those that invest less.

The limitations of the present model should be kept in mind. In particular, the model does insufficiently take account of firm entry dynamics which could have an effect on the dynamics in the firm population and market competition. The contingency of policy effects on the type of barriers highlights that it is important to understand the characteristics the technology and the adopter population when searching for appropriate instruments. Many of the results are further bound to the assumptions about the endogenous innovation and learning mechanism and the role of cross-technology spillovers in the evolution of technological knowledge stocks. An in-depth investigation of these interdependencies in the process of technological change are beyond the scope of this study but are a promising field for future research. Technological sectors may differ enormously with regard to the strength of diffusion barriers and path dependence and sectoral boundaries are not necessarily clear ex-ante when trying identify the potential population of adopters and spillovers in technological development across sectoral boundaries may exist. These restrictions should be kept in mind before deriving policy conclusions from this study.

Many approaches in the existing literature of economic climate policy analysis are based on neoclassical equilibrium models with homogeneous agents and focus on price and related market mechanisms that stimulate the substitution of conventional by green capital. The nexus of climate policy and directed technological change is represented as allocation problem. The introduction of heterogeneous and interacting agents allows to re-frame it as problem of coordination in the process of technological learning and specialization (cf. Jaeger (2013)).

In this analysis, I focus on the role of adoption barriers and introduce a distinction between two types of barriers. The technology related barrier β^A reflects an inferiority in a knowledge stock that can be traded on the market, i.e. firms can *buy* capital goods with specific productivity properties. The other barrier type β^b is related to a non-tradable knowledge stock that accumulates by individual learning at the firm level. I have shown, that market based climate policy instrument perform differently conditional of strength of either of these barriers. Taxes can help overcoming an inferiority related to tradable knowledge. That is typically the channel how climate friendly directed technological change is captured in equilibrium models (cf. Löschel 2002; Popp et al. 2010).

In contrast, overcoming the skill related barrier is a matter of *doing*. Hence, it is a question of time that is needed for learning whether the green technology permanently replaces the conventional alternative. Learning by doing can be stimulated by subsidies that compensate firms for the temporary skill dependent disadvantage in green capital utilization. In this study, endogenous innovation is a "by-product" of increased adoption and strengthens the convergence to a stable technological state. If the green technology mostly suffers from skill related inferiority and if firms investment decision is subject to financial constraints, taxes on pre-existing capital stock items can have unintended effects if they undermine firms' financial capabilities to invest in green machinery.

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.

The ABM framework does further allow to investigate dynamics in the firm population. Not every firm is successful in switching to the green technology. Firms that fail to switch to the emergent technological paradigm are not able to sustain on the market. Different policy measures have different distributional impacts. Not considered here are aspects that concern the obsolescence of technological knowledge of individual employees.

7. Discussion and concluding remarks

One comment on the interpretation of "technological superiority" of the green technology should be made before continuing. Technological superiority was assumed to take the form of reduced material input costs. Recall that this may be generalized to any type of variable cost reduction that is enabled by the adoption of a radically new technology. In this study, I neglected the "stakeholders" of the variable input that is replaced by the entrant technology. Dependent on the purpose of study and the type of interpretation of the radical technology, this might be important. In the context of skill-biased technological change these stakeholders can be employees whose jobs will be replaced by machines. In the context of climate policy, stakeholders can be the owners of natural resources and employees in the material resource extraction sector.

In the proposed model the source of the material input costs is exogenous and the costs are distributed back to households as a lump-sum transfer. Hence, there is a negative income effect for households if material inputs are not any longer required. Unemployment and distributional effects are neglected and left for future investigations.

If incorporating labor market effects the degree of mobility of employment across sectors is decisive which can be captured by the transferability of technological knowledge across sectors. The mobility is linked to the skill endowment of individual workers. A forthcoming study will address a related issue, in particular the transferability of knowledge across technology types. This has also some empirical underpinnings by (Vona et al. 2015) who found that industrial sectors with a high employment share in occupations with a non-routine, adaptive skill requirement profile are faster in the adoption of environmental technologies in response to a regulatory shock. Similar findings were made in the literature on skill- and routine-biased technical change (Autor et al. 2003). Their findings indicate that the cross-technology transferability of knowledge might be important for industries to be able to cope with radical technological change and climate policy interventions.

7.1. An alternative interpretation of the Monte Carlo experiments

This study is based on a very abstract understanding of green and conventional technology. The use of the *eco-innovation* concept is highly flexible in terms of interpretation. An eco-technology is every technology that is less detrimental for the climate than the incumbent alternative. Hence, the concept of eco-innovation can be applied to any economic sector.

Technological sectors may differ enormously with regard to the strength of diffusion barriers and path dependence and sectoral boundaries are not necessarily clear ex-ante when trying identify the potential population of adopters and spillovers in technological development across sectoral boundaries may exist.

Different sectors face different barriers and it is not clear whether and how heterogeneous sectors with heterogeneous barriers can be studied as a macroeconomic aggregate. In particular, interactions among sectors and within the evolution of sector specific barriers are likely. A technological breakthrough in one sector may facilitate innovation in another sector.

In the framework of the model, perfect substitutability of eco- and conventional capital in terms of produced output was assumed. The model could be interpreted not only in a macroeconomic aggregate sense, but also as a within-sector competition study. Within a specific technological field, there are two technological solutions that compete, comparable to the sectoral scope within the studies by e.g. Arthur (1988); Kitahara and Oikawa (2017); Mowery and Rosenberg (1999). Broadening the scope, technological sectors may differ enormously with regard to entry conditions and the strength of path dependence. Also the boundaries of sectors can be questioned when technological change is disruptive. For example, in the transition towards renewable energy the coupling of formerly separated sectors is decisive. That means to transform the systems of electricity production, transportation, heating and industry simultaneously. Such aspects of coevolution supply and demand, and the heterogeneity in terms of barriers to adoption on different levels have been rarely considered in the macroeconomic literature.

Having this in mind, the experiments on the different levels of barriers can be interpreted as a cross-sector study where different barrier combinations represent alternative sectors that are faced with market entering eco-innovations. In this interpretation, a single simulation run with a specific barrier setting represents a single sector and the average across simulation runs is interpreted as macroeconomic aggregate. This neglects interactions among the sectors, but could serve as rough approximation if sectors are sufficiently distant.

Linking this interpretation with the findings of the policy experiments, it becomes clear that there is no *one-size-fits-all* optimal policy. The effectiveness of policy is sensitive to sector specific and evolving levels of the two types diffusion barriers.

7.2. Summing up and outlook

Core finding of the study is that technological uncertainty is costly.

As seen above 5.2, the switch scenarios performed significantly worse in terms of aggregate output and productivity variables. This is due to the *wasted resources* when it is for a long time unclear in which type of R&D to invest and which types of technological skills to learn. This insight is also informative for the design of policies. As shown above, policies may be detrimental if the transition does not take place because they retard the process of technological specialization. Hence, policy measures should only be applied if the technological transition is taken seriously. Insufficient stringency of policy increases technological uncertainty and may have adverse effects. For a proper design of policy, one should take account of the heterogeneous nature of diffusion barriers, policies should be sufficiently strict and long-termed and should not end abruptly such that firms can anticipate the end of policy when making strategic pricing and investment decisions. Technological uncertainty can be also seen as lack of technological coordination. Hence, it should be a guideline for policy not only to allocate resources efficiently, but also to ensure that economic agents to not act in opposite directions.

Summing up, the present model points to multiple issues that are related to the process of green technology diffusion and conventional technology substitution. It is a diffusion model where radical innovation allows the market entry of the green technology producer. The analysis have shown that technological superiority in terms of permanent variable cost reductions are not sufficient to ensure long term diffusion. If knowledge related barriers and path dependence in technological learning affect evolution of the effective usability of green technologies, processes of initial green technology uptake can be even reversed. Innovation oriented climate policies, i.e. an environmental tax and subsidies for green investment and climate friendly products, can stimulate the diffusion process and the probability of a technological regime shift. Though, dependent on the type of diffusion barriers, policies perform differently well. Taxes help overcoming disadvantages related to the productivity of the green alternative. Subsidies help overcoming barriers related to non-tradable capabilities at the firm level that are needed for the effective utilization of the green technologies. If barriers are only a question of lacking experience of adopters in green technology utilization, taxes can even hamper the diffusion if they undermine firms' financial capacity to invest.

One core limitation of the model are the simplifying assumptions about the cross-sectoral transferability of technological knowledge. These are introduced in the process of learning justified by qualitative insights from the literature. Though, technological knowledge is not only transferable in the process of individual learning at the level of the firm, but also in the the innovation sector across different technological fields. The analysis has highlighted that the divergence in the paths of learning and innovation play an important role for the establishment of a technological regime. An analysis of spillovers in the evolution of the two types of technological knowledge and its implications for the process of technology diffusion and a green technological transformation is beyond the scope of this study.

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A. Stylized facts and empirical calibration

The model is supposed to serve as tool for the economic analysis of green technology diffusion and scenario exploration. In order to justify the model's suitability for this objective, the model needs to be empirically validated. In this section, the model's ability to match economic stylized facts that are established in the literature. Below, I introduce stylized facts of innovative processes that were used to design the model. Stylized facts of innovation that serve for model validation are discussed in the main text body of this article.

A.1. Economic stylized facts for model validation

In this subsection, an overview of micro- and macroeconomic stylized facts that are reproduced by the model is provided. The selection of validation criteria follows the approach used in Dawid et al. (2018b). The authors discuss and motivate the use of specific stylized facts more comprehensively pointing to their counterparts in the empirical literature. Here, I give only a short overview and show a subset of validation criteria to demonstrate the models ability to reproduce empirically observed economic regularities and is expected to provide an appropriate tool for economic scenario exploration and policy analysis. All data and the corresponding R code is provided in the online documentation to allow the reader to reproduce the results. The results presented below refer to the simulation results of the baseline scenario (cf. section 5.1). The references to the empirical counterparts of the stylized facts are discussed in more detail in Dawid et al. (2018b). Here, I do only demonstrate that extended model behaves in a similar way as the original Eurace@unibi model.

1. The model is able to reproduce **growth rates, business cycle volatility and persistence patterns** similar to those documented in the empirical literature. The average growth rate of the 210 simulation runs accounts for .0156 and an average standard deviation of .0011.[29] The average growth rate is slightly lower than empirically documented values, but this is merely a matter of scaling of productivity progress parameters in the model, but does not qualitatively change the results. The variation across different simulation runs is low and indicates robustness of the model simulations.

2. **Business cycle volatility** is evaluated by the size of the cyclical component. It is measured as average of the absolute size of the percentage deviation of the time series from its bandpass filtered trend data. The average size of a business cycle accounts for .0013, i.e. aggregate output variates on average by 0.1 percent. The standard deviation of the variation accounts for .0017. Again, the variation across runs, i.e. the standard deviation of per-run average size of the business cycle (standard deviation) is low accounting for .0004 (.0005). The

[29] These values are the arithmetic mean of 210 run-specific average growth rates computed as geometric mean in bandpass filtered time series across 15.000 iterations representing roughly 60 years. The standard deviation is the average standard deviation of run specific deviations over time. The variation across runs in means (standard deviations) accounts for .0010 (.0011).

model reproduces slightly less volatile patterns than the original model. Though, as discussed in the text, this is intended and caused by the design of functions that have a smoothing effect (for example revenue recycling routines implemented via dividend and R&D budgets or governmental budget smoothing). Purpose of study is the understanding of the relevance of knowledge accumulation processes for technology diffusion. Stronger cyclical dynamics would make this analysis more difficult and are left for future investigations.

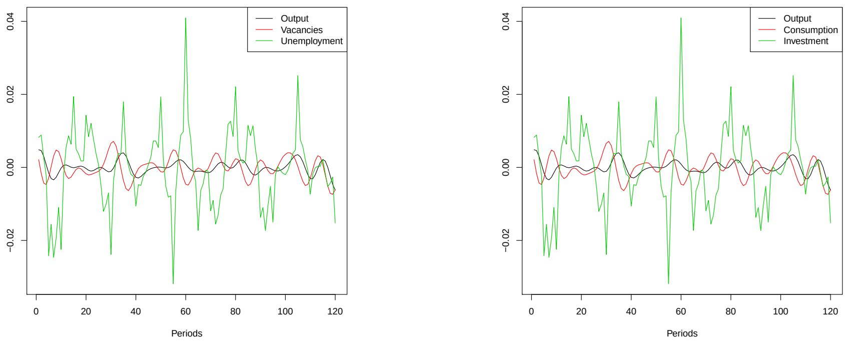
3. **Co-movement of key variables with the business cycle** is shown in table 11 by a representation of the cross-correlation structure of macroeconomic key variables and business cycle dynamics. The values in the table indicate the correlation of the cyclical part of band pass filtered time series data with the business cycle measured as output fluctuations for different time lags. The table confirms the pro-cyclical behavior consumption, investment, employment and vacancies. Anti-cyclical behavior is observed for wages, mark-ups and unemployment.

4. The **relative magnitude of fluctuations** of macroeconomic variables differs in their extent. In figure A.1a, I show the relative magnitude of the percentage variation in the cyclical argument of the bandpass filtered time series of output, consumption and investment. The plot covers a 10-year time period close to the end of simulation time and shows the time series of a randomly drawn single simulation run.[30] In line with the empirical literature, investment exhibits a higher volatility than consumption and output. Moreover, the figure reveals the lag structure of the three variables, i.e. production responds to a positive consumption shock with a time lag and an output shock precedes a boom in investment. In figure A.1b, an analogous plot is shown for the relative magnitude of variations in output, vacancies and unemployment.

5. **Labor market properties** can be summarized by a Beveridge and Phillips curve. The model reproduces a Beveridge curve (A.2b) which illustrates the relationship between unemployment and vacancies, i.e. higher unemployment is associated with a lower vacancy rate. The Phillips curve shown in A.2a shows the relationship between unemployment and inflation. The figures on show these curves for a single randomly selected run for a 20 year snapshot in the first and second half of the simulation horizon.

These presented stylized facts are only a fraction of the stylized facts that can be reproduced by the Eurace@unibi model as discussed in Dawid et al. (2018a). Here, I restrict the analysis to the facts shown above to give the reader an insight to the macroeconomic dynamics and interactions that are simulated by the model. Purpose of this short discussion is to motivate why the model is expected to deliver simulation results that can be plausibly linked to the observed economic reality.

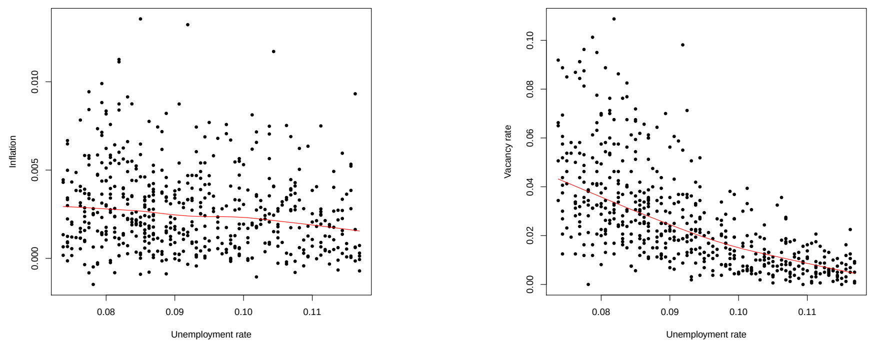
[30] All material to reproduce these plots are provided in the online documentation. The late snapshot in time is chosen because the technological transition has completed. Preliminary analyses have shown that the observed patterns are consistent across time.



(a) Output, consumption, investment

(b) Output, vacancies, unemployment

Figure A.1: These plots show the relative magnitude of fluctuations captured by the cyclical argument of macroeconomic bandpass filtered time series and measured as percentage. The shown series cover a 10 year period at the end of the simulation horizon of a randomly drawn single run out of the set of 210 simulation runs.



(a) Phillips

(b) Beveridge

Figure A.2: These figures show a Phillips and Beveridge curve for a randomly drawn simulation run. The data accounts for unsmoothened time series data covering the whole simulation period of roughly 60 years. Outliers are removed from the data.

	t-4	t-3	t-2	t-1	0	t+1	t+2	t+3	t+4
Output	-.126	.233	.609	.894	1.00	.894	.609	.233	-.126
	(.084)	(.066)	(.036)	(.010)	(.000)	(.010)	(.036)	(.066)	(.084)
Consumption	-.470	-.468	-.330	-.070	.249	.536	.705	.709	.555
	(.065)	(.066)	(.068)	(.066)	(.061)	(.062)	(.063)	(.062)	(.062)
Unemployment	.150	-.205	-.583	-.875	-.992	-.896	-.619	-.247	.113
	(.082)	(.066)	(.042)	(.024)	(.022)	(.023)	(.039)	(.064)	(.081)
Vacancies	-.150	.011	.204	.379	.489	.501	.414	.258	.079
	(.063)	(.060)	(.081)	(.113)	(.134)	(.134)	(.116)	(.088)	(.068)
Price	.010	.135	.253	.330	.345	.294	.193	.072	-.039
	(.106)	(.122)	(.144)	(.158)	(.155)	(.136)	(.111)	(.099)	(.105)
Wage	.082	.097	.098	.075	.029	-.034	-.099	-.151	-.177
	(.091)	(.093)	(.098)	(.101)	(.101)	(.101)	(.104)	(.110)	(.114)
Debt	-.129	-.025	.102	.216	.286	.294	.241	.149	.047
	(.124)	(.130)	(.126)	(.114)	(.100)	(.090)	(.090)	(.095)	(.010)
Inflation	-.351	-.328	-.216	-.044	.139	.278	.338	.310	.218
	(.099)	(.091)	(.087)	(.096)	(.113)	(.121)	(.115)	(.101)	(.090)
Productivity	.107	-.016	-.155	-.270	-.326	-.305	-.216	-.089	.037
	(.111)	(.096)	(.104)	(.131)	(.150)	(.148)	(.126)	(.099)	(.089)
Investment	-.231	-.161	-.053	.071	.179	.245	.256	.215	.143
	(.087)	(.086)	(.097)	(.110)	(.116)	(.111)	(.097)	(.083)	(.083)
Price eco	-.141	-.272	-0.345	-.336	-.248	-.111	.031	.137	.185
	(.104)	(.118)	(.129)	(.127)	(.114)	(.103)	(.102)	(.106)	(.105)
Mark ups	-.170	.065	.315	.510	.595	.549	.391	.173	-.037
	(.107)	(.107)	(.137)	(.174)	(.190)	(.174)	(.135)	(.098)	(.097)

Table 11: This table shows cross correlation patterns in the volatility of macroeconomic time series with (lagged) business cycle dynamics, i.e. variation in aggregate output. All variables are measured as cyclical argument of the underlying time series. The first row corresponds to the autocorrelation of a business cycle. The presented values are averages of the run-wise correlations. In parentheses, I the standard deviation across simulation runs is shown.

A.2. Stylized facts of (eco-)innovation

The Eurace@unibi-eco model is designed and validated along a number of stylized facts that can be derived from the empirical studies. It can be distinguished between characteristics of (eco-)innovation that served as priors for the model design and observed patterns that are used for validation. In this subsection, an overview stylized facts of (eco-)innovation is given and it is briefly explained how these aspects are incorporated in the Eurace@unibi-eco model. The observed patterns related to model validation are discussed in the main article (esp. 5.1).

1. **Uncertainty and the stochastic nature of innovation:**
   Innovation processes are subject to different types of uncertainty, in particular uncertainty with regard to success in the research process at the inventor's stage, uncertainty about the market value of successful innovation, and uncertainty on the adopters level about the benefits and optimal timing of adoption (cf. Dosi 1988; Nelson and Winter 1977; Windrum 1999). In Eurace@unibi, innovation success is probabilistic, the pricing of the innovative outcome follows an adaptive process of learning about the market value of the innovative outcome, and adopters' decisions are based on estimations about the evolution of the uncertain market environment rather than optimality calculations.

2. **Incremental nature of innovation:**
   "Standing on the shoulders of giants", inventors build on previous knowledge when

researching for technological novelties (cf. Dosi 1988). In Eurace@unibi, IG firms *incrementally* shift upwards their technological frontier through innovation.

3. **Technological change is (partly) embodied in capital:**
   Technology is the means that transforms specific inputs into a valuable output good. Part of these means is embodied in the type of production capital that can be bought on the market. This can be the technical characteristics of physical machinery, but it can also be a codified type of technical knowledge that can be bought on the market as human capital. If other types of capital are used in production, technology is changed (e.g. Romer 1990; Windrum 1999). This is also captured in Eurace@unibi where technological change in the quantitative (productivity growth) growth) and qualitative (technology type) dimension is channeled through the adoption of new capital goods.

4. **Tacit knowledge as second dimension of technology:**
   The non-capital type of technology is referred as to know-how. Technological change does not only occur through the replacement of capital, but might also refer to non-tradable, tacit knowledge that is applied in the utilization of inputs that can be bought on the market. Tacit knowledge accumulates through learning processes and not via market transactions. At the firm level, tacit knowledge and technological learning imposes a trade-off between static and dynamic efficiency when the adoption of a superior technology is hindered if the required level of technological capabilities is not yet available but would be accumulated after adoption (cf. Dawid 2006; Di Stefano et al. 2012; Dosi 1991; Windrum 1999). Tacit knowledge is represented in the Eurace@unibi model in the form of evolving technology specific skills of a firm's workforce that are needed to effectively use capital goods.

5. **Heterogeneity of innovation adopters:** Costs and benefits of innovation adoption can be heterogeneous. This can be due to heterogeneous preferences and experiences, different adoption costs dependent on capabilities and the compatibility with current endowments (Allan et al. 2014; Nelson and Winter 1977). In the model, this is captured by the heterogeneity of CG firms in terms of capabilities, expectations, capital endowments and financial capacities.

6. **Spillovers and knowledge externalities:**
   Spillovers and knowledge externalities are positive externalities that arise from and during the development and diffusion of a new technology. These spillovers occur via different channels, and typically refer to the public good nature of technological knowledge or to the process of corporate learning that is either associated with the influx of externally acquired technological knowledge via labor mobility or by learning that is triggered by the exposure to a technological novelty. (Allan et al. 2014; Gillingham et al. 2008; Pizer and Popp 2008). In the model, spillovers do not refer to knowledge flows in R&D processes, and are only captured by the spillovers in the evolution of tacit knowledge, i.e. cross-technology spillovers in learning and the dependence of learning on the technical characteristics of production capital, and additionally via labor mobility.

7. **Creative destruction and technological obsolescence:** Creative destruction and/ or technological obsolescence refer to the phenomenon of replacement of an incumbent technology by a new one. This process is associated with a loss in the value of the old technology, equipment and skills that are complementary to the old, but not or only imperfectly transferable to the utilization of the new technology (Klimek et al. 2012; Köhler et al. 2006). This feature enters the model in the way of technology specific skills. When firms adopt an other technology type, their capabilities in the utilization of the replaced technology are not required any longer and experience a loss in value.

8. **Sunk costs and the vintage structure of capital as adoption barrier:** Investment and the adjustment of capital is not instantaneous. Rather, firms invest at certain points in time and the undertaken investment is available for the firm until it is fully depreciated. After being paid once, investment costs are considered as sunk-costs. Besides variable costs of capital utilization, relative costs and benefits of different investment opportunities are not relevant for the firm's production planning. This may inhibit the adoption of a new technology even if is superior (Ambec et al. 2013; Dosi 1991; Kemp and Volpi 2008; Metcalfe 1988). The *Eurace@unibi-eco* model applies a vintage capital approach, i.e. firms have a capital stock that is composed of different vintages of capital that depreciate over time and undertake new investments at a given periodicity if old capital needs to be replaced or a capacity expansion is intended.

B. Technical appendix: Model documentation

B.1. Investment goods sector

B.1.1. Production

To produce IGs, firms need only labor as input. For reasons of simplification, the IG firms are not integrated in the labor market and use only *virtual* labor with constant returns to scale, i.e.

$$k_{ig}^{v} = \alpha^{v} \cdot L \tag{15}$$

where α^v is a scaling factor determining the amount of labor L needed to produce one unit of capital goods. The scaling factor depends on the ratio of the productivity of the least productive vintage $v = 1$ that is currently supplied to the vintage v. Hence, it is more expensive to produce a more productive vintage, but successful innovation shifts the ratio (see 3.2.2). *Virtual* means that labor is not explicitly modeled, hence without the incorporation of labor market feedbacks if IG firms adjust their production quantity. The *virtual* labor input is costly and the price for labor follows the same development as average wages in the economy. In order to ensure the model's closure, the costs for labor inputs are recycled back to the economy as a transfer to households. This assumption can be interpreted as a separated labor market. Hence, there are some invisible households who receive a labor income from their work in the capital goods sector and consume in the same proportions as households working in the CG sector. The use of *virtual* labor as input implies that capacity constraints are assumed away.

B.1.2. Pricing

IG firms impose an adaptive mark-up over unit production costs captured by the wage proxy mentioned above (B.1.1). Adaptive pricing rules are a common approach for heuristic pricing rules in agent-based models for example in Assenza et al. (2015). The price $p_{ig,t}^{v}$ of vintage v is given by

$$p_{ig,t}^{v} = p_{t}^{lab,v} \cdot (1 + \mu_{ig,t}) \tag{16}$$

where $p_t^{lab,v}$ are labor costs for producing one unit of capital v, and $\mu_{ig,t}$ is an adaptive mark-up over production costs that is imposed by firm ig. Labor unit costs are vintage specific and proportional to the relative productivity of a vintage, i.e. $p_t^{lab,v} = p_t^{lab} \cdot \frac{A_{ig}^{v}}{A_{ig,t}^{1}}$ where $A_{ig,t}^{1}$ is the productivity of the least productive vintage $v = 1$ currently offered by firm ig. More productive vintages are assumed to require relatively more labor to produce and are consequently more costly in production. These higher production costs are reflected in the final vintage price. The firm specific mark-up $\mu_{ig,t}$ follows an updating rule that takes account of trends of firms' pricing, market shares and profits in a given horizon of past periods. The adaption rule is given by

$$\mu_{ig,t} = \begin{cases} \mu_{ig,t-1} \cdot (1 + \delta^{\mu}) & \text{if case A} \\ \max[\bar{\mu}, \mu_{ig,t-1}] \cdot (1 - \delta^{\mu}) & \text{if case B} \\ \mu_{ig,t-1} & \text{else} \end{cases} \tag{17}$$

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

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

i) They have increased the mark-up in past periods but did not lose market share $\omega_{ig,t}$ measured in relative sales, i.e. $\left[\Delta_t \mu_{ig,t} \geq 0 \wedge \Delta_t \omega_{ig,t} \geq 0\right]$ where Δ indicates the deviation from the average over a given number of past periods.

ii) They have increased the mark-up and lost market share, but profits $\pi_{ig,t}$ where rising, i.e. $\left[\Delta_t \mu_{ig,t} \geq 0 \wedge \Delta_t \omega_{ig,t} < 0 \wedge \Delta_t \pi_{ig,t} > 0\right]$.

iii) They have decreased the mark-up and the market share weakly increased but profits decreased, formally $\left[\Delta_t \mu_{ig,t} < 0 \wedge \Delta_t \omega_{ig,t} \geq 0 \wedge \Delta_t \pi_{ig,t} < 0\right]$. From this observation firms conclude that the mark-up was too low to be profit maximizing even though they gained a higher market share.

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

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

ii) Firms decreased the mark-up, gained weakly market share but made lower profits, i.e. $\left[\Delta_t \mu_{ig,t} < 0 \wedge \Delta_t \omega_{ig,t} < 0 \wedge \Delta_t \pi_{ig,t} < 0\right]$. Theoretically, a firm can make higher profits even though it has decreased prices and lost market share. This can happen if the market size has increased sufficiently which might be caused by the price decrease. The combined condition of $[\Delta_t \omega_{ig,t} < 0 \wedge \Delta_t \pi_{ig,t} < 0]$ indicates that the decrease in profits is not (only) due to changes in the demand on the IG market but at least partly results from a suboptimal pricing strategy.

The minimum threshold ensures that the mark-up never falls below a given minimum value.

In the remaining cases, e.g. when firms decreased prices, lost market share but made higher profits, they are uncertain about the strategy and keep the price constant.

B.1.3. Revenue allocation

IG firms revenue is composed of two parts. The first part accounts for the *virtual* wage payments for labor inputs to IG production. The amount is fueled back into the economy as a lump-sum transfer that is uniformly allocated across households. The remaining part of IG firms' revenue accounts for profits $\pi_{ig,t}$ stemming from the mark-up pricing. A given share $\lambda \in (0,1)$ is reinvested in R&D. The remaining share $(1-\lambda)$ of profits is paid as dividends to shareholders. The R&D expenditures are smoothed to iron out short term volatility of CG firms investment activity. Hence, monthly R&D expenditures are computed as a running average of past profits $\pi_{ig,t}$ over the R&D budgeting horizon T^{rd}, i.e.

$$R\&D_t^{ig} = \frac{1}{T^{rd}} \sum_{\tau=1}^{T^{rd}} \lambda \pi_{ig,t-\tau}. \tag{18}$$

R&D expenditures in the real economy account mostly for the wages of researchers. Because there is no labor market for R&D labor in the present model version, these payments have to be transfered back to the economy to ensure model closure. This is done by treating R&D expenditures as dividends that are paid to shareholders, i.e. to households that have invested in risky assets. A similar smoothing routine is applied to the labor cost dummy such that transfer payments exhibit a lower volatility than firms' investments.

B.2. Consumption goods sector

B.2.1. Investment decision

At a given periodicity of time, firms invest to replace depreciated and/or obsolete capital and to expand their capacity. When firms invest they are faced to a decision in which vintage to invest and how many items to buy. Hence, they have to decide about the quantity K^v, the productivity A^v and the technology type ig of the capital good they want to buy. This decision is based on the net present value (NPV) of an investment option and firms chose the option that is expected to have the highest NPV. The NPV is given by the expected, discounted profit $\hat{\pi}^v$ conditional on an investment in $I_{i,t}^v$ less investment costs, i.e.

$$NPV_{i,t}^v = -\tilde{p}_t^v \cdot I_{i,t}^v + \sum_{\tau=0}^{T^{inv}} \left(\frac{1}{1+\rho}\right)^\tau \cdot \hat{\pi}_{i,t+\tau}^v \tag{19}$$

where $\tilde{p}_t^v$ is the unit price of a certain vintage and I_t^v the amount of capital items to be bought. Expected profits $\hat{\pi}_{i,t}^v$ take account of expected revenues, labor, resource input costs and financial costs from previous credit installments, are accumulated over the time horizon T^{inv} and discounted with rate ρ. When computing the expected profits, firms anticipate market developments and learning dynamics of employees (see 3.2.3).

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 a credit from private banks.

C. Simulations

C.1. Parameter settings

Parameter name	Symbol	BAU value	Remarks
CG market parameters			
Depreciation rate		.03	Depreciation of capital (value).
Linear depreciation month		60	Depreciation of capita (units).
Discount rate	ρ	.01	Discounting e.g. in firms' investment decision.
Investment time horizon	T^{inv}	60	Number of periods for NPV calculation.
Wage wealth ratio		.2	
# of incomes for consumption budget		4	Number of last incomes used by HH to determine current consumption budget (consumption smoothing).
Pricing periodicity		2	
	γ^{const}	15	Strength of competition, price sensitivity of final goods consumers.
Investment periodicity		4	
Investment steps		1.0	
Maximal # investment steps		5	
Maximal # vintages under consideration		5	
Efficiency coefficient	e	1	Efficiency of natural resource use.
Endogenous firm birth hazard rate		1	Switch on/ off endogenous probability, i.e. founding of new firms more likely the less firms are active on the market.
# installment periods		15	Number of periods for credit installment.
Long-term horizon		72	Length of horizon for firm's longterm expectations on market development.
Short-term horizon		12	Analogously.
Learning parameters			
General skill level	b_h^{gen}	$\{1, 2\}$	Households' general skill level. Random choice with equal likelihood.
Absorptive capacity	$\chi(b_h^{gen})$	$\{.0125, .03703\}$	Households' absorptive capacity (dependent on general skill level).
Minimum learning intensity	χ^{int}	.5	Lower bound to learning intensity.
Spillover intensity	χ^{spill}	.5	Learning spillovers across technology types.
Labor market			
Wage reservation update		.05	Amount by which reservation wages are updated after non-successful job application.
Fraction maximum dismissals		.15	Maximum share of workforce that can be dismissed in a month.

Table 12: CG and labor market parameters

IG market parameters			
Returns to R&D	η	1.0	Exponent of R&D influence on innovation probability.
Exogenous innovation probability	$\bar{p}$	2.5	
Exogenous productivity progress	ΔA	.04	
Maximal # offered IGs	V	6	
Maximal # last prices for adaptation		12	Length of horizon taken into consideration in mark-up adaptation mechanism.
Maximal # last prices for smoothing		12	Length of horizon taken into consideration for price smoothing.
IG price smoothing		.05	
IG minimal mark-up		.05	
IG mark-up constant		.25	Constant used for initialization.
Strength IG transfer smoothing		.1	Responsiveness of IG transfers paid to HH to IG sales, i.e. to volatility of investment.
# months IG transfer smoothing		90	Smoothing of IG revenue paid to HH as proxy for labor income in IG sector.
# months IG R&D budget smoothing	T^{rd}	60	
Eco IG market entry			
Day of market entry	t_0	600	
% initial specific skill difference	β^b	.05	Can be scaled by strength of entry barriers. When random set to .15.
% initial technology difference	β^A	.05	Can be scaled by strength of entry barriers
Innovation periodicity after entry		6	The entrant does not enter the market with the full range of vintages, rather it adds every six months a new vintage to the supply array until it has reached the maximal length.

Table 13: IG market and market entry parameters

Policy parameters			
ECB interest rate		.05	
Unemployment benefit (%)		.7	% of last income that is paid as unemployment benefit.
Government budget horizon		96	
Adaptive tax rates		1	Taxes adapt such that gov. budget is long term balanced.
Debt limit		1	

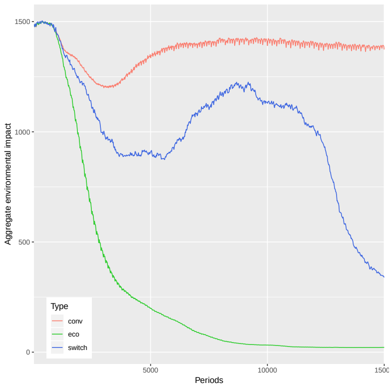
Table 14: Policy parameters

C.2. Plots and tables

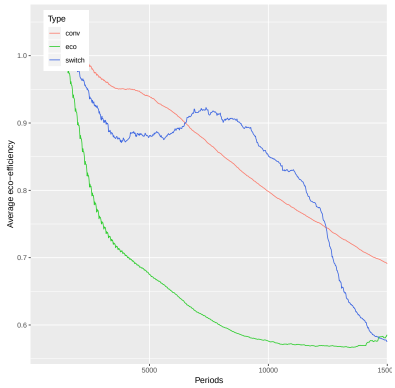
C.2.1. Baseline scenario

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 C.1a 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 C.1b). Though 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 and Kemp 2009).

The Wilcoxon test confirm the significance of differences in particular for the switch and the other two scenarios. In the beginning, before the green capital producer enters



(a) Aggregate environmental impact



(b) Average eco-efficiency

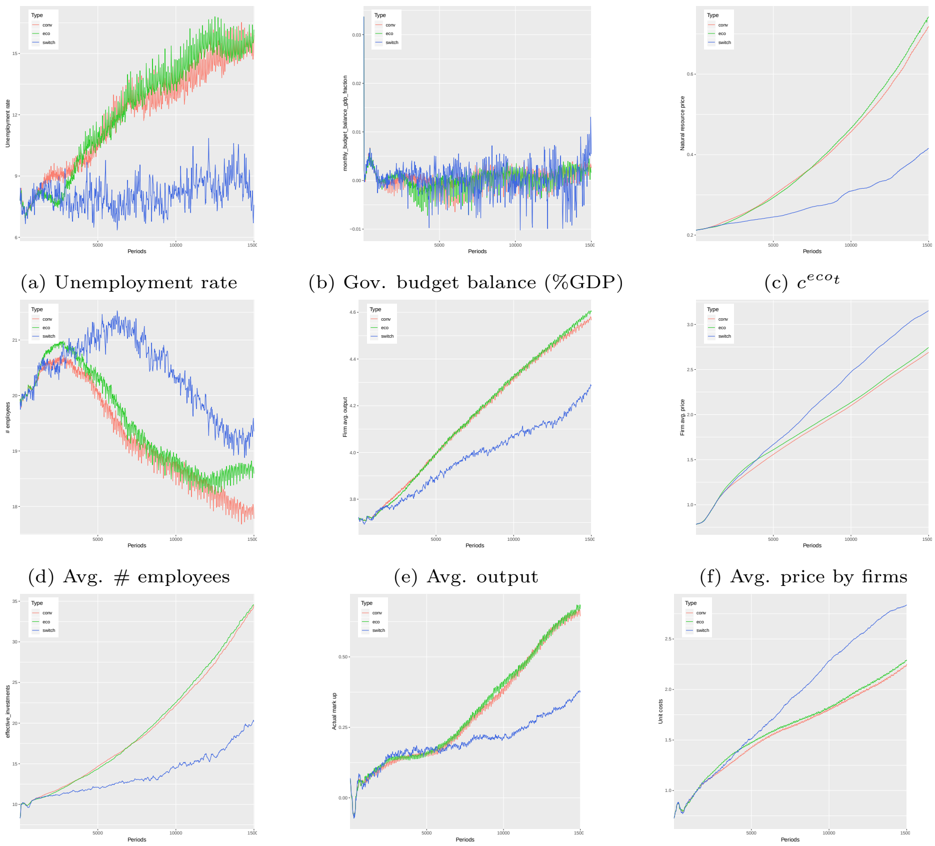
Figure C.1: These figures show the evolution of the aggregate environmental impact and eco-efficiency as environmental impact per unit of output. The colors indicate the scenario type (see text)

t	Mean (Std) *eco*	*conv*	*switch*	p-value *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

Table 15: In this table the results of a Wilcoxon test on equality of means are shown. The means are computed as average over the a subset of periods and disaggregated by 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.

the market, the differences are not significant but a considerable divergence is observable thereafter. 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. Though, 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.

It is not shown here that the transition to the green economy is associated with temporary learning costs. Aggregate output is significantly lower in the eco scenarios, but only in the initial phase of technology diffusion ($t \in [601, 3000]$). This difference diminishes after the economy has converged to the final technological state.



(a) Unemployment rate (b) Gov. budget balance (%GDP) (c) $c^{eco}{}_t$

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

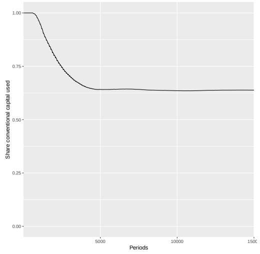
(g) Avg. effective investment (h) Avg. mark up (i) Avg. unit costs

Figure C.2: These figures show the evolution of macroeconomic and firm-level key indicators. The different colors indicate the technological regime type. The jumpy behavior (esp. for the number of active firms) of the blue line (indicating *switch* scenarios is due to the small number of runs within the set).

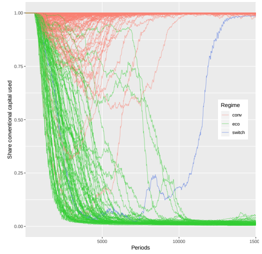
C.2.2. Random barrier experiment

	Mean (Std)		p-value	Mean (Std)		p-value
t	*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			

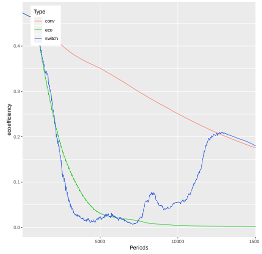
Table 16: In this table the results of a Wilcoxon test on equality of means are shown. The means are computed as average over the a subset of periods and disaggregated by run. The time interval [601, 3000] corresponds to the first ten years after market entry. In this phase, technological uncertainty is high. [3001, 5400] corresponds to the subsequent decade. [5401, 15000] to a phase of convergence to the final technological state in most of the simulation runs.The interval [0, 150000] accounts for the sample average.



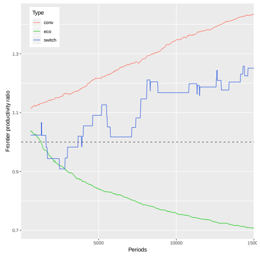
(a) ν_t^c batch



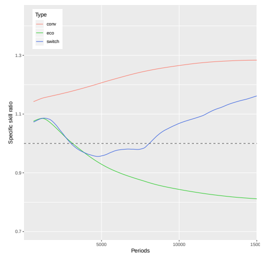
(b) ν_t^c by regime type



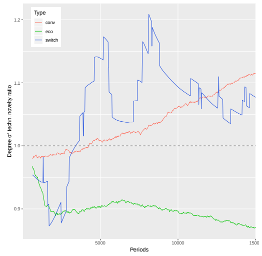
(c) Eco-efficiency



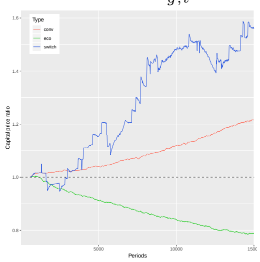
(d) $\alpha_t = \frac{A^V_{c,t}}{A^V_{g,t}}$



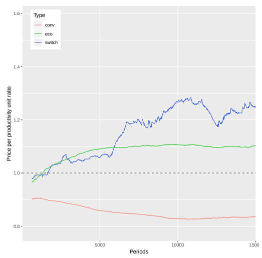
(e) $\beta_t = \frac{b^c_t}{b^g_t}$



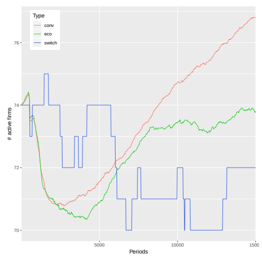
(f) $\frac{A^V_{c,t}/b^c_t}{A^V_{g,t}/b^g_t}$



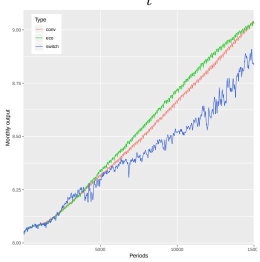
(g) $\frac{p^c_t}{p^g_t}$



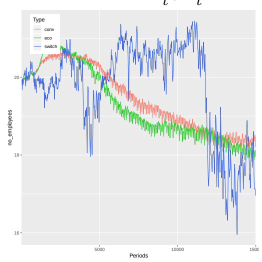
(h) $\frac{p^c_t/A^c_t}{p^g_t/A^g_t}$



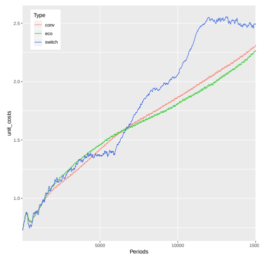
(i) # active firms



(j) Monthly output



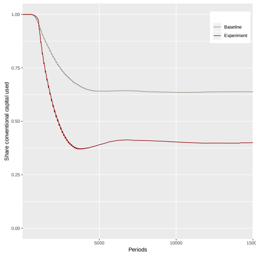
(k) Avg. # employees per firm



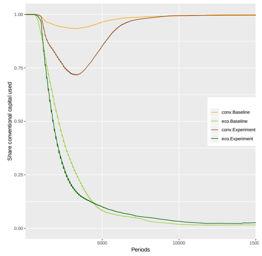
(l) Unit costs

Figure C.3: These figures summarize the technological and macroeconomic outcome of the random barrier experiment disaggregated by regime type. Note that the number of *switch* regimes (blue line) is one which explains the jumpy behavior of the time series. Again, the switch regimes exhibits a less strong divergence in the relative knowledge stocks which are decisive for the stabilization of a technological regime. Further, the switch regimes is associated with costs of technological uncertainty in terms of lower productivity and output.

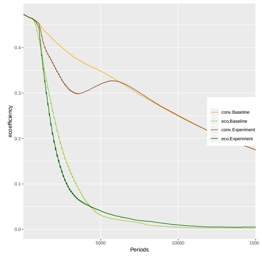
C.2.3. Policy experiments



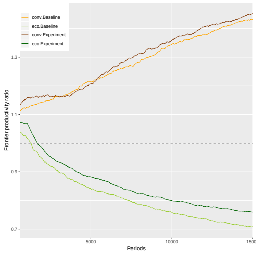
(a) ν_t^c batch



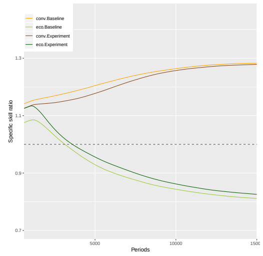
(b) ν_t^c by regime type



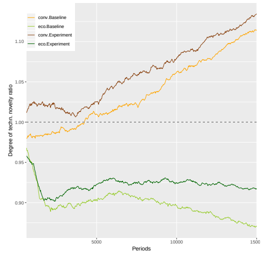
(c) Eco-efficiency



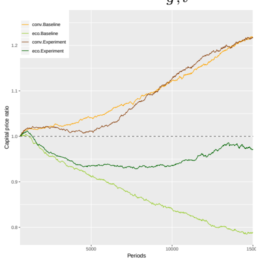
(d) $\alpha_t = \frac{A^V_{c,t}}{A^V_{g,t}}$



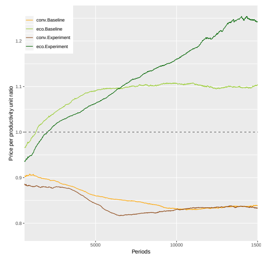
(e) $\beta_t = \frac{b^c_t}{b^g_t}$



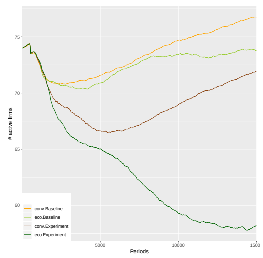
(f) $\frac{A^V_{c,t}/b^c_t}{A^V_{g,t}/b^g_t}$



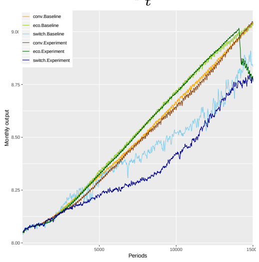
(g) $\frac{p^c_t}{p^g_t}$



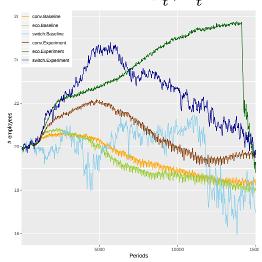
(h) $\frac{p^c_t/A^c_t}{p^g_t/A^g_t}$



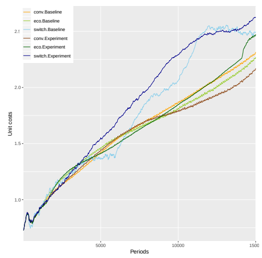
(i) # active firms



(j) Monthly output



(k) Avg. # employees per firm



(l) Unit costs

Figure C.4: These figures summarize the macroeconomic and technological characteristics of the policy experiments with randomized diffusion barriers (6.1.2) in comparison to the baseline scenario with randomized barriers, but without policy (5.2).

D. Abbreviations

List of abbreviations

ABM Agent-based Model(ing)

CG Consumption good

IG Investment good

NPV Net present value

VAT Value added tax

List of indices

i Index of CG firm $i \in \{1, ..., I\}$

ig Index of IG sector $ig \in \{c, g\}$. It also indicates the technology type of capital goods that are produced in this sector.

v Index of vintage of a capital good with properties $(A^v, \mathbb{1}(v))$

List of parameters

b_h^{gen} Household h's general skill level

χ^{int} Minimum technology specific learning factor representing learning spillovers across technology types

χ^{spill} Intensity of cross-technology learning spillovers

e Efficiency coefficient for the use of material and energy inputs

η Returns to R&D

$\bar{\mu}$ Minimum mark-up in IG sector

$\bar{p}$ Fix minimum probability of innovation success in IG sector

ρ Discount rate

T^{inv} Investment time horizon

T^{rd} R&D budgeting horizon

t_0 Day of eco-IG firm's market entry

V Maximal number of vintages that can be supplied by IG producers and simultaneously index for the most productive vintage (technological frontier)

List of variables

$A_{h,t}^{ig}$ Average productivity level of capital of type ig of household h's employer

$A_{i,t}^{Eff_v}$ Effective productivity of vintage v for firm i in t

$A_{ig,t}^{V}$ Technological frontier in IG sector ig in time t

A^v Labor productivity of vintage v

$B_{i,t}^{ig}$ Average specific skill level of employees in firm i for technology ig

$b_{h,t}^{ig}$ Technology specific skills of household h in t for technology type $ig \in \{c, g\}$

c_t^{eco} Unit costs for natural resource inputs

$\mathcal{D}_t$ Aggregate environmental impact

$\Delta b_{h,t}^{ig}$ Learning gap between the employer's technology and household's skills

δ^μ Percentage adjustment of mark-ups in IG sector

$\mathbb{1}(v)$ Binary indicator for conventional technology with $\mathbb{1}(v) = 1$ and $\mathbb{1}(v) = 0$

I_t^v Investment in vintage v in units of capital goods

L Labor

$L_{i,t}$ Number of employees of firm i

$\mu_{ig,t}$ Mark-up in sector ig

$\nu_{h,t}^{ig}$ Share of capital of type $ig \in \{c, g\}$ in the used capital stock of household h's employer

$\omega_{ig,t}$ Market share of firm ig

$\hat{\pi}_{i,t}^v$ Expected period profit conditional on an investment in vintage v

$\pi_{ig,t}$ Profit of firm ig

$\mathbb{P}_{ig,t}$ Probability of successful innovation

$p_t^{lab,v}$ Marginal labor costs in IG production of vintage v

$\tilde{p}_t^v$ Investor price for capital vintage v

$p_{ig,t}^v$ Supply price of v

$Q_{i,t}$ Consumption good output

$\widehat{R\&D}_{ig,t}$ R&D intensity in sector ig

σ_t^{cons} Price support for environmentally sound produced products

σ_t^{inv} Subsidy for investments in green capital

θ_t^{eco} Environmental tax imposed on natural resource inputs

$w_{i,t}$ Mean wage of firm i in t