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Skill transferability and the stability of transition pathways:

A learning-based explanation for patterns of diffusion

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Skill transferability and the stability of transition pathways

A learning-based explanation for patterns of diffusion

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Technological know-how is necessary to make effectively use of new machinery and capital goods. Firms and employees accumulate technology-specific knowledge when working with specific machinery. Radical innovation differs by technology type and pre-existing knowledge may be imperfectly transferable across types. In this paper, I address the implications of cross-technology transferability of skills for firm-level technology adoption and its consequences for the direction of macroeconomic technological change. I propose a microeconomically founded model of technological learning that is based on empirical and theoretical insights of the innovation literature. In a simulation study using the macroeconomic ABM Eurace@unibi-eco and applied to the context of green technology diffusion, it is shown that a high transferability of knowledge has ambiguous effects. It accelerates the diffusion process initially, but comes of the cost of technological stability and specialization in the long run. For firms, it is easy to adopt, but also easy to switch back to the conventional technology type. It is shown how different types of policies can be used to stabilize a technological transition pathway. The findings are summarized in a general taxonomic framework to characterize technologies. It represents a bottom-up approach to the study of technology transitions.

Keywords: Technological transition; technology diffusion; technological knowledge; learning; climate policy; absorptive capacity; agent-based model.
JEL: O11, D83, O33, Q55, Q58, C63

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1. Introduction

Two major technological challenges characterize the dawn of the 21st century, climate change and digitization. The avoidance of irreversible climate risks requires a fast and deep transformation of the economy towards zero emissions until the second half of the century [IPCC, 2018]. Digitization has the potential to alter established modes of production and occupations obsolete [Brynjolfsson and McAfee, 2012]. Both technology trends can be thought as a large scale substitution process in which an incumbent technology is going to be replaced by an emergent entrant. Both trends are likely to be associated with disruptive consequences in terms of distribution at the level of individual households, firms, regional and national economies. Disruption is caused when occupational skill requirements and the valuation of tangible and intangible assets change in a short time.

In this study, a theory of evolving substitutability is developed. The theory is based on a microeconomic model of technological learning dependent on the characteristics of competing technologies. This theory is a bottom-up approach to the multi-layer perspective in transition studies [cf. Geels, 2002, Geels and Schot, 2007]. Its insights are valuable for policy makers being interested in the acceleration of sustainability transitions and smoothing disruptive side-effects of technological change [Safarzyńska et al., 2012].

The microeconomic learning model is implemented in the macroeconomic agent-based model (ABM) Eurace@unibi-eco that is used to simulate a race between an entrant green and incumbent conventional technology with stochastic elements [Hötte, 2019b].

The design of the model is inspired by insights of the theoretical and empirical literature on technology diffusion at the firm, industry and macroeconomic level. The majority of studies in the diffusion literature applies a linear model of technological change in terms of productivity growth, but puts little emphasis on the role of substitution dynamics.

Comin et al. [2006] have shown empirically that diffusion curves may exhibit very heterogeneous patterns ranging from s-shapes, convex, concave to inverted u-shapes. Cross-national differences in technology adoption and diffusion patterns across nations are often explained by differences in the endowment with technological capabilities [Nelson and Phelps, 1966, Lall, 1992, Mayer et al., 2001]. Dechezleprêtre et al. [2011] has shown that the *type* of pre-existing knowledge matters for the cross-national transfer of climate friendly technologies.

Technological knowledge is sector and technology-specific [e.g. Kogut and Zander, 1992]. On the industry and firm-level, Cohen and Levinthal [1990] refer to capabilities as industry-specific absorptive capacities. Absorptive capacity enables firms to successfully adopt technologies developed in other sectors. Non-matching skill-sets that are required to use a technology may result in a biased perceptions of technological alternatives and limited adoption capabilities and cause path dependence in future technological development [Dosi, 1982, Dosi and Nelson, 2010, Popp et al., 2010, Aghion et al., 2016, Sarr and Noailly, 2017].

Firms' technological capabilities are (partly) embedded in the skills of their employees. Vona et al. [2015] found that the transferability and adaptability of employees' skills may be decisive for firms and industries to cope with changing technological environments. This has implications for both, the success of innovation diffusion, but also for the disruptiveness of its effects on the market structure, on the labor market and income distribution. Vona and Consoli [2014] argue that the transferability of technological knowledge may be important to explain distributional effects on the labor market associated with the obsolescence of technological capabilities.

The compatibility and adaptability of employees' skills with emerging technologies is important to understand firms' and industries ability to successfully adapt if technological circumstances change [Kogut and Zander, 1992].

In this paper, technology diffusion is studied as co-evolutionary transition process where an incumbent conventional technology is possibly replaced by a green entrant. It is shown that the success, pace and stability of the diffusion process is sensitive to the characteristics of competing technologies and their implications for the co-evolution of firms' absorptive capacity.

This study builds on a model of two competing technologies and endogenous learning dynamics. The model is a refined version of the eco-technology extension of the macroeconomic ABM *Eurace@unibi* introduced in Hötte [2019a].

Technology is embodied in substitutable capital goods that differ by technology type. Technology-specific skills are required to make effective use of capital. The skill requirement imposes a limit to input substitution in the production of final goods. In this study, I provide the theoretical motivation of a firm-level learning function. The shape of the learning function reflects the properties of competing technologies, namely their similarity and difficulty. The technological similarity is a measure for the transferability of technological knowledge across technology types [cf. Jaffe and De Rassenfosse, 2017]. I show how the *relative* accumulation of technology-specific capabilities depends on these properties.

Endogenous learning and endogenous innovation influence the evolution of substitutability in the long run. If paths of endogenous accumulation of skills and supplied productivity sufficiently diverge, the economy converges to one of the two technologies which can be interpreted as lock-in in a technological regime [cf. Dosi, 1982, Arthur, 1989]. This observation matches the observation made by Acemoglu [2002], Hanlon [2015] who found that path dependence in innovation may induce long-term factor demand curves to be upward sloping. This study adds the perspective that path dependence does not (entirely) arise from the intended allocation of R&D resources, but also from the evolution of technological capabilities of adopters.

An important output of the model is a sample of simulated diffusion curves that is statistically analyzed. It is shown how the pace and pattern of diffusion depends on the characteristics of competing technologies. Technological uncertainty is costly if R&D and learning resources are invested in a technology type that is obsolete in the long run.

The simulation results are embedded in a broader, theoretical framework of macroeconomic, technological transitions. This framework is based on three core characteristics of competing technologies which can be classified as *static*, *cumulative* and *interactive* properties of technologies. The entrant technology is defined as radical innovation that allows its users to overcome a technical limitation of the incumbent technology. This is is also called *technical superiority* and interpreted as variable input cost reduction that is not achievable by the incumbent. This characteristic is a *static property* because it does not change over time and is tied to a specific technology type. Static properties reflect the socio-technical landscape in transition theory. The superiority of a technology is a matter of the appreciation within a specific context. It may reflect e.g. resource endowments, oil prices, cultural values etc., but is beyond the influence of technology developers and users [Geels, 2002].

The second property is *cumulative.* The incumbent technology benefits from accumulated experience. Firms and employees have developed the appropriate skill set, built up the complementary infrastructure and networks to make effective use of the technology. In contrast, before firms and employees can exploit the full productive potential of the entrant technology they have to learn how to use it. Accumulated knowledge stabilizes the technological regime.

The two technologies are different but may have technical commonalities. Part of the skills that are required to operate the incumbent may be transferable to the utilization of the entrant technology. This is called technological similarity. It is an *interactive* property because it affects the *relative* pace of knowledge accumulation and technological specialization. The relative pace is measured in comparison to the competitor.

In the simulations it is shown that the different groups of characteristics have different implications for probability of successful green technology diffusion and for the shape of a diffusion curve. A market entering technology has the chance to diffuse if it is sufficiently superior in the context of the technological landscape. It must be superior in terms of input requirements, consumer preferences or production costs. Accumulated knowledge reflects the maturity of supplied technology and the know-how of technology users. By definition, an incumbent technology is endowed with larger accumulated knowledge stocks. This represents an adoption barrier that might be prohibitively high such that it prevents the diffusion of the entrant technology. It may also be the source of path dependence if the accumulation of knowledge in the entrant technology is not fast enough. In such case, an initial diffusion of the entrant is reversed and the economy relapses into the conventional state. Interactive properties determine the pace of *relative* accumulation of technological know-how.

Two results are worth to be highlighted here: (1) The transferability of technological knowledge facilitates initial diffusion, but comes at the cost of long term stability of a technological regime shift. If technological knowledge is highly transferable, it is relatively easy for technology adopters to switch to the green technology. At the same time it is easy to switch back if relative prices and relative performance of the technologies change.

In contrast, a low transferability of skills across technology types reinforces path dependence. Initial adoption comes at high costs of learning. If initial diffusion is sufficiently high, endogenous learning after green technology adoption strengthen the permanence of the technological regime shift. If initial uptake is sufficiently low the low transferability operates in the opposite direction. These stylized insights are relevant for the strength and timing of policy interventions aimed to achieve a sustainable technological transition.

(2) Further, the transferability of technological knowledge may have implications for the disruptiveness of technological change and the emerging market structure. If knowledge is easily transferable large, incumbent firms can incrementally replace parts of their

technology with the green alternative without having struggle with the incompatibility of systems. In contrast, technologies that require disjoint capabilities make it difficult to incrementally switch to an alternative technological system. Disjoint means that the green capital requires other skills than those required to operate the incumbent capital. In consequence, to operate efficiently firms specialize on either green or conventional capital. Endogenous learning dynamics strengthen the specialization pattern.

In a policy experiment, three different market-based diffusion policies are tested. The instruments affect the static superiority of the entrant. A tax on the utilization of the conventional technology (e.g. a carbon tax) reinforces the superiority of the entrant. An investment subsidy reduces the price for green capital goods which is analogue to a reduction in green technology production costs. A price support reduces the price for green consumption goods. This is analogue to a higher willingness to pay. It is shown that all policies may reinforce and stabilize an ongoing diffusion process, but increase technological uncertainty if the economy is locked in in the incumbent regime. The different instruments have different implications for the pace of technological specialization.

The consumption subsidy is responsive to the level of green technology utilization. It is in tendency stabilizing because it reinforces an ongoing technological evolution. It neutralizes if the economy is locked in.

The interaction between green technology diffusion policies and technological characteristics reveals qualitative differences in the mechanisms of different market-based instruments. Policies that stimulate the creation of green markets are not effective if the two competing technologies are sufficiently dissimilar. In contrast, a tax, that makes the utilization of the incumbent technology more expensive, works well for distant technologies.

In the subsequent section, I provide an overview of the related literature on technological change and the nature of technological capabilities of countries, industries, firms and individual employees. A link to the transition literature is drawn. In section 3, I introduce the main mechanisms of the model used in this analysis and explain the design of simulation experiments. Section 4 is dedicated to the discussion of a series of simulation experiments. It is investigated how the characteristics of technologies have an influence on the pace and stability of diffusion processes and the policy experiment is introduced. Section 5 concludes with a generalization of the results and the proposition of a reconciling framework that can be linked to the multi-level perspective of technology transitions and can be used for the empirical classification of competing technologies.

2. Background

In this study, I introduce the microfoundations of technological learning within the context of macroeconomic directed technological change in a competitive economy with heterogeneous firms. The model is based on insights of the management literature on firms' acquisition of technological capabilities as enabling factor to absorb technological novelties.

2.1. Technological knowledge and learning in the literature

Technological knowledge and human capital as enabling factors to adopt new technology and sources of endogenous growth have a long tradition in economics [e.g. Nelson and Phelps, 1966, Romer, 1990]. In this literature little is said about the *types* of technology that are developed and adopted. Motivated by increasing concerns about climate change and the distributional consequences of skill-biased technical development, the interest in the directional nature of technological change became increasingly important [e.g. Acemoglu, 2002, Löschel, 2002]. In these models, different types of technology are modeled as different types of knowledge that is required to develop and use specific types of capital goods. It can be acquired via type-specific R&D investments or learning by doing. The majority of macroeconomic studies on directed technological change in the endogenous growth literature focus on technology suppliers and the allocation of R&D investments across different technology types. R&D investments enable the development of more productive capital goods of a specific technology type that are adopted by final goods producing firms. These models were used to study distributional consequences if changes in the endowment with skilled and unskilled labor alter relative factor prices and the expected profits of R&D investments in specific types of technology [Acemoglu, 2002]. The climate analogue is the effect of climate policy or resource scarcity on relative factor prices and the associated effects on relative profitability of R&D in climate-friendly technology [Löschel, 2002].

An implicit underlying assumption of these models is the immediate adoption and ability to exploit the full productive potential on newly developed machinery once a technology is available. This is at odds with insights from the diffusion literature emphasizing that the process of adoption is slow [e.g. Metcalfe, 1988, Kemp and Volpi, 2008, Pizer and Popp, 2008]. Micro-level reasons of sluggish diffusion range from incomplete information, to heterogeneous benefits of adoption, investment cycles and learning-by-doing effects on the side of suppliers and adopters [Allan et al., 2014].

Aggregate approaches to explain initially slow technology uptake are based on learning curves. In learning curves, it is assumed that usability of specific technologies improves by cumulative experience measured as time, installed capacity or R&D expenditures [e.g Gillingham et al., 2008, Thompson, 2012, Wiesenthal et al., 2012]. Learning is represented as self-enforcing mechanism of diffusion of a specific technology. However, learning curves of single technologies say little about initial technology selection, substitution dynamics and possible interdependencies among competing alternatives. McNerney et al. [2011] consider technologies as composites of different components. They find that similarities of different technologies in the process of technological development can be important to explain the pace of learning. They confirm that the ability of efficient technology utilization depends on the context provided by pre-existing technologies.

Interactions across technologies at the sectoral level can be analyzed using similarity metrics derived from production and innovation networks [Antony and Grebel, 2012, Carvalho, 2014, Boehm et al., 2016, Acemoglu et al., 2016]. Input-output flows between industries capture cross-sectoral interdependencies. Boehm et al. [2016] argue that similarities in input-output use can be used to identify the sectors in which firms have *core* *competences.* These core competences can be interpreted as technology-specific knowledge. Similarly, Carvalho and Voigtländer [2014] interpret the capability to productively combine inputs as technology. Technological similarity facilitates the adoption of a new input when adopters can make use of pre-existing technological knowledge.

Analogous metrics have been derived on the basis of overlapping citation links in patent documents. The portfolio of cited patents reveals qualitative information about the technological knowledge of the patent owner. If inventors cite similar patents they are able to combine similar technological knowledge that is embodied in a patent. The have similar technological knowledge themselves [Jaffe and De Rassenfosse, 2017]. Acemoglu [2002] and Huang [2017] have used this metric to predict the direction of future research. Antony and Grebel [2012] used patent portfolios at the firm-level to derive measures for the absorptive capacity of technological knowledge that is developed in other technological sectors.

The terms technological capabilities and knowledge is also used in the evolutionary and management literature. However, there is no consensus about the definition of technological knowledge and its use in economic theory [cf. Kogut and Zander, 1992, Teece and Pisano, 1994, Cowan et al., 2000, Johnson et al., 2002, Thompson, 2012]. Often, the distinction between *know-what* and *know-how* is made. The former is closely linked to information that is to some degree transferable across firms and has public good properties. The latter is understood as a type of non-transferable procedural knowledge that is tied to a specific firm or organization [Cowan et al., 2000]. Procedural knowledge enables a firm to make productive use of given inputs to deliver a final product to the market.

Technological capabilities of firms are partly embodied in a firms' workforce and its organizational structure [cf. Kogut and Zander, 1992]. Important characteristics of technological capabilities are their *cumulative* nature and their *tacit, non-transferable* dimension. Kogut and Zander [1992] argue that the learning of new capabilities of a firm is dependent on the compatibility with its current capabilities.

This mechanism is a microeconomic determinant of path dependence at the industry and sector level [e.g. Dosi and Nelson, 2010]. From the perspective of a firm, technological change manifests in the appearance of technical novelties and changing market environments. The adaptiveness of procedural knowledge to changing circumstances (*dynamic capabilities*) is decisive for firms' capacity to cope with new technology [Teece and Pisano, 1994].

Vona et al. [2015] link the insights on firms' capacity to deal with changing market environments with the characteristics of individual skills of employees. In an empirical study, they found that industries are more likely to successfully adopt green technologies in response to environmental regulations if the industry is characterized by skill requirements that can be classified as *adaptive* and *flexible.* Using the classification scheme of employees' skills developed by Autor et al. [2003], Vona and Consoli [2014] argue that adaptive, non-routine skills are particularly important in phases of technological transitions. In transition phases, technological knowledge is not yet translated into specialized codes and skills that can be traded on the (labor) market in the form of specific occupations or training programs.

These insights can be summarized by four stylized facts on technological learning that are used to build a theoretical model of technological learning.

1. Technological capabilities of industries (firms) are embedded in the technological skills of firms (employees).
2. Technological capabilities are *technology-specific* and their accumulation depends on the type of production technology that is used in an industry (firm).
3. A new technology is easier to adopt if previously accumulated know-how is compatible with the new capabilities required to make effective use of the new technology.
4. The accumulation of technology-specific capabilities is decisive for the direction of technological change and the stabilization of a technological regime.

These observations motivate the microeconomic foundations of a model of technological learning. The model is used to study the competitive process of technology substitution and emergent macroeconomic patterns of directed technological change.

2.2. Technology transitions

Macroeconomic directed technological change is the result of one or more transition processes. A technological transition occurs if a new technology enters the market, diffuses and gradually replaces an incumbent alternative [Geels, 2002]. It is associated with a *technological regime shift*. A technological regime is reflected in the prevalent *technological paradigm* that is defined as set of prevalent cognitive, regulatory and normative rules. It reflects shared heuristics and beliefs of a community of technological practitioners [Nelson and Winter, 1977, Dosi, 1982].[1]

Transitions are large-scale system changes that are associated with structural changes in consumption patterns, institutional and organizational structures. The processes are often subject to technological lock-in effects and increasing returns to scale, myopic behavior, group dynamics and the imperfect spread of information [Safarzyńska et al., 2012].

A common approach to study transitions is the multi-level perspective. A socio-technical system is composed of three levels, i.e. the niche-, regime- and landscape level. Incumbent technologies dominate at the regime level. New technologies are developed at the niche-level. Niches are markets with specialized needs and provide a protected space for experimentation and learning. Technologies are developed and used within the context of a landscape layer that represents external forces (e.g. customer needs, natural resource availability, regulations, complementary technologies). These forces are external to technology users and developers. If the landscape changes and the dominant technology at the regime level is not able to adapt to new circumstances, a niche technology may enter the regime level. It possibly replaces the incumbent alternative if it outperforms the incumbent alternative within the new environment [Geels, 2002]. An prominent example

[1] It is also reflected in the technical paradigm. The technical paradigm is more narrow defined and represents the mindset of engineers and their way of defining a technological problem and its solution.

are energy transitions in the context of climate change. Fossil fuel energy determines the technological regime and is challenged by different types of renewables originally developed in protected market niches [Unruh, 2000, Safarzyńska et al., 2012].

Transition processes are characterized by multi-level interactions. Challenges for policies that aim to stimulate a sustainable transition are increasing returns to scale and technological lock-in effects, group dynamics, bounded rationality, and the co-evolutionary emergence of structures and behavior. The term co-evolution refers to the mutual behavioral influence of evolutionary subsystems such as industries, social groups or regional economic systems [Safarzyńska et al., 2012].

The analysis here is based on a macroeconomic agent-based simulation model. Agent-based models offer an analytical and methodological framework that allows to simulate the co-evolutionary nature of technology transitions and their underlying dynamics [Dawid, 2006, Farmer et al., 2015]. Sustainability transitions within agent-based macroeconomic frameworks had been studied by Gerst et al. [2013], Wolf et al. [2013], Rengs et al. [2015], Lamperti et al. [2018]Acemoglu et al. [2012], Lemoine [2018] have studied (climate friendly) directed technological change within an analytical framework. This study differs from previous studies by its explicit focus on learning dynamics in the presence of heterogeneous absorptive capacity. Aim of this paper is to improve the qualitative understanding of the conditions of transition success and its implications for policy design.[2]

3. The Model

In this section, I provide a conceptual description of technology and technological capabilities. These concepts are part of the agent-based macroeconomic framework that is serves as emulator of a virtual, fully fledged economy. The most relevant parts of the technical implementation of the technology module are formally explained. A comprehensive and formal introduction to the model can be found in Hötte [2019b].

3.1. The concept of technology

Adopting the definition of technology used by Comin et al. [2006], technology is

> *"a manner of accomplishing a task especially using technical processes, methods, or knowledge".*

In general words, it is ability of producers to combine inputs such that an economically valuable output is produced. In this paper, a race between two mutually substitutive

[2] In contrast to the majority of previous studies on innovation oriented climate policies, the key question addressed in this paper is not *whether* a green transition is beneficial, but *how* to achieve and accelerate it. It has been shown sufficiently by climate scientists that a fast transformation is an existential question and that the time window for effective action is closing [IPCC, 2018, Steffen et al., 2018]. In this study, it is shown that the economic consequences of a technological transition are sensitive to the stability of the pathway of technological change.

production technologies. One of the two technologies is incumbent and can possibly be replaced by a new entrant technology. Both technologies can be used by firms to produce an output that is equally valued by consumers, but require different types of inputs. In figure 1, the concept of technology and learning is shown as a flowchart for the two-technology case of green g and conventional c technologies.

Each of the two types of production technology is represented by two intangible, cumulative stock variables. These stocks are interpreted as *codified* A and *tacit* B technological knowledge. These intangible stocks embodied in physical production inputs labor L and capital K and accumulated by different mechanisms.

Codified technological knowledge is embodied in the technical properties of the capital stock and is acquired on the capital goods market by investments. Innovation and technical progress in the capital goods market is driven by endogenous innovation. The productive properties are called *theoretical productivity* A of capital K.

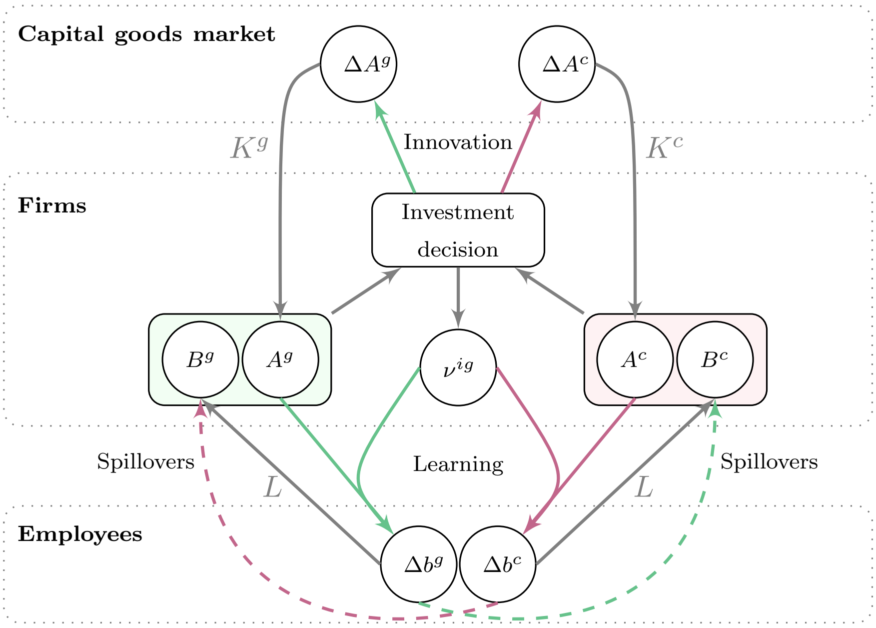
To make effective use of codified knowledge embodied in machines, firms' employees need to have the appropriate technology-specific skills. These skills are called *tacit* technological knowledge B. Tacit knowledge is firm-specific, i.e. firms may be differently productive even if they use the same type of physical production capital. In contrast to codified knowledge that can be bought on the capital market, tacit knowledge is *not tradable* and is accumulated through a learning process. Employees who are working with a specific type of capital learn over time how to use it. Employees' knowledge as an aggregate represents the stock of tacit technological knowledge of a firm. The relative pace of learning a specific type of skills depends on the relative time of working with a specific technology type. This is captured by ν^{ig} that describes the share of technology type $ig = c, g$ that is used in current production.

Theoretically, capabilities of individual employees could be acquired on the labor market, but ex-ante, the endowment with technology-specific skills it is not fully transparent to the firm. It is assumed that individual, technology-specific skills are not observable for firms. Firms can only observe a general education level and the productive outcome of the aggregate workforce. This enables the firm to draw conclusions about its aggregate stock of tacit knowledge B^{ig}.

Technology is heterogeneous by type $ig = c, g$ and represented by different stocks of codified and tacit knowledge. If technologies are similar, part of the knowledge is transferable to the use of the other technology type. This is a cross-technology spillover effect in the learning process of employees.

In this study, I consider a two technology case of one incumbent and one entrant technology. The entrant is a green technology that can possibly replace an incumbent conventional alternative. A static property of the entrant technology is its technical superiority. It allows the adopter to save part of variable input costs. In the case of green technologies, this is interpreted as natural resource input that is required to operate conventional capital. One unit of the resource is needed to use one unit of conventional capital. The conceptual framework can be generalized to other types and a larger number of competing technological alternatives. Key assumption is that the input cost savings can not be achieved in the same way by the incumbent alternative. It can also be interpreted as the replacement of specific tasks of human labor that can be replaced by machines.

Figure 1: Illustration of the learning mechanism.



Firms' technological capabilities consist of two technology type-specific bundles of knowledge, i.e. *tacit* B^{ig} and *codified* A^{ig}, $ig = c, g$. Investment in capital K^{ig} affects the theoretical productivity A^{ig} and the type-composition ν^{ig}, $ig = c, g$ of a firm's capital stock. Technology-specific skills B^{ig} are learned during work dependent on the quality A^{ig} and the composition ν^{ig} of the capital stock. Green (red) colored arrays track the flow of endogenous innovation in the capital market ΔA^{ig} and endogenous learning of employees Δb^{ig}. Dashed arrays indicate learning spillovers across technology types.

The green entrant is technically superior in terms of resource efficiency, but suffers from lower cumulative stocks of tacit and codified "green" technological knowledge. At the time of market entry, the green alternative is technologically less productive. Firms and employees have – compared to the incumbent technology – not yet developed the capabilities to effectively use the green technology. Firms can acquire different types of capital and substitute them one for each other. Substitutability between technology types is limited by the transferability of tacit technological knowledge across types. Hence, employees who know how to make productive use of conventional capital do not necessarily know how to use the climate friendly alternative. The cross-technology transferability is higher if the two technologies are similar.

Firms are active in a fully-fledged, competitive macroeconomy that is composed of individual households, capital goods producers and a financial system including banks and a stylized financial market. The macroeconomic background is introduced in more detail in Dawid et al. [2018b]. More detail about the green technology extension can be found in Hötte [2019b]. In the following section, I motivate the representation and formalization of technology in more detail.

3.2. Technological learning and spillovers

Technological learning at the macroeconomic level is the aggregate of learning by individual employees working in heterogeneous firms. Firms' learning is reflected in the improvements of firms' *effective* productivity using technology type $ig = c, g$. This is embodied in the bundle of codified and tacit knowledge $(A^{ig}_{i,t}, B^{ig}_{i,t})$ of firm i in time t. *Codified* technological knowledge is represented as average productivity of the firm's capital stock items of technology type ig. Tacit knowledge is given by the average technology-specific skill level of the firm's employees.[3]

3.2.1. Consumption goods firms' production technology

The effective productivity of firms determines how effectively a firm can transform inputs into final consumption goods $Q_{i,t}$. Production inputs are a stock of capital $K_{i,t}$, a stock of employees $L_{i,t}$ and, in case of conventional capital, natural resource inputs. Inputs are combined in a constant returns to scale Leontief production function. The adjustment of labor and capital is sluggish. Capital stepwise depreciates and is stepwise expanded by investment. Similarly, a firm can dismiss only a given fraction of employees and if hiring new employees (in discrete units) it is not certain whether the firm is able to fill all vacancies immediately [see for more detail Dawid et al., 2018b].

The capital stock is composed of different vintages v of capital that may differ by productivity A^v and technology type $ig \in \{c, g\}$. The properties of a vintage are given by $(A^v, \mathbb{1}(v))$ where $\mathbb{1}(v)$ indicates the technology type. It takes the values $\mathbb{1}(v) = 1$ (0) for conventional (green) capital. Formally, the amount of capital goods of a certain vintage v within the total capital stock $K_{i,t}$ of firm i in time t is given by $K^v_{i,t} := \{k \in K_{i,t} | A^v(k) = A^v, \mathbb{1}(k) = \mathbb{1}(v)\} \subseteq K_{i,t}$. Moreover, I use the notation $K^c_{i,t}$ $(K^g_{i,t})$ for the sum of capital stock items of type c (g) that are *used* for production in t.

Theoretically, vintages are perfectly substitutable across technology types. But in practice, the exploitation of the productivity of a given vintage at the firm-level is constrained by its stock tacit knowledge. The effective productivity $A^{Eff_v}_{i,t}$ of a capital good v is given by

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

The theoretical productivity A^v of a specific capital vintage is constant and uniform across firms. Tacit knowledge (know-how) required for the exploitation of the productive value differs across employees, across firms, and changes over time when a firm's employees learn. The effective productivity of a given capital good with the properties $(A^v, \mathbb{1}(v))$ is specific to the firm i and time t.

[3] The concept of codified and tacit knowledge can be expanded to a more general interpretation. Codified knowledge refers to any production input that is explicitly purchasable on the market. Whether it accumulates at the firm-level is dependent on the assumptions about the "depreciation" rate. In the case of intermediates, the depreciation rate accounts for 100% per period. Tacit knowledge is not traded on the market, i.e. it is different from the knowledge that can be acquired by hiring specific occupations. It refers to all types of supporting factors that are accumulated during the utilization of inputs, i.e. it may also cover supporting infrastructure and routines that are developed over time within a firm.

This leads to the production function of firm i in t given by

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

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. The term $\max\big[0, L_{i,t} - \sum_{k=v+1}^{V} K_{i,t}^k\big]$ captures the fact that firms can only use as much capital as workers are available in the firm to operate the machines. *Ordered* capital refers to the running order of capital that is determined by the cost effectiveness of capital goods. Firms do not necessarily utilize their full capacity. This occurs when the firm does not have sufficient employees to use the full capacity or expected demand is lower than the maximal output and using costs of capital exceed the expected revenue. In such case, most cost effective capital goods are used first.

The cost effectiveness $\zeta_{i,t}^v$ is given by the amount of output $A_{i,t}^{Eff_v}$ producible by a given vintage v divided by its using costs, i.e. wage $w_{i,t}$ and, if it is a conventional capital good, unit energy and material costs c_t^{eco}.[4] Formally, this can be written as

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

The decision of firms about the quantity to produce is dependent on demand estimations and inventory stocks. Based on estimated demand curves, firms determine the profit maximizing price-quantity combination. Because the estimation is in most cases imperfect and prices can not be immediately adjusted, the consumption goods market does not necessarily clear. Further information on the production decision and market environment can be found in Dawid et al. [2018b].

3.2.2. Accumulation of tacit and codified knowledge

Codified knowledge at the firm-level is acquired via investments in capital goods. The productive properties A^v of capital contribute to the firm's stock of codified knowledge $A_{i,t}^{ig}$ of type ig. It is given by the average productivity of used capital goods of type ig, i.e. $A_{i,t}^{ig} = \frac{1}{K_{i,t}^{ig}} \sum_{v \in K_{i,t}^{ig}} (K_{i,t}^v \cdot A^v)$ where $K_{i,t}^{ig}$ is the amount of capital of type ig that is used in current production.

Two representative capital goods producers supply a range of vintages that differ by productivity level A^v and technology type ig. The firm has to choose the optimal combination of the investment quantity, productivity level and technology type. This decision is based on the firms' expectations about the marginal profit of the different options. The firm computes and compares the net present values of different quantity-productivity-type combinations taking account of expected demand, prices, costs, skill

[4]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.

developments and financial constraints.[5] More detail on the investment decision and capital supply is provided is provided in Hötte [2019b].

Tacit knowledge $B^{ig}_{i,t} = \frac{1}{L_{i,t}} \sum_{l \in L_{i,t}} b^{ig}_{l,t}$ is embedded in the capabilities of the firm's employees. Employees $l \in L_{i,t}$ are characterized by their learning ability and two types of technology-specific skills. Workers' ability to learn is captured by a time-invariant general skill level b^{gen}_l of employees and moderates the speed of learning. General skills can be interpreted as educational attainment.

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

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

$$\Delta b^{ig}_{l,t+1} = \chi^{gen}_l \cdot \left(\left[\left(\psi^{ig}_{l,t}\right)^{(1+\chi^{dist})} \left(\psi^{-ig}_{l,t}\right)^{(1-\chi^{dist})} \right]^{1/2} - 1 \right). \tag{4}$$

$\psi^{ig}_{l,t} \geq 1$ represents "amount" of knowledge learned in one period during the utilization of a specific technology type ig. Part of this knowledge is transferable across technology types. It contributes to the accumulation of the endowment with the alternative skill type $-ig$ with $ig \neq -ig$ and $ig, -ig \in \{c, g\}$. The parameter $\chi^{dist} \in [0, 1]$ describes the technological distance between the two technologies which is a source of state dependence. The functional form is inspired by models on state dependent technological change.[6]

The skill update by learning by doing $\psi^{ig}_{l,t}$ is dependent on the technical difficulty of the technologies χ^{int}, the relative amount of effort $\nu^{ig}_{l,t}$ and the technical novelty $\tilde{b}^{ig}_{l,t}$. More complex technologies are more difficult to learn and require a higher amount of effort, or a higher *intensity of learning*. The updating step also depends on the technical novelty $\tilde{b}^{ig}_{l,t}$ of capital ig which reflects the potential amount of knowledge an employee l can learn. The updating step is given by

$$\psi^{ig}_{l,t} = 1 + \left(\nu^{ig}_{l,t}\right)^{\chi^{int}} \cdot \tilde{b}^{ig}_{l,t}. \tag{5}$$

[5]For reasons of reducing the computational complexity, the set of investment options is limited.

[6]These models are used to investigate the implications of scarce time and R&D resources that can be invested in the production of technological knowledge and an associated allocation trade-off [cf. Acemoglu, 2002]. The Acemoglu version of state dependence builds on two main assumptions, i.e. (1) the resources that can be invested in R&D are scarce (in terms of a limited amount of researchers that can be allocated across technological sectors), and (2) there can be spillovers in the generation of knowledge. One sector may be able to use the knowledge that is generated in the alternative sector. Both aspects can be plausibly transfered to the process of learning of employees who have (1) a limited amount of time to learn specific tasks, and (2) knowledge about specific tasks might be useful for both technology types.

The relative intensity of learning in a specific technology category ig is dependent on the relative amount of technology ig that is used $\nu_{i,t}^{ig} = (K_{i,t}^{ig}/K_{i,t})$ in the firm. This can be understood as proxy for the amount of time that invested in the learning to use a specific type of machinery [cf. Cohen and Levinthal, 1990]. Learning in category ig is faster if the relative amount of this type in the used capital stock higher. The parameter χ^{int} captures marginal returns. In the baseline scenario, I assume weakly decreasing marginal returns in the learning process, i.e. the first hour of learning is more effective than the last one. A conceptual interpretation of χ^{int} is the *difficulty of learning*. If χ^{int} is close to zero, employees learn how to use the machinery irrespectively of the time invested in working with the machine. If technologies are more difficult learn, the learning progress is more sensitive to the amount of time invested in learning.

$\tilde{b}_{l,t}^{ig} = \max[0, (A_{i,t}^{ig} - b_{l,t}^{ig})]$ represents the technical novelty. It is given by the gap between the codified technological knowledge of the employer $A_{i,t}^{ig}$ and the employee's current skill level $b_{l,t}^{ig}$. A larger the gap indicates a larger amount of potential technological knowledge that can be learned and is associated with a faster pace of learning. This accounts for the fact that employees learn only when they are exposed to (codified) technological knowledge they that is new to them, i.e. if there is something new to learn [cf. Thompson, 2012].

Firms can not observe the skill endowment of individual employees, but observe the effectiveness of the production process. They know the amount of inputs and the amount of output and draw conclusions about their aggregate stock of tacit knowledge $B_{i,t}^{ig}$.

3.2.3. Learning in a nutshell

There is a difference between the codified knowledge that is *existing* in the economy and the codified knowledge that is *adopted* even though both are interrelated.

Existing knowledge is exogenous to CG firms. It is the embodied in the productivity level of supplied capital goods. It increases through endogenous innovation ("learning by searching") driven by sector-specific R&D investments. CG firms only indirectly influence the pace by their investment decisions because R&D investments in an IG sector ig are dependent on ig's profits.

Adopted codified knowledge is firm-specific and corresponds to the technological knowledge that is actually used in production. It is embodied in a firm's capital stock and accumulated by investments. Adopted codified knowledge and tacit knowledge together constitute productivity.

Three factors determine the speed learning by doing:

1. The learning intensity $\nu_t^{ig} = K_{i,t}^{ig}/K_{i,t}$ determines how intensively employees are working with a specific type of technology. Increasing returns in the learning process χ^{int} are related to the difficulty of learning. If it is zero, workers learn independently of the extent to which they are using a certain type of capital. If χ^{int} is larger one, returns to learning are increasing in the relative extent to which employees are working with a technology type.

2. The quality of the learning environment is captured by the *technical novelty* $\tilde{b}^{ig}_{l,t} = \max[0, A^{ig}_{l,t} - b^{ig}_{l,t}]$ of individual workers l. Employees learn faster if capital goods are technically new to them.

3. Spillovers or the *transferability of technological knowledge* are negatively dependent on the technological distance χ^{dist}. If the distance is low, technologies are similar and knowledge is transferable across technology types. Learning in one technology class contributes to the stock of know-how in the other class.

The relative speed of learning and innovation is sensitive to the investment decisions of the firm. It is decisive whether a technology type survives on the market and stabilizes the technological regime.

3.3. Simulations and experiments

A technology race between an incumbent conventional and green entrant technology is simulated. The entrant technology suffers from entry barriers in terms of lower accumulated knowledge stocks. Green capital goods becomes available at a given point in time. At the day of market entry, green capital goods are technologically less mature than the incumbent alternatives. The entrant capital producer supplies capital goods that are less productive than those supplied by the incumbent. In other words, g produces at a lower technological frontier, i.e. $A^V_{g,t_0} = (1 - \beta^A)A^V_{c,t_0}$. Employees l and firms have less experience in using the entrant technology represented as $b^g_{l,t_0} = (1 - \beta^b)b^c_{l,t_0}$. The parameters $\beta^A, \beta^b > 0$ describe the relative disadvantage and are interpreted as diffusion barriers. The entrant technology is superior in terms of long term using costs because its utilization does not require the costly natural resource input.

The simulations are subject to stochasticity. For example, capital producers' innovation success, the matching mechanism at the labor market and consumers' consumption decision are probabilistic [see Dawid et al., 2018b, Hötte, 2019b]. In the experiments presented below, sets of 210 simulation runs are generated and the simulated time series data are statistically analyzed. One simulation run consists of 15000 iterations and corresponds to a time horizon of approximately 60 years. One iteration corresponds a working day and 240 working days constitute a year. During the simulation horizon, both technologies compete for market share. Finally the economy converges to a state in which only one of the two technologies is effectively used. The dominance of the green (conventional) technology is called green (conventional) *technological regime*.

Increasing returns to learning and market induced endogenous innovation reinforce the process of technological convergence within a single simulation run. Convergence is interpreted as stabilization of a technological regime.

Which of the two technologies succeeds depends on the type and strength of diffusion barriers in relation to the technical superiority of the entrant and the characteristics of the learning process. If barriers are sufficiently strong, path dependence in technological learning may reverse the process of initial green technology diffusion that is triggered by its input-cost superiority. The economy is locked in the incumbent technological regime. If barriers are weak, firms incrementally substitute conventional for green capital. A *technological transition* takes place. A more detailed discussion of the role of diffusion barriers and diffusion policies can be found in Hötte [2019a].

In this study, technologies are characterized by initial diffusion barriers, technical superiority and interactive properties of the learning process χ^{int} and χ^{dist}. The simulations allow to isolate the influence of technological distances χ^{dist} and difficulty in learning χ^{int} on individual technology adoption and the emerging pathways of transition. Three different types of experiments are run.

1. To compare the effects of different degrees of state dependence, time series simulated with different discrete levels of the learning parameters $\chi^{dist} \in \{0, .5, 1\}$ and $\chi^{int} \in \{0, .5, 2\}$ are compared.

2. To make a statistical analysis of the effect of the learning parameters on the micro- and macroeconomic outcome, a Monte Carlo analysis drawing random values of the learning parameters from a uniform distribution on the interval $\chi^{dist} \in [0, 1]$ and $\chi^{int} \in [0, 2]$ is done.

3. In a previous study, it was shown that barriers are decisive and have possibly non-linear effects on the transition probability [Hötte, 2019a]. Policies can be used to stimulate a green transition. In an additional experiment, the interplay between the level of barriers $\beta^A, \beta^B \in [0, .1]$, the qualitative characteristics of technological knowledge $\chi^{int} \in [0, 2], \chi^{dist} \in [0, 1]$ and different diffusion policies is run. Policies are modeled as two different types of subsidies and a tax on the natural resource θ. The first subsidy ς^i is a percentage investment subsidy that is granted for investments in green capital. The second subsidy ς^c is a price support for green products whose amount is dependent on share of green capital that is used by the producer.

The experiments are evaluated in comparison to a baseline scenario. In all experiments, the conditions of market entry are set such that it is ex-ante not clear which of the two competing technologies will finally dominate the market.

4. Results

Three major questions are addressed in this analysis.

- How does the success and pattern of diffusion depend on the characteristics of the two competing technologies?
- Which are the drivers of technological convergence and how do these relate to the stability of the diffusion process?
- Which macroeconomic side effects occur?

These questions are addressed by an analysis of simulated time series data. The core indicator to evaluate the diffusion success is the share of conventional technology utilization at the firm-level $\nu^c_{i,t} = K^c_{i,t}/K_{i,t}$. It describes the share of conventional capital that is used in production in t by firm i. It measures diffusion at the intensive margin. It can be aggregated across firms to obtain a macroeconomic diffusion curve ν^c_t. The stability of the diffusion process is evaluated by the standard deviation of the diffusion measure $\sigma^{\nu}_{i,t}$ over a moving time window of 2.5 years. A diffusion process is called *unstable* if firms switch between the two technology types.

In a preceding study on barriers to technology diffusion it was found that relative stocks of technological knowledge $\alpha_t = A^c_t/A^g_t$ and $\beta_t = B^c_t/B^g_t$ represent a source of path dependence in technological change [Hötte, 2019a]. Both stocks are endogenously accumulated dependent on the relative profitability in the IG sector and relative intensity of technology use. This is also called *state* or *path dependence* [cf. Acemoglu, 2002]. If knowledge stocks diverge, the economy becomes increasingly locked in the relatively more productive technology irrespective of relative factor input costs. These variables help describing the technological state of the economy.

4.1. Baseline scenario

In the baseline scenario, the parameters of the learning function are fixed at intermediate levels, i.e. $\chi^{dist} = .5$ and $\chi^{int} = .5$. Relative knowledge stocks of the entrant technology are by 3% lower than those of the incumbent, i.e. $\beta^A = \beta^b = .03$. These simulation settings are used to generate a sample of diffusion curves and macroeconomic time series data. The simulated diffusion curves show a pattern of technological divergence. The economy converges to one of two possible technological states, either with almost 100% or 0% green technology utilization at the end of simulation time.

Independent of the resulting technological state, the curves exhibit a phase of initial technology uptake triggered by the technical superiority of the green technology. The initial uptake is not necessarily permanent. In some of the simulation runs, initial diffusion is reversed by the effects of path dependence resulting from technological legacy.

Multiple reversions in the slope of the diffusion curve may occur until the economy converges to one of the two technological states.[7] This is dependent on the dynamics of adoption and competition on the IG market and the stochastic elements in the innovation process.

The different final states are called *technological regimes*. The technological regimes are classified by the share of conventional technology used ν^c_T in $T = 15000$. A regime is called *green* (*conventional*) if $\nu^c_T < .5$ ($\nu^c_T \geq .5$). This is illustrated in the time series of the diffusion curves for each single run in the appendix B.1b. In 142 out of 200 simulation runs the economy converges to a green technological regime corresponding to a transition probability of 71%.

In the appendix B.1, an overview of the main technological and macroeconomic indicators is provided. I refrain from a discussion of the baseline scenario simulation

[7] These patterns are in line with the empirical (mostly historical) literature on technological substitution processes. The reversion can be interpreted as a "last gasp" of the incumbent. In some cases it may be sufficient to cause a lock-in in an inferior technology [e.g. Grübler, 1991, Mowery and Rosenberg, 1999, Hall, 2004].

results here. This short section is only aimed to introduce some general features of the transition curves. The validation criteria are available in the supplementary material I. More detail on this set of baseline simulation runs is available in Hötte [2019b]. A longer discussion of a similar simulation experiment is provided in Hötte [2019a].[8]

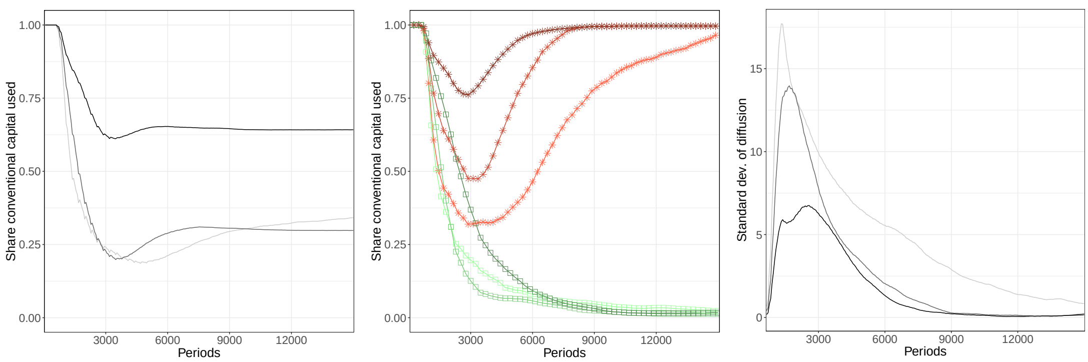
4.2. State dependence in the process of learning

Different economic sectors rely on different types of technological know-how. If a new technology becomes available and serves as substitute for an incumbent, part of the technological know-how may be applicable in the utilization of the new technology. Technological know-how may be differently easy to learn. These two properties reflect the degree of state dependence of technological change and are captured by the learning parameters χ^{dist} and χ^{int}.

4.2.1. The technological distance

In a first experiment the role of cross-technology spillovers facilitated by the similarity of the two competing technologies is studied. A lower distance is analogue to a higher technological similarity associated with a higher transferability of knowledge across types. In an experiment, the distance is varied in discrete steps taking the values $\chi^{dist} \in \{0, 0.5, 1\}$ holding $\chi^{int} = .5$ constant.

Figure 2: Green technology diffusion



(a) ν_t^c batch (b) ν_t^c by regime type (c) $\sigma_{i,t}^{\nu}$ batch

These figures show the diffusion process measured by the share of conventional capital used ν_t^c. The time series in the middle are disaggregated by the type of the technological regime. Different line shapes indicate regime types (□: eco, ∗: conv). Darker color indicates a higher level of χ^{dist}, i.e. a higher degree of state dependence.

In figure 2, the time series of the diffusion measure for the different spillover levels are shown. The lines are disaggregated by parameter value and in figure 2b by technological

[8]For reasons of transparency and to ensure reproducibility, the simulation model, the simulated data and a selection of results of descriptive statistics is available in a separate data publication [Hötte, 2019c].

regime. Throughout this article, different line shapes and colors indicate different technological regimes. Darker color indicates a higher technological distance.

Figure 2a shows the evolution of the diffusion measure for different parameter levels without a disaggregation by technological regime. This aggregate measure is informative about the relationship between the level of spillovers and the probability of a technological regime shift.

The relationship between the level of spillovers and the transition frequency has an inverted u-shape. If the distance is high ($\chi^{dist} = 1$), a green transition occurs in 76 out of 210 simulation runs corresponding to a transition frequency of 36%. The frequency is higher if spillovers are perfect ($\chi^{dist} = 0$). In this case, 139 transitions occurred amounting to 66%. With 71%, the transition frequency is highest for an intermediate level of spillovers ($\chi^{dist} = .5$).

The plot of the aggregate time series points to a possible explanation for the inverted u-shape. If spillovers are perfect, initial green technology adoption is highest, but this initial lead is not necessarily permanent. Soon after the initial phase of diffusion, the effects of path dependence become effective.[9] In some simulation runs, path dependence dominates and the economy relapses into the conventional regime. These returns occur most often if spillovers are high.

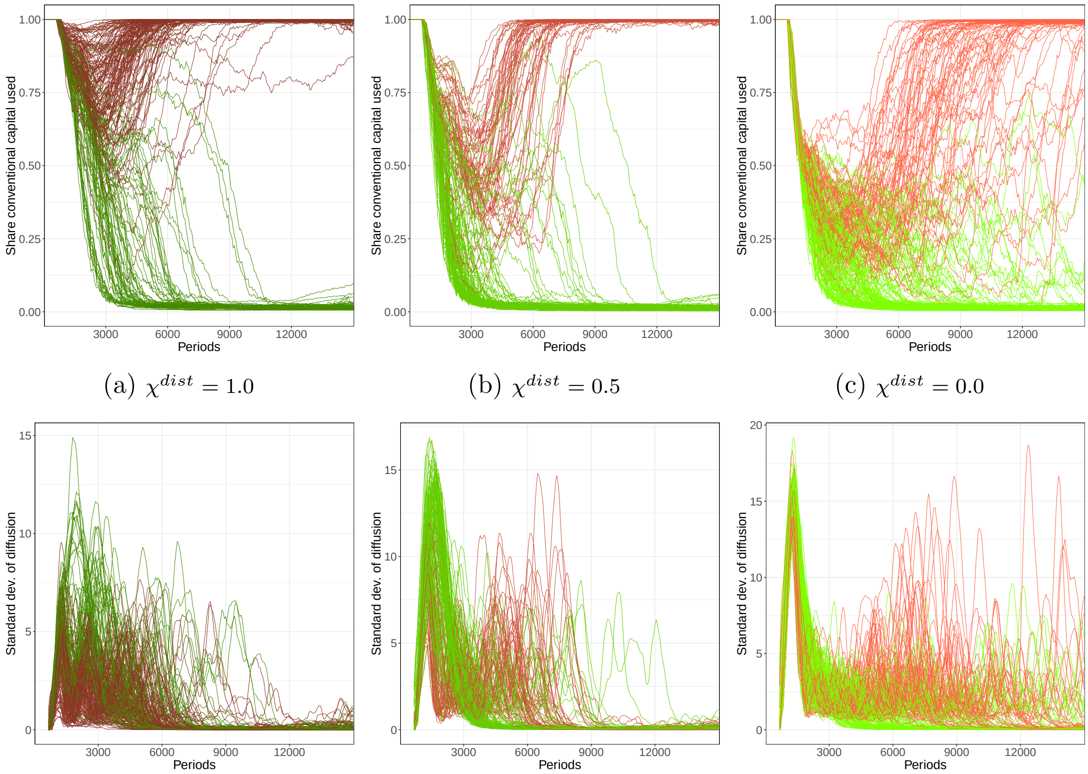
If the technological distance is small it is easy to adopt new technology, but it is also easy to switch back to the incumbent technology type. This pattern is also reflected in the time series of the diffusion measure disaggregated by the type of technological regime (figure 2b) and its standard deviation σ_t^ν (figure 2c). The standard deviation σ_t^ν of μ_t^c measured in percentage points is computed over a time window of 30 months.[10] A high deviance is an indicator for technological uncertainty and a high number of changes in the direction of diffusion. It serves also as measures for the pace of convergence. The lower σ_t^ν is, the faster the economy converges to the final technological regime. Shortly after the day of market entry, the deviation jumps upwards which is caused by high adoption rates in the beginning. It settles down in the subsequent years, but it remains highest for the case of perfect spillovers. This is an indication for technological instability.

This finding is confirmed by a disaggregated view on diffusion patterns of single simulation runs. In figure 3, diffusion curves and the diffusion volatility of single simulation runs are shown for the different parameter subsets. A higher technological distance is associated with an earlier and more pronounced divergence of the diffusion curves. In figure 3a, the diffusion curve for $\chi^{dist} = 1.0$ is shown. The economy quickly converges to one of the two technological states. The diffusion volatility σ_t^ν, shown in figure 3d, is low in the second half of the simulation horizon. In contrast, if spillovers are perfect, i.e. $\chi^{dist} = 0.0$, it is not clear whether the economy converges at all. Many single-run diffusion curves exhibit enduring fluctuations between the two possible technological

[9] The average level of green technology use in T does not necessarily coincide with the transition frequency. A transition is defined by a share of green technology use of more than 50% in T. The average share of green (conventional) technology use may range well below 100% in the subset of green (conventional) regimes. The average ν_T^c account for $\{34.16\%, 29.80\%, 64.20\%\}$ for $\chi^{dist} = 0, 0.5, 1$.

[10] Further information about its computation and relation to other measures of convergence is available in the technical appendix A.

Figure 3: Green technology diffusion



(a) $\chi^{dist} = 1.0$ (b) $\chi^{dist} = 0.5$ (c) $\chi^{dist} = 0.0$

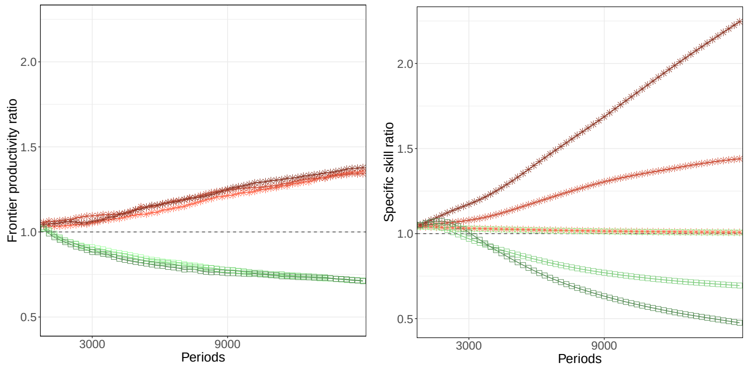
(d) $\chi^{dist} = 1.0$ (e) $\chi^{dist} = 0.5$ (f) $\chi^{dist} = 0.0$

These figures illustrate show diffusion curves ν_t^c of all 210 single simulation runs within the different parameter subsets with $\chi^{dist} = \{.0, .5, 1\}$.

states (cf. figure 3c). This is also reflected in a high diffusion volatility in the second half of the simulation time as shown in figure 3f.

Previous analyses have shown that the relative technological performance is decisive for the stabilization of the technological evolution [Hötte, 2019a]. That means that the convergence to a stable technological state with one clearly dominating technology goes hand in hand with the divergence of relative stocks of technological knowledge represented as ratio of the technological frontier $\alpha_t = (A_{c,t}^V / A_{g,t}^V)$ and ratio of skill endowments $\beta_t = (b_t^c / b_t^g)$ shown in figure 4. The evolution of β_t reveals the mechanism through which the distance parameter operates. The divergence of the curves between the two technological regimes is stronger if the distance is high. If spillovers are perfect, the curve of relative tacit knowledge β_t does not even diverge because learning in one technology category equally contributes to the stocks of tacit knowledge of both technology types. In such case, the convergence to a stable technological state is mainly driven by market induced innovation if the frontier of the dominant technology type grows relatively faster. Other technological indicators on relative real and nominal capital prices, the

Figure 4: Overview of time series of relative knowledge stocks

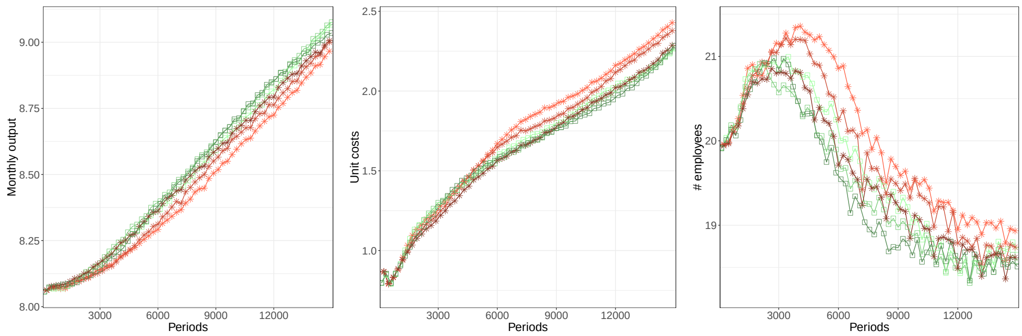


(a) $\alpha_t = \frac{A^V_{c,t}}{A^V_{g,t}}$ (b) $\beta_t = \frac{b^c_t}{b^g_t}$

The different line shapes indicate different regime types (□: eco, $*$: conv). Darker color indicates a higher level of χ^{dist}.

degree of technological novelty reflect the same pattern. A summary of these indicators is provided in appendix B.2.

Figure 5: Overview of time series of economic indicators



(a) Monthly output (b) Avg. unit costs (c) Avg. # employees

The different line shapes indicate different regime types (□: eco, $*$: conv). Darker color indicates a higher level of χ^{dist}.

Different levels of distance between the incumbent and entrant technology do also have implications for the market structure captured by firm exit dynamics during the transition phase and the evolution of firm size (cf. B.2). The early phase of diffusion is associated with a high number of firm exits. The market entry of the green technology is associated with increased price competition and not all firms are able to sustain on the market. Some firms exit the market. When the technological regime stabilizes, new firms successfully enter the market and the number of firms increases again. Firms' entry decisions are not fully endogenized in the model and should not be over-interpreted.

Cross-parameter comparisons and the exit dynamics after the day of market entry are informative, but not the number of entries in general.[11] It is important to note that it is not sufficient to study the effects of different parameter settings at the aggregate. The effects differ across time and across regime types.[12]

Higher levels of spillovers imply that path dependence in the process of knowledge accumulation is low. In the initial phase of diffusion, large incumbent firms have a high endowment of conventional capital. This may be a competitive disadvantage when the green technology starts diffusing and pre-existing knowledge becomes obsolete. This effect is weaker if spillovers are high. Figure 5c shows the evolution of the average firms size disaggregated by regime. In the later phases of diffusion, firms are on average larger if spillovers are high. A Wilcoxon test confirms that this difference is significant, independently of the technological regime (cf. II.1).

In a preceding study (Hötte [2019a]) it was shown that technological uncertainty is costly. Learning and R&D resources are (partly) invested in a technology type that is obsolete in the long run. Above in figure 3 it was seen that high spillovers are associated with long-lasting technological uncertainty. Spillovers retard the specialization and firms ongoingly switch between the two technology types. This explains why monthly output is on average lower in the lock-in scenarios at the late phase of diffusion (cf. figure 5a) and unit costs are on average higher (cf. 5c).

All effects discussed here are statistically significant which is confirmed by a series of Wilcoxon signed rank tests at different phases of diffusion and for different aggregation levels. A comprehensive overview of test statistics is available in the supplementary material II.1.

4.2.2. The ease of learning

In a second experiment, the ease of learning χ^{int} is discretely varied. A higher value of χ^{int} implies that the learning progress in ig is more sensitive to the relative amount of working time with type ig captured by the share of used capital $\nu^{ig}_{t,i}$. It is varied between $\chi^{int} = 0$ when the pace of learning is independent of $\nu^{ig}_{i,t}$, decreasing $\chi^{int} = 0.5$ and increasing returns in learning $\chi^{int} = 2$.

The results show that the difficulty of learning is of minor importance in the presence of moderate cross-technology spillovers. The time series plots of macroeconomic and technological indicators are available in the supplementary material (II.2), but do not exhibit profound difference across different parameter settings. At the aggregate level, a Wilcoxon test confirms for the initial phase that green technology diffusion is faster if the technologies are easy to learn, i.e. if learning is independent of the intensity of effort $\chi^{int} = 0$. This is reflected in the diffusion measure ν^c_t and the faster divergence of

[11] Firms' market entry is probabilistic, but the probability of entry is constant over time. Further explanation is provided in Hötte [2019b].

[12] This becomes even more complex, when it comes to firm-level data. Firms differ by their responses to the market entry of green capital. Their performance is not only conditional on their own behavior, but also on the question whether they made the "right" technology choice.

relative stocks of codified and tacit knowledge. It is also associated with higher aggregate output in the early phase of diffusion.[13]

In the later phase of diffusion, the effects of increasing returns to learning are only weakly visible at the aggregate level because they differ across firms. They depend on the investment behavior and the stability of the technological trajectory (at the firm-level). A faster specialization resulting from increasing returns to learning is only beneficial if the path is stable. A series of Wilcoxon test supports this interpretation. If the economy is locked in higher returns to learning are associated with a lower diffusion volatility. The opposite holds true in case of a transition. Building up green skills is more difficult in the beginning because technological legacy of pre-existing conventional capital undermines the specialization effect.

Conceptually, the parameter χ^{int} reflects the difficulty to learn a new technology. The difficulty is most important in the early phase when a new technology becomes available. In this situation, there might be a trade-off whether to invest time to acquire a new type of skills or to invest the time in the specialization in the pre-existing technology. Such trade-off does not exist if learning is independent of the intensity of learning, i.e. if skills can be acquired without explicitly investing effort in learning.

A lower difficulty of learning has, similarly as spillovers, an ambiguous effect. It facilitates adoption in the beginning, but may be associated with increased technological uncertainty. It reduces *technology switching costs*. This effect holds true in both directions, i.e. when switching from green to brown technology and vice versa.[14]

It needs to be mentioned that these effects are analyzed in the presence of cross-technology spillovers. In preceding analyses that are not shown here, it was found that the difficulty of learning has a strong negative association with the transition probability if spillovers are absent. The technological difficulty is not an impediment to diffusion if the new technology is sufficiently similar to the incumbent type. In the next section, the interaction between both learning parameters is studied in more detail.

4.3. Monte Carlo experiments

The preceding experiments have illustrated the mechanisms how the technological and economic evolution of the transition depend on the characteristics of technology and learning.

Until now, possible interactions between the two determinants of the learning process were neglected. Technological similarity undermines the effect of increasing returns to learn. Spillovers from a sufficiently similar technology stimulate learning that is independent of the time of learning a specific technology.

[13]It should be noted that the returns to scale in the process of learning might have an effect on aggregate output in general. Increasing returns may positively affect the pace of technological specialization and exploitation of more productive capital in the absence of technological uncertainty. Under the given design of experiment and calibration, this effect does not exist.

[14]This is also reflected in the results of the Wilcoxon tests where the signs in the differences between the parameter pairs differ between the comparison of zero to intermediate and intermediate to increasing returns to effort and suggest a non-linear relationship.

In the following experiments, the levels of both learning parameters are drawn independently at random from a uniform distribution.

4.3.1. Marginal effects of technological learning

Table 1: Initialization of learning parameters

		eco	*conv*	
	Mean (Std)	Mean (Std)	Mean (Std)	p-value
χ^{int}	.9937 (.5985)	1.051 (.6040)	.8908 (.5783)	.0793
χ^{dist}	.4792 (.2954)	.4230 (.2768)	.5803 (.3026)	.0003

The column at the left hand side shows the mean (standard deviation) of the initialization across all runs. The other two columns show the average initial conditions within the subsets of green and conventional regimes. The last column indicates the p-value of a two-sided Wilcoxon signed rank test for equality of means of initial conditions in both subsets.

In the first experiment, the diffusion barriers at the day of market entry are fixed at a level of 3% ($\beta^A = \beta^b = .03$) as before. The learning parameters are drawn at random, i.e. $\chi^{dist} \in [0, 1]$ and $\chi^{int} \in [0, 2]$. In this setting, 135 out of 210 simulation runs converge to a green technological regime, corresponding to a transition probability of 64%.

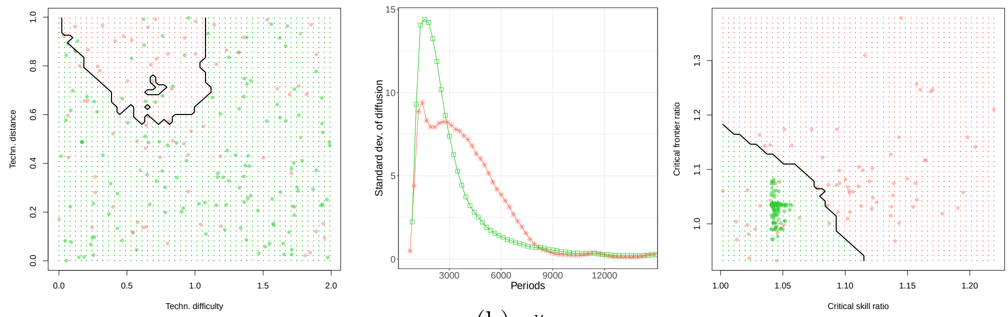
In table 1, means and standard deviation of initial conditions are summarized for the subsets of green and conventional regimes. The p-value in the last column indicates, whether the difference in means between the two regime types is significant. A higher transferability of knowledge seems to be positively associated with the transition probability. The average mean of the distance χ^{dist} is significantly lower in the subset of green regimes. The difference in the difficulty of learning χ^{int} is only weakly significant at a 10% level. Some general descriptive information of these simulations such as time series plots and test statistics on cross-regime differences of technological and macroeconomic indicators are provided in the supplementary material III.1.

These descriptive observations about the association of learning parameters and the transition probability can also be represented as *transition boundary* plot. A transition boundary can be understood as dividing line in the space of χ^{int} and χ^{dist} that separates green from conventional regimes. The relationship between the technological distance, the difficulty of learning and the resulting technological regime is illustrated in figure 6a. The vertical (horizontal) axis represents the distance χ^{dist} (difficulty χ^{int}). The points in the plot represent single simulation runs and the corresponding parameter setting. Colors indicate the resulting technological regime. The boundary line is derived by a k-nearest neighbors non-parametric clustering function trained on the prediction of the resulting technological regime using the learning parameters as input.[15] Points whose color does not match with the color in the decision area are misclassified.

The transition boundary separates a u-shaped cluster of lock-in regimes in the upper left corner of the figure. This is a region with a high technological distance and moderate difficulty to learn. This pattern can be explained by the transition dynamics and the influence of the parameters on the knowledge accumulation process.

[15] Further information about its computation is available in the appendix A.

Figure 6: Transition properties



(a) Transition boundary in the $(\chi^{dist}, \chi^{int})$-space

(b) $\sigma^{\nu}_{i,t}$

(c) Transition boundary in the (α^*, β^*)-space

Figure 6a and 6c show a decision boundary derived by a k-nearest neighbors clustering algorithm with $k = 25$ in the space of learning parameters $(\chi^{dist}, \chi^{int})$ and critical knowledge stocks α^*, β^*. Further information about the clustering and the derivation of critical knowledge stocks is available in the appendix A.

In all simulation runs, the green technology initially diffuses triggered by its technical superiority of the green technology. Whether the diffusion is permanent is dependent on the degree of state dependence of the learning process. In the initial phase, the incumbent technology has a dominant position in the capital stock of firms. Employees continue to accumulate conventional skills. If technologies are similar, this also contributes to the stock of green skills. More interesting is the role of increasing returns to learning. The decision region for green regimes has an ambiguous relationship with technological difficulty. If the technology is very easy to learn, i.e. learning is independent of the share of green capital in firms' capital stock, a transition is more likely. On the other hand, increasing returns in the learning function also have a positive association with the transition probability. In this case, increasing returns strengthen the specialization in green technology during the initial surge of green technology diffusion. This makes a relapse into the conventional regime less likely. This effect is conditional on a sufficiently high green-technology uptake in the beginning.

A regression analysis of the diffusion measure ν^c_i evaluated at firm-level at the end of the simulation horizon T on the learning parameters and a set of micro- and macroeconomic controls confirms the observations made before. The share of conventional technology utilization in the last period is close to zero or one. Its rounded value can be used as binary indicator for the technological regime. It takes the value one if the economy is locked in. A regression analysis is used to study the association of the transition probability with initial conditions.[16] The decision whether or not to include an explanatory variable and/ or its interaction or squared term in the analysis is based on a stepwise, automated model

[16]This interpretation of the diffusion measure and the association of other micro- and macroeconomic control variables with the transition probability is discussed comprehensively in Hötte [2019a].

Table 2: Firm-level regression analyses with randomly drawn learning parameters and fix barriers

	ν_i^c OLS	ν_i^c Probit	t_i^* IV	$\left(A_i^+/A_i^-\right)^*$ IV	$\left(B_i^+/B_i^-\right)^*$ IV	$(\sigma_i^\nu)^2$ IV
(Intercept)	.3563***	-.4136***	5054***	1.106***	1.105***	8.15***
	(.0053)	(.0163)	(632.9)	(.0102)	(.0068)	(2.123)
χ^{dist}	.1000***	.2867***	-425.6*	.0614***	.0568***	-2.471***
	(.007)	(.0215)	(177.9)	(.0107)	(.0068)	(.3588)
χ^{int}	-.0743***	-.2217***	542.8**	.0284**	.0267***	.1888
	(.0053)	(.0167)	(196.3)	(.0098)	(.0068)	(.3227)
$\chi^{dist} \cdot \chi^{int}$	-.0290***	-.0780***				.0275
	(.0053)	(.0163)				(.1327)
$\mathbb{I}(eco)$			-4560***	-.1581***	-.1584***	-.3138
			(1005)	(.0158)	(.0104)	(3.448)
$\mathbb{I}(eco) \cdot \chi^{dist}$			612**	-.0744***	-.0692***	3.877***
			(220.2)	(.0158)	(.0101)	(.4156)
$\mathbb{I}(eco) \cdot \chi^{int}$			-5540**	-.0478***	-.0367***	
			(197.3)	(.0137)	(.0098)	
A_c^V	.0755***	.2195***	-68.88			.2271
	(.0088)	(.0268)	(77.37)			(.2726)
B_i^c	-.0184**	-.0552**	97.38.			.1602
	(.0057)	(.0175)	(50.73)			(.1565)
$output_i$			-121.1**	-.0062*	-.0040**	-.1550
			(38.24)	(.0028)	(.0015)	(.1264)
$price_i$			113.5**	-.0055**		.0331
			(38.45)	(.002)		(.1066)
$\#firms$	-.0525***	-.1736***	140.9*		.0051***	.1761
	(.0054)	(.017)	(70.05)		(.0015)	(.2327)
p^{eco}/w^r	-.0610***	-.1805***	141.9**	-.0094**		.5617***
	(.0096)	(.0288)	(50.75)	(.0029)		(.1489)
R^2	.1543	.2048	.0894	.1005	.1254	.0781

Significance codes: 0 '***' .001 '**' .01 '*' .05 '.' .1 ' ' 1.

The first two columns show the diffusion measure ν_i^c evaluated at the end of simulation. Column 3 illustrates a regression of the duration t_i^* until the firm-level adoption curve stabilizes. $\left(A_i^+/A_i^-\right)^*$ ($\left(B_i^+/B_i^-\right)^*$) are measures for the relative stock of codified (tacit) knowledge at firm-level in time t_i^*. The variance $(\sigma_i^\nu)^2$ is a measure for the volatility of the diffusion process computed over the whole simulation horizon. The results in column 3-6 are the results of an instrumental variable regression with the type dummy $\mathbb{I}(eco)$ as endogenous variable. Further info is provided in the main text and the technical notes section A.

selection procedure using the Bayesian Information Criterion (BIC). The explanatory variables and controls are scaled by their standard deviation to facilitate the comparison of coefficients obtained in the regression. Further technical information about the model specification, its selection procedure and the data pre-processing is provided in the appendix A.[17] Results of an analysis at the macroeconomic level are available in the supplementary material III.1 in table III.11.

Interpreting ν_i^c as probability of a lock-in in the conventional technological state, a higher technological distance χ^{dist} is associated with a lower transition probability $(1-\nu_i^c)$.

[17] The model presented here is kept as simple as possible to maintain the readability and to allow the comparison with the policy experiment that includes additional regressors. The findings should be interpreted as correlation study. More complex econometric approaches are available in the data publication [Hötte, 2019c].

In contrast, returns to scale in the learning process χ^{int} are positively related to the transition probability, but quantitatively weaker than the technological distance. The role of the other control variables is explained in the III.1 and a more comprehensive discussion of their role for the diffusion process can be found in Hötte [2019a]. The coefficient of the interaction term ($\chi^{int} \cdot \chi^{dist}$) is negative, but quantitatively small. This indicates that the negative association of the distance with technology diffusion is less strong if returns to learning are high. The positive effect of χ^{int} on technology diffusion might be conditional on the strength of diffusion barriers. Barriers are low in this experiment ($\beta^A = \beta^b = .03$). Increasing returns in the learning process favor the dominant technology. If entry barriers for the green technology are sufficiently low, the green technology rapidly achieves a sufficiently high diffusion level to benefit from increasing returns.

A guiding question of this study is the relationship between state dependence in technological learning and the stability and pace of technological convergence. To address this question, a set of additional indicators is introduced. The volatility during the diffusion process is captured by the variance $(\sigma_i^{\nu})^2$ of $\nu_{i,t}^c$ computed over the full time horizon. Further, the duration t_i^* until the diffusion process becomes monotone is measured. t_i^* is defined as the point in time when the last change of the sign of the slope of the diffusion curve $\nu_{i,t}^c$ is observed. That means that after t_i^* the diffusion measure starts converging to one of the two possible technological states. A low level of t_i^* suggests *technological certainty*, i.e. at an early point in time the path of the technological evolution is clarified and a process of stabilization and specialization begins. A high level t_i^* suggests that it takes a lot of time until the final technological path is established. Across firms, t_i^* may differ and using the aggregate measure ν_t^c to compute an aggregate t^* likely underestimates the time until stabilization at the microlevel t_i^*.[18]

In a regression analysis, the duration t_i^* is used as dependent variable with the learning parameters χ^{dist}, χ^{int} and initial micro- and macroeconomic conditions as controls. The core explanatory variables of interest are the two learning parameters χ^{dist} and χ^{int} and their interaction terms. A dummy variable for the type of the technological regime $\mathbb{I}(eco)$ is included to capture fix differences and differences in the interaction patterns across the two technological regimes. It takes the value 1 if a transition took place. To rule out possible endogeneity of the type dummy, i.e. possible correlatedness of the error term and the regime type, the type dummy is included through an instrumental variable regression.[19] As before, the specification of the regression equations on the first and second stage is automatically determined using a stepwise model selection procedure based on the BIC.

The regression analyses support the observation that state dependence may have

[18] Because of the possibly non-smooth shape of the depreciation process at firm-level one-year smoothed values of $\nu_{i,t}^c$ are used to compute the threshold level t_i^*. For the regression analysis, only a subset of data is used excluding trivial patterns where the diffusion process is stable from the beginning onwards. Further information is provided in the appendix A.

[19] Additional technical and explanatory detail about the IV approach and alternative model specifications based on finite mixture models can be found in the appendix A. Test statistics on the IV approach and the regression results of alternative model specifications and results are available in an accompanying data publication [Hötte, 2019c].

an ambiguous association with the time until technological stabilization. Whether the association is positive or negative is conditional on the transition. In general, the stabilization is earlier if a transition occurs. This is in line with figure 6b showing that the diffusion volatility in the subset of green regimes is high in the beginning, but rapidly diminishes in the later phase. In contrast, in the subset of lock-in regimes, the volatility decreases more slowly. A Wilcoxon test confirms the significance of the difference (cf. III.1).

This is also reflected in the coefficient of the type dummy in the regression analysis of the variance $(\sigma_i^\nu)^2$ discussed below. If a transition occurs, a higher distance retards the technological specialization. The distance increases the strength of path dependence. If the distance is high, it is more difficult for firms to overcome the relative disadvantage in terms of lower knowledge stocks when beginning to use green technology. In contrast, the distance has a accelerating effect on the time of specialization if the economy is locked in. This supports the interpretation that the distance exacerbates the effect of initial diffusion barriers. The opposite holds true for the difficulty of learning χ^{int}. The retarding effect in the lock-in case can be (again) explained by the high technology uptake in the early diffusion phase. This retards the relapse into the conventional regime.

The divergence of relative knowledge stocks is a driver of technological convergence. To understand the link between relative performance measured by relative knowledge stocks and state dependence in learning, I introduce a measure for *technological thresholds*. These are levels of relative technological performance beyond which the divergence is clear cut. These levels are given by relative knowledge stocks evaluated at t_i^*.

The threshold levels are illustrated in figure 6c. The black line in the figure is interpreted as transition boundary beyond which the technological path has stabilized. The vertical (horizontal) axis represents the relative technological frontier $A^V_{c,t^*}/A^V_{g,t^*}$ (skill endowment $B^c_{t^*}/B^g_{t^*}$) evaluated in the aggregate t^*. In this figure, relative knowledge stocks were used as training input for a k-nearest neighbors clustering algorithm to derive a transition boundary. The boundary serves only for the purpose of illustration here.[20] Apparently, relative knowledge stocks have a high explanatory power for the resulting technological regime. The number of mis-classified simulation runs is low compared to the boundary illustrated in figure 6a that is trained on the learning parameters.

In another regression, the sensitivity of the divergence of the relative performance with respect to the learning parameters is analyzed. Relative performance is defined as the ratio of skills $\beta_i^* = (B^+_{i,t_i^*}/B^-_{i,t_i^*})$ and productivity $\alpha_i^* = (A^+_{i,t_i^*}/A^-_{i,t_i^*})$ of the superior $(+)$ over the inferior $(-)$ technology. A technology type is called *superior* if it dominates at the end of the simulation horizon.

Superior is defined as the technology that dominates at the end of the simulation horizon. The relative performance measure equals one if both technology types are at par. A higher relative performance α_i^*, β_i^* is associated with a more pronounced technological divergence.

The regression supports the observation that state dependence in learning captured by χ^{int} and χ^{dist} reinforces barriers to green technology diffusion. The relationship between

[20]Technical detail can found in the appendix A.

state dependence and the degree of technological divergence differs across technological regimes. If a green transition does (not) occur, the ratio is negatively (positively) associated with the level of state dependence. This indicates that the technological advantage of the dominant technology is more pronounced in the lock-in regime if state dependence is high. The opposite is true in the transition case. Hence, the technological race is more difficult for the green technology and the regime shift is less clear cut in the evolution of relative knowledge stocks. Despite this relative disadvantage, the green technology can succeed because of its technical superiority given by input cost savings.

The variance $(\sigma_i^\nu)^2$ is an indicator for technological stability. It corresponds to the variance of the diffusion measure computed for individual firms over the whole simulation horizon. It is an indicator for firms' switching behavior between green and conventional technologies. The regression indicates that a higher distance is associated with higher stability but only if a transition does not occur. In case of a transition, it may increase technological uncertainty. The distance is negatively associated with the threshold levels of relative performance. A higher distance exacerbates the effect of barriers. This retards the technological specialization in the transition process.

The qualitative findings are robust across a large variety of alternative model specifications.The results of some of these alternative specifications are available in the accompanying data publication [Hötte, 2019c] and a longer discussion can be found in the appendix A.

4.3.2. Barriers to diffusion

Table 3: Initialization of random parameters

	Mean (Std)	*eco* Mean (Std)	*conv* Mean (Std)	p-value
β^A	.0495 (.0306)	.0358 (.0266)	.0564 (.0301)	6.4e-6
β^b	.0482 (.0283)	.0323 (.0231)	.0561 (.0274)	8.9e-9
χ^{int}	.9942 (.5563)	1.044 (.5635)	.9694 (.5531)	.3715
χ^{dist}	.4878 (.2916)	.4075 (.2866)	.5279 (.2868)	.0041

The column at the left hand side shows the mean (standard deviation) of initial conditions across all runs. The other two columns show the initial conditions computed as averages within the subset of green and conventional regimes. The p-value indicates whether the technological regimes significantly differ by initial conditions.

In a previous study [Hötte, 2019a], it was found that market entry conditions in terms of lower relative knowledge stocks of the entrant technology are decisive for the diffusion success of a technology. Lower relative knowledge stocks are interpreted as diffusion barriers. In this section, I sketch a second experiment with randomly drawn levels of learning parameters (χ^{dist}, χ^{int}) and diffusion barriers (β^A, β^b). This experiment serves as benchmark scenario for the policy simulations. In this experiment, barriers to diffusion measured as percentage difference β^A, β^B in the initial frontier A^V_{ig,t_0} and initial endowment with tacit knowledge b^{ig}_{l,t_0} are drawn at random from the interval $[0, .1]$. Within this setting, the transition probability accounts for 30%, i.e. 70 out of 210 simulation runs converge to a green technological state.[21] In table 3, initial conditions of the experiment are summarized. Descriptively, it can be seen that lower diffusion barriers seem to be positively associated with the transition probability. In the subset of green regimes, initial barriers are on average lower compared to the average initial conditions in the subset of conventional regimes. A Wilcoxon test confirms that these differences are significant.

A similar observation can be made for the role of state dependence in learning. The differences across regimes are significant for the technological distance, but not for the difficulty. On average, the distance is lower in the subset of transition regimes. The interpretation is the same as before. The interplay of barriers and learning parameters will be discussed below in more detail in the context of a policy experiment.

The description of this experiment is held short because the main interest of this article is dedicated to the policy analysis. These results are only shown here because the results serve as benchmark scenario for the experiment. Additional information about this experiment and a short summary of the main insights of this experiment is provided in the appendix B.3 and supplementary material III.1.

4.4. Technological learning and the effectiveness of diffusion policy

Technological change is a consequence of the diffusion of new technologies. It is a key determinant of economic development and represents an important area for policy. For example, for the effectiveness of climate policy, it is important to accelerate the process of green technology diffusion. In the context of digitization, policy makers might be interested in guiding technological development to attenuate disruptive consequences. In an experiment, I investigate the scope of different political instruments conditional on the characteristics of the competing entrant and incumbent technology. I evaluate the impact of policies on the pace and stability of diffusion and its macroeconomic side effects.

The instruments under consideration are an eco-tax θ, an investment subsidy ς^i and a price support ς^c for eco-friendly produced goods. The tax is imposed on the material resource input, i.e. its price p_t^{eco} is multiplied by the factor $\tilde{p}_t^{eco} = (1+\theta) \cdot p_t^{eco}$. It increases the costs of conventional capital utilization. The investment subsidy reduces the price of green capital goods p_t^g, i.e. the price is multiplied by $\tilde{p}_t^g = (1 - \varsigma^i) \cdot p_t^g$. The consumption subsidy ς^c that is paid as price support for eco-friendly produced final goods $p_{i,t}$. Its amount is proportional to the share of green capital goods that are used in production, i.e. the price of final goods offered by firm i is multiplied by $\tilde{p}_{i,t} = p_{i,t} \cdot (1 - (\nu_{i,t}^g \cdot \varsigma^c))$. Firms with a higher share of green capital in production receive a relatively higher price support on product sales.

The political instruments are explained in more detail in Hötte [2019b]. The budget of the government is balanced. Expenditures for the policy measures are covered by adaptive income and corporate taxes. Taxes are increased (decreased) if the smoothed net financial inflows of the government are negative (positive).

In this policy experiment, barriers to diffusion, learning conditions and policy rates

[21] As before, overview time series plots are provided in the supplementary material III.6.

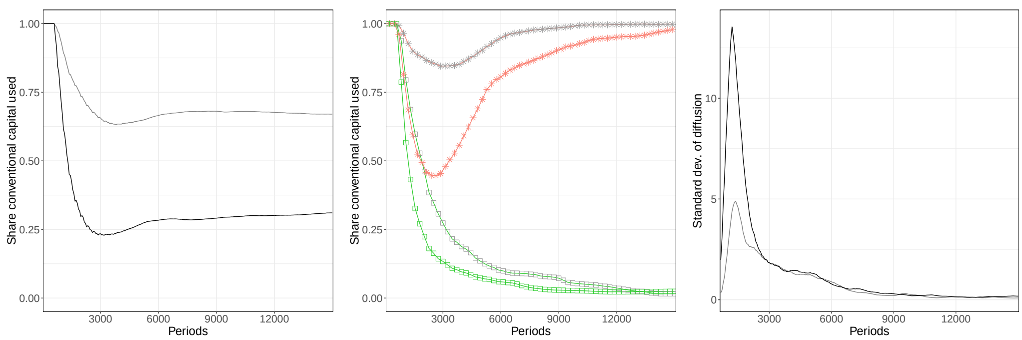
Table 4: Initialization of policy rates, barriers and learning parameters

		eco	*conv*	
	Mean (Std)	Mean (Std)	Mean (Std)	p-value
θ	.4927 (.2853)	.5087 (.2847)	.4553 (.2852)	.2346
ς^i	.0565 (.0279)	.0584 (.0263)	.0521 (.0309)	.2246
ς^c	.0129 (.0073)	.0133 (.0073)	.0121 (.0071)	.2788
β^A	.0762 (.1025)	.0595 (.0920)	.1151 (.1153)	6.e-10
β^b	.0550 (.0295)	.0511 (.0291)	.0639 (.0288)	.0034
χ^{int}	.9923 (.5687)	.9934 (.5741)	.9899 (.5605)	.9624
χ^{dist}	.4868 (.2873)	.4903 (.2849)	.4784 (.295)	.8429

The columns show mean (standard deviation) of the initial conditions for the aggregate set of simulation runs and the subsets of green and conventional regimes. The p-value indicates whether the difference of the means across the regime subsets is significant.

are drawn at random as before. The initial conditions of the policy experiment are summarized in table 4. The results of the policy experiment are compared to the experiment shortly introduced above with the same average levels of barriers and learning parameters (section 4.3.2).[22] A descriptive comparison of the diffusion results suggests the effectiveness of policies. In the absence of policy, the transition frequency accounts for 30%. This is much lower than 70% in the policy case. Figure 7 shows the macroeconomic time series of the diffusion measure for the full set of simulation runs, the disaggregation by regime and the volatility of the diffusion process measured by the standard deviation σ_t^ν.

Figure 7: Comparison of diffusion patterns



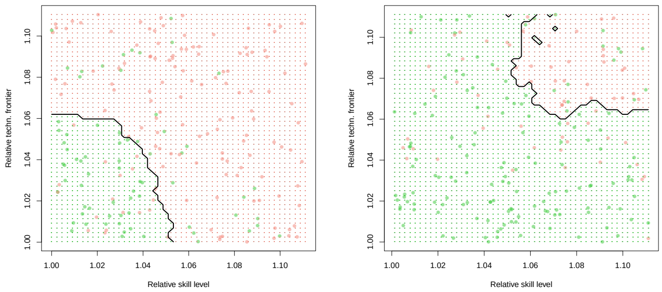
(a) Aggregate ν_t^c (b) ν_t^c by regime (c) Volatility σ_t^ν

These figures show time series patterns of the diffusion curve and its volatility over time. Gray curves represent the experiment without policy.

The effect of the policies can be thought as shift in the transition boundary. Barriers to diffusion are represented as relatively lower endowment with codified and tacit knowledge

[22]Note that this baseline scenario is not a *true* counterfactual. Initial conditions are drawn uniformly at random from the same interval, but are not identical. However, the sample size of both experiments is supposed to be sufficiently large to draw descriptive inference.

Figure 8: Shift in transition boundaries



(a) No policy (b) Policy experiment

These figures illustrate the shift in the transition boundary. The vertical (horizontal) axis represent the relative technological frontier (relative skill level). Each dot represents a simulation run, its color indicates the resulting technological regime and the position the barrier combination at the day of market entry.

and inhibit technology diffusion. Higher barriers are negatively correlated with the transition probability. A transition boundary drawn as dividing line in the two-dimensional space spanned by initial knowledge endowments that separates green from conventional regimes is shown in figure 8. The axes indicate relative knowledge stocks α_{t_0} and β_{t_0} at the day of market entry. Each point in the plot represents the parameter setting of a single simulation run and the relative endowment with technological knowledge at the macro-level at the day of market entry. Colors indicate the resulting technological regime. As before, the transition boundary is derived with a k-nearest neighbors clustering algorithm. The boundary is a non-linear function that is trained to predict the resulting regime given initial barriers to diffusion β^A and β^b. The figure on the left hand side shows the business as usual. The figure on the right hand side represents the policy case. The decision boundary is clearly shifted upwards. This indicates that the policies may compensate for technological disadvantages.

The policies reinforce the initial surge of green technology uptake independently of the resulting regime and weaken the competitive pressure for the entrant. This is reflected in the evolution of relative knowledge stocks. The divergence of the relative stocks of cumulated knowledge α_t and β_t, tends to be more (less) pronounced in the transition (lock-in) regimes (cf. figure B.3 in the appendix). This pattern holds over time and is confirmed by a regression analysis evaluating relative knowledge stocks in t_i^* when the diffusion process becomes stable (see below).

If the economy is locked in, higher initial adoption is associated with a distortion in the allocation of learning resources in favor of the green technology. This technology type is obsolete in the long run and the misallocation is associated with efficiency losses. This may result in a worse environmental performance per unit of output. This and other macroeconomic side effects of the policy are discussed in the appendix B.4. Here, I focus on the technological effects of policy.

In table 5, the results of a regression analysis of the diffusion measure at the end of simulation time and other technological indicators evaluated in t_i^* are shown. The dependent variables are regressed on the policy instruments θ, ς^i, ς^c, initial diffusion barriers β^A and β^b and learning parameters χ^{int} and χ^{dist} are shown. Technically, the same model selection procedure was applied as before. For the sake of a simpler representation, only those explanatory variables are presented in the table that are discussed in the text. A table with the coefficients of the complete regression models is provided in the supplementary material III.3. In the subsequent discussion, I refer only to effects that are significant at a $< .1\%$ level if not explicitly mentioned otherwise.

The core observations can be summarized as follows:

All policy instruments are effective and have a positive association with the transition probability. This is indicated by the negative coefficients in the regression of the diffusion measure ν_i^c. The effect on the diffusion volatility and the time until stabilization t^* differs across instruments.[23]

The effectiveness of the consumption subsidy as diffusion stimulus is undermined and might be even reversed if the technological distance χ^{dist} and/ or increasing returns to learning χ^{int} are large. In contrast, the effectiveness of the tax is reinforced by the distance, but weakened by the level of returns to learning. The effectiveness of the investment subsidy is least sensitive to the shape of the learning function.

The distance χ^{dist} is positively associated with the diffusion volatility if a transition occurs. In contrast, if the economy is locked in the association between the distance and the volatility is negative. This supports the interpretation that the distance reinforces the strength of path dependence. It also explains the pattern observed in figure 7 where the diffusion volatility over time and the diffusion curve disaggregated by regime type are shown. In case of a lock-in, the distance reinforces the specialization in the conventional technology. The interaction terms of policies and the distance have a positive association with the volatility even after controlling for the interaction effect of the distance and green regime dummy ($\mathbb{I}(eco) \cdot \chi^{dist}$).

The duration until technological stabilization t^* is increasing in the level of the tax θ, but decreasing in the level of subsidies if the economy is locked in. The opposite is true in the transition regime, taxes accelerate (subsidies postpone) t^*. The payment of subsidies is conditional on the utilization of green technology, i.e. the consumption subsidy ς^c is paid proportionally to the amount of green capital utilization and the investment subsidy is only due if green capital goods are bought. Independent

[23] With some limitations, quantitative inference about the effectiveness can be drawn. The effect of the consumption subsidy on the diffusion measure is quantitatively the strongest. Recall that all explanatory variables were scaled and demeaned to allow a comparison of coefficients. But the size of the intervals from which the parameters are drawn is not entirely comparable especially in the presence of non-linearities. Further, the effects of the interaction terms are quantitatively difficult to compare with the direct effects. The interaction terms are the product of two scaled variables which makes the values numerically small. A longer discussion of the *quantitative* inference is available in the appendix A.

of the regime, the investment subsidy compared to the consumption subsidy is associated with a later begin of specialization t_i^*. For ς^c, the strength of policy support is more sensitive to the utilization of green capital is stronger compared to ς^i. Hence, it is less distorting once a technological pathway has emerged. The effective incentive of ς^c disappears if green capital is not used but becomes stronger the higher the share of green capital utilization. In contrast, the strength of the investment subsidy is constant.

If the technological distance is large, the investment subsidy (tax) tends to postpone (accelerate) the stabilization as indicated by the positive coefficient of the interaction terms $\chi^{dist} \cdot \varsigma^i$ $(\chi^{dist} \cdot \theta)$.

The diffusion volatility is negatively (positively) associated with the tax and the investment subsidy if a transition does (not) occur. Hence, both instruments stabilize the diffusion process in the transition regime but increase technological uncertainty if the economy is locked in. This is also visible in figure 7. In contrast, the consumption subsidy has a negative association with the volatility in the lock-in case and is neutral in the transition.

The strength of the relationship between the diffusion variance and the policy variables is conditional on the learning parameters. The interaction term of the distance χ^{dist} with any of the policy parameters has a positive association with the volatility. This indicates that the technological evolution is less stable. The policies and the distance operate in opposite directions. Policies favor green technology uptake and stimulate initial diffusion. The distance increases the strength of path dependence arising from pre-existing knowledge stocks. It operates in favor of the incumbent technology if the level of green technology use is not yet sufficiently high. Hence, independent of the emerging regime, the combination of strict policies and high distances intensifies the technological competition.

The technological divergence and the volatility exhibit (mostly) coefficients with opposite signs for all explanatory variables. That means that factors that lead to a stronger technological divergence captured by $(A_i^+/A_i^-)^*$ and $(B_i^+/B_i^-)^*$, are associated with lower technological uncertainty. Hence, the diffusion variance tends to be negatively correlated with the divergence of relative knowledge stocks. This qualifies relative technological knowledge as a decisive driver of the direction of the technological evolution and the convergence to a technological regime. In the long run, the higher effective productivity embedded in cumulative knowledge offsets the role of relative prices and marginal using costs.[24]. This effect was also observable in the analysis above in the absence of policy (table 2), but less significant and less striking across the set of regressors.

Diffusion barriers may be prohibitively high and prevent the diffusion of green technology. The strength of barriers is associated with a lower (higher) technological

[24]It is an explanation for long-term upwards sloping factor demand curves discussed by Acemoglu [2002], Hanlon [2015]

divergence in case of a transition (lock in). The negative effect of the technical barrier β^A is decreasing in the technological distance. If the competing technologies are sufficiently distant, the technological performance becomes relatively less important for diffusion compared to other factors. In contrast, the inhibiting effect of β^b is even stronger if the distance is large. The lack of spillovers in the process of relative knowledge accumulation makes it more challenging to overcome the skill related diffusion barrier. A high distance indicates that firms are challenged by the incompatibility of pre-existing technological know-how when adopting the green technology and non-productivity related factors as variable input costs become more important. This can also be concluded from increasing effectiveness of the tax reflected in the negative coefficient of $\chi^{dist} \cdot \theta$ in the regression of the diffusion meansure. .

The different policy instruments operate through different channels. The tax and the investment subsidy have an instantaneous effect on the relative profitability of a technology. The tax compensates permanently for the technical disadvantage if adopting a less productive technology (reflected in β^A). It operates through the channel of relative utilization costs. A vintage of capital that is once adopted remains in the capital stock until it is depreciated or taken out of use. This explains why the tax may reduce the duration until stabilization in case of a regime shift.

The investment subsidy has an instantaneous effect on relative investment costs, but is neutral with regard to the relative technological performance over time. It does not represent a permanent compensation.

In contrast, the effectiveness of the consumption subsidy is sensitive to the current technological state. The level of support is proportional to the share of green capital that is used at the firm-level for production. In the beginning when a firm adopts green capital but has a large share of pre-existing conventional capital, the level of support of the subsidy is relatively weak. The adoption decision is rather influenced by the relative endowment with technological know-how and the relative performance of the technologies.

In line with the findings of a preceding study [Hötte, 2019a], the consumption subsidy can be interpreted as stimulus for the creation of green markets. It is a stabilizing policy instrument because it reinforces ongoing transition processes, but diminishes if the green technology is not used. It is asymmetric across firms depending on the type of technology that is used by firms. This may have distributional side effects on the market structure [cf. Hötte, 2019a].

The instruments do also differ with regard to their economic performance. In the transition case, the consumption subsidy serves as demand stimulus on the consumption goods market and may stabilize the economic evolution. However, this stimulating effect is not sustainable and conditional on the presence of the policy. This has important implications for a possible phasing out of policy. Some additional discussion of the side effects of policies can be found in the appendix B.4.

Table 5: Firm-level regression analysis on the effect of policies, barriers and learning conditions

	ν_i^c OLS	ν_i^c Probit	t_i^* IV	$\left(A_i^+/A_i^-\right)^*$ IV	$\left(B_i^+/B_i^-\right)^*$ IV	$(\sigma_i^\nu)^2$ IV
(Intercept)	.3381***	-.4684***	3794***	1.099***	1.097***	6.548***
	(.0043)	(.0144)	(70.63)	(.0031)	(.0029)	(.1399)
χ^{dist}	-.0130**	-.0898***	-471.0***	.0141***	.0213***	-.9603***
	(.0044)	(.0151)	(65.99)	(.0041)	(.0031)	(.1172)
χ^{int}	.0081.	-.0161	-117.2***	.0085***	.0078***	-.0240
	(.0043)	(.0145)	(31.42)	(.0017)	(.0012)	(.0535)
θ	-.0300***	-.1119***	788.9***	-.0297***	-.0296***	2.267***
	(.0043)	(.0145)	(70.37)	(.0037)	(.0029)	(.1218)
ς^c	-.0401***	-.1730***	-318.1***	.0085***	-.0065*	-.1806***
	(.0044)	(.0151)	(77.99)	(.0018)	(.0032)	(.0536)
ς^i	-.0205***	-.0763***	-310.8***	-.0369***	-.0286***	1.506***
	(.0045)	(.0149)	(58.73)	(.0037)	(.0030)	(.1090)
β^A	.1139***	.4650***	8.747	.0395***	.0069***	-.3212***
	(.0046)	(.0196)	(27.75)	(.0049)	(.0016)	(.0482)
β^b	.0946***	.2974***	-501.0***	.0478***	.0519***	-2.894***
	(.0044)	(.0149)	(65.63)	(.0040)	(.0035)	(.1436)
$\chi^{dist} \cdot \theta$	-.0504***	-.1177***	-119.3***	-.0110***	-.0063***	.4541***
	(.0044)	(.0149)	(28.46)	(.0019)	(.0014)	(.0609)
$\chi^{int} \cdot \theta$	.0460***	.1706***	-143.2***			
	(.0040)	(.0137)	(28.06)			
$\chi^{dist} \cdot \varsigma^c$	.0289***	.0972***			-.0070***	.4550***
	(.0044)	(.0156)			(.0016)	(.0601)
$\chi^{int} \cdot \varsigma^c$	.0163***	.0466***				
	(.0042)	(.0139)				
$\chi^{dist} \cdot \varsigma^i$		.0522**	140.0***	-.0099***	-.0073***	.4853***
		(.0160)	(25.38)	(.0018)	(.0013)	(.0561)
$\chi^{int} \cdot \varsigma^i$				.0049***		-.7356***
				(.0015)		(.0552)
$\chi^{dist} \cdot \beta^A$	-.0378***	-.1738***	195.1***			.5285***
	(.0044)	(.0199)	(23.1)			(.0442)
$\chi^{dist} \cdot \beta^b$	.0447***	.1624***	301.8***		.0092***	.2984***
	(.0046)	(.0163)	(37.7)		(.0015)	(.0711)
$\mathbb{I}(eco) \cdot \chi^{dist}$			1144***	-.0222*	-.0213***	2.658***
			(146.8)	(.0089)	(.0064)	(.2647)
$\mathbb{I}(eco) \cdot \theta$			-1070***	.0540***	.0532***	-3.919***
			(135.8)	(.0076)	(.0059)	(.2298)
$\mathbb{I}(eco) \cdot \varsigma^c$			671.4***		.0239***	
			(149.1)		(.0066)	
$\mathbb{I}(eco) \cdot \varsigma^i$			843.7***	.0952***	.0772***	-2.392***
			(140.9)	(.0090)	(.0075)	(.2719)
$\mathbb{I}(eco) \cdot \beta^A$				-.0413***		
				(.0060)		
$\mathbb{I}(eco) \cdot \beta^b$			786.3***	-.0908***	-.1064***	4.706***
			(137.2)	(.0084)	(.0074)	(.31)
R^2	.1868	.266	.2071	.2483	.2699	.315

Significance codes: 0 '***' .001 '**' .01 '*' .05 '.' .1 ' ' 1.

This table show an excerpt of the results of a regression analysis of different technological indicators on a initial conditions and control variables. For the sake of readability, only the coefficients are shown that are discussed in the text, i.e. learning parameters, policy instruments, barriers and interaction terms. Micro- and macroeconomic controls are dropped. A table with the full models is available in the supplementary material (table III.15).

5. Discussion

Technological distances, the difficulty of learning and the strength of diffusion barriers can be used to characterize technologies within certain economic sectors. Investigating the interplay between the strength of barriers and the technological distance to pre-existing technology may be an explanation for empirically observed large variation in technology diffusion rates [cf. Allan et al., 2014]. This info is important for the design of effective diffusion policies.

A more general observation is the relationship between the pace and pattern of diffusion and the evolution of relative knowledge stocks. Analogously to the parameters of the learning function and diffusion barriers, political instruments can be interpreted as characteristics of the technology pair when neglecting the fiscal implications. The level of the tax reflects the technical superiority of the entrant technology. It is imposed on material input costs and makes the utilization of the conventional technology more expensive. The level of the investment subsidy reflects the relative production costs of green capital goods. The consumption subsidy can be interpreted as consumer preference and willingness to pay for eco-friendly produced goods. It reflects the market potential for green products.

5.1. Towards a general characterization of technology

The different groups of technology parameters in the model are part of a more general characterization of technologies. They differ by their implications for the evolutionary dynamics. Three broader groups of characteristics may be distinguished:

Static properties are fixed and do not change over time. These properties are input requirements for the utilization of a technology, consumers' willingness to pay for specific output characteristics and the production costs of the technology. In transition terminology, static properties reflect the socio-technical landscape.

Stock variables are the stocks of codified and tacit technological knowledge that are accumulated by intended research and learning by using. The ratio of stocks accumulated in the different sectors describes the maturity of an entrant technology compared to the incumbent.

Interactive variables influence the accumulation process of *relative* knowledge stocks and the pace of divergence in the level of technical maturity.

In this study, static properties were captured by the set of policy variables and stock variables by the relative stocks of tacit and codified knowledge. Interactive properties were presented as parameters of the learning function. This analysis was restricted to the evolution of the stock of *tacit* knowledge. An application to the process of accumulation codified knowledge is left for future work.[25]

[25]In a broader sense, knowledge has the same effect as complementary infrastructure and institutions that facilitate the effective utilization of a technology. The difference between tacit and codified

Static properties are are fix and exogenously given for technology developers and users, but their relative importance compared to the properties embodied in the stock variables may change over time. In the analysis, it was shown that the technical superiority embodied in the static properties may trigger an initial wave of adoption. This superiority may be offset by the benefits derived from accumulated stock variables. Stock variables determine the degree of the path dependence in a static sense. Interactive variables describe how easily path dependence can be overcome.

This characterization of technologies can be integrated into the typology of transition pathways proposed by Geels and Schot [2007]. The typology is based on the multi-level perspective which is a concept in transition studies. The socio-technical system can be described by three layers composed of niches, the socio-technical landscape and technological regime. A transition occurs if the landscape changes and a sufficiently mature niche technology enters the regime. The landscape captures all external characteristics which is analogue to the static properties of the technology, i.e. its superiority and the valuation by consumers. The entrant technology is developed in a market niche and its maturity is described by its relative endowment with knowledge stocks compared to the incumbent.

Whether the entrant can successfully replace the incumbent depends on its maturity and the pressure on the incumbent caused by the changed landscape. Along historical case studies of transitions and theoretical debates in the transition literature, Geels and Schot [2007] identify different types of transition pathways. The pathways are dependent on the scale, scope and pace of landscape pressure, the maturity of niche technologies and the interaction across layers.

In this study, transitions were studied from a different, but close related perspective. The characteristics of the technological system are modeled as characteristics of competing technologies.[26] It is a bottom-up approach inspired by analogies found in empirical and theoretical studies in the literature on management, innovation and macroeconomic directed technological change (cf. section 2). One contribution of this study is the reconciliation of various isolated theories and the proposition of a framework for future empirical and theoretical analyses on the macroeconomic and on the sector level.

This analysis was tied to the case of green technology diffusion for which the societal need of understanding transition dynamics is the most obvious. The framework and simulation model can be straightforwardly applied to other fields of technology studies.

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is the uniform availability for technology users. Codified is available to all and is reflected in the productivity. The access to the tacit analogue is heterogeneous across users. It is not necessarily tied to individual employees, but can also be location- or firm-specific. It may be costly to accumulate these supporting structures and the ease of accumulation may differ across technology types.

[26]The characteristics of technologies are not independent of its socio-technical environment. For example, the metrics imposed on static properties of technologies are a question of valuation that is dependent on consumer preferences and resource endowments. A technology is only valuable if it fulfills a societal purpose [cf. Geels, 2002].

5.2. Concluding remarks and outlook

Directed technological change is the consequence of diffusion of a (radically) new technology. In most cases, directed technological change comes as a transition. It does not only concern the adoption of a new technology, but also the replacement of the incumbent system (technological regime). Historical case studies have shown that this process is often non-smooth, highly competitive and associated with a process of redistribution when tangible and intangible assets of the incumbent technology become obsolete [Grübler, 1991]. This analysis has shown that the characteristics of the two competing technologies and the pace of relative knowledge accumulation (technological learning) are decisive to understand the technological and economic evolution of transitions. In a policy experiment, the relationship between the effectiveness of diffusion policies and the technology characteristics was analyzed.

The core insights of this study can be summarized as follows:

1. The technological distance between competing technologies describes how well technological know-how can be transfered across technology types. It facilitates initial technology uptake, but may undermine the pace of specialization and stabilization within a technological regime. If technologies are similar, it is easy for technology users to switch to the new technology. But it is also easy to switch back if relative prices or the relative technological performance of supplied technology change. An enduring phase of switching between two technologies is interpreted as *technological uncertainty.* It can be macroeconomically costly because learning and R&D resources are wasted if they are invested in a technology that becomes obsolete in the long run. Increasing returns in the learning process are interpreted as measure for technological difficulty, but are of minor importance if spillovers are sufficiently high, but may contribute to the stabilization of a technological regime. Here, the case of symmetric technologies was studied. In reality, competing technologies may be differently difficult to learn and flows of knowledge across different sectors may be asymmetric. This might be particularly relevant if more than two technologies are considered and flows of multiple interdependent sectors contribute to knowledge accumulation in one technology class. An extension to asymmetric flows is left for future investigation and represents a promising field for empirical research.

2. Diffusion barriers interpreted as an inferior technical performance of the entrant technology and lower technological know-how of adopters are decisive for the permanent diffusion of green technology. The relative importance of codified knowledge measured as productivity performance is decreasing in the technological distance. If the two competing technologies are very different, the cross-technology transferability of tacit knowledge is low. If the distance is high, adopters struggle with the acquisition of required know-how (tacit knowledge) and the productivity performance is less important. Other factors that relate to the long term superiority of a technology. For example, relative using costs become increasingly important and a tax that is imposed on the utilization of incumbent, conventional capital is

more effective if technologies are dissimilar.

3. The three political instruments analyzed in this article are two types of subsidies and a tax imposed on the environmental resource. A consumption subsidy is paid as price support for eco-friendly goods and stimulates the creation of green markets. An investment subsidy reduces the investment costs for green capital goods. All political instruments were found to be effective as diffusion stimuli, but have different effects on the stability of the diffusion process. The consumption tax reinforces ongoing transition dynamics, but is neutralized if the economy is locked in. This may have a smoothing effect on the diffusion process. An alternative interpretation of the consumption tax is a higher willingness to pay for green goods.

The analysis in this paper is based on the theoretical macroeconomic simulation model Eurace@unibi-eco. It was used to build theories about the relationship between the characteristics of technologies and the dynamics of transition. A general contribution of this study is the development of a taxonomic framework to study technologies characterized by static, stock and interactive properties. The framework may provides taxonomy for future empirical and theoretical studies of technological transitions.

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Appendix

A. Technical notes on regression analyses

Data: For the regression analyses, one year average smoothed data is used. Observations represent monthly snapshots captured at different iterations, e.g. $t = 600$ for tests on initial conditions and $t = 15000$ as final state. The intervals used as smoothing range from $[600, 820]$ and $[14780, 15000]$ covering 12 months. One month consists of $t = 20$ iterations interpreted as working days.

The set of firms studied in the regression analyses is truncated. The data of firms exhibits the structure of an unbalanced panel with entries and exits. For dependent variables that are only meaningful if the full life time of a firm is considered, only firms are studied that survive from the beginning until the end of the simulation horizon. That is particularly true when studying the diffusion variance during the full time horizon. For other dependent variables, the lack of completeness is ignored.

Explanatory variables: Conceptually, it is distinguished between explanatory variables and controls. Explanatory variables capture the mechanisms that underlie the theory developed in this paper. Controls are not of major interest, but capture differences between different simulation runs and differences between firms.

Core explanatory variables are the technological difficulty χ^{int} and distance χ^{dist}, and possibly, initial barriers to diffusion β^A, β^B and policy rates θ, ς^i and ς^c. These variables are included as identities, squared and interaction terms. The procedure to select relevant terms is explained below.

In some analyses, a dummy variable $\mathbb{I}(eco)$ is included to control for systematic differences the two technological regimes. It is included as identity capturing fix differences and as interaction term with explanatory variables.

In the regression analyses, explanatory variables and controls are normalized to obtain quantitatively comparable coefficients in the regression analyses. The data were demeaned and scaled by division by the standard deviation. Normalization was made using the R-function *scale()* [R Core Team, 2018].

Scaling facilitates a quantitative comparison of the coefficients in the regression analysis with some limitations. For example, the relative effectiveness of policies may be partly due to the design of the experiment. The mean values of the intervals from which the random values of the policy parameters are drawn have been determined in preceding analyses such that all policies have roughly the same transition probability. More information about this procedure is provided in Hötte [2019a]. The scaling facilitates the comparison of coefficients, but the size of the intervals from which the parameters are drawn is not entirely comparable. In the presence of non-linearity, the interpretation as marginal effects is not applicable, but serves as rough approximation here. Further, the effectiveness of policies, barriers and learning parameters might be sensitive to other parameters in the model. For example, the effectiveness of the consumption subsidy ς^c is most likely sensitive to the price responsiveness of consumers. The role of barriers β^A is likely sensitive to the pace of progress ΔA and $\bar{p}$.

The effects of the interaction terms are quantitatively difficult to compare with the direct effects. The interaction terms are the product of two scaled variables which makes the values numerically small.

Micro- and macroeconomic control variables: The controls included in the regression analyses at the macroeconomic level are the aggregate stock of codified A_c^V and tacit technological knowledge B^c, the number of active firms as proxy for the competitive environment, aggregate output Y and the real price of the natural resource input p^{eco}/w^r. The knowledge stocks do not measure the difference in the relative endowment with green and conventional knowledge, but capture technological progress in general that occurred until the day of market entry. Note that the differences in the levels of macroeconomic indicators capture differences between simulation runs that arose in the first 600 iterations until the green technology producer entered the market.

Macroeconomic indicators (except from the aggregate stock of tacit knowledge) are also included in the analyses at firm-level and capture cross run differences, but are identical for the set of firms within a single simulation run.

Firm-level microeconomic controls are firm-level stocks of tacit knowledge B_i^c, the number of employees and output as proxies for firm size, age, price and unit costs.

Dependent variables: For some analyses, critical levels of certain technological indicators are computed and used as dependent variable. A critical level corresponds to the technological state observed in time t_i^* (t^*) when the last change in the direction of the firm-level (macro-level) green technology diffusion occurred within a single simulation run. The critical time t_i^* (t^*) is defined as the last local extremum in the smoothed diffusion curve given by the share of conventional capital use $\nu_{i,t}^c$ (ν_t^c).

Hence, after t_i^*, firm i does not any longer switch between green and conventional capital. At the macroeconomic level, the economy starts converging to one of the two possible technological states. Due to the possibly non-smooth behavior of the depreciation function at the firm-level, one-year average data of the diffusion measure is used to identify t_i^* and t^*. If data at the macroeconomic aggregate is considered, it might be possible that individual firms continue to switch between technology types. Hence, the macro-level time of stabilization t^* likely underestimates t_i^*.

Technological indicators evaluated at t_i^* are interpreted as threshold levels in the relative performance that are a measure for degree of technological divergence beyond which the direction of technological change is trivial. The degree of divergence can be measured by the ratio of technological knowledge stocks such as productivity, skills and using intensity comparing the superior with the inferior technology. *Superior* is defined as the winner of the technology race, i.e. if the resulting regime type is green (conventional) the green (conventional) technology is said to be the winner.

The core indicators of interest are the ratio of the stocks of codified $\alpha_i^* = (A_{i,t^*}^+/A_{i,t^*}^-)$ and tacit knowledge $\beta_i^* = (B_{i,t^*}^c/B_{i,t^*}^-)$, (and their macroeconomic analogues) where $+$

(−) indicates the superior (inferior) technology type $ig = c, g$. These indicators may be informative about the relationship between qualitative technological distances and relative technological performance.

The data set used for the analyses of performance thresholds and the stabilization time t_i^* (t^*) is truncated. In particular, all observations are removed in which t_i^* (t^*) corresponds to the last or first observation.

In some cases, t^* coincides with the day of market entry. In this case, the diffusion pattern is *trivial* because the technological trajectory is clear from the beginning. The green technology does (not) diffuse without any competitive race among the two technology types.

In these cases, diffusion either stabilized at the very beginning which indicates that no technological competition took effectively place. This may occur if barriers are prohibitively high that diffusion is prevented or such low that diffusion is straightforward. If $t^* = 15000$, diffusion did not stabilize until the end of simulations and it is not necessarily clear whether one of the two technologies won the race. Hence, the technological variables evaluated at this point in time can not be interpreted as performance thresholds.

I tested an alternative approach using a finite mixture model that may account for *zero inflation* pattern (i.e. a stabilization in t_0) [cf. Stasinopoulos et al., 2017]. The procedure is (partly) documented in the data publication [Hötte, 2019c]. The findings do not substantially differ from the results presented in the main article. I decided to use the OLS approach for reasons of simplification that are explained in more detail below.

The variance $(\sigma_i^\nu)^2$ of the diffusion measure $\nu_{i,t}^c \in [0, 1]$ is computed for each agent i over the whole simulation horizon for each single simulation run. In the regression analysis, it is scaled by 100 because otherwise, it is numerically to small for a proper computational analysis and subject to rounding errors. Note that $(\sigma_i^\nu)^2$ is different from the standard deviation shown in the time series plots (e.g. figure 2c) because it is computed over the whole time horizon. The standard deviation shown in the time series is computed over a 2.5 year window.

Model selection procedure: The specifications of the regression equations were chosen using a stepwise model selection procedure based on the Bayesian Information Criterion (BIC). This procedure is implemented in the R functions *stepAIC()* (*stepGAIC()* for Probit) [Venables and Ripley, 2002, Stasinopoulos et al., 2017]. A full set of pairwise interaction terms for all explanatory variables (policy, barriers and spillovers) was included in the input term for the stepwise model selection functions. The functions return the model specification that is associated with minimum BIC.

The OLS and Probit functions were mainly chosen for reasons of simplification. One might be concerned about possibly better fitting assumptions about the underlying distribution to be fitted. In additional analyses, a series of regression analyses was carried out using the R function *fitDist()* of the GAMLSS package which may provide guidance for the selection of an appropriate distribution function [Stasinopoulos et al., 2017]. It sequentially regresses the objective variable on a constant using different families of distribution. Even if these analyses yielded a good fit and improved the fit remarkably when using macroeconomic aggregate data, I refrain from the use of these automatically selected functions for mainly two reasons. First, the selected distributions vary over different data sets and impede the comparability over experiments. Second and related to the first concern, is the trade-off between precision and generalizability. The fit achieved with OLS and Probit is sufficiently well. These models allow the comparison over experiments, are more commonly known than exotic distributional families and the coefficients of OLS are straightforward to interpret. The reader should keep in mind that the purpose of this study is not to perfectly fit the simulated data, but rather to use the simulated data as tool for illustration of the underlying theory. It is simulated data and the number of degrees of freedom in the model design and parameter space of the model is high. Hence, robustness, simplicity and ease of interpretation are the main guidelines for the model selection instead of a particular high statistical precision.

Instrumental variable approach The analyses of the variance, technological divergence and duration until stabilization incorporate a dummy variable that indicates whether a transition took place $\mathbb{I}(eco)$. The time series that are disaggregated by the type of the technological regime exhibit quite different patterns, not only with regard to the outcome, but also with regard to the variation over time. This raises concerns about the possible endogeneity of the resulting technological regime. The type dummy may be subject to reverse causation and may be correlated with the error term.

This concern is addressed by an instrumental variable (IV) approach. Similar as before, the set of instruments and explanatory variables for the type dummy are identified using an iterative BIC based model selection procedure and ensuring that the number of instruments exceeds the number of explanatory variables in the second stage regression. Different specifications of the IV regression are tested, i.e. a simple linear version and a version using a Probit regression on the first stage but the results do not exhibit profound qualitative differences between model specifications. In the result summary in the main text body, the results with the Probit model on the first stage are shown using *ivglm()* of the R-package *ivtools* [Sjolander et al., 2019].

To determine the set of instruments, a heuristic procedure based on a repeated BIC based model selection procedure was used. The model selection procedure was performed separately at the first and second stage of the regression using fitted type dummies as input at the second stage. Note that the first stage corresponds to the Probit regression on the diffusion measure. All variables that were excluded by the BIC on the second stage were included as instrument on the first stage. The selection procedure is rather a heuristic, but not analytically justified approach. It roughly ensures that the instrument is not or only weakly related to the dependent variable in the second stage regression.

A Wu-Hausmann test on the linear model confirms that the IV model is preferable compared to the standard model treating $\mathbb{I}(eco)$ as exogenous. Further, the approach is evaluated for the weakness of instruments. A Sargan test is used to confirm the exogeneity of instruments. The diagnostics confirm the appropriateness of the modeling approach. The full test statistics and related R-scripts are available in the data publication [Hötte, 2019c].

In an instrumental variable regression, the R^2 is not straightforward to compute because it is not clear how to incorporate the residuals of the first stage regression. Main purpose of the R^2 in this analysis is the illustration of the explanatory power of the variables included in the second stage regression of a specific dependent variable compared to their relevance for other dependent variables. For reasons of simplification, I show the R^2 of the second stage regression using the manually fitted type dummy as input but ignoring the residuals of the first stage regression.

An alternative approach to capture the multi-modal nature of the final distribution, are finite mixture models. Finite mixture models are based on the assumption that the mixing probabilities are not known, but can be estimated from the data. In this example, the mixing probabilities are a measure that is similar to the regime type. In a mixture model, the regime type is not deterministic but estimated from the data.[27] In this example, the approach is conceptually similar to the IV approach where the binary regime indicator is estimated. In a mixture model the analysis is not split into two steps. The mixing probabilities and the (shared) coefficients are computed simultaneously using an expectation maximization (EM) algorithm. In this analysis, alternative specifications based on a finite mixture models assuming a bi-modal distribution in the data were tested. The analyses were made using the *gamlssMX()* function of the *gamlss* package [Rigby and Stasinopoulos, 2005]. The core insights that can be derived from such analysis do not deviate from the more common approaches presented in this article. An overview of the procedure is available in the data publication. I decided not to present the results of this approach in the paper for mainly two reasons. First, mixture models require additional assumptions about e.g. shared parameters, the number of modes in the distribution and some technical assumptions. Even though there are good data driven heuristics to make these assumptions, it is not certain how well these assumptions can be generalized to other data sets and it confounds the presentation of representation of results with much detail that is not necessary to underline the core message of this article. Second, the methods presented in the paper are more common for a broad audience. Adding additional detail does not contribute new insights that can not be derived from simpler methods. The reader should keep in mind that it is *simulated data* and the goal of this article is not to perfectly reproduce the simulated patterns, but rather to develop an intuitive theory of technology substitution that is underlined by quantitative analyses.

Transition boundaries: A K-nearest neighbors clustering algorithm with a given number of nearest neighbors was used to train the classification model that is used to draw the transition boundary. This was made by the use of the *knn3()* function of the R-package *caret* [Kuhn, 2018]. The appropriate number of nearest neighbors depends on the sample size and affects the smoothness of the curve, but there is no analytical rule to determine the optimal number. Here, 25 neighbors were used for macroeconomic data and 75 for firm-level data. The decision on the number was based on a series of trials with different parameters. It was found that the results are robust across different,

[27] Technically, the mixing probabilities do not necessarily coincide with the regime type. However, for most of the dependent variables under consideration the bimodality coincides with the regime type.

non-extreme specifications. The final decision is mainly based on aesthetic reasons, i.e. the boundaries are relatively smooth.

The plots in the article show the critical levels of relative knowledge stocks, initial diffusion barriers and learning conditions (cf. figure 6 and 8). Colors indicate the final regime type. For the training of the classification algorithm, relative knowledge stocks were used to predict the type of the resulting technological regime.

Transparency and reproducibility: The simulation model, all data and programming code that was used for the simulation and statistical evaluation of simulated data is available online as separate data publication [Hötte, 2019c]. Additionally, the data publication does also contain a set of descriptive statistics generated as text output of the statistical analysis and that is used in the article. It provides information about the statistical procedure, alternative model specifications that were tested in the regression analyses. It also contains additional figures and tables of simulated data that were not discussed in the article, but give insights about the dynamics of the model.

B. Simulation results

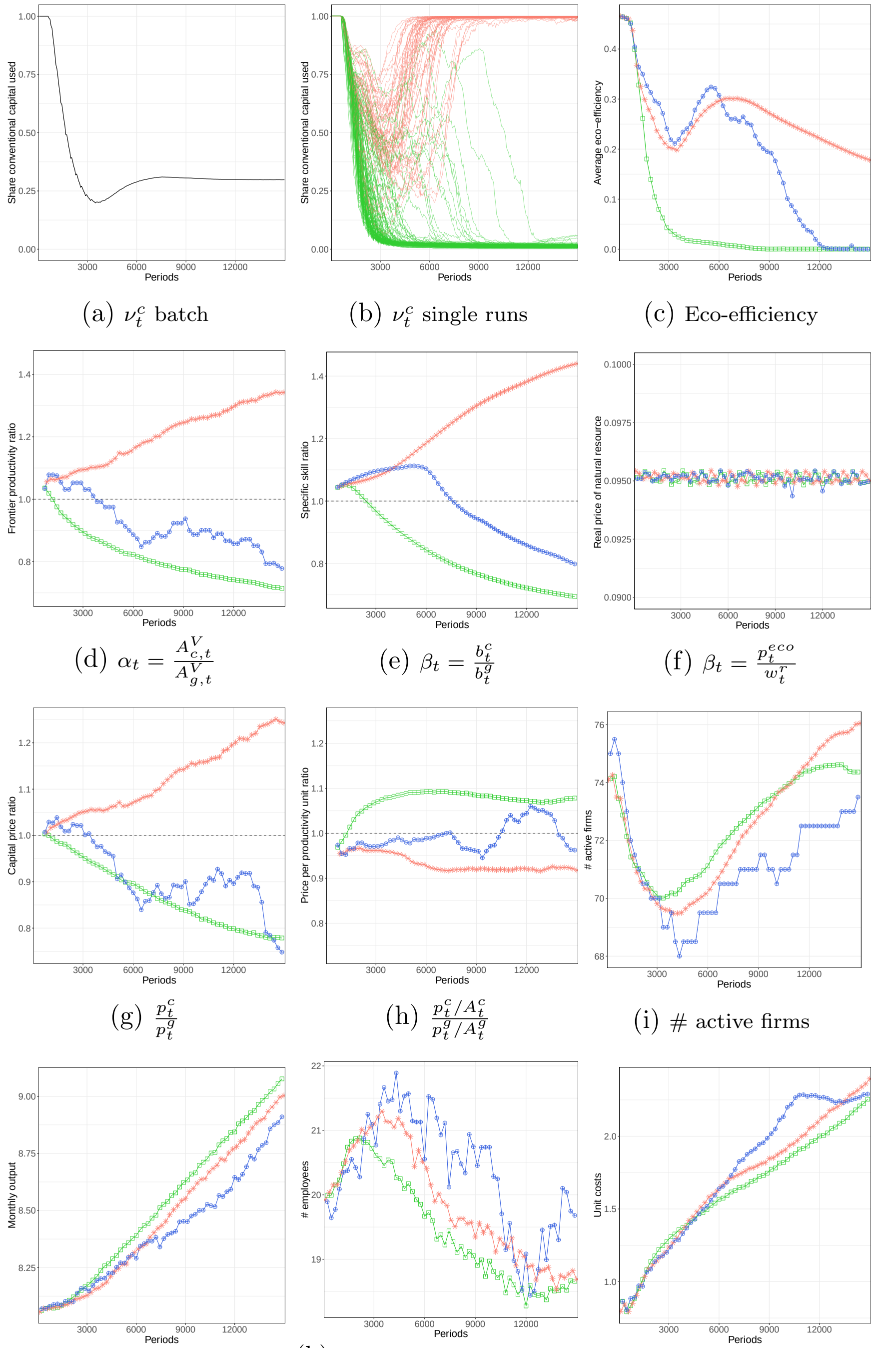
B.1. Baseline scenario

The time series plots of the baseline (figure B.1) are not discussed in this article and only shown for reasons of comparability. A short explanation and discussion of the observed patterns of these simulations is provided in Hötte [2019b]. The interested reader is further referred to Hötte [2019a] where a more detailed discussion of a similar experiment is provided that exhibits qualitatively similar features. A difference to the discussion in Hötte [2019a] is given by lower entry barrier of the green technology and another specification of the learning function.[28]

A core insight of this analysis is that instability of the transition process interpreted as *technological uncertainty* is costly. This is illustrated in figure B.1 by separating the set of simulation runs into green, conventional and so-called *switching regimes*. A single simulation run is classified as *switching regime* if the transition process is characterized by long lasting switches between the green and conventional technology. This is associated with wasted resources because R&D and learning time are invested in a technology that becomes obsolete in the long run. It is associated with a delayed technological specialization, lower productivity and lower aggregate output compared to the green or conventional regimes with a more clear-cut technological path selection (cf. figure B.1). In the supplementary material, a table with the results of a two sided Wilcoxon test is shown to illustrate whether the differences between green and conventional regimes are significant (see table I.3).

[28]The adjustment of the learning function was made for reasons of smoothing, but does not have a qualitative effect on the simulation results.

Figure B.1: Overview of macroeconomic and technological indicators of the baseline scenario



(a) ν_t^c batch (b) ν_t^c single runs (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) $\beta_t = \frac{p^{eco}_t}{w^r_t}$

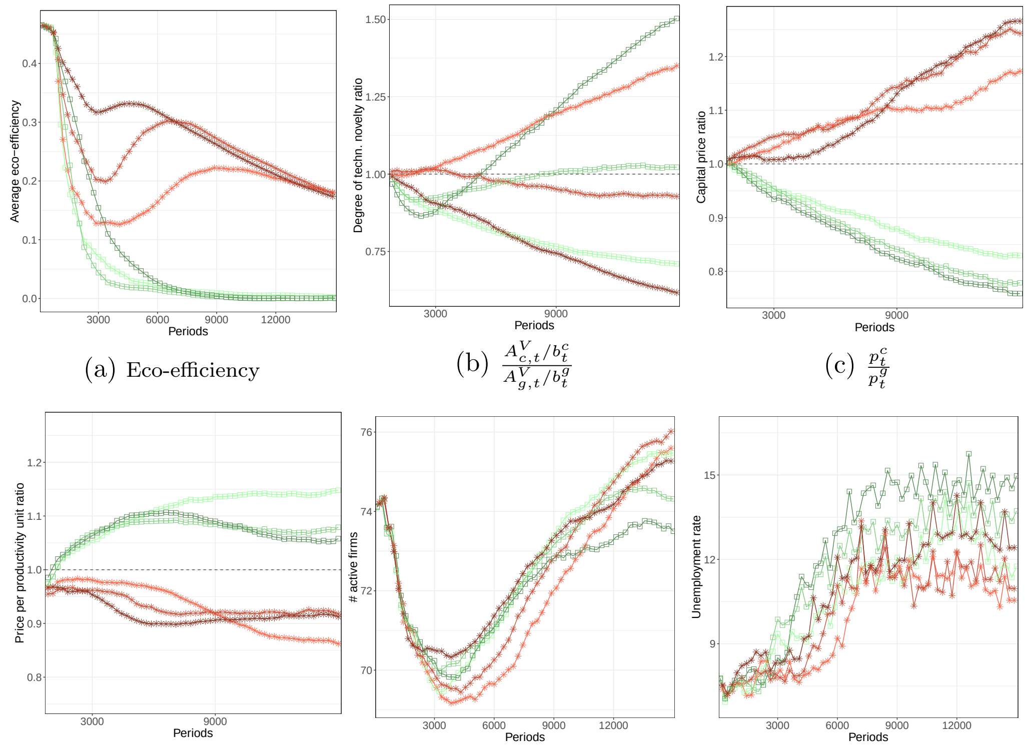
(g) $\frac{p^c_t}{p^g_t}$ (h) $\frac{p^c_t/A^c_t}{p^g_t/A^g_t}$ (i) # active firms

(j) Monthly output (k) Avg. # employees per firm (l) Unit costs

These figures give an overview of the time series of macroeconomic and technological indicators. The different line shapes indicate different regime types (□: eco, $*$: conv, ⊕: switch). Switch scenarios refer to simulation runs that are characterized by high technological uncertainty.

B.2. Spillover experiments

Figure B.2: Overview of additional technological and economic indicators



(a) Eco-efficiency (b) $\frac{A^V_{c,t}/b^c_t}{A^V_{g,t}/b^g_t}$ (c) $\frac{p^c_t}{p^g_t}$

(d) $\frac{p^c_t/A^c_t}{p^g_t/A^g_t}$ (e) # firms (f) Unemployment

The different line shapes indicate different regime types (□: eco, $*$: conv). Darker color indicates a higher level of χ^{dist}.

The time series of macroeconomic indicators are shown in figure B.2. The technological indicators such as prices for capital goods, the degree of novelty and the price per productivity unit show a pattern of divergence between the different regime types.

B.3. Barriers to diffusion and learning

This simulation experiment with randomly initialized diffusion barriers and learning parameters serves as baseline scenario for the policy experiment. An overview in terms of plotted time series and summary statistics comparing green and conventional regimes is provided in the supplementary material (III.2). Here, the main observations concerning the interaction between barriers and learning parameters are summarized.

A regression analysis of technological indicator variables illuminates the role of the relative pace of learning in the presence of differently strong barriers to diffusion. As before, the analysis is run on the full set of explanatory variables and interaction terms which are stepwise tested for exclusion using the BIC as model selection criterion. The model configurations with the smallest BIC are chosen as final version and summarized in table B.1.

As expected, barriers reduce the probability of a transition. A higher technological distance χ^{dist} is negatively associated with the transition probability. Further, the distance reinforces the inhibiting effect of the skill related barrier β^b. Hence, a skill related barrier is more difficult to overcome if the technological distance is high. The distance reinforces path dependence in the accumulation of tacit knowledge.

The interaction of the distance and the technical barrier $\chi^{dist} \cdot \beta^A$ is not clear from this analysis because the coefficients of the interaction term differ across the OLS and Probit specification. This can be explained by the different functional forms of the two models and suggests non-linearities in the relationship between the level of barriers and the degree of spillovers.

Barriers in general have a postponing effect on t^*. Previous analyses have shown that barriers are decisive for the resulting technological regime. The effect on the diffusion volatility is ambiguous. Both, very high and very low barriers have a negative effet on t^*. On the one hand, sufficiently high barriers prevent the diffusion process very early. On the other hand, very low barriers do not represent a burden for the entrant technology and the transition may be fast and relatively stable. The role of barriers was more comprehensively discussed in a previous article [Hötte, 2019a].

The variance of the diffusion process $(\sigma_i^\nu)^2$ is generally higher if the transition occurs and the difference to the lock-in case is even larger in the strength of barriers, the technological distance and difficulty.

In the regression of relative knowledge stocks $\left(A_i^+/A_i^-\right)^*$ and $\left(B_i^+/B_i^-\right)^*$, the coefficients of the knowledge barrier β^b and the technological difficulty are negative in the transition regime. Hence, the divergence of relative knowledge stocks is less pronounced. This indicates that the diffusion of the green technology is more challenging in the presence of high skill related barriers and state dependence in the learning process.

Table B.1: Relation between the level of diffusion barriers and the conditions of learning

	ν_i^c OLS	ν_i^c Probit	t_i^* IV	$\left(A_i^+/A_i^-\right)^*$ IV	$\left(B_i^+/B_i^-\right)^*$ IV	$(\sigma_i^\nu)^2$ IV
(Intercept)	.6599***	.8293***	3519***	1.112***	1.07***	2.569***
	(.0033)	(.0203)	(183.3)	(.0178)	(.0138)	(.3278)
χ^{dist}	.0934***	.6556***	1220***	.075***	.0955***	-.698***
	(.0037)	(.0238)	(120.5)	(.0106)	(.0079)	(.1326)
χ^{int}	-.0027	-.028.	492.9***	.0176*	.0086	-.4932***
	(.0034)	(.0145)	(110.1)	(.0087)	(.0063)	(.1009)
$\chi^{dist} \cdot \chi^{int}$						-.8477***
						(.0493)
β^A	.1532***	.7162***	1168***	.0487***	.0437***	-.454**
	(.0038)	(.0218)	(111.3)	(.0057)	(.0056)	(.1491)
β^b	.1871***	.8811***	368.6***	.0987***	.0915***	-1.654***
	(.0034)	(.0194)	(81.76)	(.0091)	(.007)	(.1448)
$\chi^{dist} \cdot \beta^A$	-.0209***	.1041***		.0221***	.0155***	
	(.0034)	(.016)		(.0046)	(.0033)	
$\chi^{dist} \cdot \beta^b$	.0328***	.4102***		.0311***	.0222***	-.0574
	(.0033)	(.0191)		(.0082)	(.0062)	(.0872)
$\chi^{int} \cdot \beta^A$	-.0542***	-.1541***				.1126
	(.0033)	(.0141)				(.0747)
$\chi^{int} \cdot \beta^b$			-305.5***	-.0109***	-.0069**	
			(44.51)	(.0032)	(.0023)	
$\mathbb{I}(eco)$			-699.8	-.1107*	-.0499	9.839***
			(449.1)	(.0497)	(.0384)	(.889)
$\mathbb{I}(eco) \cdot \chi^{dist}$			-2428***	-.0541.	-.0974***	1.203***
			(198.4)	(.0282)	(.0209)	(.3091)
$\mathbb{I}(eco) \cdot \chi^{int}$			-1305***	-.0579**	-.0295*	2.158***
			(236.1)	(.0188)	(.0134)	(.2425)
$\mathbb{I}(eco) \cdot \beta^A$			-929.1***			-.4974.
			(198.5)			(.2705)
$\mathbb{I}(eco) \cdot \beta^b$				-.1210***	-.1156***	3.997***
				(.0111)	(.0075)	(.2980)
A_c^V		.1455***		.0171***	.0225***	-.3407***
		(.0232)		(.0020)	(.0031)	(.0789)
B_i^c			-151.4***	-.0061***	-.0054***	
			(31.66)	(.0018)	(.0013)	
$\#employees_i$			-263.7***	-.0111***	-.0097***	
			(31.96)	(.0022)	(.0024)	
$output_i$	.0159***					
	(.0046)					
$price_i$	.0251***	.049***			-.0039*	.0682
	(.0047)	(.0142)			(.0018)	(.0418)
$\#firms$	-.0105**	-.0720***				-.3611***
	(.0033)	(.0137)				(.0429)
p^{eco}/w^r	-.0167***	.1000***			.0149***	-.3424***
	(.0043)	(.0294)			(.0035)	(.0919)
R^2	.3417	.4952	.1626	.3436	.4168	.2759

Significance codes: 0 '***' .001 '**' .01 '*' .05 '.' .1 ' ' 1.

The first two columns show the diffusion measure ν_i^c evaluated at the end of simulation. The third column illustrates the relationship between initial conditions and the duration t^* until the diffusion process stabilizes defined by the last change in the sign of the slope of the diffusion curve. $\left(A_i^+/A_i^-\right)^*$ ($\left(B_i^+/B_i^-\right)^*$) are measures for the relative stock of codified (tacit) knowledge at firm-level in time t_i^*. The variance $(\sigma_i^\nu)^2$ is a measure for the volatility of the diffusion process computed over the whole simulation time. The results in column 3-6 are the results of an instrumental variable regression taking account of the potential endogeneity of the type dummy $\mathbb{I}(eco)$. Further info on the computation of variables and the regression procedure is provided in the main text and the technical note section A.

B.4. Policy experiment

In this section, some additional information about the macroeconomic and technological side effects of policy are illustrated by time series plots and briefly explained. In figures B.3a to B.3e the evolution of technological indicators is shown comparing the aggregate outcome of the policy simulations with the baseline. The difference in the subset of conventional regimes between the policy and business as usual case is remarkable. In the early simulation phase, policies trigger a higher green technology uptake, independently of the resulting regime. This has positive effects on the environmental performance in the short run. The environmental impact per output unit ("eco-efficiency") is lower in the beginning, but not necessarily in the long run. If the economy is locked in and does not switch to the green regime, eco-policies cause a distortion in the allocation of learning and R&D resources. The specialization in the conventional technology is retarded which has a negative effect on productivity compared to the baseline scenario without policy. This is also visible in the evolution of relative knowledge stocks α_t and β_t.

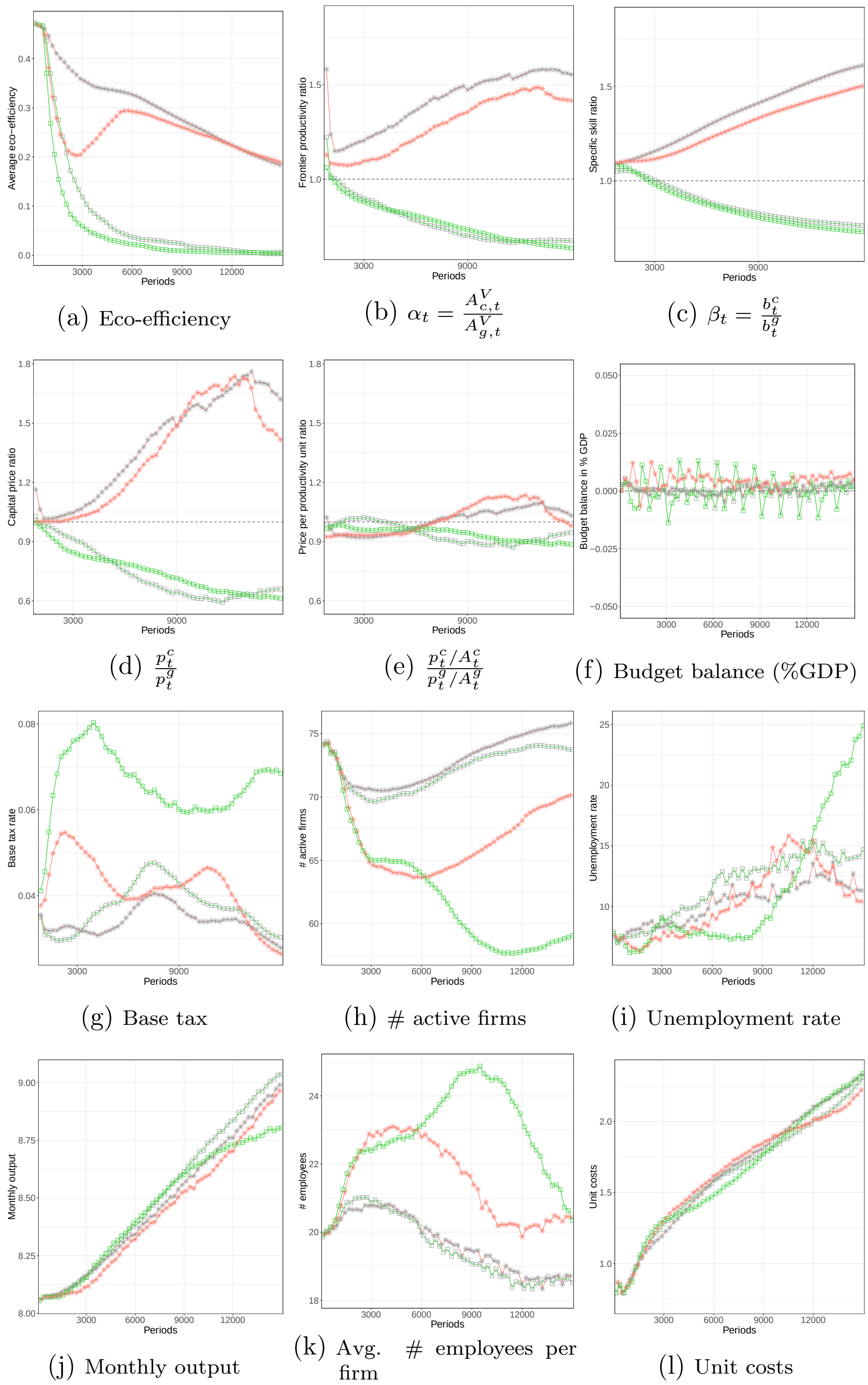
In figure B.3f the budget balance measured as percentage GDP is shown. It fluctuates around zero which confirms that the budget is balanced on average. The fluctuations are largest for the green transition regimes in the policy scenario. This is largely explainable by the pro-cyclical behavior of the subsidy payments which are correlated with sold quantity of green goods and investment dynamics in green capital. If green capital is not adopted, subsidies are not paid. Figure B.3g illustrates the functioning of the budget balancing mechanism. The base income tax is incrementally adapted such that the budget is balanced in the long run. It is not only responsive to the expenditures and income of green policies, but also to the payment of unemployment benefits, corporate tax rates and government's involvement in the financial sector, i.e. via the government's interest income and payment.

The day of market entry causes severe distortions in the economic system. It is associated with increased competition and a series of market exits independent of the resulting technological regime and independent of the policy as shown in figure B.3h. The series of market exits is associated with a growth of the firm size. Note that the market entry dynamics in this model are highly stylized and probabilistic. Only the survival rate of entrants and the number of exits is endogenous and responsive to the technological evolution and policies.

In the policy scenario, the distortions are stronger and seem to be a side effect of relatively higher green technology adoption rates. This is partly reflected in monthly output with a short phase of stagnation that can be explained by learning costs incurred in the beginning. Recall that also in the lock-in regimes, inefficiencies arise because some firms take up the green technology. This is observable in the rise of unit costs in figure B.3l. Unit costs steeply increase immediately after the day of market entry.

The simulations in the model tend to exhibit "technological unemployment" that is not compensated by consumption growth. If productivity grows, firms dismiss labor, but the dismissal rates are low. In the baseline case, the unemployment rate increases over a horizon of roughly 60 yeas from 5 to 12.5%. In the presence of policy, this behavior is different and largely explainable by the consumption subsidy. The consumption subsidy

Figure B.3: Overview of macroeconomic and technological indicators



(a) Eco-efficiency

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

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

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

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

(f) Budget balance (%GDP)

(g) Base tax

(h) # active firms

(i) Unemployment rate

(j) Monthly output

(k) Avg. # employees per firm

(l) Unit costs

These figures give an overview of the time series of macroeconomic and technological indicators. The different line shapes indicate different regime types (□: eco, $*$: conv). Gray colored lines indicate the baseline scenario.

makes green consumption goods cheaper. Hence, it is only paid if green technology is used. In the case green policy regimes, this price support is sufficient to stimulate demand such that the tendency of "technological unemployment" is overcome. But this effect is not permanent and conditional on the subsidy.

Recall that all the phenomena discussed here apply to Monte-Carlo simulations with different levels of initial barriers, learning parameters and policy strength that are independently drawn at random from continuous intervals. Dependent on these conditions, the dynamics may be more extreme or modest. The discussion above refers to the average outcome, but preceding simulations and experiments have shown that these patterns are quite robust and, even if no guarantee can be given, this simple method of scenario aggregation seems eligible for the given parameter ranges.

Supplementary material

The subsequent simulation results are included in this supplementary material for reasons of transparency and documentation, and should help the reader to develop an intuition for the dynamics underlying the Eurace@unibi-eco simulation model. The results summarized in this supplementary material largely have a direct reference to indications made in the main article.

Note that there is a separate data publication that provides additional information that was not mentioned in the article, but adds transparency [Hötte, 2019c]. The data publication contains the simulation model, the statistical software and scripts of analysis and simulated data. Next to the raw data, the data publication also contains a section with edited data and results such as tables, plots and text files that provide additional information and are not mentioned in the main article.

I. Baseline validation

In this subsection, an overview on the basic properties of the baseline scenario is provided. This overview may be also informative for validation purposes. Average growth rates and the size of business cycle variation are summarized in table I.1. In table I.2, the cross correlation patterns between business cycle dynamics and lagged macroeconomic indicators such as investment, consumption and prices are shown. Figure I.1 shows the relative volatility of output, consumption and investment and output, vacancies and unemployment. In figure I.2 plots of a Phillips and Beveridge curve using the simulated data are shown.

The selection of these validation criteria is motivated in Dawid et al. [2018a]. These criteria and the computation of the indicators in the application to the Eurace@unibi-eco model are discussed in more detail in Hötte [2019a].

In table I.3, a comparison between green and conventional regimes is shown as discussed in the article and appendix. The table shows the results of a two sided Wilcoxon test comparing green and conventional regimes. The test statistics confirm that the observations of the plotted time series about the divergence in the technological indicators are significant. Further, investment activities, monthly output, but also unemployment

Table I.1: Growth rate and business cycle

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

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

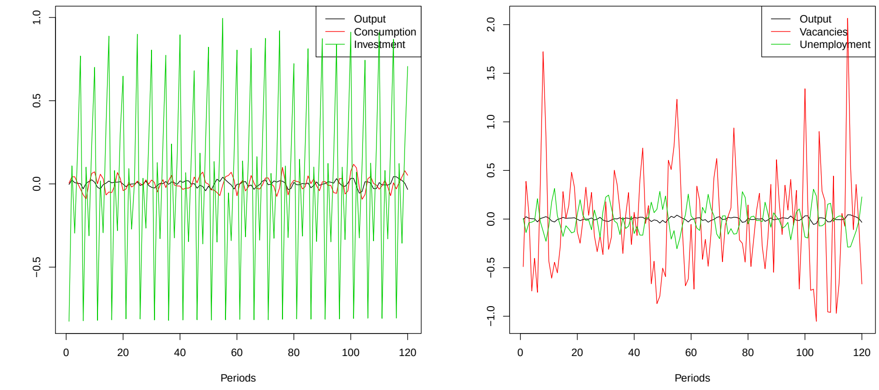
Table I.2: Cross correlation patterns

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

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

are higher in the conventional regime. Unit production costs are lower in the green regime which might be a result of higher investment in more productive capital, but also a result from material input costs savings.

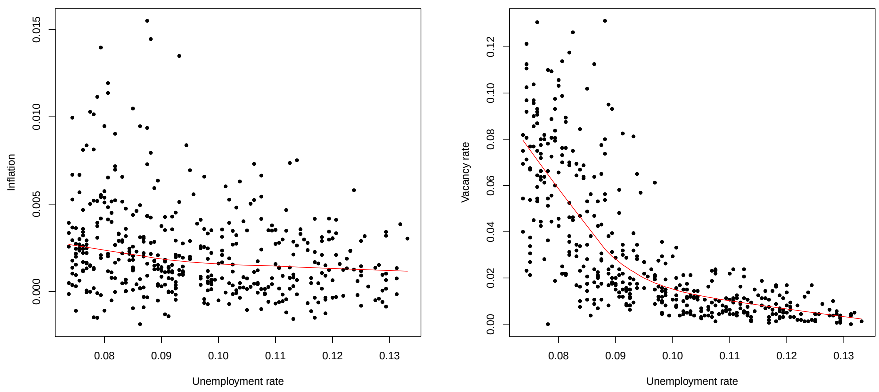
Figure I.1: Relative volatility plots



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

These plots show the relative magnitude of fluctuations captured by the cyclical argument of macroeconomic bandpass filtered time series and measured in percent. The 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.

Figure I.2: Beveridge and Phillips curve.



(a) Phillips (b) Beveridge

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

Table I.3: Wilcoxon test on equality of means for different snapshots in time

t	*eco*	*conv*	*eco, conv*	*eco*	*conv*	*eco, conv*
	Share conventional capital used			Eco-price-wage-ratio		
[601,3000]	.4690 (.1046)	.6660 (.1003)	.0000	.0951 (1e-04)	.0952 (.0000)	.0000
[3001,5400]	.0771 (.1320)	.5929 (.1869)	.0000	.0951 (1e-04)	.0951 (1e-04)	.4373
[5401,15000]	.0257 (.0521)	.9724 (.0419)	.0000	.0951 (.0000)	.0951 (.0000)	.2072
[1,15000]	.1438 (.0641)	.8638 (.0664)	.0000	.0951 (.0000)	.0951 (.0000)	.0026
	Frontier ratio			Skill ratio		
[601,3000]	.9597 (.0523)	1.072 (.0511)	.0000	1.024 (.0232)	1.061 (.0153)	.0000
[3001,5400]	.8620 (.0882)	1.115 (.0874)	.0000	.9152 (.0664)	1.115 (.0549)	.0000
[5401,15000]	.7657 (.121)	1.258 (.1787)	.0000	.7592 (.0532)	1.326 (.0823)	.0000
[1,15000]	.8793 (.0931)	1.252 (.1286)	.0000	.8379 (.0462)	1.238 (.0614)	.0000
	Monthly output			Unemployment rate		
[601,3000]	8.108 (.0186)	8.095 (.0111)	.0000	7.912 (.6208)	7.780 (.3550)	.5287
[3001,5400]	8.261 (.0614)	8.198 (.0503)	.0000	10.54 (3.047)	8.271 (1.144)	.0000
[5401,15000]	8.715 (.1407)	8.643 (.1292)	7e-04	13.31 (7.610)	11.31 (4.196)	.0541
[1,15000]	8.519 (.0968)	8.461 (.0892)	1e-04	11.77 (5.290)	10.10 (2.831)	.0062
	# active firms			Share conv. capital on firm-level		
[601,3000]	71.38 (1.036)	71.32 (1.158)	.6033	.4715 (.1804)	.6771 (.1916)	.0000
[3001,5400]	70.30 (2.000)	69.64 (1.864)	.0284	.0592 (.1558)	.6102 (.2759)	.0000
[5401,15000]	73.34 (3.439)	73.40 (2.811)	.6414	.012 (.0579)	.979 (.0488)	.0000
[1,15000]	72.57 (2.388)	72.49 (2.073)	.4405	.1534 (.1743)	.8812 (.097)	.0000
	# employees			Unit costs		
[601,3000]	20.09 (6.741)	20.12 (6.811)	.8152	1.073 (.1300)	1.040 (.1195)	.0000
[3001,5400]	20.09 (6.090)	20.71 (6.726)	.0000	1.408 (.1169)	1.414 (.1209)	.0019
[5401,15000]	18.51 (5.758)	18.98 (5.513)	.0000	1.890 (.2843)	1.991 (.2622)	.0000
[1,15000]	18.52 (5.824)	18.89 (5.816)	1e-04	1.635 (.3140)	1.695 (.3187)	.0000
	Investment			Mark up		
[601,3000]	11.22 (1.185)	10.75 (1.010)	.0000	.1134 (.1115)	.1157 (.1097)	.0232
[3001,5400]	13.92 (1.881)	12.39 (1.429)	.0000	.1423 (.0936)	.1451 (.0921)	.0072
[5401,15000]	24.00 (5.877)	21.39 (4.833)	.0000	.4118 (.2585)	.3792 (.2053)	.0039
[1,15000]	19.64 (5.012)	17.69 (4.224)	.0000	.3034 (.1842)	.2837 (.1511)	.0406

The columns indicate the mean value (standard deviation) of the time series data for different subsets in time and disaggregated by the type of technological regime. The entry in the last column of each triple of columns corresponds to the p-value of a two-sided Wilcoxon test on equality of means across technological regimes. Means are computed over the early, medium, late phase of technology diffusion and the full time series, i.e. period $\{[601, 3000], [3001, 5400], [5401, 15000], [1, 15000]\}$.

II. Different degrees of state dependence

II.1. Technological distance

The following tables give an overview of the results of Wilcoxon test statistics comparing the simulation results of different parameter pairs of the technological distance $\chi^{dist} \in \{0, .5, 1\}$. It underlines the comparative discussion of observed differences in the time series patterns in the main article.

Table II.4: Results of two-sided Wilcoxon test at different phases of diffusion and different subsets of data.

initial	[601,3000]	*aggr*		*eco*		*conv*	
# employees							
(.0,.5)	Mean	20.71 20.65	.236	20.68 20.65	.5908	20.78 20.64	.2126
	(Std)	(5.047) (5.06)		(5.07) (5.031)		(5.003) (5.13)	
(.0,1.0)	Mean	20.71 20.6	.0379	20.68 20.6	.2582	20.78 20.59	.0406
	(Std)	(5.047) (5.107)		(5.07) (5.042)		(5.003) (5.144)	
(.5,1.0)	Mean	20.65 20.6	.386	20.65 20.6	.4969	20.64 20.59	.6265
	(Std)	(5.06) (5.107)		(5.031) (5.042)		(5.13) (5.144)	
Unit costs							
(.0,.5)	Mean	1.08 1.072	.0000	1.081 1.071	.0000	1.077 1.076	.7736
	(Std)	(.0662) (.0676)		(.0661) (.0672)		(.0662) (.0682)	
(.0,1.0)	Mean	1.08 1.041	.0000	1.081 1.043	.0000	1.077 1.041	.0000
	(Std)	(.0662) (.0625)		(.0661) (.0623)		(.0662) (.0626)	
(.5,1.0)	Mean	1.072 1.041	.0000	1.071 1.043	.0000	1.076 1.041	.0000
	(Std)	(.0676) (.0625)		(.0672) (.0623)		(.0682) (.0626)	
medium	[3001,5400]	*aggr*		*eco*		*conv*	
# employees							
(.0,.5)	Mean	20.9 20.56	.0000	20.87 20.58	.0000	20.94 20.52	.0000
	(Std)	(5.041) (4.954)		(5.003) (4.954)		(5.115) (4.953)	
(.0,1.0)	Mean	20.9 20.55	.0000	20.87 20.4	.0000	20.94 20.63	1e-04
	(Std)	(5.041) (4.972)		(5.003) (4.908)		(5.115) (5.006)	
(.5,1.0)	Mean	20.56 20.55	.6292	20.58 20.4	.0185	20.52 20.63	.3193
	(Std)	(4.954) (4.972)		(4.954) (4.908)		(4.953) (5.006)	
Unit costs							
(.0,.5)	Mean	1.412 1.407	.0000	1.409 1.406	.0739	1.418 1.408	.0000
	(Std)	(.0926) (.0915)		(.0943) (.0912)		(.0889) (.0922)	
(.0,1.0)	Mean	1.412 1.38	.0000	1.409 1.374	.0000	1.418 1.384	.0000
	(Std)	(.0926) (.102)		(.0943) (.1018)		(.0889) (.102)	
(.5,1.0)	Mean	1.407 1.38	.0000	1.406 1.374	.0000	1.408 1.384	.0000
	(Std)	(.0915) (.102)		(.0912) (.1018)		(.0922) (.102)	
end	[5401,15000]	*aggr*		*eco*		*conv*	
# employees							
(.0,.5)	Mean	19.26 19.01	.0000	19.25 18.96	.0000	19.28 19.13	.0235
	(Std)	(4.377) (4.557)		(4.41) (4.542)		(4.312) (4.593)	
(.0,1.0)	Mean	19.26 18.99	.0000	19.25 18.96	.0000	19.28 19.01	.0000
	(Std)	(4.377) (4.642)		(4.41) (4.64)		(4.312) (4.643)	
(.5,1.0)	Mean	19.01 18.99	.2086	18.96 18.96	.3972	19.13 19.01	.042
	(Std)	(4.557) (4.642)		(4.542) (4.64)		(4.593) (4.643)	
Unit costs							
(.0,.5)	Mean	1.936 1.902	.0000	1.938 1.887	.0000	1.931 1.939	.2502
	(Std)	(.2211) (.2387)		(.2226) (.2378)		(.2182) (.2369)	
(.0,1.0)	Mean	1.936 1.86	.0000	1.938 1.831	.0000	1.931 1.877	.0000
	(Std)	(.2211) (.2366)		(.2226) (.2224)		(.2182) (.2428)	
(.5,1.0)	Mean	1.902 1.86	.0000	1.887 1.831	.0000	1.939 1.877	.0000
	(Std)	(.2387) (.2366)		(.2378) (.2224)		(.2369) (.2428)	

Table II.5: Results of two-sided Wilcoxon test at different phases of diffusion and different subsets of data.

initial	[601,3000]	*aggr*		*eco*		*conv*	
Share conventional capital used							
(.0,.5)	Mean	.466 .5262	6e-04	.4421 .469	.2375	.5128 .666	.0000
	(Std)	(.0719) (.1366)		(.0651) (.1046)		(.061) (.1003)	
(.0,1.0)	Mean	.466 .789	.0000	.4421 .6856	.0000	.5128 .8476	.0000
	(Std)	(.0719) (.1201)		(.0651) (.1091)		(.061) (.0798)	
(.5,1.0)	Mean	.5262 .789	.0000	.469 .6856	.0000	.666 .8476	.0000
	(Std)	(.1366) (.1201)		(.1046) (.1091)		(.1003) (.0798)	
Standard dev. share							
(.0,.5)	Mean	6.041 5.762	.7416	6.287 6.423	3e-04	5.559 4.143	.0000
	(Std)	(.7462) (1.474)		(.668) (1.043)		(.6533) (1.065)	
(.0,1.0)	Mean	6.041 2.896	.0000	6.287 4.332	.0000	5.559 2.081	.0000
	(Std)	(.7462) (1.588)		(.668) (1.423)		(.6533) (.9874)	
(.5,1.0)	Mean	5.762 2.896	.0000	6.423 4.332	.0000	4.143 2.081	.0000
	(Std)	(1.474) (1.588)		(1.043) (1.423)		(1.065) (.9874)	
Eco-price-wage-ratio							
(.0,.5)	Mean	.0952 .0951	.2842	.0951 .0951	.2874	.0952 .0952	.5029
	(Std)	(1e-04) (1e-04)		(1e-04) (1e-04)		(.0000) (.0000)	
(.0,1.0)	Mean	.0952 .0952	.1528	.0951 .0952	.0015	.0952 .0952	2e-04
	(Std)	(1e-04) (1e-04)		(1e-04) (1e-04)		(.0000) (1e-04)	
(.5,1.0)	Mean	.0951 .0952	.0111	.0951 .0952	.0000	.0952 .0952	.0000
	(Std)	(1e-04) (1e-04)		(1e-04) (1e-04)		(.0000) (1e-04)	
Frontier ratio							
(.0,.5)	Mean	.9859 .9922	.4242	.9584 .9597	.755	1.04 1.072	.002
	(Std)	(.0697) (.0727)		(.0584) (.0523)		(.0575) (.0511)	
(.0,1.0)	Mean	.9859 1.014	1e-04	.9584 .9471	.2019	1.04 1.053	.1868
	(Std)	(.0697) (.0741)		(.0584) (.0465)		(.0575) (.0579)	
(.5,1.0)	Mean	.9922 1.014	.002	.9597 .9471	.0887	1.072 1.053	.0095
	(Std)	(.0727) (.0741)		(.0523) (.0465)		(.0511) (.0579)	
Skill ratio							
(.0,.5)	Mean	1.036 1.035	.987	1.036 1.024	.0000	1.036 1.06	.0000
	(Std)	(.0013) (.0268)		(.0014) (.0232)		(.0012) (.0153)	
(.0,1.0)	Mean	1.036 1.089	.0000	1.036 1.055	.0000	1.036 1.108	.0000
	(Std)	(.0013) (.0393)		(.0014) (.0297)		(.0012) (.0299)	
(.5,1.0)	Mean	1.035 1.089	.0000	1.024 1.055	.0000	1.06 1.108	.0000
	(Std)	(.0268) (.0393)		(.0232) (.0297)		(.0153) (.0299)	
Monthly output							
(.0,.5)	Mean	8.102 8.104	.5452	8.105 8.108	.4139	8.097 8.095	.3824
	(Std)	(.0153) (.0177)		(.0157) (.0186)		(.0131) (.0111)	
(.0,1.0)	Mean	8.102 8.109	1e-04	8.105 8.101	.1376	8.097 8.113	.0000
	(Std)	(.0153) (.0169)		(.0157) (.0104)		(.0131) (.0183)	
(.5,1.0)	Mean	8.104 8.109	.0013	8.108 8.101	.0655	8.095 8.113	.0000
	(Std)	(.0177) (.0169)		(.0186) (.0104)		(.0111) (.0183)	
Unemployment rate							
(.0,.5)	Mean	7.811 7.874	.0983	7.861 7.912	.4768	7.713 7.78	.054
	(Std)	(.5792) (.5593)		(.5912) (.6208)		(.5457) (.3552)	
(.0,1.0)	Mean	7.811 8.121	.0000	7.861 7.809	.7796	7.713 8.298	.0000
	(Std)	(.5792) (.6919)		(.5912) (.371)		(.5457) (.7665)	
(.5,1.0)	Mean	7.874 8.121	.0000	7.912 7.809	.8226	7.78 8.298	.0000
	(Std)	(.5593) (.6919)		(.6208) (.371)		(.3552) (.7665)	
# active firms							
(.0,.5)	Mean	71.22 71.36	.3272	71.22 71.38	.3406	71.23 71.32	.735
	(Std)	(1.236) (1.07)		(1.302) (1.036)		(1.103) (1.158)	
(.0,1.0)	Mean	71.22 71.4	.247	71.22 71.49	.1943	71.23 71.35	.6623
	(Std)	(1.236) (1.061)		(1.302) (1.025)		(1.103) (1.082)	
(.5,1.0)	Mean	71.36 71.4	.8926	71.38 71.49	.609	71.32 71.35	.8364
	(Std)	(1.07) (1.061)		(1.036) (1.025)		(1.158) (1.082)	

Table II.6: Results of two-sided Wilcoxon test at different phases of diffusion and different subsets of data.

medium	[3001,5400]	*aggr*		*eco*		*conv*	
Share conventional capital used							
(.0,.5)	Mean	.2032 .2267	.0026	.1316 .0771	.0000	.3434 .5929	.0000
	(Std)	(.1536) (.2782)		(.1153) (.132)		(.1187) (.1869)	
(.0,1.0)	Mean	.2032 .6305	.0000	.1316 .214	.0176	.3434 .8668	.0000
	(Std)	(.1536) (.3567)		(.1153) (.2111)		(.1187) (.1393)	
(.5,1.0)	Mean	.2267 .6305	.0000	.0771 .214	.0000	.5929 .8668	.0000
	(Std)	(.2782) (.3567)		(.132) (.2111)		(.1869) (.1393)	
Standard dev. share							
(.0,.5)	Mean	1.779 1.623	.0024	1.497 1.014	.0000	2.331 3.111	.0000
	(Std)	(.8152) (1.38)		(.7322) (.9679)		(.6782) (1.075)	
(.0,1.0)	Mean	1.779 1.919	.3492	1.497 2.449	.0000	2.331 1.619	.0000
	(Std)	(.8152) (1.105)		(.7322) (1.16)		(.6782) (.9526)	
(.5,1.0)	Mean	1.623 1.919	3e-04	1.014 2.449	.0000	3.111 1.619	.0000
	(Std)	(1.38) (1.105)		(.9679) (1.16)		(1.075) (.9526)	
Eco-price-wage-ratio							
(.0,.5)	Mean	.0951 .0951	.005	.0951 .0951	.5008	.0952 .0951	.0019
	(Std)	(1e-04) (1e-04)		(1e-04) (1e-04)		(1e-04) (1e-04)	
(.0,1.0)	Mean	.0951 .0951	2e-04	.0951 .0951	.0231	.0952 .0951	.0000
	(Std)	(1e-04) (1e-04)		(1e-04) (1e-04)		(1e-04) (1e-04)	
(.5,1.0)	Mean	.0951 .0951	.3144	.0951 .0951	.0514	.0951 .0951	.5998
	(Std)	(1e-04) (1e-04)		(1e-04) (1e-04)		(1e-04) (1e-04)	
Frontier ratio							
(.0,.5)	Mean	.9459 .9352	.4136	.8762 .862	.4343	1.083 1.114	.0383
	(Std)	(.14) (.1446)		(.0994) (.0882)		(.1023) (.0874)	
(.0,1.0)	Mean	.9459 1.009	.0000	.8762 .8465	.1971	1.083 1.101	.3645
	(Std)	(.14) (.1649)		(.0994) (.0883)		(.1023) (.1209)	
(.5,1.0)	Mean	.9352 1.009	.0000	.862 .8465	.3365	1.114 1.101	.0905
	(Std)	(.1446) (.1649)		(.0882) (.0883)		(.0874) (.1209)	
Skill ratio							
(.0,.5)	Mean	1.026 .9731	.0000	1.025 .9152	.0000	1.028 1.115	.0000
	(Std)	(.0032) (.1105)		(.0031) (.0664)		(.0029) (.0549)	
(.0,1.0)	Mean	1.026 1.129	.0000	1.025 .9052	.0000	1.028 1.255	.0000
	(Std)	(.0032) (.2026)		(.0031) (.1137)		(.0029) (.1117)	
(.5,1.0)	Mean	.9731 1.129	.0000	.9152 .9052	.4231	1.115 1.255	.0000
	(Std)	(.1105) (.2026)		(.0664) (.1137)		(.0549) (.1117)	
Monthly output							
(.0,.5)	Mean	8.226 8.243	.0196	8.241 8.261	.0146	8.196 8.198	.9679
	(Std)	(.0552) (.065)		(.052) (.0614)		(.0489) (.0503)	
(.0,1.0)	Mean	8.226 8.24	.02	8.241 8.232	.1908	8.196 8.245	.0000
	(Std)	(.0552) (.0623)		(.052) (.0601)		(.0489) (.0632)	
(.5,1.0)	Mean	8.243 8.24	.8909	8.261 8.232	.0021	8.198 8.245	.0000
	(Std)	(.065) (.0623)		(.0614) (.0601)		(.0503) (.0632)	
Unemployment rate							
(.0,.5)	Mean	8.946 9.882	4e-04	9.449 10.54	.0015	7.96 8.271	.3437
	(Std)	(1.86) (2.832)		(2.057) (3.047)		(.7105) (1.144)	
(.0,1.0)	Mean	8.946 9.67	.0027	9.449 10.54	.1037	7.96 9.176	.0000
	(Std)	(1.86) (2.548)		(2.057) (3.248)		(.7105) (1.891)	
(.5,1.0)	Mean	9.882 9.67	.5192	10.54 10.54	.5377	8.271 9.176	2e-04
	(Std)	(2.832) (2.548)		(3.047) (3.248)		(1.144) (1.891)	
# active firms							
(.0,.5)	Mean	69.72 70.11	.0293	69.94 70.3	.0731	69.3 69.64	.2846
	(Std)	(1.867) (1.98)		(1.887) (1.999)		(1.763) (1.864)	
(.0,1.0)	Mean	69.72 70.36	7e-04	69.94 70.07	.7154	69.3 70.52	.0000
	(Std)	(1.867) (1.854)		(1.887) (1.907)		(1.763) (1.81)	
(.5,1.0)	Mean	70.11 70.36	.3102	70.3 70.07	.3106	69.64 70.52	.0051
	(Std)	(1.98) (1.854)		(1.999) (1.907)		(1.864) (1.81)	

Table II.7: Results of two-sided Wilcoxon test at different phases of diffusion and different subsets of data.

end	[5401,15000]	*aggr*		*eco*		*conv*	
Share conventional capital used							
(.0,.5)	Mean	.2938 .3003	.3262	.0443 .0257	.0052	.7823 .9724	.0000
	(Std)	(.3716) (.4335)		(.0739) (.0521)		(.1898) (.0419)	
(.0,1.0)	Mean	.2938 .6449	.0000	.0443 .0348	.2426	.7823 .991	.0000
	(Std)	(.3716) (.4623)		(.0739) (.0562)		(.1898) (.0275)	
(.5,1.0)	Mean	.3003 .6449	.0000	.0257 .0348	.0000	.9724 .991	.0000
	(Std)	(.4335) (.4623)		(.0521) (.0562)		(.0419) (.0275)	
Standard dev. share							
(.0,.5)	Mean	.8497 .2778	.0000	.4191 .1687	.0000	1.693 .5449	.0000
	(Std)	(.9089) (.4583)		(.6678) (.3826)		(.7059) (.5188)	
(.0,1.0)	Mean	.8497 .2077	.0000	.4191 .2926	.6941	1.693 .1595	.0000
	(Std)	(.9089) (.331)		(.6678) (.4171)		(.7059) (.26)	
(.5,1.0)	Mean	.2778 .2077	.022	.1687 .2926	2e-04	.5449 .1595	.0000
	(Std)	(.4583) (.331)		(.3826) (.4171)		(.5188) (.26)	
Eco-price-wage-ratio							
(.0,.5)	Mean	.0951 .0951	.4721	.0951 .0951	.9549	.0951 .0951	.1676
	(Std)	(.0000) (.0000)		(.0000) (.0000)		(.0000) (.0000)	
(.0,1.0)	Mean	.0951 .0951	.0195	.0951 .0951	.877	.0951 .0951	.0137
	(Std)	(.0000) (.0000)		(.0000) (.0000)		(.0000) (.0000)	
(.5,1.0)	Mean	.0951 .0951	.1437	.0951 .0951	.7912	.0951 .0951	.4145
	(Std)	(.0000) (.0000)		(.0000) (.0000)		(.0000) (.0000)	
Frontier ratio							
(.0,.5)	Mean	.9255 .9086	.4881	.7655 .7657	.9701	1.239 1.258	.385
	(Std)	(.2655) (.2641)		(.1125) (.121)		(.1874) (.1787)	
(.0,1.0)	Mean	.9255 1.085	.0000	.7655 .7543	.3892	1.239 1.273	.2639
	(Std)	(.2655) (.3115)		(.1125) (.1097)		(.1874) (.2184)	
(.5,1.0)	Mean	.9086 1.085	.0000	.7657 .7543	.5274	1.258 1.273	.8419
	(Std)	(.2641) (.3115)		(.121) (.1097)		(.1787) (.2184)	
Skill ratio							
(.0,.5)	Mean	1.013 .9236	.0000	1.012 .7592	.0000	1.014 1.326	.0000
	(Std)	(.003) (.2653)		(.0027) (.0532)		(.0032) (.0823)	
(.0,1.0)	Mean	1.013 1.372	.0000	1.012 .6081	.0000	1.014 1.805	.0000
	(Std)	(.003) (.6195)		(.0027) (.1024)		(.0032) (.2737)	
(.5,1.0)	Mean	.9236 1.372	.0000	.7592 .6081	.0000	1.326 1.805	.0000
	(Std)	(.2653) (.6195)		(.0532) (.1024)		(.0823) (.2737)	
Monthly output							
(.0,.5)	Mean	8.659 8.694	.0048	8.688 8.715	.0311	8.603 8.643	.0611
	(Std)	(.1206) (.1411)		(.1124) (.1407)		(.117) (.1292)	
(.0,1.0)	Mean	8.659 8.687	.0222	8.688 8.708	.1208	8.603 8.675	2e-04
	(Std)	(.1206) (.135)		(.1124) (.1437)		(.117) (.129)	
(.5,1.0)	Mean	8.694 8.687	.5353	8.715 8.708	.7244	8.643 8.675	.1585
	(Std)	(.1411) (.135)		(.1407) (.1437)		(.1292) (.129)	
Unemployment rate							
(.0,.5)	Mean	11.67 12.73	.2098	12.01 13.31	.3712	11 11.31	.4732
	(Std)	(4.429) (6.848)		(4.566) (7.61)		(4.097) (4.196)	
(.0,1.0)	Mean	11.67 13.11	.0612	12.01 14.42	.1133	11 12.37	.0321
	(Std)	(4.429) (7.577)		(4.566) (9.65)		(4.097) (6.016)	
(.5,1.0)	Mean	12.73 13.11	.6234	13.31 14.42	.4323	11.31 12.37	.245
	(Std)	(6.848) (7.577)		(7.61) (9.65)		(4.196) (6.016)	
# active firms							
(.0,.5)	Mean	73.36 73.36	.4921	73.69 73.34	.7119	72.7 73.4	.1143
	(Std)	(2.463) (3.263)		(2.454) (3.439)		(2.361) (2.811)	
(.0,1.0)	Mean	73.36 73.26	.4376	73.69 72.77	.2212	72.7 73.54	.0073
	(Std)	(2.463) (3.614)		(2.454) (4.072)		(2.361) (3.309)	
(.5,1.0)	Mean	73.36 73.26	.9687	73.34 72.77	.3417	73.4 73.54	.3891
	(Std)	(3.263) (3.614)		(3.439) (4.072)		(2.811) (3.309)	

II.2. Technological difficulty

The following figures summarize the observations made in the experiment with discretely varying levels of the technological distance $\chi^{int} \in \{0, .5, 2\}$. The tables indicate whether the differences between different parameter pairs are significant. The interpretation of the finding follows analogous arguments as in the main article.

In figure II.3, an overview of technological and macroeconomic time series is shown. The time series are disaggregated by parameter value and by technological regime. Figure II.4 illustrates diffusion curves and the diffusion volatility of single simulation runs within a parameter subset. The tables II.8 – II.10 show the results of a series of pair-wise Wilcoxon tests on equality of means in the time series of firm-level data of different parameter combinations.

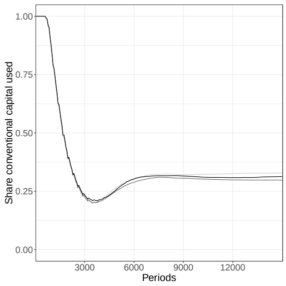
Table II.8: Results of two-sided Wilcoxon test on different parameter pairings in the early phase of diffusion and different subsets of data.

initial	[601,3000]	*aggr*		*eco*		*conv*	
Share conventional capital							
(.0,.5)	Mean	.5147 .5211	.0000	.5001 .5295	.0000	.5456 .5005	.0000
	(Std)	(.1863) (.18)		(.181) (.1833)		(.1935) (.1701)	
(.0,2)	Mean	.5147 .5199	.0235	.5001 .5286	.0000	.5456 .5	.0000
	(Std)	(.1863) (.1876)		(.181) (.1908)		(.1935) (.1787)	
(.5,2)	Mean	.5211 .5199	.0118	.5295 .5286	.0894	.5005 .5	.0909
	(Std)	(.18) (.1876)		(.1833) (.1908)		(.1701) (.1787)	
Standard dev. share							
(.0,.5)	Mean	9.829 9.939	8e-04	9.938 9.85	.0318	9.596 10.16	.0000
	(Std)	(2.669) (2.669)		(2.596) (2.75)		(2.805) (2.445)	
(.0,2)	Mean	9.829 9.811	.3807	9.938 9.739	8e-04	9.596 9.973	.0000
	(Std)	(2.669) (2.793)		(2.596) (2.849)		(2.805) (2.655)	
(.5,2)	Mean	9.939 9.811	.014	9.85 9.739	.1914	10.16 9.973	.0055
	(Std)	(2.669) (2.793)		(2.75) (2.849)		(2.445) (2.655)	
# employees							
(.0,.5)	Mean	20.66 20.65	.8137	20.65 20.63	.7667	20.7 20.7	.9389
	(Std)	(5.033) (5.059)		(5.037) (5.048)		(5.027) (5.088)	
(.0,2)	Mean	20.66 20.69	.6873	20.65 20.66	.8372	20.7 20.74	.655
	(Std)	(5.033) (5.058)		(5.037) (5.052)		(5.027) (5.072)	
(.5,2)	Mean	20.65 20.69	.5308	20.63 20.66	.6259	20.7 20.74	.7187
	(Std)	(5.059) (5.058)		(5.048) (5.052)		(5.088) (5.072)	
Unit costs							
(.0,.5)	Mean	1.075 1.072	2e-04	1.076 1.07	.0000	1.071 1.075	.0037
	(Std)	(.0679) (.0676)		(.0679) (.0673)		(.0677) (.0682)	
(.0,2)	Mean	1.075 1.072	.0077	1.076 1.071	.0000	1.071 1.074	.007
	(Std)	(.0679) (.0656)		(.0679) (.065)		(.0677) (.0669)	
(.5,2)	Mean	1.072 1.072	.2685	1.07 1.071	.1624	1.075 1.074	.8091
	(Std)	(.0676) (.0656)		(.0673) (.065)		(.0682) (.0669)	

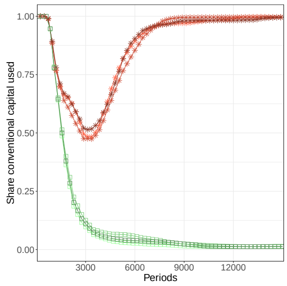
Table II.9: Results of two-sided Wilcoxon test on different parameter pairings in the intermediate phase of diffusion and different subsets of data.

medium	[3001,5400]	*aggr*		*eco*		*conv*	
Share conventional capital							
(.0,.5)	Mean	.2251 .217	.0000	.169 .2176	.0000	.346 .2157	.0000
	(Std)	(.3289) (.3102)		(.2948) (.3128)		(.3642) (.3037)	
(.0,2)	Mean	.2251 .2189	.0297	.169 .2278	.0000	.346 .1985	.0000
	(Std)	(.3289) (.3242)		(.2948) (.3264)		(.3642) (.3182)	
(.5,2)	Mean	.217 .2189	.0234	.2176 .2278	.5209	.2157 .1985	.0015
	(Std)	(.3102) (.3242)		(.3128) (.3264)		(.3037) (.3182)	
Standard dev. share							
(.0,.5)	Mean	4.241 4.643	.0000	3.674 4.572	.0000	5.463 4.818	.0000
	(Std)	(4.279) (4.403)		(3.976) (4.374)		(4.641) (4.47)	
(.0,2)	Mean	4.241 4.228	.0632	3.674 4.358	.0000	5.463 3.929	.0000
	(Std)	(4.279) (4.217)		(3.976) (4.281)		(4.641) (4.05)	
(.5,2)	Mean	4.643 4.228	.0000	4.572 4.358	.0000	4.818 3.929	.0000
	(Std)	(4.403) (4.217)		(4.374) (4.281)		(4.47) (4.05)	
# employees							
(.0,.5)	Mean	20.5 20.57	.0978	20.49 20.59	.0915	20.53 20.54	.6546
	(Std)	(4.836) (5.012)		(4.847) (4.975)		(4.81) (5.104)	
(.0,2)	Mean	20.5 20.52	.6792	20.49 20.55	.3523	20.53 20.45	.5061
	(Std)	(4.836) (4.949)		(4.847) (4.97)		(4.81) (4.9)	
(.5,2)	Mean	20.57 20.52	.2218	20.59 20.55	.4692	20.54 20.45	.2751
	(Std)	(5.012) (4.949)		(4.975) (4.97)		(5.104) (4.9)	
Unit costs							
(.0,.5)	Mean	1.396 1.407	.0000	1.395 1.406	.0000	1.399 1.409	.0000
	(Std)	(.0927) (.0915)		(.0937) (.0909)		(.0907) (.0928)	
(.0,2)	Mean	1.396 1.398	.0135	1.395 1.397	.0085	1.399 1.401	.5262
	(Std)	(.0927) (.0933)		(.0937) (.0929)		(.0907) (.0941)	
(.5,2)	Mean	1.407 1.398	.0000	1.406 1.397	.0000	1.409 1.401	1e-04
	(Std)	(.0915) (.0933)		(.0909) (.0929)		(.0928) (.0941)	

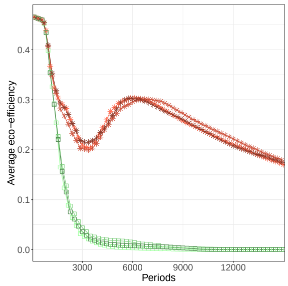
Figure II.3: Overview of macroeconomic and technological indicators



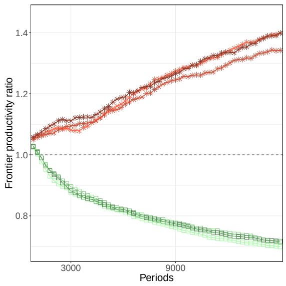
(a) ν_t^c batch



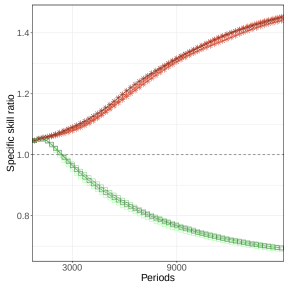
(b) ν_t^c by regime type



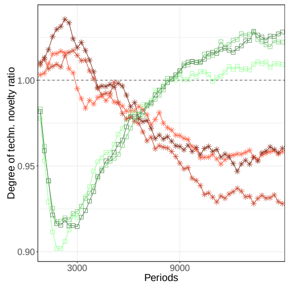
(c) Eco-efficiency



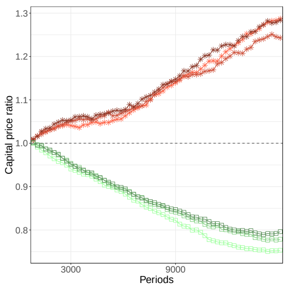
(d) $\alpha_t = \frac{A^V_{c,t}}{A^V_{g,t}}$



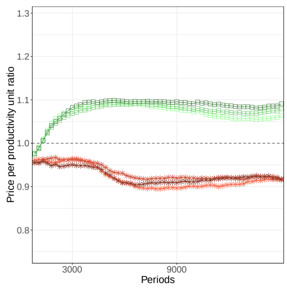
(e) $\beta_t = \frac{b^c_t}{b^g_t}$



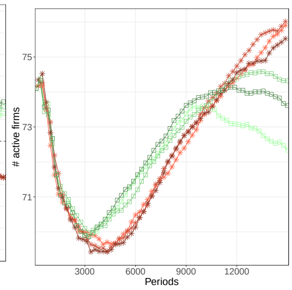
(f) $\frac{A^V_{c,t}/b^c_t}{A^V_{g,t}/b^g_t}$



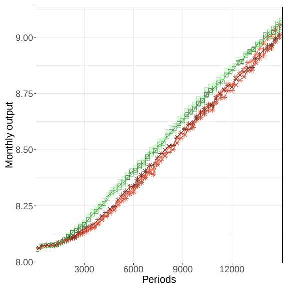
(g) $\frac{p^c_t}{p^g_t}$



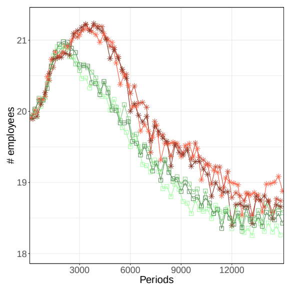
(h) $\frac{p^c_t/A^c_t}{p^g_t/A^g_t}$



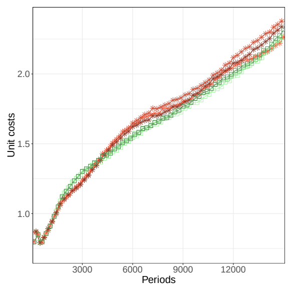
(i) # active firms



(j) Monthly output



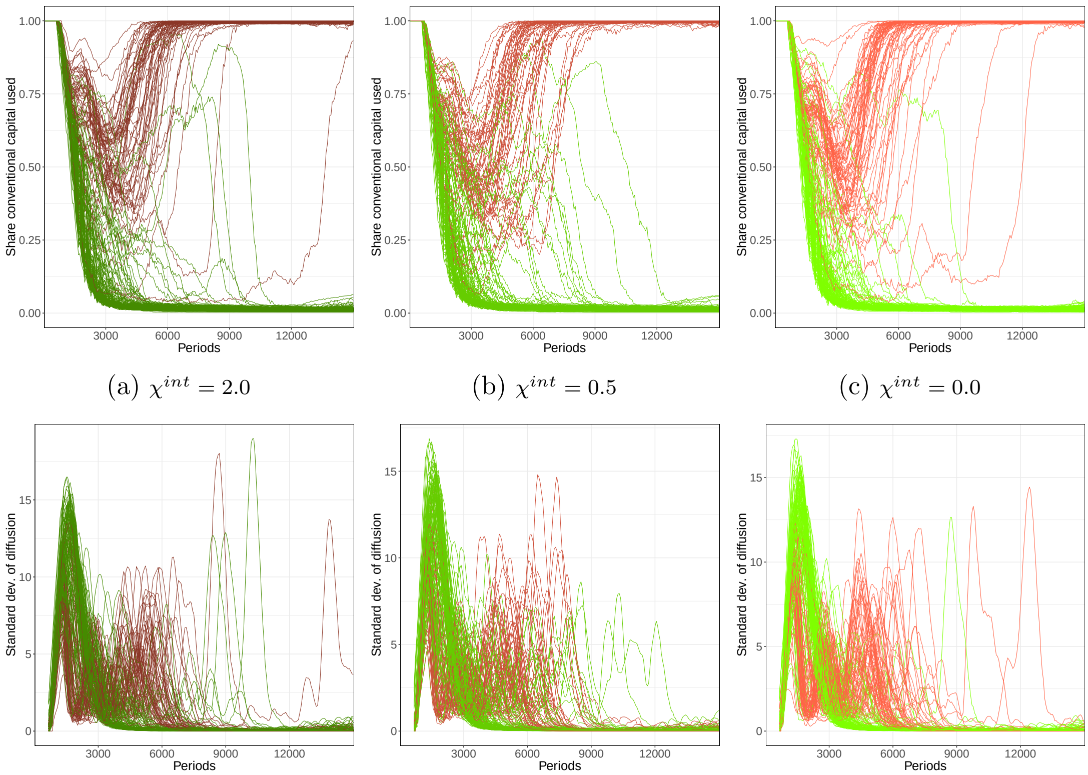
(k) Avg. # employees per firm



(l) Unit costs

These figures give an overview of the time series of macroeconomic and technological indicators. The different line shapes indicate different regime types (□: eco, ∗: conv). Darker color indicates a higher level of $\chi^{int} \in \{0.0, 0.5, 2.0\}$.

Figure II.4: Green technology diffusion



(a) $\chi^{int} = 2.0$ (b) $\chi^{int} = 0.5$ (c) $\chi^{int} = 0.0$

(d) $\chi^{int} = 2.0$ (e) $\chi^{int} = 0.5$ (f) $\chi^{int} = 0.0$

These figures illustrate show diffusion curves ν_t^c of all single simulation runs within the subsets with $\chi^{int} = \{.0, .5, 2\}$.

Table II.10: Results of two-sided Wilcoxon test on different parameter pairings in the last phase of diffusion and different subsets of data.

end	[5401,15000]	*aggr*		*eco*		*conv*	
Share conventional capital							
(.0,.5)	Mean	.3172 .2905	.5888	.188 .2816	.0000	.5787 .3116	.0000
	(Std)	(.4568) (.4407)		(.383) (.4346)		(.4818) (.4542)	
(.0,2)	Mean	.3172 .301	.4454	.188 .2932	.0000	.5787 .3182	.0000
	(Std)	(.4568) (.449)		(.383) (.4439)		(.4818) (.4595)	
(.5,2)	Mean	.2905 .301	.2367	.2816 .2932	.1796	.3116 .3182	.8809
	(Std)	(.4407) (.449)		(.4346) (.4439)		(.4542) (.4595)	
Standard dev. share							
(.0,.5)	Mean	.3772 .5487	.0000	.2994 .6059	.0000	.5349 .412	.0000
	(Std)	(.9072) (1.132)		(.8329) (1.21)		(1.024) (.9043)	
(.0,2)	Mean	.3772 .4347	.0046	.2994 .4599	.0000	.5349 .3792	.0000
	(Std)	(.9072) (.9935)		(.8329) (1.064)		(1.024) (.8135)	
(.5,2)	Mean	.5487 .4347	.0000	.6059 .4599	.0000	.412 .3792	.7718
	(Std)	(1.132) (.9935)		(1.21) (1.064)		(.9043) (.8135)	
# employees							
(.0,.5)	Mean	18.96 19.03	.045	18.88 19.05	.0026	19.11 19	.4275
	(Std)	(4.552) (4.56)		(4.534) (4.539)		(4.584) (4.61)	
(.0,2)	Mean	18.96 18.97	.747	18.88 18.96	.2248	19.11 18.99	.2586
	(Std)	(4.552) (4.572)		(4.534) (4.56)		(4.584) (4.596)	
(.5,2)	Mean	19.03 18.97	.0997	19.05 18.96	.0773	19 18.99	.7715
	(Std)	(4.56) (4.572)		(4.539) (4.56)		(4.61) (4.596)	
Unit costs							
(.0,.5)	Mean	1.868 1.9	.0000	1.859 1.91	.0000	1.887 1.878	.0066
	(Std)	(.2307) (.2377)		(.2305) (.2387)		(.2301) (.2336)	
(.0,2)	Mean	1.868 1.879	.0000	1.859 1.879	.0000	1.887 1.879	.1423
	(Std)	(.2307) (.2318)		(.2305) (.2263)		(.2301) (.2437)	
(.5,2)	Mean	1.9 1.879	.0000	1.91 1.879	.0000	1.878 1.879	.3214
	(Std)	(.2377) (.2318)		(.2387) (.2263)		(.2336) (.2437)	

III. Monte Carlo experiments

III.1. Randomly drawn learning parameters given fix barriers barriers to diffusion

This section provides additional information about the simulation experiment with randomly drawn levels of the technological distance $\chi^{dist} \in [0,1]$ and technical difficulty $\chi^{int} \in [0,2]$ given fix levels of diffusion barriers $\beta^A = \beta^b = .03$.

Here, I provide some additional explanation of the role of explanatory variables that are used in the regression analysis presented in section 4.3.1 in table 2. The association of the shape of the learning function with the probability of a technological regime shift, the duration until the diffusion process becomes stable and critical levels of relative knowledge stocks are discussed in the main article. Here, a short descriptive and explanatory summary of the role of micro- and macroeconomic circumstances is given. The level of the technological frontier A_c^V indicates the stock of codified knowledge of the conventional type that is available in the economy at the day of market entry. A higher level of A_c^V is negatively associated with the probability of a green transition and positively with the duration until the diffusion process stabilizes. A higher price for the natural resource is positively associated with the probability of a technological regime shift and the lower relative stocks of conventional technological knowledge. The level of tacit knowledge available at the firm B_i^c is a proxy to measure productivity at the firm-level, i.e. it is heterogeneous across firms. It is weakly positively associated with the probability of a technological regime shift. However, it increases technological uncertainty, i.e. it has a positive association with the diffusion volatility $(\sigma_i^\nu)^2$.

In table III.11, the coefficients of a regression of technological indicators at the *macroeconomic* level on the degree of of state dependence χ^{int} and χ^{dist} and a set of control variables are shown. The aggregation at the macroeconomic level hides heterogeneity across firms in both, the dependent and explanatory variables. Further, the number of observations is smaller. This explains why the BIC based model selection procedure leads to the exclusion of many explanatory variables. The interpretation of the dependent variables is analogue to the firm-level analyses. At the macroeconomic level, only the distance and initial endowments with technological knowledge are significantly associated with the transition probability. The coefficients of the frontier A_c^V and tacit knowledge B^c should be treated with care because the knowledge stocks at the macroeconomic level are strongly correlated. For the stabilization time, the technical performance threshold and the diffusion volatility, only the type dummy $\mathbb{I}(eco)$ remains as explanatory variable after the stepwise BIC based selection procedure. However, the R^2 is low. The distance can explains part of the variation in the skill-related performance threshold.

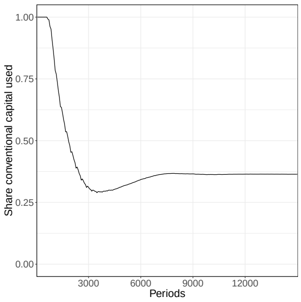
Table III.11: Macroeconomic regression results of experiment with random learning parameters and fix barriers

	ν^c_T OLS	ν^c_T Probit	t^* IV	$\left(A^V_+/A^V_-\right)^*$ IV	$\left(B^+/B^-\right)^*$ IV	$(\sigma^\nu)^2$ IV
(Intercept)	.3641***	-.4017***	2886***	1.102***	1.098***	1.449*
	(.03)	(.094)	(239.4)	(.0227)	(.0105)	(.6343)
χ^{dist}	.3739***	1.079***			.0678***	
	(.0784)	(.2476)			(.0168)	
χ^{int}					.0031	
					(.0031)	
$\mathbb{I}(eco)$			-1701***	-.1501***	-.1552***	7.903***
			(396.2)	(.0372)	(.0168)	(1.048)
$\mathbb{I}(eco)\cdot\chi^{dist}$					-.0929**	
					(.0298)	
A^V_c	.2207***	.6421***				
	(.0456)	(.1463)				
B^c	-.2998***	-.8616**				
	(.0858)	(.2663)				
R^2	.1499	.2077	.0000	.0942	.2801	.1684

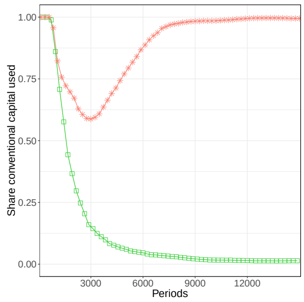
Significance codes: 0 '***' .001 '**' .01 '*' .05 '.' .1 ' ' 1.

The first two columns show the diffusion measure ν^c evaluated at the end of simulation. The third columns illustrates the relationship between the duration t^* until the diffusion process stabilizes and initial conditions. t^* is defined point in time when the last change in the sign of the slope of the diffusion curve was observed. Column (3) and (4) measure the relative performance of the dominating technology in t^* interpreted as performance thresholds. $(\sigma^\nu)^2$ is the variance computed over the full time horizon and describes the diffusion volatility. Further info is provided in the technical note section A.

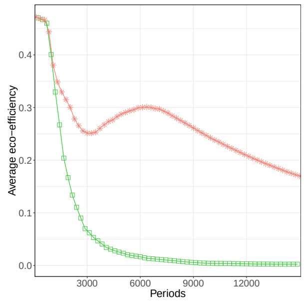
Figure III.5: Overview of macroeconomic and technological indicators



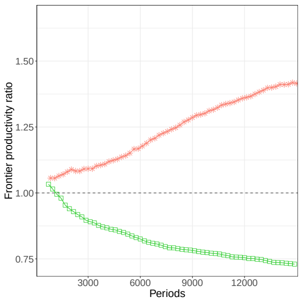
(a) ν_t^c batch



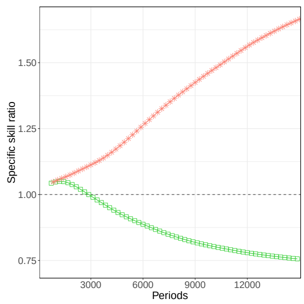
(b) ν_t^c by regime type



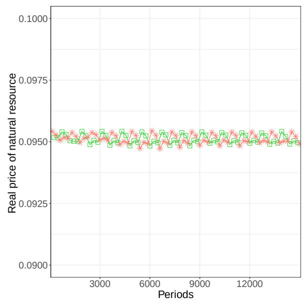
(c) Eco-efficiency



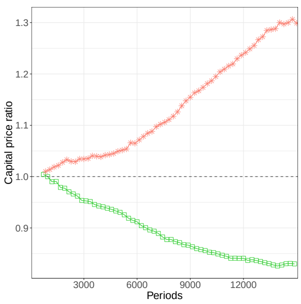
(d) $\alpha_t = \frac{A_{c,t}^V}{A_{g,t}^V}$



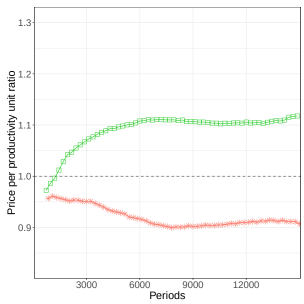
(e) $\beta_t = \frac{b_t^c}{b_t^g}$



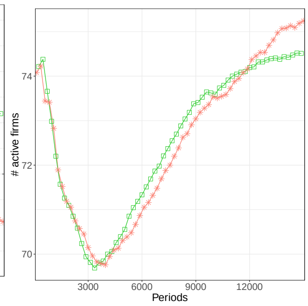
(f) $\frac{p_t^{eco}}{w_t^r}$



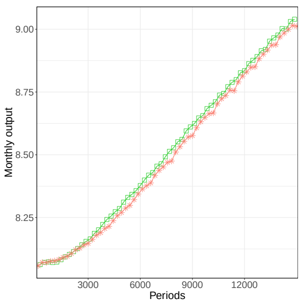
(g) $\frac{p_t^c}{p_t^g}$



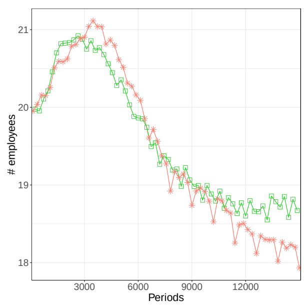
(h) $\frac{p_t^c/A_t^c}{p_t^g/A_t^g}$



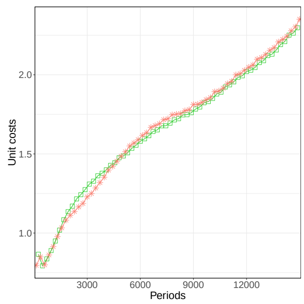
(i) # active firms



(j) Monthly output



(k) Avg. # employees per firm



(l) Unit costs

These figures give an overview of the time series of macroeconomic and technological indicators. The different line shapes indicate different regime types (□: eco, $*$: conv).

Table III.12: Wilcoxon test on equality of means for different phases of diffusion.

t	*eco*	*conv*	*eco,conv*	*eco*	*conv*	*eco,conv*
Macro-level data						
	Share conventional capital used			Variance share		
[601,3000]	.4806 (.1287)	.7229 (.148)	.0000	55.25 (20.38)	21.27 (18.02)	.0000
[3001,5400]	.088 (.1194)	.6924 (.2377)	.0000	4.014 (5.839)	8.599 (6.765)	.0000
[5401,15000]	.0226 (.0339)	.971 (.0705)	.0000	.3611 (1.196)	2.239 (3.544)	1e-04
[1,15000]	.1454 (.0495)	.8879 (.0944)	.0000	10.12 (2.565)	6.472 (5.374)	.0000
	Eco-price-wage-ratio			Frontier ratio		
[601,3000]	.0951 (1e-04)	.0952 (1e-04)	.0000	.9558 (.046)	1.074 (.0549)	.0000
[3001,5400]	.0951 (1e-04)	.0951 (1e-04)	.6508	.8659 (.083)	1.117 (.1045)	.0000
[5401,15000]	.0951 (1e-04)	.0951 (1e-04)	.2223	.7729 (.1138)	1.308 (.2116)	.0000
[1,15000]	.0951 (.0000)	.0951 (.0000)	.6888	.8836 (.087)	1.285 (.1527)	.0000
	Skill ratio			Monthly output		
[601,3000]	1.033 (.0191)	1.076 (.0324)	.0000	8.104 (.0145)	8.103 (.0168)	.6853
[3001,5400]	.9465 (.0601)	1.164 (.1073)	.0000	8.248 (.0546)	8.224 (.0627)	.0011
[5401,15000]	.8102 (.1211)	1.472 (.304)	.0000	8.702 (.1236)	8.676 (.1257)	.2074
[1,15000]	.8769 (.0844)	1.342 (.2141)	.0000	8.508 (.0847)	8.488 (.0893)	.1161
	Unemployment rate			# active firms		
[601,3000]	7.796 (.4701)	8.028 (.5456)	.0012	71.43 (1.205)	71.53 (1.052)	.8329
[3001,5400]	9.915 (2.415)	8.751 (1.686)	.0000	70.14 (2.056)	70.04 (2.01)	.5663
[5401,15000]	12.76 (6.792)	13.62 (7.664)	.4845	73.39 (3.133)	73.31 (3.141)	.6628
[1,15000]	11.3 (4.615)	11.7 (5.117)	.9113	72.58 (2.199)	72.53 (2.217)	.6914
Firm-level data						
	Unit costs			# employees		
[601,3000]	1.067 (.1215)	1.039 (.1152)	.0000	20.08 (6.806)	20.01 (6.833)	.5505
[3001,5400]	1.409 (.1071)	1.385 (.1162)	.0000	20.27 (6.2)	20.51 (6.585)	.0055
[5401,15000]	1.879 (.243)	1.907 (.2379)	.0000	18.65 (5.621)	18.46 (5.585)	.0907
[1,15000]	1.597 (.257)	1.609 (.2552)	.0023	18.61 (5.798)	18.53 (5.794)	.344

III.2. Randomly drawn learning parameters and barriers

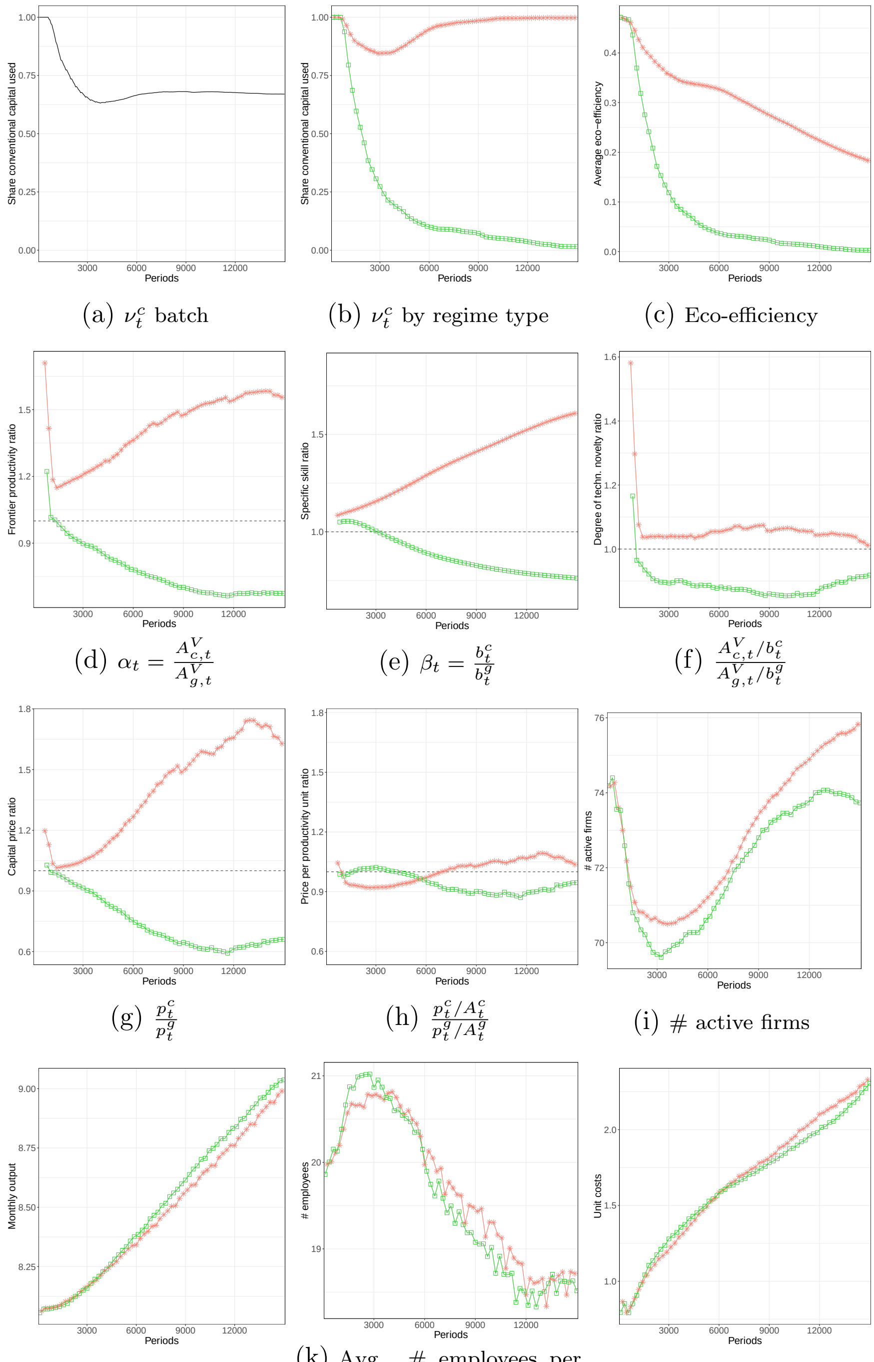
Table III.13: Macroeconomic regression analyses with randomly drawn learning parameters and random barriers to diffusion

	ν_T^c OLS	ν_T^c Probit	t^* IV	$\left(A_+^V/A_-^V\right)^*$ IV	$\left(B^+/B^-\right)^*$ IV	$(\sigma^\nu)^2$ IV
(Intercept)	.6702***	.7696***	3407***	1.101***	1.124***	.5044**
	(.0267)	(.1388)	(165)	(.0135)	(.0080)	(.1955)
χ^{dist}	.0958***	.5612***	-318.7**	.0035	.0042	
	(.0268)	(.1397)	(113.2)	(.0063)	(.0103)	
χ^{int}				.0027		
				(.0066)		
$\chi^{dist} \cdot \chi^{int}$				.0197**		
				(.0063)		
β^A	.1611***	.6022***		.0530***		
	(.0268)	(.1139)		(.0159)		
β^b	.1900***	.8461***	-315.1.		.0625***	
	(.0267)	(.1422)	(168.0)		(.0150)	
$\chi^{dist} \cdot \beta^b$		.3425*			.0090	
		(.1330)			(.0076)	
$\mathbb{I}(eco)$			-2945***	-.1974***	-.1981***	9.302***
			(345.6)	(.0363)	(.0293)	(.6622)
$\mathbb{I}(eco) \cdot \beta^A$				-.1220***		
				(.0360)		
$\mathbb{I}(eco) \cdot \beta^b$					-.1159***	
					(.0293)	
B^c					.0232	
					(.0157)	
R^2	.3065	.4672	.1327	.2470	.4955	.3380

Significance codes: 0 '***' .001 '**' .01 '*' .05 '.' .1 ' ' 1.

The first two columns show the diffusion measure ν^c evaluated at the end of simulation. The third columns illustrates the relationship between the duration until the diffusion process stabilizes and initial conditions. t^* is defined point in time when the last change in the sign of the slope of the diffusion curve was observed. The remaining columns show technological indicator variables evaluated at this point in time. Further info is provided in the technical note section A.

Figure III.6: Overview of macroeconomic and technological indicators



(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

These figures give an overview of the time series of macroeconomic and technological indicators in the experiment with randomly drawn barriers and learning parameters. The different line shapes indicate different regime types (□: eco, $*$: conv).

Table III.14: Wilcoxon test on equality of means for different snapshots in time.

t	*eco*	*conv*	*eco,conv*	*eco*	*conv*	*eco,conv*
Macro-level data						
	Share conventional capital used			Variance share		
[601,3000]	.5644 (.1833)	.896 (.1352)	.0000	43.58 (25.75)	6.647 (13.84)	.0000
[3001,5400]	.1784 (.2207)	.8721 (.1944)	.0000	6.511 (7.308)	3.918 (6.892)	.0000
[5401,15000]	.0563 (.1295)	.9844 (.059)	.0000	1.548 (4.063)	.9348 (2.656)	8e-04
[1,15000]	.1949 (.1267)	.9529 (.0801)	.0000	9.381 (3.396)	2.384 (4.31)	.0000
	Eco-price-wage-ratio			Frontier ratio		
[601,3000]	.0951 (1e-04)	.0952 (.0000)	.0089	.9979 (.0994)	1.248 (.3503)	.0000
[3001,5400]	.0951 (1e-04)	.0951 (1e-04)	.0198	.8525 (.0934)	1.262 (.4185)	.0000
[5401,15000]	.0951 (1e-04)	.0951 (.0000)	.0105	.7024 (.1206)	1.501 (.4829)	.0000
[1,15000]	.0951 (.0000)	.0951 (.0000)	7e-04	.8431 (.0925)	1.46 (.4077)	.0000
	Skill ratio			Monthly output		
[601,3000]	1.04 (.0327)	1.118 (.0568)	.0000	8.105 (.0156)	8.109 (.0155)	.0475
[3001,5400]	.9566 (.0752)	1.207 (.1259)	.0000	8.248 (.0524)	8.238 (.0573)	.1979
[5401,15000]	.817 (.1339)	1.453 (.3109)	.0000	8.703 (.1374)	8.649 (.1267)	.0027
[1,15000]	.8841 (.0978)	1.345 (.2238)	.0000	8.509 (.0925)	8.474 (.0892)	.0042
	Unemployment rate			# active firms		
[601,3000]	7.833 (.4145)	8.2 (.5608)	.0000	71.08 (1.11)	71.5 (1.172)	.0163
[3001,5400]	9.526 (1.944)	8.656 (1.415)	.001	69.99 (1.738)	70.63 (1.978)	.0431
[5401,15000]	13.5 (7.506)	11.45 (4.828)	.0152	72.87 (3.36)	73.78 (2.92)	.1165
[1,15000]	11.71 (4.954)	10.32 (3.264)	.0068	72.18 (2.256)	72.92 (2.124)	.0531
Firm-level data						
	Variance share			# employees		
[601,3000]	134.5 (83.81)	36.42 (63.04)	.0000	20.12 (6.796)	19.97 (6.832)	.2411
[3001,5400]	63.37 (89.33)	39.38 (68.29)	.0000	20.44 (6.193)	20.35 (6.56)	.7528
[5401,15000]	19.6 (70.98)	5.535 (18.52)	.0000	18.58 (5.723)	18.82 (5.584)	5e-04
[1,15000]	49.17 (74.48)	16.15 (32.74)	.0000	18.6 (5.842)	18.73 (5.82)	0.164
	Unit costs			Share conv. capital on firm-level		
[601,3000]	1.052 (.1297)	1.027 (.1158)	.0000	.5701 (.2423)	.9027 (.1653)	.0000
[3001,5400]	1.399 (.1061)	1.359 (.1144)	.0000	.1621 (.2581)	.88 (.2172)	.0000
[5401,15000]	1.87 (.2544)	1.925 (.2415)	.0000	.0387 (.127)	.9866 (.0599)	.0000
[1,15000]	1.587 (.2657)	1.612 (.2628)	.0000	.2018 (.2057)	.9595 (.0837)	.0000

III.3. Policy experiment

Table III.15: Regression results of policy experiment

	ν_i^c OLS	ν_i^c Probit	t_i^* IV	$(A_i^+/A_i^-)^*$ IV	$(B_i^+/B_i^-)^*$ IV	$(\sigma_i^\nu)^2$ IV
(Intercept)	.3381***	-.4684***	3794***	1.099***	1.097***	6.548***
	(.0043)	(.0144)	(70.63)	(.0031)	(.0029)	(.1399)
χ^{dist}	-.013**	-.0898***	-471***	.0141***	.0213***	-.9603***
	(.0044)	(.0151)	(65.99)	(.0041)	(.0031)	(.1172)
χ^{int}	.0081.	-.0161	-117.2***	.0085***	.0078***	-.024
	(.0043)	(.0145)	(31.42)	(.0017)	(.0012)	(.0535)
$\chi^{dist} \cdot \chi^{int}$	-.0291***	-.0701***				
	(.0045)	(.0158)				
θ	-.03***	-.1119***	788.9***	-.0297***	-.0296***	2.267***
	(.0043)	(.0145)	(70.37)	(.0037)	(.0029)	(.1218)
ς^c	-.0401***	-.173***	-318.1***	.0085***	-.0065*	-.1806***
	(.0044)	(.0151)	(77.99)	(.0018)	(.0032)	(.0536)
ς^i	-.0205***	-.0763***	-310.8***	-.0369***	-.0286***	1.506***
	(.0045)	(.0149)	(58.73)	(.0037)	(.003)	(.109)
β^A	.1139***	.465***	8.747	.0395***	.0069***	-.3212***
	(.0046)	(.0196)	(27.75)	(.0049)	(.0016)	(.0482)
β^b	.0946***	.2974***	-501***	.0478***	.0519***	-2.894***
	(.0044)	(.0149)	(65.63)	(.004)	(.0035)	(.1436)
$\chi^{dist} \cdot \theta$	-.0504***	-.1177***	-119.3***	-.011***	-.0063***	.4541***
	(.0044)	(.0149)	(28.46)	(.0019)	(.0014)	(.0609)
$\chi^{int} \cdot \theta$	.046***	.1706***	-143.2***			
	(.004)	(.0137)	(28.06)			
$\chi^{dist} \cdot \varsigma^c$	.0289***	.0972***			-.0070***	.4550***
	(.0044)	(.0156)			(.0016)	(.0601)
$\chi^{int} \cdot \varsigma^c$	.0163***	.0466***				
	(.0042)	(.0139)				
$\chi^{dist} \cdot \varsigma^i$		.0522**	140***	-.0099***	-.0073***	.4853***
		(.016)	(25.38)	(.0018)	(.0013)	(.0561)
$\chi^{int} \cdot \varsigma^i$				.0049***		-.7356***
				(.0015)		(.0552)
$\chi^{dist} \cdot \beta^A$	-.0378***	-.1738***	195.1***			.5285***
	(.0044)	(.0199)	(23.1)			(.0442)
$\chi^{dist} \cdot \beta^b$	.0447***	.1624***	301.8***		.0092***	.2984***
	(.0046)	(.0163)	(37.7)		(.0015)	(.0711)
$\chi^{int} \cdot \beta^A$	-.0171***	-.1635***				
	(.0044)	(.0199)				
$\chi^{int} \cdot \beta^b$	.0301***	.0975***				-.2552***
	(.0044)	(.0149)				(.0485)
$\mathbb{I}(eco)$			-2718***	-.1695***	-.1753***	2.874***
			(144.4)	(.0071)	(.0061)	(.3324)
$\mathbb{I}(eco) \cdot \chi^{dist}$			1144***	-.0222*	-.0213***	2.658***
			(146.8)	(.0089)	(.0064)	(.2647)
$\mathbb{I}(eco) \cdot \theta$			-1070***	.054***	.0532***	-3.919***
			(135.8)	(.0076)	(.0059)	(.2298)
$\mathbb{I}(eco) \cdot \varsigma^c$			671.4***		.0239***	
			(149.1)		(.0066)	
$\mathbb{I}(eco) \cdot \varsigma^i$			843.7***	.0952***	.0772***	-2.392***
			(140.9)	(.009)	(.0075)	(.2719)
$\mathbb{I}(eco) \cdot \beta^A$				-.0413***		
				(.006)		
$\mathbb{I}(eco) \cdot \beta^b$			786.3***	-.0908***	-.1064***	4.706***
			(137.2)	(.0084)	(.0074)	(.31)
A_c^V	-.017***		102.9***	.0066***	.0072***	-.2764***
	(.0044)		(26.88)	(.0018)	(.0012)	(.0548)
B_i^c						-.2179***
						(.0569)
$\#employees_i$	-.143***	-.4386***				.3848***
	(.0257)	(.0873)				(.0562)
$output_i$	.1674***	.5116***				
	(.0259)	(.0886)				
$price_i$	.0254***	.0634***				
	(.0057)	(.0191)				
$\#firms$	.0272***	.0988***	-120***		-.0035***	
	(.0043)	(.0142)	(25)		(8e-04)	
R^2	.1868	.266	.2071	.2483	.2699	.315

Significance codes: 0 '***' .001 '**' .01 '*' .05 '.' .1 ' ' 1.

In this table, the coefficients of the full regression models on firm-level data are shown. Additional detail on the specification of the regression equations is provided in the main article and appendix.