Skill transferability and the stability of transition pathways

A learning-based explanation for patterns of diffusion

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Abstract Understanding and governing technology transitions is essential to cope with major challenges of the 21st century such as climate change or digitization. In this paper, a learning-based approach is developed to explain the dynamics of different transition pathways. Technological know-how is necessary to make effective 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. This paper addresses the implications of cross-technology transferability of skills for firm-level technology adoption and its consequences for the direction of macro-level technological change. A microeconomically founded model of technological learning is introduced. The model is based on empirical and theoretical insights from 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 at the cost of long-term technological stability and specialization. For firms, it is easy to adopt new technology, but also easy to switch back to the incumbent type. Technological instability can be macroeconomically costly.

Keywords Technological transition · technology diffusion · technological knowledge · knowledge spillover · learning · absorptive capacity · agent-based model
JEL O11, O33, D21, Q55, C63

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1 Introduction

To reduce the existential risk of triggering irreversible dynamics of self-reinforcing climate change, the transition to green technology needs to be accelerated [Rogelj et al., 2016, IPCC, 2018, Steffen et al., 2018]. This requires a large-scale substitution process in which an incumbent technology is replaced by a new one. This process can be associated with disruptive consequences 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 [Grübler, 1991, Geels, 2018, Brynjolfsson and McAfee, 2012, Bower and Christensen, 1995]. To design effective policies to accelerate a green transition and to attenuate disruptive side effects, it is important to know the factors that influence the pace and pattern of transitions and its macroeconomic consequences [cf. Safarzyńska et al., 2012].

In this paper, a theory of evolving substitutability is developed that links the characteristics of competing technologies with different pathways of transition. The theory is based on a microeconomic model of technological learning. It is a bottom-up approach to the multi-layer perspective in transition studies [cf. Geels, 2002, Geels and Schot, 2007, Hötte, 2020].

This study builds on a model of two competing technologies à la Arthur [1989] (green and brown) with endogenous learning dynamics. Technology diffusion is studied as a co-evolutionary transition process in which an incumbent conventional technology is possibly replaced by a green entrant. The model is a refined version of the eco-technology extension of the macroeconomic agent-based model (ABM) *Eurace@unibi* [cf. Dawid et al., 2019, Hötte, 2020, 2019b].

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 substitution between technology types. A learning function describes the process of skill accumulation at the level of heterogeneous firms. The microfoundations of the function are based on insights from different branches of the empirical and theoretical literature on technological knowledge, learning, and technological change. The *relative* pace of accumulating of technology-specific knowledge depends on the similarity and difficulty of competing technologies.

The model is used to generate a sample of simulated diffusion curves and macroeconomic time series that is statistically analyzed. Endogenous learning and innovation influence the long-term substitutability across technology types. If firms' endowments with technology-specific skills and the productivity levels of supplied capital diverge sufficiently, the economy converges to one of two stable states, in which one of the two technologies clearly dominates. This is interpreted as technological regime [cf. Dosi, 1982, Arthur, 1989, Breschi et al., 2000]. In the long run, accumulated knowledge may dominate the role of relative prices in input substitution decisions. Delayed technological convergence is associated with technological uncertainty. This is costly because R&D and learning resources are invested in a technology type that is obsolete in the long run.

It is shown that the success, pace, and stability of the diffusion process is sensitive to the characteristics of competing technologies. A market entering technology has the chance to diffuse if it is sufficiently superior when it becomes available.

An incumbent technology is typically endowed with larger accumulated knowledge stocks reflecting a relatively higher maturity. This is an adoption barrier that might be prohibitively high such that it prevents the diffusion of the entrant technology. Initial endowments can be a source of path dependence in the presence of increasing returns to endogenous learning and innovation [cf. Arthur, 1989]. The macro-level coordination among heterogeneous agents in the learning process is important for the stability and pace of technology transitions. It is shown that the stability of the diffusion process has an effect on the (macro)economic and industry-level outcome.

Two key results are derived from this analysis: (1) The transferability of technological knowledge facilitates initial diffusion, but this is at the expense of long term stability of the transition process. If technological knowledge is highly transferable, it is relatively easy for firms to switch to the new technology. But it is also easy to switch back if relative prices or the relative technical performance change. Hence, technology adopting firms tend to switch more often between different technology types. This undermines the pace of productivity-enhancing specialization. In contrast, a low transferability of skills across technology types reinforces path dependence but stabilizes an ongoing transition and facilitates the specialization in one technology type.

(2) Knowledge transferability may have implications for the disruptiveness of technological change and the emerging market structure. If knowledge is easily transferable, large incumbent firms can replace parts of their technology by the new alternative incrementally without struggling with the incompatibility of knowledge. In contrast, technologies that require radically different capabilities make it difficult to switch incrementally.

The insights of this study improve the understanding of transition processes. This is valuable for the design of effective diffusion policies that are responsive to the peculiarities of specific technologies, markets, and different groups of technology users.

This study expands the existing literature in mainly three ways. First, a microeconomically founded function of technological learning at the firm-level is introduced and embedded into a macroeconomic model. To the best of my knowledge, this is the first model that links the properties of competing technologies with the process of technological learning by adopters to study emergent patterns of transition.

Second, this study is a bottom-up approach to study technology transitions. It is shown, how different transition pathways can be explained on the basis of technological characteristics and their implications for the process of learning. This is a new perspective for the systematic analysis and comparison of technology transitions in different countries and industries.

Third, methodologically, this work expands the literature on macroeconomic, agent-based analyses of directed technological change and technology transitions. The modeling framework allows to evaluate the relationship between learning pathways, industrial organization and (macro)economic performance [cf. Breschi et al., 2000].

In the next section, I summarize studies on technological knowledge and their link to the transition literature. In Sec. 3, the model is introduced. Sec. 4, summarizes the results. Sec. 5 offers a discussion and Sec. 6 concludes.

2 Related literature

The learning model developed in this paper is based on insights from management literature on capabilities to absorb technological novelties. The model is embedded in a broader concept of macroeconomic technology transitions.

2.1 Technological knowledge and learning

In the macroeconomic literature, technological knowledge and human capital are enabling factors to adopt new technology and sources of endogenous growth [e.g. Nelson and Phelps, 1966, Romer, 1990]. Concerns about climate change and the distributional consequences of non-neutral technology shifted the focus of study to the direction of technological change [e.g. Acemoglu, 2002, Grübler et al., 2002, Popp et al., 2010, Brynjolfsson and McAfee, 2012]. Technologies are modeled as knowledge required to develop and use capital. This knowledge may differ across technology types.

Knowledge can be acquired by type-specific R&D investments or learning by doing [Löschel, 2002, Popp et al., 2010]. The majority of economic studies on directed technological change focuses on technology suppliers and the allocation of R&D. Changing factor prices, possibly manipulated by policy, influence the allocation of R&D and the direction of technological change [cf. Acemoglu, 2002, Löschel, 2002, Popp et al., 2010, Acemoglu et al., 2012].

In this paper, I add the dimension of co-evolving absorptive capacity acknowledging that technology diffusion may be sluggish [cf. Metcalfe, 1988, Kemp and Volpi, 2008, Pizer and Popp, 2008, Hötte, 2020]. Micro-level reasons for sluggish diffusion are incomplete information, heterogeneous benefits of adoption, investment cycles, and learning-by-doing on the side of suppliers and adopters [Allan et al., 2014].

Learning curves are aggregate approaches to explain sluggish technology uptake. It is assumed that the 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 a self-enforcing mechanism of diffusion, but learning curves tend to neglect the determinants of initial technology selection, substitution dynamics and possible interdependencies among competing alternatives [McNerney et al., 2011, Adner and Kapoor, 2016].

Cross-technology learning interactions have been studied by similarity metrics derived from production and innovation networks [Antony and Grebel, 2012, Carvalho, 2014, Boehm et al., 2016, Acemoglu et al., 2016, Jaffe and De Rassenfosse, 2017]. Technological similarity facilitates the adoption of new technology when adopters can make use of pre-existing knowledge. Breschi et al. [2000] have shown that the properties of knowledge required to innovate may explain emergent patterns of industrial organization.

Capabilities, skills, and knowledge are important topics in the evolutionary and management literature [cf. Kogut and Zander, 1992, Teece and Pisano, 1994, Cowan et al., 2000, Johnson et al., 2002, Thompson, 2012, Nelson and Winter, 1982]. One can distinguish *know-what* and *know-how*. The former refers to information that is to some degree transferable across firms and has public good properties. The latter is 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.

Technological capabilities are embodied in a firms' workforce and organizational structure [cf. Kogut and Zander, 1992]. Capabilities are *cumulative* have a *tacit, non-transferable* dimension. Kogut and Zander [1992] argue that firms' capacity to learn new capabilities is dependent on the compatibility with their existing capabilities. This compatibility is a microeconomic determinant of path dependence at the firm and industry level [e.g. Dosi and Nelson, 2010].

Building on Simon's [1957] theory of organizational decision-making, Nelson and Winter [1982] argue that firms follow clear objectives, but are constrained by imperfect foresight and limited information-processing capacity. From the firm perspective, 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]. Dynamic capabilities encompass the adaptiveness of everyday routines and firms' long term planning in changing technological environments [Arndt and Pierce, 2017].

Vona et al. [2015] link the insights on firms' capacity to deal with changing market environments with the characteristics of skills of employees. Using Autor et al.'s task classification, they have shown that industries tend to adopt green technologies more rapidly in response to regulation, if the industry has a high share of occupations requiring adaptive and flexible skills. Vona and Consoli [2014] argue that adaptive skills are particularly important in phases of technological transitions. In transition phases, technological knowledge is not yet translated into codes and skills that can be traded on the (labor) market in the form of specialized training.

These insights can be summed up as follows:

1. Technological knowledge is embedded in the technological skills of firms and their employees [Vona et al., 2015, Kogut and Zander, 1992, Teece and Pisano, 1994].
2. Technological knowledge is *technology-specific* and its accumulation depends on the type of production technology that is used in an industry (firm) [Cowan et al., 2000, Boehm et al., 2016].
3. A new technology is easier to adopt if previously accumulated knowledge is compatible with the knowledge required to make effective use of the new technology [Carvalho and Voigtländer, 2014, Boehm et al., 2016, Cohen and Levinthal, 1990].
4. The accumulation of technology-specific knowledge is decisive for the direction of technological change and the stabilization of a technological regime [Vona and Consoli, 2014, Lemoine, 2018, Geels and Schot, 2007].

These observations motivate the microeconomic model of technological learning used in this paper.

2.2 Technology transitions

A technological transition occurs if a new technology enters the market, diffuses and gradually replaces an incumbent alternative [Geels, 2002, Lachman, 2013, Köhler et al., 2019]. This is associated with a *technological regime shift*. A technological regime is reflected in the dominant *technological paradigm* defined as a 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]

Breschi et al. [2000] use the term *technological (learning) regime* to describe the process of knowledge accumulation in an industry by the characteristics of technology and its implications for Schumpeterian patterns of innovation. While their characterization aims to explain competition among incrementally innovating firms within an industry, I associate the term *technological regime* with the discrete choice between different technology types.

Technology transitions are large-scale system changes that are associated with changing consumption patterns, institutional and organizational structures. Transitions 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].

The multi-level perspective is a common approach in transition studies [Geels, 2002, Lachman, 2013, Köhler et al., 2019]. It decomposes a socio-technical system into 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 and mature in the protected space of niche markets. Technologies evolve within the context of external landscape conditions (e.g. customer needs, resource availability, regulations, complementary technologies) that can not be directly influenced by technology developers and users.

If the landscape changes and the dominant technology is not able to adapt to new circumstances, a niche technology may possibly replace the incumbent alternative if it is superior within the new environment [Geels, 2002]. For example, in the energy sector, 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 market entrants are increasing returns to scale and lock-in effects, group dynamics, bounded rationality, and the co-evolutionary emergence of institutions, infrastructure, and behavior [Safarzyńska et al., 2012].

This paper is based on a macroeconomic agent-based simulation model. Agent-based models offer an analytical and methodological framework to simulate the co-evolutionary nature of transition dynamics [Dawid, 2006, Köhler et al., 2018]. Sustainability transitions within agent-based macroeconomic frameworks had been studied by Gerst et al. [2013], Wolf et al. [2013], Rengs et al. [2020], Lamperti et al. [2018], Hötte [2020], Hötte [2020]. This study differs from previous studies by its explicit focus on learning dynamics.

3 The Model

In this section, I start with a conceptual description of the modeling of technology before I describe the model more formally and explain the simulation settings.

[1] The *technical* paradigm is more narrowly defined and represents the mindset of engineers and their way of defining a technological problem and its solution.

Comprehensive, formal introduction to macroeconomic ABM that is used are available in Dawid et al. [2019] and Hötte [2019b].

3.1 The concept of technology

Production technology is the capability to combine inputs such that an economically valuable output is produced. In this paper, I simulate a race between two mutually substitutive production technologies. One of the two technologies is incumbent. It can possibly be replaced by a new entrant technology, called *green* technology. Both technologies can be used by firms to produce an output good that is equally valued by consumers but requires different types of inputs. In Fig. 1, the concept of technology and learning is shown as a flowchart for the two-technology case of a green g that competes with an incumbent conventional alternative c. The framework is not restricted to this example and can straightforwardly be applied to other examples of competing technologies and more than two technologies. Time indices are dropped in this schematic introduction.

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 are embodied in labor L and capital K and accumulated by different mechanisms.

Codified technological knowledge is embodied in the technical properties of the capital stock and acquired on the capital goods market by investments. Technical progress in the capital goods market is driven by endogenous innovation that increases the productivity A of supplied capital K.

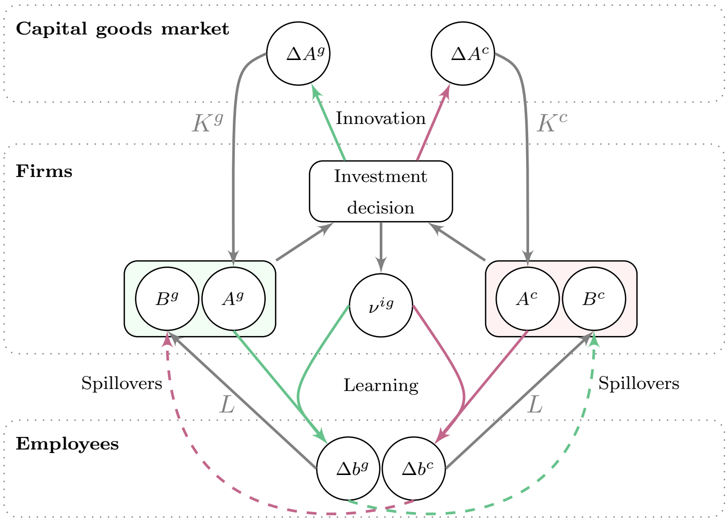
To make effective use of codified knowledge A, firms' employees need to have the appropriate technology-specific skills. These skills are called *tacit* technological knowledge B. Tacit knowledge is firm-specific, i.e. firms may be differently productive even if they use the same type of physical capital. In contrast to codified knowledge that can be bought on the capital market, tacit knowledge is *not tradable* and accumulated by learning. Employees 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.

Firms can use both types of technology at the same time, i.e. their capital stock may consist partly of green, partly of conventional capital. 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^{τ} which is the share of technology type $\tau = c, g$ that is used in current production.

Theoretically, skills of individual employees could be acquired on the labor market, but ex-ante, an employee's endowment with technology-specific skills it is not fully transparent to the firm. 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^{τ}.

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

Fig. 1: Illustration of firms' production technology



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

In this study, a technology race between one incumbent and one entrant is considered.[2] The entrant is assumed to be technically superior because the use of its technology allows adopters to save a fix fraction of variable input costs. In this stylized example 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. By assumption, these cost savings cannot be achieved in the same way by the incumbent alternative.

However, the use of the entrant technology is not necessarily more cost-effective because the entrant suffers from lower cumulative stocks of tacit and codified "green" knowledge. At the time of market entry t_0, the green alternative is less productive, i.e. $A^g_{t_0} < A^c_{t_0}$, and firms and employees have not yet accumulated the knowledge to use the green technology efficiently, i.e. $B^g_{t_0} < B^c_{t_0}$. This reduces the realized productivity of green capital.

Firms' capital stock may be composed of both technology types. Both types can be used simultaneously to produce a homogeneous consumption good. Dependent on their endowment with technology-specific knowledge, firms are differently efficient in operating green or brown machinery. Limited transferability of tacit knowledge

[2] Note that this is a technology race between competing technologies in the presence of increasing returns à la Arthur [1989]. It should not be confused with a *patent race* where multiple innovators compete for first attaining a patent for a given technological problem [e.g. Doraszelski, 2003].

across technology types reduces the substitutability of capital. Employees who know how to make productive use of conventional capital do not necessarily know how to use the green alternative. The transferability is higher if the two technologies are similar.

The green technology is interpreted as an eco-innovation that is environmentally less harmful than the incumbent alternative and allows its users to save material input costs in the long run [Arundel and Kemp, 2009]. Material input costs can be also interpreted as regulatory compliance costs that make the use of environmentally harmful technology more expensive.[3]

The green technology is possibly adopted by firms. Firms can invest in green or conventional capital. Their technology choice is dependent on the realized productivity and variable input costs composed of wages and, if conventional, material inputs. The green technology diffuses if firms incrementally replace conventional by green capital.

Theoretically, accumulated technology-specific skills can be also interpreted as firm-level infrastructure, learned routines and other cumulative factors that facilitate the effective utilization of a technology type. For example, the adoption of renewable, decentralized electricity production requires the build-up of distribution infrastructure and load management that accounts for volatile, small scale generation patterns. Another example are passenger transportation or delivery service enterprises. The adoption of electric vehicles may save fuel costs, but requires different refuel facilities.[4] It digital technologies that e.g. save traveling costs, but are subject to learning costs during the transition phase.

In this paper, I study a stylized theoretical example. It is aimed at highlighting the mechanisms through which the characteristics of learning processes influence the emergent transition pattern, but it should not represent any specific empirical technological history.

Firms are active in a macroeconomy that is composed of individual households, capital goods producers and a financial system including banks and a stylized financial market [see also Dawid et al., 2019, Hötte, 2019b]. In the next section, a formal introduction to the technology model follows.

[3] In another paper, it is shown that this framework can be generalized to a green entrant technology that is favorable because consumers have a higher willingness to pay for green products or lower production costs of green machinery [Hötte, 2020]. Other models in climate and environmental economics frame the problem of green technology diffusion as an externality problem with unequal social and private costs. This study is aimed at improving the understanding of learning when a new technology suffers from lower maturity. Climate research has sufficiently shown that the problem of climate economics is not the search for optimal abatement levels trading off costs and benefits of mitigation. Rather, it is important to understand how the transition can be accelerated [cf. Steffen et al., 2018, IPCC, 2018]. Moreover, the trade-off of mitigation costs and benefits is extremely sensitive to the assumptions of technological change [Löschel, 2002]. This underlines the relevance of improving the understanding of change. However, it is possible to extend the model and to incorporate climate-induced damage functions and to frame the analysis as an optimal policy problem that can be numerically approached.

[4] This example has actually a historical counterpart, when delivery services for milk, bread or postal services used electric vehicles in the 60-70s [Høyer, 2008]. A similar example refers to the diffusion of organic farming, which was mainly driven by consumer preference, but lacking experiences in farming practices, regulatory compliance procedures and marketing were reasons for re-conversion to conventional farming [Flaten et al., 2010].

3.2 Technological learning and spillovers

Learning leads to improvements of firms' *effective* productivity when using technology type $\tau = c, g$. This is modeled through the bundle of codified and tacit knowledge $(A^{\tau}_{i,t}, B^{\tau}_{i,t})$ of firm i in time t. *Codified* technological knowledge is the average productivity of i's capital stock items of technology type τ. Tacit knowledge is given by the average technology-specific skill level of i's employees.

3.2.1 Consumption goods firms' production technology

The effective productivity determines how effectively a firm can transform inputs into final consumption goods $Q_{i,t}$. Production inputs are capital $K_{i,t}$, labor $L_{i,t}$ and, in case of conventional capital, natural resource inputs. Inputs are combined in a constant returns to scale Leontief production function, i.e. one employee is needed to operate one unit of capital. The adjustment of labor and capital is sluggish. Capital step-wise depreciates and is 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., 2019].

The capital stock is composed of different vintages v of that may differ by productivity A^v and technology type $\tau \in \{c, g\}$. The properties of a capital vintage are given by $(A^v, \mathbb{1}(v))$ where $\mathbb{1}(v)$ indicates the technology type with $\mathbb{1}(v) = 1$ (0) if v is conventional (green). Formally, the amount of capital goods of vintage v in i's total stock $K_{i,t}$ in time t is given by $K^v_{i,t} := \{k \in K_{i,t} | A^v(k) = A^v, \mathbb{1}(k) = \mathbb{1}(v)\} \subseteq K_{i,t}$. The notation $K^c_{i,t}$ $(K^g_{i,t})$ is used for the sum of capital 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 productivity A^v at the firm-level is constrained by i's stock tacit knowledge. The effective productivity $A^{Eff_v}_{i,t}$ of a vintage is given by

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

The productivity A^v is constant and uniform across firms. Tacit knowledge required to exploit the full potential productivity A^v. Tacit knowledge differs across employees, across firms, and changes over time when employees learn.

The production function i in t given by

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

where $L_{i,t}$ is the number of employees, and $\sum_{v=1}^{V} K^v_{i,t}$ is the firm's *ordered* capital stock composed of V different capital stock items. The term $\max\big[0, L_{i,t} - \sum_{k=v+1}^{V} K^k_{i,t}\big]$ 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 produce at full capacity. This occurs when the firm does not have sufficient employees to produce at full capacity or expected demand is too low and using costs of capital exceed the expected revenue. Then, most cost-effective capital goods are used first.

The cost effectiveness $\zeta^v_{i,t}$ is given by the amount of output $A^{Eff_v}_{i,t}$ 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 material input costs κ^c_t. Formally, this can be written as

$$\zeta^v_{i,t} = \frac{A^{Eff_v}_{i,t}}{w_{i,t} + \mathbb{1}(v) \cdot \kappa^c_t}. \tag{3}$$

Firms' decision about the quantity to produce depends on demand estimations and inventory stocks. Based on estimated demand curves, firms determine the profit-maximizing price-quantity combination. Because the estimation is imperfect in most cases and prices cannot be immediately adjusted, the consumption goods market does not necessarily clear [see for more detail Dawid et al., 2019].

3.2.2 Accumulation of tacit and codified knowledge

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

Two representative capital producers supply a range of vintages that differ by productivity level A^v and technology type τ. The firm i has to choose the optimal combination of the investment quantity, productivity level and technology type. This decision is based on the i's expectations about the marginal profit of the different options. It computes and compares the net present values of different quantity-productivity-type combinations over the subsequent 5 years [cf. Bacon, 1992]. It takes account of expected demand, prices, costs, skill developments and financial constraints and chooses the option that seems most profitable given its expectations. More detail on the investment decision and capital supply is provided in Hötte [2019b].

Because firms can not perfectly anticipate the future, their investment decision is not necessarily optimal. Firms might revise their decision and switch to an alternative technology type at a later time when expectations or the relative performance of supplied capital have changed.

Tacit knowledge $B^\tau_{i,t} = \frac{1}{L_{i,t}} \sum_{l \in L_{i,t}} b^\tau_{l,t}$ is embodied in the capabilities of i's employees. An employee $l \in L_{i,t}$ is characterized by her learning ability and two types of technology-specific skills. The learning ability is captured by a time-invariant general skill level b^{gen}_l. It determines the speed of learning. General skills are similar to human capital in macroeconomic models with neutral technological change [cf. Nelson and Phelps, 1966]. It is reflected in e.g. educational attainment.

Technology-specific skills $b^\tau_{l,t}$ represent the employee's capability to work productively with a specific type of capital $\tau \in \{c, g\}$. These skills are modeled as stock variables that increase by step-wise updates through a learning process. The learning process is dependent on the ability χ^{gen}_l and the technological properties of the capital stock used in firm i where the employee is working. Two sources of learning exist. Employees are learning by doing when working with a specific technology type and they can learn via cross-technology spillovers.

Skills are updated each period in discrete steps. The step-size $\Delta b^{\tau}_{l,t+1} = b^{\tau}_{l,t+1} - b^{\tau}_{l,t}$ is given by

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

$\psi^{\tau}_{l,t} \geq 1$ is the "amount" of knowledge learned in one period during the utilization of technology τ. Part of this knowledge is transferable across technologies. It contributes to the accumulation of skills of the alternative type $-\tau$ with $\tau \neq -\tau$ and $\tau, -\tau \in \{c, g\}$. The parameter $\chi^{dist} \in [0, 1]$ describes the *technological distance* between the two technologies. It is inversely related to the transferability of knowledge. The functional form is inspired by models on state-dependent technological change [cf. Acemoglu, 2002].

The skill update by learning by doing $\psi^{\tau}_{l,t}$ is dependent on the technical difficulty of the technologies χ^{int}, the relative amount of effort $\nu^{\tau}_{l,t}$ and the technical novelty. 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* $\max[0, (A^{\tau}_{i,t} - b^{\tau}_{l,t})]$ of capital τ. It is given by the gap between the employer's codified knowledge $A^{\tau}_{i,t}$ and the employee's current skill level $b^{\tau}_{l,t}$. A larger gap indicates a larger amount of potential technological knowledge that can be learned. It is associated with a faster pace of learning. This accounts for the fact that employees learn only when they are exposed to (codified) knowledge that is new to them, i.e. if there is something new to learn [cf. Thompson, 2012].

The updating step is given by

$$\psi^{\tau}_{l,t} = 1 + \left(\nu^{\tau}_{l,t}\right)^{\chi^{int}} \cdot \max[0, (A^{\tau}_{i,t} - b^{\tau}_{l,t})]. \tag{5}$$

The relative learning intensity in a category τ is dependent on the relative amount of technology τ that is used $\nu^{\tau}_{i,t} = (K^{\tau}_{i,t}/K_{i,t})$ in the firm. This is a proxy for the amount of time invested in technology-specific learning [cf. Cohen and Levinthal, 1990]. Learning in τ is faster if the share of τ in the used capital stock higher.

The parameter χ^{int} captures marginal returns to the time of learning. In the baseline scenario, I assume weakly decreasing marginal returns, 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 $\chi^{int} = 0$, the technology is very easy to learn and workers learn irrespective of the time of working with it. If $\chi^{int} > 1$, the technology is more difficult and requires employees to be concentrated at work and returns to learning are increasing in $\nu^{\tau}_{i,t}$.

3.2.3 Learning in a nutshell

Codified knowledge that is *existing* in the economy is different from codified knowledge that is *adopted*. *Existing* knowledge is exogenous to firms. It is embodied in supplied capital goods. It rises by endogenous innovation ("learning by searching") driven by sector-specific R&D investments. Firms only indirectly influence the pace by their investment decisions because R&D investments in capital sector τ are dependent on τ's profits.

Adopted codified knowledge is firm-specific and corresponds to the knowledge that is actually used. It is accumulated by capital investments. Adopted codified and tacit knowledge together constitute the productivity of a technology.

Tacit knowledge increases by "learning by doing". The speed of learning is determined by three factors:

1. The share of capital $\nu_{i,t}^{\tau} = K_{i,t}^{\tau}/K_{i,t}$ determines how much *relative* time employees spend to work with technology τ. If returns to learning are increasing ($\chi^{int} > 1$) in $\nu_{i,t}^{\tau}$, employees learn faster if they work with only one technology. Returns to learning are positively related to the difficulty of learning.
2. The quality of the learning environment is captured by the *technical novelty* $\max[0, A_{l,t}^{\tau} - b_{l,t}^{\tau}]$ of individual workers l. Employees learn faster if capital goods are technically new to them [cf. Thompson, 2012].
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 investment decisions of the firm. The relative speed 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 two technologies are characterized by initial knowledge stocks, input requirements, and the properties of the learning process χ^{int} and χ^{dist}. The simulations allow isolating the influence of χ^{dist} and χ^{int} on individual adoption and emerging pathways of transition.

The entrant technology suffers from diffusion barriers in terms of lower accumulated knowledge. Green capital becomes available at a given time t_0. In t_0, green capital is technologically less mature than the incumbent. The entrant 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. $A_{g,t_0}^{V} = (1 - \beta^A) A_{c,t_0}^{V}$. Employees l and firms have less experience in using the entrant technology represented as $b_{l,t_0}^{g} = (1 - \beta^b) b_{l,t_0}^{c}$. The parameters $\beta^A, \beta^b > 0$ describe the relative disadvantage and are interpreted as diffusion barriers [cf. Hötte, 2020]. The entrant technology is possibly superior in the long run because its utilization does not require costly resource inputs.

The simulations are subject to stochasticity. For example, capital producers' innovation success, the matching mechanism at the labor market and households' consumption decision are probabilistic [see Dawid et al., 2019, Hötte, 2019b]. In the experiments presented below, sets of 210 simulation runs for each parameter setting are generated and the simulated time series data are statistically analyzed. One simulation run consists of 15000 iterations which corresponds to a time horizon of roughly 60 years which is in line with empirical, historical transitions that typically took several decades to unfold [Geels and Schot, 2007]. One iteration represents 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 used. The dominance of the green (conventional) technology is called green (conventional) *technological regime*.

Learning by doing (LBD) and learning by searching (LBS) from demand-induced, endogenous innovation in the capital goods market are subject to (mutually) increasing returns. Employees learn faster if they are working more intensively with one technology type and if the productivity of this type is higher. Capital producers' profit is increasing in sales. They re-invest a fraction of profits in type-specific R&D which increases the probability of innovation success and the productivity of supplied capital. These mutually reinforcing processes strengthen 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 (resource cost savings) and the characteristics of the learning process. If barriers are sufficiently strong, path dependence in 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.

Two different types of experiments are run:

1. To analyze the role of learning function, simulated time series with different discrete levels of the learning parameters $\chi^{dist} \in \{0, .5, 1\}$ are compared. An analysis of χ^{int} can be found in A.3 and Hötte [2019c].
2. To analyze 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.

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.

1. How does the success and patterns of transitions depend on the technological similarity and on the ease of learning?
2. What are the drivers of technological convergence and how do these relate to the stability of the transition process?
3. Which economic side effects occur and can the effects be attributed to the characteristics of competing technologies?

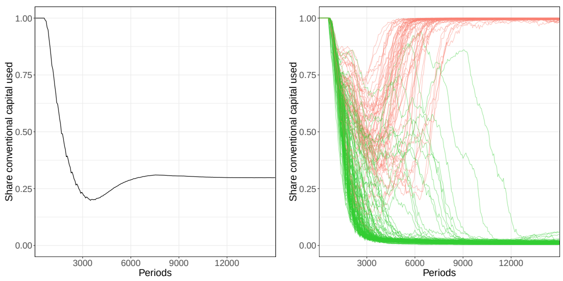
The core indicator to evaluate the transition success is the share of conventional technology used at the firm-level $\nu^c_{i,t} = K^c_{i,t}/K_{i,t}$ in t. It measures diffusion at the intensive margin. It can be aggregated across firms to obtain a macroeconomic diffusion curve ν^c_t. The stability of the transition is evaluated by the standard deviation $\sigma^{\nu}_{i,t}$ of the diffusion measured in percentage points. It is calculated over a moving time window of 2.5 years.[5] A transition is called *unstable* if firms switch between the two technology types or if the technology-choice is non-homogeneous across firms. This coincides with a high level of $\sigma^{\nu}_{i,t}$.

In a preceding study [Hötte, 2020] on diffusion barriers it was found that relative stocks of technological knowledge $\alpha_t = A^c_t/A^g_t$ and $\beta_t = B^c_t/B^g_t$ are sources of path dependence in technological change. Both stocks are endogenously accumulated dependent on relative profits in the capital goods sector and relative intensity of technology use. If knowledge stocks diverge, the economy becomes increasingly locked in the relatively more productive technology irrespective of relative factor input costs.

4.1 Baseline scenario

A benchmark scenario with intermediate levels of $\chi^{int} = \chi^{dist} = .5$ and moderate diffusion barriers $\beta^A = \beta^b = .03$ serves as reference case. The simulation settings are used to generate a sample of diffusion curves and macroeconomic time series data.

Fig. 2: Diffusion curves



(a) ν^c_t batch (b) ν^c_t single runs

Fig. 2a shows the share of conventional capital use ν^c_t aggregated across all runs. Fig. 2b shows the simulated curve of single simulation runs. Different colors indicate different regime types (□: transition, ∗: lock-in).

The simulated diffusion curves ν^c_t of single simulation runs are shown in Fig. 2b. The curves exhibit diverging patterns. The economy converges to one of two possible technological states, either with almost 100% or 0% green technology utilization at the end of simulations. The final states are called *technological regimes* and are classified by the share of conventional technology used ν^c_T in the last period $T = 15000$. A regime is called *green* (*conventional*) if $\nu^c_T < .5$ ($\nu^c_T \geq .5$). This is a heuristic definition. It does not seem to be very strict and does not give any information about the stability of a technological regime. In the majority of simulation runs, ν^c_t has converged to a level close to zero or one and a more

[5] Further information about its computation and relation to other convergence measures can be found in the supplementary material SM.II.

rigorous definition of transition regimes could be applied. The average ν_T^c accounts for 99.6% (1.3%) in lock-in (transition) regimes with a standard deviation of .004 (.008).

In this baseline, the economy converges to a green regime in 71% of the runs characterized by $\nu_T^c > .5$. Fig. 2a shows the average ν_t^c across runs which converges to the transition probability if the regimes converge to $\nu_t^\tau \to 1$ for $\tau = c, g$.

In this baseline and all experiments introduced below, 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. Trivial patterns of immediate diffusion or perfect lock-in are avoided. The green technology diffuses immediately if it is too superior and the pace of diffusion is only a matter of capital prices and depreciation. The economy is perfectly locked in if entry barriers are too high and the green technology does not diffuse at all. Here, the conditions are set such that the outcome of technological competition is ex-ante uncertain.

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. This is dependent on the dynamics of adoption and competition on the capital market and the stochastic elements in the innovation process. Additional detail and descriptive information about this baseline scenario is offered in Appendix A.2. The empirical model validation criteria are explained in SM.I. A longer introduction to the simulated transition dynamics is provided in a previous study [Hötte, 2020].

4.2 The technological distance

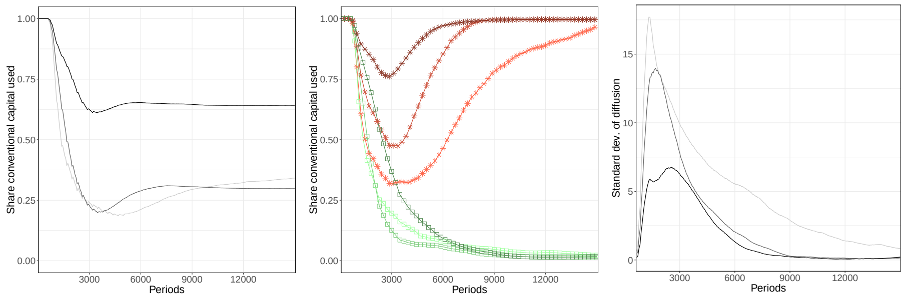
In an experiment, I illustrate the relationship between the technological distance χ^{dist}, emergent diffusion patterns and economic side effects. Three extreme cases of perfect, intermediate and no spillovers, i.e. $\chi^{dist} \in \{0, .5, 1\}$ are compared. The technological difficulty is fixed at $\chi^{int} = .5$.

4.2.1 Patterns of diffusion

Fig. 3a shows the evolution of the diffusion measure ν_t^c for different χ^{dist} without distinction by green or conventional regime. Darker color indicates a higher χ^{dist}. This aggregate measure is informative about the relationship between the level of spillovers and the probability of a regime shift. The relationship between the χ^{dist} and the transition frequency has an inverted u-shape. The observed frequency of transition accounts for 36% if $\chi^{dist} = 1$ and 66% if spillovers are perfect, i.e. $\chi^{dist} = 0$. With 71%, the transition frequency is highest for the intermediate level of spillovers, i.e. $\chi^{dist} = .5$.[6] In the majority of simulations, ν_t^c has converged to a level close to zero or one. The average ν_T^c across all runs and all levels of χ^{dist} in

[6] The average level of green technology use in T does not necessarily coincide with the transition frequency. 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 accounts for $\{34.16\%, 29.80\%, 64.20\%\}$ for $\chi^{dist} = 0, 0.5, 1$.

Fig. 3: 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 (b) are dis-aggregated by the type of technological regime. Different line shapes indicate regime types (□: transition, $*$: lock-in). Darker color indicates a higher distance $\chi^{dist} \in \{0, .5, 1\}$.

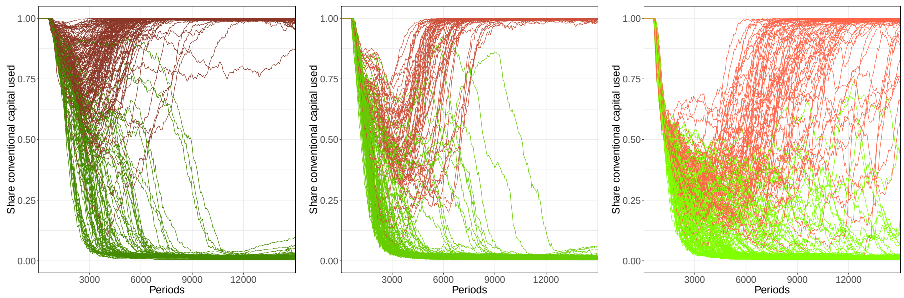
lock-in (transition) regimes accounts for more than 98.7% (less than 1.79%) with a standard deviation of 0.045 (0.036). Only in the case of perfect spillovers, few outliers exist that have not converged.

Fig. 3b shows the aggregate time series of ν_t^c for two different subsets of simulation runs classified by the final technological regime. Green (red) color indicates the subset of transition (lock-in) regimes. The distinction between the different regimes shows that initial green technology adoption, irrespective of the final regime, is highest if spillovers are perfect, i.e. $\chi^{dist} = 0$. However, the initial adoption lead is not necessarily permanent. Soon after the initial phase of diffusion, the effects of path dependence become effective. This undermines the convergence to green technology in the transition regimes measured by the pace at which ν_t^c approaches zero.

In the lock-in regimes, the economy returns to conventional technology despite the average ν_t^c fell below 32% around $t = 3000$, i.e. roughly 10 years after market entry. These returns occur most often if spillovers are high. The statistical significance of these observations is confirmed by a series of Wilcoxon tests comparing different time intervals (cf. SM.III.1).

In Fig. 4, the time series of ν_t^c for single runs within the aggregated subsets of green and conventional regimes are shown. Comparing the plot for $\chi^{dist} = 1$ (4a) to the figure for $\chi^{dist} = 0$ (4c), it can be seen that the diffusion curves in the case of perfect spillovers exhibit much higher, enduring volatility. It is not even clear whether the curves converge at all. A measure for the pace of convergence and the diffusion volatility is the standard deviation $\sigma_{i,t}^{\nu}$ of $\nu_{i,t}^c$ (Fig. 3c). A high $\sigma_{i,t}^{\nu}$ is an indicator of technological uncertainty and a large number of changes in the direction of diffusion. The lower $\sigma_{i,t}^{\nu}$ is, the faster the economy converges to a stable 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 remains high for the case of perfect spillovers. This indicates technological instability. The convergence to a stable regime with one clearly dominating technology is accompanied by the divergence of relative

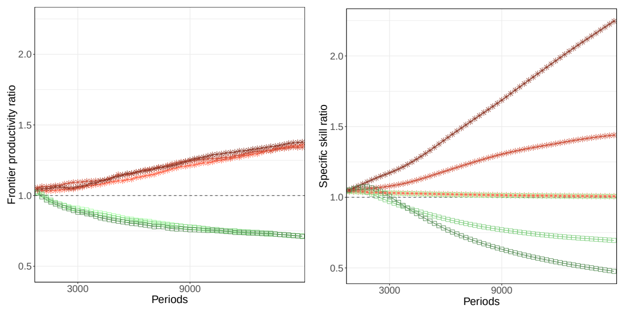
Fig. 4: Green technology diffusion



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

These figures show diffusion curves ν_t^c of single simulation runs for different parameters with $\chi^{dist} = \{.0, .5, 1\}$.

Fig. 5: 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 (□: transition, $*$: lock-in). Darker color indicates a higher level of χ^{dist}.

stocks of technological knowledge measured as ratio of the productivity frontier $\alpha_t = (A^V_{c,t}/A^V_{g,t})$ and ratio of skill endowments $\beta_t = (b^c_t/b^g_t)$ shown in Fig. 5. The evolution of β_t reveals the mechanism through which the χ^{dist} operates. The divergence of the curves between the two technological regimes is stronger if χ^{dist} is high.

If spillovers are perfect, i.e. $\chi^{dist} = 0$, the curve of relative tacit knowledge β_t does not diverge because learning in one technology category equally contributes to tacit knowledge accumulation of both technology types. In this case, the convergence to a stable state is driven by market induced innovation if the frontier of the dominant type grows relatively faster.

Other technological indicators on relative real and nominal capital prices, the degree of technological novelty reflect the same pattern. An overview of these indicators is available in SM.III.1.[7]

4.2.2 Economic side effects

Spillovers and the stability of the diffusion process have implications for the market structure and the macroeconomic performance. In Table 1, the results of two pooled OLS regression analyses of different (macro)economic indicators are shown. The regressions are run separately for the two subsets of different technological regimes. To take account of the panel-like structure of the data, standard errors clustered by run and time are used. The dependent variables are regressed on dummies that indicate different levels of χ^{dist} and the lagged diffusion volatility σ_t^{ν}. Note, that σ_t^{ν} is computed over a lagged moving time window of 2.5 years. It controls for different transition phases since it converges to zero if the economy converges, but the time until convergence is very heterogeneous across runs and independent of the regime.

The regression reveals that technological uncertainty measured by σ_t^{ν} is costly in terms of aggregate output, but lower unemployment in both regimes. It is associated with a smaller number of firms, but lower market concentration measured by the Herfindahl-index.

A χ^{dist} has ambiguous effects. If the transition occurs, it is positively correlated with market concentration and negatively with the number of active firms. It tends to have an increasing effect on unemployment. If the transition does not occur, χ^{dist} is negatively correlated with output. Triggered by the initial superiority of the green technology, diffusion in the first 10 years after market entry is high (cf. Fig. 3). Path dependence is stronger if χ^{dist} is high. It makes the switch back to the conventional technology expensive. The share of green technology in firms' capital stock undermines the pace of specialization in the incumbent technology. This is associated with lower productivity.

These observations are also reflected in a set of time series (cf. SM.III.1). Robustness tests and alternative regression model specifications are discussed in SM.II.

4.3 Interactions of spillovers and the ease of learning

Next to spillovers, also the ease of learning has an impact on the pattern of transition. Its impact is moderate in the presence of knowledge spillovers. A short discussion of an experiment on different assumptions about χ^{int} is offered in A.3

[7] It should be noted that the pricing mechanism for capital goods is important for the convergence. In the model, capital prices are adaptively adjusted in response to changes in the relative demand. The frontier is only a stabilizing mechanism if relative technological progress is faster than the relative increase in nominal prices. This is an assumption but alternative configurations are possible in which the economy does not converge because the leading technology becomes too expensive. This might be the case if, for example, resources to produce capital goods are scarce and type-specific. In other words, this mechanism is sensitive to the price elasticity of capital goods supply. In these simulations, the price responsiveness is sufficiently moderate that convergence is possible even when spillovers are perfect.

Table 1: Regression of macroeconomic and industry-level indicators

	$Output_t$	$\#firms_t$	$Herfindahl_t$	$Unemployment_t$
Lock-in				
(Intercept)	8.6356***	72.97***	159.6***	11.32***
	(.0161)	(.2612)	(.5650)	(.4267)
σ_t^ν	-.0755***	-.4441***	-.2306**	-.5597***
	(.0039)	(.0433)	(.0848)	(.0601)
$\mathbb{1}(0.5)$	-.0397**	.1537	-.3681	-.2211
	(.0135)	(.3433)	(.7439)	(.4946)
$\mathbb{1}(1.0)$	-.0710***	.0191	.5892	.2500
	(.0127)	(.3004)	(.7208)	(.5009)
R^2	.2692	.0695	.0049	.05009
Transition				
(Intercept)	8.620***	73.07***	159.9***	11.87***
	(.0125)	(.1916)	(.4662)	(.3104)
σ_t^ν	-.0657***	-.2642***	-.4031***	-.6222***
	(.0025)	(.0265)	(.0643)	(.0463)
$\mathbb{1}(0.5)$	.0072	-.2056	1.470*	.9184.
	(.0105)	.2629	(.6723)	(.5312)
$\mathbb{1}(1.0)$	-.0053	-.6200.	3.134**	1.622*
	(.0135)	(.3613)	(1.092)	(.8182)
R^2	.3009	.0375	.0198	.0633

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

This table shows the results of two pooled OLS regressions with run and time clustered standard errors in the subsets of transition and lock-in regimes. Dependent variables: log monthly output, the number of active firms, the Herfindahl-Index (multiplied by 10000) and the unemployment rate. Explanatory variables: dummies for the different parameter settings $\mathbb{1}(\chi^{dist})$ and the standard deviation of the diffusion measure σ_t^ν (cf. SM.II).

and more comprehensively discussed in the working paper [Hötte, 2019c]. Here, I focus on the interactions between both learning parameters.

The interaction effect of spillovers and the difficulty of learning on the transition probability is illustrated as a transition boundary shown in Fig. 6a. A transition boundary is a dividing line in the space of χ^{int} and χ^{dist} that separates green from conventional regimes.

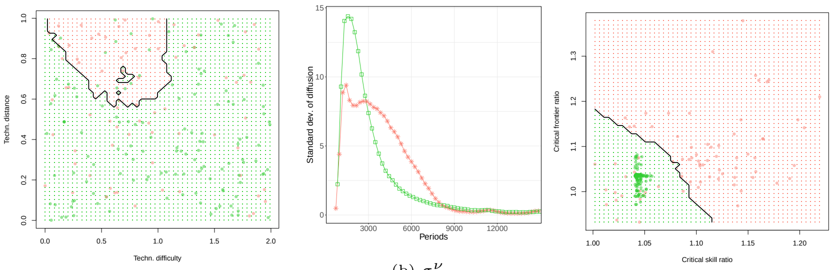
This boundary is derived from the data of a Monte-Carlo experiment with learning parameters that are randomly drawn from a uniform distribution, i.e. $\chi^{dist} \in [0, 1]$ and $\chi^{int} \in [0, 2]$.[8] The vertical (horizontal) axis represents the distance χ^{dist} (difficulty χ^{int}). The points 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.[9] Points whose color does not coincide 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 χ^{dist} and moderate χ^{int}. In all simulation runs, the green technology initially diffuses triggered by its technical superiority. Whether this diffusion is permanent, depends on the path dependency in the learning process. In the initial phase, the incumbent technology has a dominant position in firms' capital stock. Employees continue to accumulate

[8] A technical explanation of this experiment is available in the A4.3 and a short discussion of the results can be found in the SM.III.2.

[9] Further information about its computation is available in the SM.II.

Fig. 6: Transition properties



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

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

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

Fig. 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^*. t^* is run-specific and indicates the time when the diffusion process becomes monotone. Technical information is available in the SM.II.

conventional skills. If technologies are similar, this also contributes to the stock of green skills.

The transition probability has an ambiguous relationship with χ^{int}. If the technology is very easy to learn, i.e. if learning is independent of $\nu^c_{i,t}$, a transition is more likely. On the other hand, increasing returns in learning can be positively correlated with the transition probability when increasing returns accelerate the specialization in green technology during the initial surge of green diffusion. This makes a return to the conventional regime less likely. This effect is conditional on a sufficiently high green-technology uptake in the beginning.

4.3.1 The transition probability

A regression analysis of the diffusion measure ν^c_i evaluated at firm-level in T on the learning parameters and a set of micro- and macroeconomic controls confirms the previous observations. The data of control variables is demeaned and scaled to facilitate the comparison of coefficients. The role of the other control variables is explained in SM.III.2. Additional information about the data pre-processing, the model specification and model selection is available in the technical notes in SM.II. ν^c_i is almost binary in T taking the values zero or one. It is interpreted as measure for the inverse of the transition probability.

A higher distance χ^{dist} is associated with a lower transition probability $(1 - \nu^c_i)$. In contrast, the difficulty χ^{int} is positively related to the transition probability. The coefficient of the interaction term $(\chi^{int} \cdot \chi^{dist})$ is negative, but quantitatively small. This indicates that the negative relationship of χ^{dist} with technology diffusion is weaker if χ^{int} high.

4.3.2 The pace of convergence

The pace of convergence is analyzed by the diffusion volatility $(\sigma^{\nu}_i)^2$ and the duration until the diffusion process becomes stable t^*_i. $(\sigma^{\nu}_i)^2$ is the variance $(\sigma^{\nu}_i)^2$

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

	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)	.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)
$\mathbb{1}(eco)$			-4560***	-.1581***	-.1584***	-.3138
			(1005)	(.0158)	(.0104)	(3.448)
$\mathbb{1}(eco) \cdot \chi^{dist}$			612**	-.0744***	-.0692***	3.877***
			(220.2)	(.0158)	(.0101)	(.4156)
$\mathbb{1}(eco) \cdot \chi^{int}$			-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)
π^c/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. The results in column 3-6 are the results of an instrumental variable regression with the type dummy $\mathbb{1}(eco)$ as endogenous variable (see also SM.II).

of $\nu_{i,t}^c$ computed over the full time horizon. The duration t_i^* is defined as the time when the last change of the sign of the slope of the diffusion curve $\nu_{i,t}^c$ is observed. After t_i^*, $\nu_{i,t}^c$ starts converging to one of the two possible technological states. A low level of t_i^* suggests *technological certainty*, i.e. the process of stabilization and specialization begins early.

To capture fix differences and differences in the interaction patterns across the regimes, a dummy variable for the regime $\mathbb{1}(eco)$ is included with $\mathbb{1}(eco) = 1$ if the transition occurs and zero otherwise. To account for possible endogeneity of $\mathbb{1}(eco)$, i.e. possible correlation of the error term and the regime, it is included through an instrumental variable regression.[10]

State dependence in learning has an ambiguous relationship with t_i^*. Whether it impact is positive or negative is conditional on the transition success. In general, the t^* is earlier if a transition occurs. This is in line with Fig. 6b showing that the diffusion volatility in the subset of green regimes is high in the beginning, but rapidly diminishes. A Wilcoxon test confirms the significance (cf. SM.III.2).

The variance $(\sigma_i^\nu)^2$ measures firms' switching behavior between green and conventional technologies. In the lock-in regimes, the regression indicates that a higher χ^{dist} is associated with higher stability.

[10] More detail about the IV approach, alternative model specifications and results can be found in SM.II and Hötte [2019d].

If a transition occurs, a higher χ^{dist} retards the technological specialization. A higher χ^{dist} reinforces the effect of barriers makes it more difficult for firms to overcome the relative disadvantage of lower knowledge stocks when beginning to use green technology. This retards the specialization and leads to a higher diffusion volatility in the transition process. In contrast, it has an accelerating effect on the technological convergence if the economy is locked in. χ^{dist} exacerbates the effect of initial diffusion barriers. The opposite holds true for χ^{int}.

4.3.3 Sources of stability

The link between relative knowledge stocks and state dependence in learning can be illustrated by *technological thresholds*. These thresholds are shown in Fig. 6c. The black line in the figure is interpreted as transition boundary beyond which the diffusion process is stable. The vertical (horizontal) axis represents the relative technological frontier $\alpha^* = A^V_{c,t^*}/A^V_{g,t^*}$ (skill endowment $\beta^* = B^c_{t^*}/B^g_{t^*}$) evaluated in the aggregate t^*. The transition boundary is derived by a k-nearest neighbor clustering algorithms using relative knowledge stocks as training input.[11]

The relationship between these performance thresholds and the learning parameters is analyzed by the regressions shown in columns (4) and (5) in Table 2. $\left(A^+_i/A^-_i\right)^*$ $(\left(B^+_i/B^-_i\right)^*)$ measure the relative stock of codified (tacit) knowledge at firm-level in time t^*_i. $+$ $(-)$ indicates the technology type that is dominant (inferior) in T. The regression indicates that the divergence in the relative technological performance is less (more) strong in transition (lock-in) regimes if χ^{int} and χ^{dist} are high. This makes the technology race for the green technology more difficult. A longer discussion of these findings can be found in SM.III.2.

The qualitative findings are robust across a large variety of alternative model specifications (see also SM.II and [Hötte, 2019c,d].

5 Discussion

The three questions formulated in Sec. 4 can be answered as follows:

How does the success and pattern of diffusion depend on the properties of technological learning? The transition probability is ambiguously related to spillovers and the difficulty. A high transferability of knowledge reduces path dependence and facilitates the adoption of new technology. But it may also operate in the opposite direction. If the knowledge transferability is high, it is easy to adopt new technology, but it is also easy to switch back to the incumbent technology type if relative performance of supplied technology changes.

What are the drivers of technological convergence and how do these relate to the stability of the diffusion process? Diverging stocks of relative codified and tacit knowledge contribute to the convergence to a stable technological regime. A higher technological distance is associated with a more pronounced divergence. If the divergence is sufficiently strong, the economy is locked in a stable regime.

[11] Technical detail can found in SM.II.

Which economic side effects occur and can the effects be attributed to the characteristics of competing technologies? Retarded technological specialization is a result of technological uncertainty. This is macroeconomically is costly. Other effects depend on the success of a transition. If a transition occurs, a higher distance facilitates the specialization, but makes it difficult for late adopters to catch up. This may lead to a higher market concentration. It has an opposite effect if the economy is locked-in.

The simulated emerging patterns of industrial organization in terms of market concentration and entry-exit dynamics are in line with empirical studies linking Schumpeterian patterns of innovation to the processes of industrial learning [Breschi et al., 2000]. The authors found that firm hierarchies are more stable and innovative behavior tends to be more concentrated if firms can build on pre-existing knowledge when introducing an innovation.

Technological distances and the difficulty of learning characterize competing technologies. This characterization is dependent on the economic context given by an industry, region, etc. and the type of incumbent technology. The technological distance is a measure for the disruptiveness of the market entering technology in relation to the incumbent. Differences in the ease of learning and the technological distance may be an explanation for heterogeneity of diffusion patterns across countries, sectors, and firms [cf. Allan et al., 2014].

The cross-technology transferability of knowledge offers a way to link theories about the task-content of technological change to patterns of diffusion [e.g. Autor et al., 2003]. Technological skills required for the execution of non-routine tasks can be more easily transferred across technology types. For example, Vona et al. [2015] have shown that firms whose workforce consists of a high share of occupations characterized by a high share of non-routine tasks are rapid adopters of new technology when the market environment changes.

Another way to link the proposed characterization to economic data is the concept of technological distances [cf. Carvalho and Voigtländer, 2014, Boehm et al., 2016, Jaffe and De Rassenfosse, 2017]. Carvalho and Voigtländer [2014] have shown that the adoption of new technology in a given industry is more likely if the distance is small.

Transferability is associated with technological flexibility and adaptiveness. If external conditions change, it might be superior to switch to a new, market entering technology. Switching to new technology is easier if the transferability of skills is high. But this may come at the cost of stability and specialization. This is a trade-off between exploitation and exploration.

This analysis was applied to the case of green technology diffusion but the model can be straightforwardly applied to other technologies. The model may help understanding processes of successful diffusion but also patterns of lock-in. This model offers an explanation to understand whether and how transitions successfully unfold. To understand a lock-in, the incumbent's capacity for adaptive innovations is decisive. In the stylized green technology example, this refers to the incumbent's capacity to cope with the disadvantage of relying on costly resource inputs.

6 Concluding remarks and outlook

In this paper, a technology race between an entrant and an incumbent technology is studied using an eco-technology extended version of the macroeconomic ABM *Eurace@unibi*. Core feature of this extension is a microeconomic model of technological learning. Competing technologies are characterized by their similarity and difficulty. It is shown that the characteristics of competing technologies and the pace of relative knowledge accumulation are decisive to understand the technological and economic evolution of transitions. The core insights of the simulation study can be summarized as follows:

1. The technological distance between competing technologies describes how well technological know-how can be transferred across technology types. It facilitates initial technology uptake, but undermines the pace of specialization and stabilization. If technologies are similar, it is easy for technology users to switch to new technology. But it is also easy to switch back if relative prices or the relative technological performance change. An enduring phase of switching between two technologies is macroeconomically costly because learning and R&D resources are wasted. Increasing returns in the learning process may contribute to the stabilization of a technological regime.
2. Relative endowments with codified and tacit technological knowledge are embodied in the productivity performance of supplied capital and adopters' absorptive capacity. Diffusion barriers for the entrant are lower stocks of knowledge. If the two competing technologies are dissimilar, the cross-technology transferability of tacit knowledge is low and adopters struggle with the acquisition of required know-how (tacit knowledge). External conditions such as resource prices can be an important trigger for the diffusion process. This can be the starting point for market-based green diffusion policies.
   If technologies are dissimilar and the new technology successfully diffuses, it is difficult for late adopters to catch up and they may exit the market.

This study is subject to two major limitations. First, symmetric technologies were 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 is a promising field for empirical research.

Second, this study is restricted to the study of the transferability of technology-specific skills at the level of individual firms assuming that intended research in the R&D sector is pulled by the demand of adopters. Assumptions about the expectations of agents are kept simple. For a policy application, it would be interesting to expand the analysis to spillovers in the R&D sector and to incorporate a more sophisticated modeling of expectations.

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Compliance with ethical standards

The author declares that she has no conflict of interest.

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A Simulation results

A.1 Settings

Table A.1: Simulation settings

Agents		Notes
#capital producers	2	Fix heterogeneity by technology type, evolving by performance.
#firms	74	The seemingly arbitrary number is a result of the calibration procedure with endogenous firms entry-exit. Evolving heterogeneity by economic performance and expectations.
#households	1600	Fix heterogeneity by general skills, evolving by specific skill endowments, income, wealth.
#government	1	Only regulatory and redistributive function.
#banks	2	Financial intermediaries.
Simulations		
#iterations	15000	Corresponds to roughly 60 years (one iteration is one working day, 240 working days are one year).
β^A	0.03	
β^b	0.03	
Baseline		
# runs	200	200 simulations were run for the baseline. The difference to the number of runs in the experiments is due to different technical equipment (esp. number of available kernels) used for the simulations.
χ^{dist}	0.5	
χ^{int}	0.5	
Spillover-experiment		
# runs	210	210 runs per χ^{dist}-level
χ^{dist}	$\{0, 1\}$	Compared to baseline with $\chi^{dist} = 0.5$
χ^{int}	0.5	
Monte-Carlo experiment		
# runs	210	
χ^{dist}	$\in [0, 1]$	Drawn from a uniform interval.
χ^{int}	$\in [0, 2]$	Drawn from a uniform interval.

This table gives an overview of the most important parameters of the simulations and the experiments. Additional information about other technical and economic parameters that have been specifically calibrated for the eco-extension of the *Eurace@unibi* model are documented in [Hötte, 2019a].

A.2 Baseline

Here, only some general features of the simulated time series data are shown. Information about the empirical validation is available in SM.I. More detail on this baseline simulations is available in Hötte [2019b]. A longer discussion of a similar simulation is provided in Hötte [2020]. A difference to the simulations in Hötte [2020] is given by lower diffusion barriers of the green technology and another specification of the learning function.The simulation model, the simulated data and a selection of results of descriptive statistics is available in a separate data publication [Hötte, 2019d].

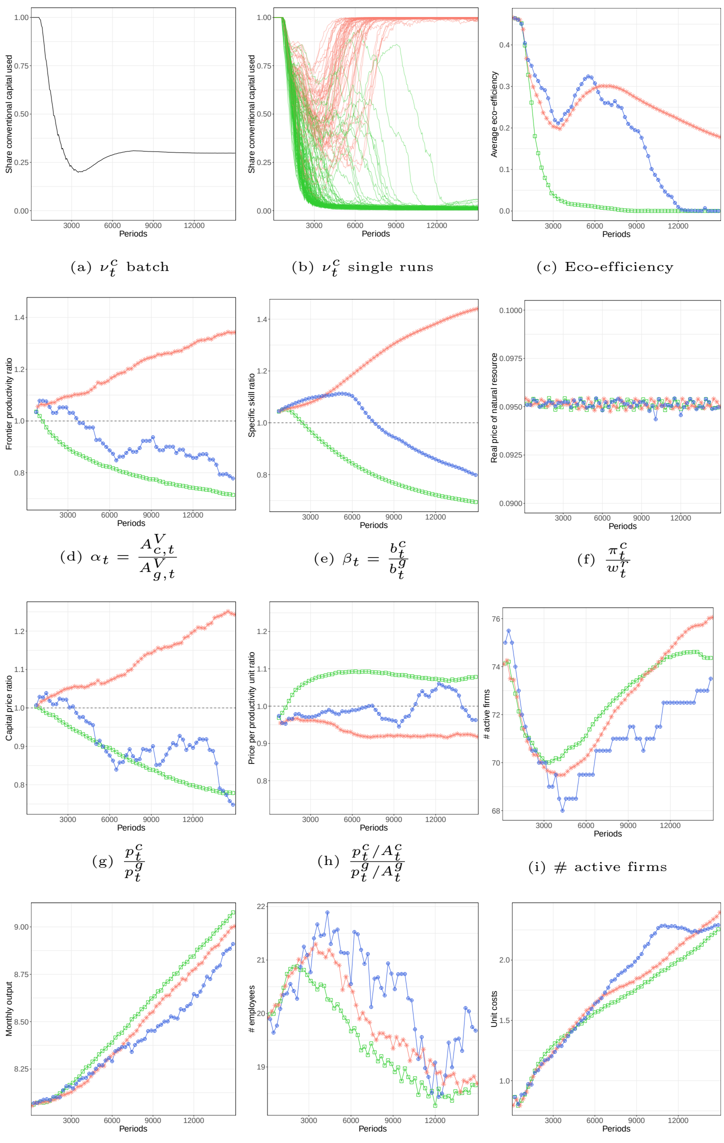
In Fig. A.1, the time series are dis-aggregated into green, conventional and so-called *switching regimes*. A simulation run is classified as *switching regime* if the diffusion process is very volatile, i.e. when ν_t^c heavily fluctuates between low and high levels or when ν_t^c has not converged to more than 90% or less than 10% in T [cf. Hötte, 2020]. This is associated with uncertainty about the final technological state. The time series data illustrate that *"technological uncertainty"* is costly in terms of aggregate (log) output (Fig. A.1j). It is associated with wasted resources because R&D and learning time are invested in a technology that becomes obsolete in the long run. This leads to a delayed technological specialization compared to the green or conventional regimes with a more clear-cut technological path selection. Fig. A.1d and Fig. A.1e show that this is associated with a delayed divergence in relative knowledge stocks which is a reason and a result of uncertainty.

Fig. A.1g shows the evolution of relative prices for capital goods and Fig. A.1h shows this price normalized by the relative productivity. Fig. A.1f illustrates the price for material resource inputs normalized by real wages. The price evolves such that it accounts for roughly 9.5% of wage costs for an average firm during the whole time horizon.

Fig. A.1c illustrates an alternative environmental performance measure, called eco-efficiency, that measures the environmental impact (here amount of natural resource inputs) per unit of produced output. The eco-efficiency also improves when the productivity performance in the lock-in regime improved by technical progress which is a *relative decoupling* of production from environmental damages. Principally, there can be a trade-off between the specialization in the conventional technology and the switch to green technology if the success of the transition is uncertain. However, modeling this trade-off is very sensitive to the modeling assumptions regarding the environmental impact, initial conditions about the available technology options and productivity improvements in both sectors. In this study, the focus is on replacement dynamics in a theoretical way which allows to be agnostic about assumptions that may critically affect such a trade-off analysis.

A two-sided Wilcoxon test indicates that the differences between green and conventional regimes a (cf. Fig. A.1) are significant (see SM.I.3).

Fig. A.1: Time series of macroeconomic and technological indicators



(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) $\frac{\pi^c_t}{w^r_t}$

(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

(l) Unit costs

Different line shapes indicate different regime types ($\square$: transition, $*$: conv, $\oplus$: switch).

A.3 The ease of learning

The pace of relative technological learning is also dependent on the technological difficulty χ^{int}. If a technology is very easy to learn, i.e. $\chi^{int} = 0$, the learning progress is independent of the time invested in learning which is proxied by $\nu^c_{i,t}$. If χ^{int} is high, the progress is sensitive to $\nu^c_{i,t}$, i.e. learning is more effective if employees work only with one technology type. In an experiment that is longer discussed in Hötte [2019c], it had been shown that χ^{int} is only of minor importance in the presence of cross-technology spillovers.

The impact of the difficulty on the learning speed is most critical in times when firms are transitioning to alternative technology. During a phase of technology change, a trade-off in the allocation of the learning time exists. This trade-off is more pronounced when a technology is difficult to learn. A technology that is easier to learn is associated with lower technology switching costs. This may have an ambiguous effect on green technology diffusion. It is easier to switch to green technology, but it is also easier to switch back if the difficulty is symmetric. Whether increasing returns to learning stabilize an ongoing diffusion process, depends on the extent to which the green technology is adopted in the first years.

The adoption in the early phase is facilitated by cross-technology spillovers reflected in a lower distance χ^{dist}. If the transferability is sufficiently low, increasing returns to learning contribute to the stabilization of the technological regimes.

A.4 Interactions between spillovers and the ease of learning

Table A.2: Initialization of learning parameters

		transition	*lock-in*	
	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 Monte-Carlo experiment in Sec. 4.3, the learning parameters are drawn at random, i.e. $\chi^{dist} \in [0, 1]$ and $\chi^{int} \in [0, 2]$. Diffusion barriers at the day of market entry are fixed at a level of 3% ($\beta^A = \beta^b = .03$) as before. The transition probability accounts for 64%.

In Table A.2, means and standard deviation of the initialization are summarized as aggregate and dis-aggregated by regime subsets. The p-value in the last column indicates whether the difference in means between the two regime types is significant. The average mean of the distance χ^{dist} is significantly lower in the subset of green regimes. The difference in the χ^{int} is only weakly significant at a 10% level. Some general descriptive information of these simulations is provided in SM.III.2.

Supplementary Material

SM.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 SM.I.1. In table SM.I.2, the cross correlation patterns between business cycle dynamics and lagged macroeconomic indicators such as investment, consumption and prices are shown. Figure SM.I.1 shows the relative volatility of output, consumption and investment and output, vacancies and unemployment. In Fig. SM.I.2 plots of a Phillips and Beveridge curve using the simulated data are shown.

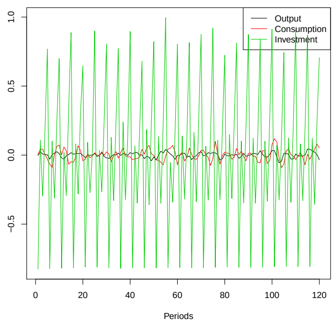
Table SM.I.1: Growth rate and business cycle

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

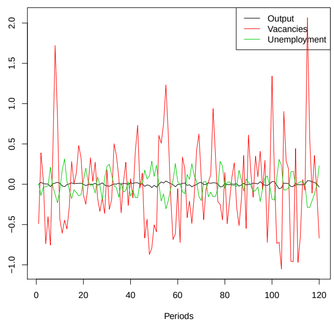
The mean (standard deviation) of the growth rate is the arithmetic mean of the geometric means of the within-run growth rate. The size of the business cycle (BC) is evaluated as percentage deviation of time series data from the band-pass filtered trend. The within-run variation is the mean of the within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

The selection of these validation criteria is motivated in Dawid et al. [2018]. These criteria and the computation of the indicators in the application to the *Eurace@unibi-eco* model are discussed in more detail in Hötte [2020].

Fig. SM.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 band-pass 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.

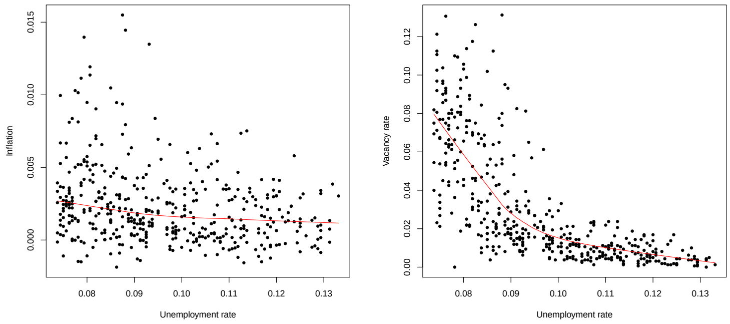
Table SM.I.2: Cross correlation patterns

	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 auto-correlation of a business cycle. The presented values are averages of the run-wise correlations. In parentheses, the standard deviation over simulation runs is shown.

In Table SM.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 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.

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

t	*transition*	*lock-in*	*transition,lock-in*	*transition*	*lock-in*	*transition,lock-in*
	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 dis-aggregated 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 $\{[601, 3000], [3001, 5400], [5401, 15000], [1, 15000]\}$.

SM.II Technical notes

SM.II.1 Experiment on the technological distance

In Sec. 4.2, the results of a regression of macroeconomic indicators on χ^{dist}-dummy variables and the standard deviation of the diffusion measure σ_t^{ν} are shown. The data was split into two subsets, one for each technological regime (green transition and lock-in). In Table 1, the coefficients of a regression on the data within each regime-subset are shown. σ_t^{ν} captures qualitative properties of different *phases* of the diffusion process. These qualitative properties differ from pure time effects. A high σ_t^{ν} indicates that the prevalent technological regime is unstable and firms switch between different technology types or are heterogeneous in their investment strategies.

The data exhibits a panel structure with group clusters. The unit of observation is a single run and the time index is given by the number of periods. The regression is a pooled OLS regression and aimed to reveal structural relationships and correlations between the parameter settings and the outcome. Standard errors are clustered by run and time indices using the R-function `coefftest(x, vcov=vcovHC(x,type="HC0"))` of the `lmtest` package [Zeileis and Hothorn, 2002].

Robustness was tested by different panel methods, i.e. random effects and a between estimator. The results of these models are quantitatively and qualitatively consistent, but partly differ in the significance levels of coefficients.

Fixed effects and first difference models eliminate the fix differences of the type and parameter dummy that is constant within each run-time indexed subset, but confirm the dominance, significance and qualitative nature of the influence of σ_t^{ν}. Alternative functional forms of the regression model confirm the robustness of the qualitative insights of this analysis. The results and the statistical code is available online in the accompanying data publication [Hötte, 2019d].

SM.II.2 Monte Carlo analyses

Data: In the regressions, one year average smoothed data is used. Observations are 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 $[14780, 15000]$ and cover 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 full data $t \in [0, 15000]$ of firms exhibits the structure of an unbalanced panel with entries and exits. Some dependent variables (esp. $\sigma_{i,t}^{\nu}$) are only meaningful if the full life time of a firm is considered. In this case, only firms are studied that survive from the beginning until the end of the simulation horizon.

Explanatory variables: Core explanatory variables are the technological difficulty χ^{int} and distance χ^{dist}. 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 $\mathbb{1}(eco)$ 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 are 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. In the presence of non-linearity, the interpretation as marginal effects is not applicable, but serves as rough approximation here. 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 π^c/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.

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: In the regressions, threshold levels for the duration until stabilization of the transition process t_i^* and the relative technological performance $\alpha_i^* = (A_{i,t^*}^+/A_{i,t^*}^-)$ and $\beta_i^* = (B_{i,t^*}^+/B_{i,t^*}^-)$ are computed. The duration t_i^* is defined as the last local extremum in the smoothed diffusion curve given by the share of conventional capital use $\nu_{i,t}^c$. It is the time when the last change in the direction of the firm-level green technology diffusion occurred within a single simulation run. After t_i^*, firm i does not any longer switch between green and conventional capital. 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^*.

The relative performance indicators $\alpha_i^* = (A_{i,t^*}^+/A_{i,t^*}^-)$ and $\beta_i^* = (B_{i,t^*}^+/B_{i,t^*}^-)$ are evaluated at t_i^*. They are interpreted as thresholds in the relative performance and measure the degree of technological divergence beyond which the direction of technological change is stable. These measures are the ratio of stocks of technological knowledge stocks comparing the superior with the inferior technology. $+$ $(-)$ indicates the superior (inferior) technology type $\tau = c, g$. *Superior* is defined as technology type that is the "winner" of the technology race and dominates in $T = 15000$. If the resulting regime type is green (conventional) the green (conventional) technology is said to be the winner.

The data set used for the analyses of performance thresholds and the stabilization time t_i^* (t^*) is truncated. 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. It may also occur if the firm i runs into bankruptcy before it achieved a stable pathway. If $t_i^* = 15000$, diffusion did not stabilize until the end of simulations and it is not necessarily clear whether one of the two technologies won the race. The technological variables evaluated at this point in time cannot be interpreted as performance thresholds.

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 too 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 that is computed over a 2.5 year window (e.g. Fig. 3c).

Model selection procedure: The specifications of the regression equations are chosen using a step-wise 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 step-wise model selection functions. The functions return the model specification that is associated with minimum BIC.

The OLS and Probit functions are 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. This impedes the comparability across models. 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 across experiments, are more commonly known than exotic distributional families, the coefficients of OLS are straightforward to interpret, and sufficiently fulfill the purpose to illustrate the underlying theory.

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 $\mathbb{1}(eco)$. The time series that are dis-aggregated 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 are excluded by the BIC on the second stage are 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 $\mathbb{1}(eco)$ 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, 2019d]. As alternative model specification, robustness tests were made with a Gaussian finite mixture model using `gamlssMX()`. The results are qualitatively consistent but not chosen as modeling approach to facilitate the interpretation of the model.

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.

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

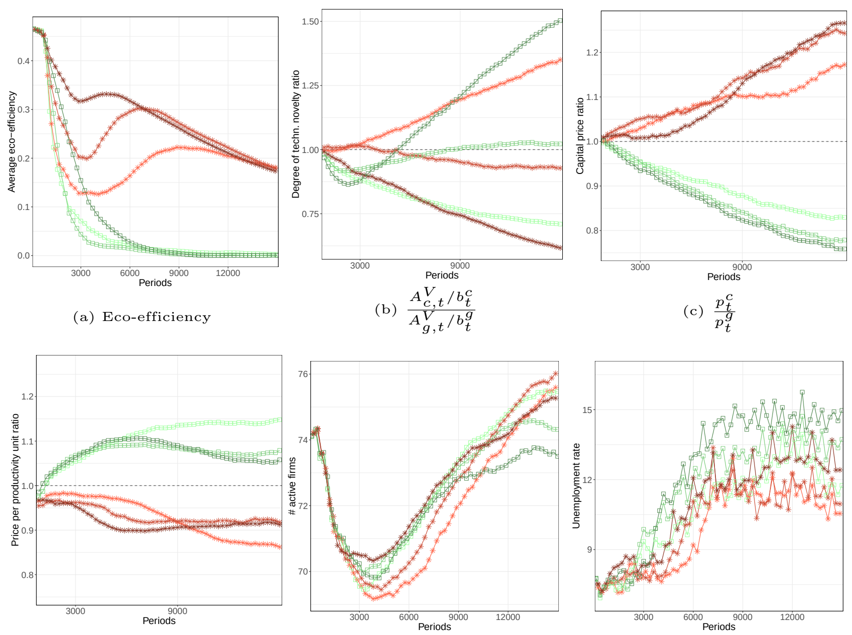
The plots in the article show the critical levels of relative knowledge stocks, initial diffusion barriers and learning conditions (cf. Fig. 6). Colors indicate the final regime type. For the training of the classification algorithm, relative knowledge stocks are used to predict the type of the resulting 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, 2019d]. 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 are tested in the regression analyses. It also contains additional figures and tables of simulated data that are not discussed in the article, but give insights about the dynamics of the model.

SM.III Experiments

SM.III.1 Technological distance

Fig. SM.III.3: 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) $\frac{p^c_t}{p^g_t}$

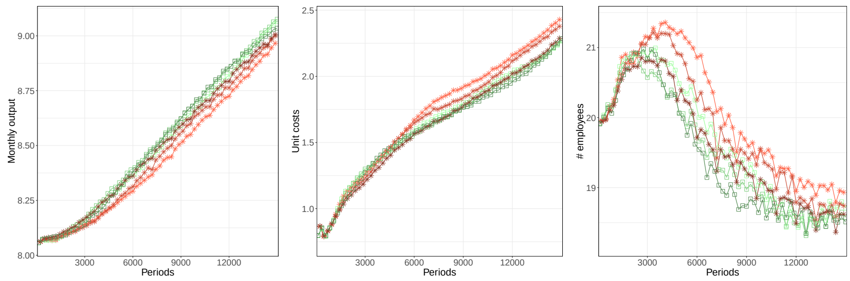
(d) $\frac{p^c_t/A^c_t}{p^g_t/A^g_t}$ (e) # firms (f) Unemployment

The different line shapes indicate different regime types (□: transition, ∗: lock-in). Darker color indicates a higher level of χ^{dist}.

The time series of macroeconomic indicators are shown in Fig. SM.III.3. 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.

Different levels of distance between the incumbent and entrant technology also have implications for the market structure captured by market exit dynamics during the transition phase and the evolution of firm sizes (cf. SM.III.3). The early phase of diffusion is associated with a high number of market exits by consumption goods producing firms. The market entry of the green technology is associated with increased price competition and not all firms are able

Fig. SM.III.4: 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 (□: transition, ∗: lock-in). Darker color indicates a higher level of χ^{dist}.

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 meaningful, but not the number of entries in general.[12] The effects of different χ^{dist} differ across time and across regime types.[13]

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. Fig. SM.III.4c shows the evolution of the average firms size dis-aggregated 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. SM.III.1).

In a preceding study [Hötte, 2020] 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. 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. Fig. SM.III.4a) and unit costs are on average higher (cf. SM.III.4c).

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 tables below.

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.

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

[13] This becomes even more complex, when considering 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.

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

initial	[601,3000]	*aggr*			*transition*			*lock-in*		
# 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*			*transition*			*lock-in*		
# 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*			*transition*			*lock-in*		
# 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 SM.III.5: Results of two-sided Wilcoxon test at different phases of diffusion and different subsets of data.

initial	[601,3000]	*aggr*		*transition*		*lock-in*	
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 SM.III.6: Results of two-sided Wilcoxon test at different phases of diffusion and different subsets of data.

medium	[3001,5400]	*aggr*		*transition*		*lock-in*	
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 SM.III.7: Results of two-sided Wilcoxon test at different phases of diffusion and different subsets of data.

end	[5401,15000]	aggr		transition		lock-in	
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)	

SM.III.2 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 Sec. 4.3 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 are discussed in the main article. Here, a short overview of the regression of relative knowledge stocks and a descriptive and explanatory summary of the role of micro- and macroeconomic circumstances is given.

In column (4) and (5) of Table 2, a regression of the relative performance of the superior technology is shown. Superior is defined as the technology that dominates at the end of the simulation horizon. 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. 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 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 role of the macro- and microeconomic controls can be explained as follows. 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 $(\sigma_i^\nu)^2$.

Table SM.III.8: Wilcoxon test on equality of means for different phases of diffusion.

t	*transition*	*lock-in*	*transition,lock-in*	*transition*	*lock-in*	*transition,lock-in*
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