PARIS-1 SORBONNE-PANTHÉON

&

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DOCTORAL THESIS

Facilitation of change: Macroeconomic studies of technology transitions

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Kerstin HÖTTE

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Résumé long en français

Motivation

Les découvertes scientifiques sur l'évolution du changement climatique sont effrayantes. Il ne reste que peu de temps pour lutter efficacement contre le changement climatique. Si la transformation durable de l'économie n'est pas accélérée considérablement, les dynamiques de changement climatique risquent de devenir incontrôlables pour l'homme. Cela veut dire qu'il est nécessaire d'accélérer le développement de technologies vertes ainsi que de promouvoir le remplacement du système de production et consommation en vigueur, basé sur l'épuisement de ressources naturelles, par des solutions durables. Une telle transformation en profondeur peut passer par des redistributions et des disruptions des structures établies, associées à des dévalorisations de capacités et d'actifs matériels. L'Accord de Paris est l'illustration d'une volonté politique d'agir, mais le processus de changement technologique est lent et les efforts déployés sont insuffisants pour atteindre les objectifs climatiques.

Cette thèse cherche une explication économique aux raisons de la lenteur des changements et des stratégies visant à faciliter la transformation technologique. Elle a pour sujets d'étude l'accélération, le gouvernance et les conséquences économiques de transformations technologiques. Des recherches empiriques ont montré que les modèles de transition technologique d'ampleur varient selon les pays, les technologies et les secteurs industriels. Les processus de transition socio-technologiques sont complexes et rien ne garantit que leurs résultats soient optimaux. De petits événements historiques peuvent avoir des conséquences permanentes s'ils sont renforcés par des rendements croissants. L'accumulation de capacités technologiques, tangibles et intangibles, les infrastructures en vigueur et les routines comportementales peuvent entraîner un verrouillage technologique.

Dans cette thèse, je développe une analyse économique des différences observées. Je propose une théorie des capacités appliquée à la technologie et à l'apprentissage technologique. Cette théorie explique les différences d'adoption de nouvelles technologies par les entreprises. Elle s'appuie sur un modèle macroéconomique multi-agents.

Le modèle est une extension des technologies hétérogènes du modèle multi-agents Eurace@unibi, appliquée aux technologies vertes. Le modèle initial, Eurace@unibi, est un modèle exhaustif qui peut être utilisé pour simuler une macroéconomie complète. Le modèle est empiriquement validé et a été utilisé dans de nombreuses précédentes études. Le modèle étendu, appelé Eurace@unibi-eco est l'un des produits de cette thèse.

Le modèle est utilisé pour simuler les dynamiques d'une course entre des technologies concurrentes dans laquelle une nouvelle technologie verte pourrait remplacer la technologie conventionnelle établie. Les dynamiques de concurrence dépendent des évolutions des capacités technologiques et des caractéristiques des technologies rivales. Les résultats des simulations peuvent expliquer la vitesse, la trajectoire et la stabilité d'une transition technologique. Dans des simulations, je teste le potentiel de mesures de politique permettant d'accélérer et de stabiliser le processus de transition.

La thèse est composée d'une introduction, de trois principaux chapitres et d'une conclusion. Dans l'introduction, j'explique les motivations sous-jacentes à ces recherches ainsi que leur contexte général et la méthodologie choisie dans cette thèse. La série de chapitres généralise progressivement la perspective théorique sur les connaissances technologiques et leur pertinence pour les dynamiques de transition. Chacun des chapitres est un article de recherche indépendant comprenant une partie théorique et une étude de simulation utilisant Eurace@unibi-eco. En plus, la thèse contient une documentation exhaustive du modèle de simulation. Par la suite, les trois principaux chapitres sont introduits dans plus de détails.

Chapitre 2: *Comment accélérer la diffusion des technologies vertes? Changement technologique guidé, en présence d'une capacité d'absorption coévolutive*

La dépendance au sentier peut expliquer la diffusion lente des technologies vertes. Les entreprises investissement dans du capital, qui diffère selon le type de technologie, et accumulent un savoir-faire technique spécifique à la technologie employée. Il ne peut pas être acquis sur le marché et les entreprises ne peuvent l'apprendre que par la pratique. La progression de l'apprentissage dépend de l'intensité avec laquelle une entreprise utilise un type de technologie spécifique. L'adoption de la technologie constitue une source d'avantages hétérogènes au niveau de l'entreprise.

La dépendance au sentier provient des connaissances accumulées qui se manifestent dans la productivité du capital offert sur le marché ainsi que dans les capacités technologiques des entreprises. Des rendements décroissants découlent de l'innovation endogène et de l'apprentissage par la pratique. Un équipement initial inférieur pour des connaissances technologiques données constitue une barrière à la diffusion de nouvelles technologies. Ce chapitre propose une courte introduction éclairant comment ces mécanismes sont implémentés dans l'extension aux technologies vertes du modèle multi-agents *Eurace@unibi*.

Le modèle est utilisé pour générer un échantillon de courbes de diffusion. Je montre comment l'évolution des connaissances technologiques relatives peut expliquer les formes des courbes. Au cours du temps, l'économie converge vers l'un des deux régimes technologiques possibles caractérisé par l'utilisation d'une seule des deux technologies. Je montre que l'incertitude technologique est économiquement coûteuse si des ressources de recherche et développements et de l'apprentissage par la pratique sont gaspillées dans une technologie qui s'avère être obsolète à long terme.

Dans une expérience de simulation de mesures de politique, j'analyse comment l'efficacité des politiques de diffusion dépend du type et de l'intensité des obstacles à la diffusion. Des taxes environnementales peuvent compenser efficacement un désavantage de productivité inférieure. Des subventions peuvent fonctionner si des capacités technologiques insuffisantes empêchent les entreprises d'adopter une technologie suffisamment mature.

Cette étude contribue à la littérature sur le changement technologique dirigé en proposant une théorie de capacité d'absorption coécolutive. Le problème d'une transition durable est présenté en tant qu'un problème de coordination entre adoptants hétérogènes de technologies. C'est une nouvelle approche méthodologique et théorique dans la littérature économique sur le changement climatique.

Chapitre 3: *La transférabilité des capacités technologiques et la stabilité de voies de transition: Une explication de la diffusion basée sur l'apprentissage*

Dans ce chapitre, j'examine les effets de la transférabilité des compétences d'une technologie à l'autre sur les décisions d'adoption de ces technologies par des entreprises individuelles. J'étudie les implications de la diffusion pour la trajectoire émergente au niveau macroéconomique. Pour qu'une technologie soit utilisée efficacement, les entreprises ont besoin d'un savoir-faire spécifique au type de technologie utilisée. Les employé.e.s des entreprises accumulent le savoir-faire en travaillant avec des machines d'un type technologique spécifique. Le savoir-faire peut-être transféré si les technologies sont similaires. Une innovation radicale se caractérise par un changement de type technologie et une transférabilité des compétences faible.

En m'appuyant sur la littérature empirique et théorique au sujet de l'innovation, je propose un modèle de l'apprentissage technologique avec des fondations microéconomiques. Dans une simulation avec le modèle étendu Eurace@unibi-eco, je montre que la transférabilité des compétences a des effets ambigus. Une transférabilité forte accélère initialement la diffusion, mais elle est associée à de l'incertitude technologique et retarde la spécialisation technologique à long terme. Pour les entreprises, il est plus facile d'adopter une nouvelle technologie, mais il est également aussi facile de revenir au type de technologie antérieur.

Dans la littérature existante, les modèles microéconomiques d'apprentissage au niveau des entreprises sont rares. J'introduis une théorie de l'apprentissage et je montre ses implications pour les formes émergentes de diffusion au niveau macroéconomique. Ce type d'analyse et les résultats avancés sont une nouveauté dans la littérature sur le changement technologique macroéconomique.

Chapitre 4: *Voies de transition et caractéristiques des technologies concurrentes: Une taxonomie des technologies et une expérience politique*

Dans les deux premiers chapitres, j'ai montré que les caractéristiques de technologies concurrentes et les facteurs extérieurs peuvent contribuer à une explication des formes des courbes de diffusion. Les courbes de diffusion sont une représentation formelle des trajectoires de transition. Empiriquement, les trajectoires de transitions varient entre les pays, les secteurs industriels, les entreprises et entre technologies différentes. Parfois, les nouvelles technologies sont adoptées rapidement. Parfois, ce processus est très instable et associé à des perturbations de la structure du marché. Dans d'autres cas, il arrive que des économies ou des industries soient bloquées avec la technologie en place. La compréhension de ces trajectoires différentes est importante lorsqu'il s'agit de proposer des mesures de diffusion efficaces et de développer une intuition des effets macroéconomiques d'une transition approfondie.

Dans ce chapitre, je développe une taxonomie visant à caractériser des technologies concurrentes. Cette taxonomie est basée sur une collection de faits stylisés, eux-mêmes tirés d'une revue de la littérature sur la diffusion technologique et les transitions sociotechniques historiques et contemporaines. Cette taxonomie est liée à une perspective multicouche de la théorie de la transition. La perspective multicouche est un cadre conceptuel fréquemment utilisé dans le domaine de la recherche sur la transition sociotechnique (Köhler et al., 2019; Lachman, 2013). Ce cadre conceptualise les transitions en tant que processus co-évolutionnels dynamiques dans lesquels des technologies de niche émergentes finissent par remplacer le régime sociotechnique en place. Les conditions externes sont favorables ou défavorables aux technologies entrantes.

Cette typologie reflète les qualités d'une technologie compte tenu des circonstances sociotechniques extérieures ainsi que de la maturité relative de la nouvelle technologie émergente. Les interactions dans le processus de spécialisation technologique dépendent de la transférabilité des capacités technologiques et des infrastructures de soutien accumulées. Cette taxonomie est une généralisation du concept de technologie présent dans le modèle Eurace@unibi-eco. Je montre comment les caractéristiques de technologies concurrentes peuvent expliquer les trajectoires de transitions émergentes et je commente des exemples empiriques.

Des mesures de politique économique peuvent affecter les circonstances extérieures à la concurrence entre différentes technologies. Dans une expérience de simulation avec le modèle Eurace@unibi-eco, je montre comment des instruments politiques ciblant le marché peuvent accélérer et stabiliser une trajectoire de transition technologique. La performance de ces instruments diffère et dépend des caractéristiques des technologies concurrentes.

Les résultats des simulations contribuent à la compréhension de pourquoi les trajectoires de transition et l'efficacité des politiques varient selon les pays, les industries et les groupes de technologie. Ces aperçus sont importants pour l'élaboration de mesures. Le manque de formalisation et l'imprécision des concepts sont des faiblesses majeures dans les études sur les transitions sociotechniques. Dans ce chapitre, je propose un cadre théorique qui peut être utilisé pour systématiser et formaliser des données empiriques.

Publications

Au moment de la rédaction de cette thèse, le chapitre 2 a été accepté pour publication par le journal *Energy Economics* (Hötte, 2019e). Les chapitre 3 et 4 ont été soumis et en attente de décision. Les résultats présentés dans les chapitres sont publiés dans des documents de travail exhaustifs (Hötte, 2019b,f), dans un rapport technique de description détaillée (Hötte, 2019d) et dans deux publication de données pour assurer la transparence et la reproductibilité des résultats (Hötte, 2019a,c,g).

Chapter 1

General introduction: Facilitation of change

> *Things do change. The only question is that since things are deteriorating so quickly, will society and man's habits change quickly enough?*
> *(Isaac Asimov)*

1.1 Motivation

Why is it important to study the facilitation of (technological) change? The latest scientific observations on the dynamics of climate change are alarming. The acceleration of socio-technical change to carbon-neutral systems of production and consumption might be an existential question. This thesis searches for an economic approach to facilitate such transition process.

Steffen et al. (2018) have shown the human impact already led to a shift in the climate trajectory out of the stable cyclical dynamics (*interglacial limit cycle*) that characterize the oscillations between two glacial states. The direction of the future *Earth trajectory* is uncertain, but a significant risk exists that the earth is tipped into a trajectory with catastrophic and potentially life-threatening consequences for human societies. If anthropogenic emissions are not radically reduced, global warming continues and certain thresholds in the earth system are crossed, an irreversible series of tipping cascades of warming dynamics may be triggered. These cascades can drive the dynamics of climate change out of human control. Global warming would move into self-reinforcing dynamics, resulting in a significantly higher temperature than in the entire Holocene and significant sea-level rise. Such a state is also known as *Hothouse Earth*. Steffen et al. (2018) have shown the existence of threshold levels in the global temperature that must not be crossed if the irreversible shift into a Hothouse Earth trajectory wants to be avoided. The authors have also shown that the threshold may be two degrees or even lower. To remind, the *Intended Nationally Determined Contributions* (INDC) agreed upon in the Paris Agreement 2015 collectively imply a median warming of 2.6-3.1 degrees Celsius by the end of the century (Rogelj et al., 2016).

Human activity had and has a measurable impact on the direction of the future trajectory. There are alternative pathways of active *Earth stewardship* that provide adequate living conditions. It is up to humans to choose which pathway is taken and how to cope with changing climatic conditions. If radical action is not undertaken today, the time window for effective climate change mitigation will be closed and we incur the risk of shifting into an irreversible Hothouse Earth trajectory (Hagedorn et al., 2019; IPCC, 2018).

In August 2018, students of the Fridays for Future movement around the globe began leaving school to express their anger at the lack of action in effectively combating climate change (Warren, 2019). Since January 2019, tens of thousands of scientists worldwide have expressed their support: *"Concerns of young protesters are justified"* (Hagedorn et al., 2019). Climate change is an existential threat, but action is slow.

The existential dimension of climate change calls for two types of change in economic behavior. First, the climate is changing. This requires the rapid, *reactive* adaptation of techno-economic systems of human civilization to new climatic conditions. Second, *active* change is needed to transform the economy to carbon-neutrality and even negative net emissions in the second half of the century if existential climate risks shall be avoided.[1] The technological solutions are available and known, but their widespread diffusion is sluggish. The Paris Agreement was an expression of the political will to change, but this is not sufficient given the gap between proclaimed targets and undertaken action.

In this thesis, I examine how processes of technological change pass off. I search for economic explanations why it appears to be so difficult to change. This thesis develops a macroeconomic understanding for the sluggishness of technology diffusion and seeks to identify levers to accelerate socio-technical change.

1.1.1 Two-sided uncertainty: Reasons to ask questions differently

What is the economic approach to the problem of climate change? *"Climate Change: The Ultimate Challenge for Economics"* is the title of a recent essay written by W.D. Nordhaus in which he summarizes the main achievements, approaches and open challenges of roughly 40 years of research on the nexus of climate change and economics (Nordhaus, 2019). To date, many efforts in climate economics are dedicated to the study of the trade-off between the costs

[1]Throughout this thesis, I refer to *carbon emissions* and natural resource depletion as a short cut to avoid a more complex explanation of sustainability. *Earth stewardship* as postulated by Steffen et al. (2018) goes beyond and acknowledges the concept of interdependent planetary boundaries (Rockström et al., 2009). This underlines the complexity and uncertainty associated with human interventions in the climate dynamics. It does not have an impact on the theoretical findings of this thesis but underlines that one should be cautious when bringing the term *sustainable technology* to data.

of emission reduction, so-called *abatement costs*, and the *benefits of avoided damage*. This theoretical perspective on the economics of climate change imposes two major premises: Abatement costs *and* benefits are known or can be reliably estimated for a time horizon of at least several decades. These two premises have formed the working basis for numerous studies ranging from the controversies about appropriate discount rates (Drupp et al., 2018; Pindyck, 2013), the incorporation of technological change (Popp, 2019; Popp et al., 2010) or the challenges to come up with reliable damage functions (Auffhammer, 2018).

In this thesis, I adopt another agenda. I do not search for optimal temperature levels. Instead, I ask why it seems to be so difficult to live more sustainably? More formally, I search for the foundations of abatement costs. Abatement costs are the costs of switching to another type of technology whereby the term *technology* has a very broad meaning. In transition theory, it is defined as a means to fulfill a societal function (Geels, 2004). Hence, technology does not only refer to techniques and physical artifacts but also to its functionality and use. I acknowledge that the relevance of this perspective is based on the *normative* assumption that it is desirable to govern the process of change (cf. Köhler et al., 2019). I take it as given that a technology transition is in the course of happening, either because it is politically and societally desired to combat climate change or because it is externally enforced through changing climatic, economic or technological conditions. The theoretical results of this thesis can be straightforwardly applied to other topics like digitization, development and globalization. Green technologies are only one example, but an example where the relevance of the research question is pressing.

The guiding question of this thesis is: *How to facilitate a technology transition?* The word *facilitation* means to make it easy to change. It goes beyond a mere acceleration which relates only to the technological dimension. It imposes economic and societal constraints. A transition is not *easy* if it raises much opposition because it is extremely costly or disrupts established structures. Facilitation also has a communicative and social-psychological dimension. It had been shown that resistance to change at the individual level is easier to be overcome if future pathways and their associated trade-offs are elucidated clearly and negotiated in a transparent way (Rosenbloom, 2017; Watson, 1971). In this thesis, I study the techno-economic dimension of transition processes and their side effects at a macroeconomic, theoretical level.[2]

I adopt this alternative perspective on climate economics for four major reasons that are theoretically and ethically motivated. First, reliable estimates of long-term damage and abatement costs are difficult, if not practically infeasible, to obtain. Many economic assumptions about pathways of technological progress and climate change, substitutability in production and consumption

[2] By *techno-economic* I mean the dimension of change that is reflected in economic variables. That can be technology-related indicators as productivity or market shares. Broader patterns of societal change can be reflected in market structures and consumer preferences. These broader dimensions of socio-technical change will not be considered here.

behavior, ethical and economic preferences need to be made. These assumptions come on top of a series of uncertainties along the pathway from estimated life-cycle emissions and other environmental impacts from human activities, temperature trajectories, adaptive capacities of and interactions with ecological and geophysical systems. And finally, these dynamics need to be *translated* into economic damages (cf. Auffhammer, 2018; Farmer et al., 2015; Pindyck, 2013; Steffen et al., 2018).[3]

Second, even if it would be theoretically and practically feasible to come up with reliable estimates, how much does it help to know the optimal temperature level if the pathway how to get there is opaque? Given the gap between proclaimed mitigation targets of the Paris Agreement and the INDC, the transition needs to be radically accelerated.

Third, both the impact of climate change but also technology transitions are non-linear (Stern, 2016). The crossing of tipping points in the climate system is irreversible and global warming dynamics may become self-reinforcing. Beyond these tipping points, the control of the temperature level in marginal levels is infeasible. Also technological change is non-linear and subject to irreversibilities and tipping points. Increasing returns and technological lock-in are well documented in the theoretical and empirical innovation literature (e.g. Arthur, 1989; Safarzyńska et al., 2012; Unruh, 2000). Both the dynamics of climate change and the dynamics of technological change are critical determinants of damage and abatement cost functions. Climate change damages are a function of simulated climate dynamics. Abatement costs depend on the technology-dependent substitutability of resource-intensive production and consumption patterns (e.g. Popp et al., 2010; Sarr and Noailly, 2017). Acknowledging the two-sided of non-linearity in the underlying dynamics, marginal costs and benefits are (most likely) non-linear too. This impedes attempts in marginal cost-benefit analysis and makes the results extremely sensitive to the underlying assumptions. A pragmatic approach to deal with the increased complexity and uncertainty is to ask other questions, i.e. questions that concern the governance of the process instead of evaluating the optimality of the outcome of emerging dynamics.

The fourth reason for adopting this agenda is related to the boundaries of social science that is aimed to be politically relevant. The estimation of marginal

[3]This statement should not undermine the relevance of climate-economic modeling in general. At the local level, these estimates are critically important to evaluate local and sectoral adaptation needs taking climate change as an exogenous shock. The aggregation to global, long-term developments and the incorporation of *mutual* climate-economy feedbacks are much more difficult. Any normative statement about the relative, *quantitatively* justified economic desirability of specific emission trajectories and temperature targets is extremely vulnerable to technical assumptions and undermines the credibility of a whole branch of research (e.g Auffhammer, 2018; Pindyck, 2013). An example is the prominent controversy about discount rates (cf. Nordhaus, 2007). When acknowledging - normatively - the desirability of a sustainability transition to reduce existential risks, economic optimality becomes a question of political feasibility that demands a more complex understanding of social welfare.

costs and damages is subject to ethical assumptions about inter- and intragenerational justice and substitutability (Dasgupta, 2008; Devarajan and Fisher, 1981). Focusing on the facilitation of a contemporaneous transition allows circumventing these assumptions and makes the normative dimension of the research objective transparent. The critical normative assumption, that needs to be made, is the desirability of a (sustainability) transition. Whether or not it is desirable, should be decided by society and policymakers. This thesis contributes to the understanding how it might be achieved.[4] Searching for ways to facilitate a transition can be also seen as a concession to those who have reservations against it. It is an attempt to understand (heterogeneous) barriers to change and to make it easy to overcome them.

Nonetheless, the agenda of this thesis has theoretical implications for the welfare-oriented perspective of traditional climate economics: Working on the foundations of socio-technological change is a step forward in the endogenization of abatement and damage costs. Knowing and stimulating the determinants of change has an impact on abatement costs if it becomes cheaper to abate emissions. It has also an impact on damage costs if technological strategies help to adapt to changing climatic conditions. The analytical difference is a modification of the objective function. The new objective is the acceleration of a transition given a set of technical and political feasibility constraints.

Steffen et al. (2018) have shown that human activity already led to a shift in the climate system. The outcome of the current trajectory is uncertain, but they have also shown that the future pathway can be shaped. Taking these insights as given allows circumventing theoretical discussions about the desirability of different levels of change, that are practically infeasible to evaluate over the relevant time horizon and likely beyond human control. Designing processes of change is important to accelerate the transition to low-carbon technologies, but it is also insightful for adaptation to climate change and applications in other contexts like digitization or globalization.

Change is a basic principle of economic evolution, but individual, societal, organizational and economic reactions to change are ambiguous. Change is perceived as desirable if it is incremental. Incremental change is associated with phrases of improvement, "excitement" and growth. But it is subject to resistance if it discontinues established principles and its outcome is uncertain and difficult to envision. This ambiguous reaction has been observed in social psychology, organizational research, sociology and different fields of innovation economics (e.g. Feygina et al., 2010; Pardo del Val and Martínez Fuentes, 2003; Watson, 1971; Wells and Nieuwenhuis, 2012). This thesis develops an economic interpretation of the resistance to and drivers

[4] I admit that the theoretical justification of this research agenda is much easier to justify under the technical assumption of a two-sided non-linearity of technology and climate change when the existence of marginal trade-offs is questionable. Under this setting, the analytical problem is (possibly) reducible to the choice of discount rates but becomes interesting when political feasibility constraints are included.

of change. An understanding of both is critical to provide guidance for the technology challenges societies are faced today.

1.1.2 Different questions require different methods

Technology transitions are inherently complex. Transitions are processes of large-scale system changes in which established ways of consumption, production and (economic) thinking are replaced by an emergent alternative. This does not only relate to the techniques that are used to produce final goods. It also relates to the way how technological and societal problems are defined, how technological and political practitioners search for solutions and it refers to the type of material and non-material inputs that are used to develop solutions. Dosi (1982) refers to this bundle of features as a *technological paradigm*.

Sociology of technology goes even further and defines the incumbent technological system as *socio-technical* regime that is manifested in technology, market and industry structures, consumer practices, culture and symbolic meaning, knowledge and policy (Geels, 2002; Kemp, 1994). Transitions from one regime to another are often associated with structural changes in consumption patterns, institutional and organizational structures. They may be 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-dimensional coevolution of technology, societal and institutional structures is widely acknowledged in the empirical and theoretical transition literature (cf. Geels, 2004; Köhler et al., 2019; Safarzyńska et al., 2012). Mutually reinforcing dynamics from multi-dimensional feedbacks are sources of increasing returns. Small, hardly predictable events in one dimension of the socio-technical evolution do not necessarily average out in the presence of increasing returns. These small events may tip the technological evolution into a direction that is not necessarily optimal (Arthur, 1989; Geels, 2002). The cumulative effects of self-reinforcing dynamics may result in a technological lock-in that is difficult to escape and one of the major challenges in the low-carbon transformation of the economy (Kemp, 1994; Unruh, 2000).

These properties make transitions inherently complex, i.e. the emerging outcome can not necessarily be deduced from observed, single events. Acknowledging complexity and associated uncertainty requires a revision of the applied methodology (Safarzyńska et al., 2012) and the epistemic perspective of studies of technological change. In an interview, W. Brian Arthur described the conceptual and epistemic difference between complexity theory and deductive approaches as follows (Arthur, 1999):

> *Complexity theory is really a movement of the sciences. Standard sciences tend to see the world as mechanistic. That sort of science puts things under a finer and finer microscope. [...] The movement that*

> *started complexity looks in the other direction. It's asking, how do things assemble themselves? How do patterns emerge from these interacting elements? Complexity is looking at interacting elements and asking how they form patterns and how the patterns unfold. It's important to point out that the patterns may never be finished. They're open-ended.*
>
> *(W. Brian Arthur)*

This quote describes one major aim of this thesis: It is about gaining an understanding of the dynamic interplay of technology, its users and emerging macroeconomic patterns. One key insight of the complexity perspective is that the final outcome is difficult if not even infeasible to manage and hardly measurable in continuous metrics (see also Knudsen, 2005). That is why I focus on the *process* of emergence, instead of the outcome. Understanding the process and factors of dynamic influence might help to identify intervention points that may alter the direction and pace of the technological evolution and might allow governing macroeconomic side effects.

In this thesis, I use a macroeconomic, agent-based model (ABM) that can capture these coevolutionary dynamics of technology diffusion and development. The model is used to gain an understanding of replacement dynamics in which an incumbent, fossil-fuel-based technology is replaced by a climate-friendly alternative.[5]

ABMs are computational simulation programs. In an economic context, an agent represents an entity that acts and interacts in the economy. Typical agents are consumption and capital goods firms, households, banks and a government. An agent executes specific functions such as the purchasing of goods, production and investment decisions or imposes specific policies. Functions of agents are written as explicit routines in the simulation program that is stepwise executed in a predetermined order. Agents interact through the exchange of goods, information and money. These interactions are explicitly modeled through mutual updates in the set of variables that represent an agent. These behavioral functions may incorporate stochastic elements at the micro- and/ or macroeconomic level (Tesfatsion, 2006). For example, innovation success in the R&D sector or purchasing decisions of consumers may entail stochastic noise.

ABMs are typically run multiple times and the simulated time-series data can be statistically analyzed. It is a particular feature of these models that the dynamics triggered by small stochastic events at the micro level do not necessarily average out and can be the source of emergent, macroeconomic fluctuations. Over the years, the field of agent-based computational economics (ACE) advanced considerably. Improvements in empirical validation techniques, computational methods and standards in the analysis of simulated data increased the recognition of this class of models as a serious tool for macroeconomic analyses. An overview of recent advances in macroeconomic

[5]The model can be also applied to other contexts of directed technological change than climate policy, for example, digitization, economic development and catch-up.

ACE and the peculiarities of this class of models in macroeconomic analyses can be found in Dawid and Gatti (2018).

Why are ABMs suitable for transition studies? Transition processes are characterized by multi-dimensional interactions of heterogeneous actors. Agents suffer from limited foresight and use simplified heuristic rules in their decision making, but they learn and adapt over time. The interplay of uncoordinated behavior and heterogeneity at the micro-level and uncertainties associated with innovative processes make it challenging to study transitions by the use of analytical, equilibrium-based models that are prevalent in the majority of climate economic models (Balint et al., 2017). The complex, dynamic processes of technology transitions can be incorporated into ABMs which qualifies this methodology as a particularly suited means of analysis (Ciarli and Savona, 2019; Dawid, 2006; Safarzyńska et al., 2012).

In search for complementary modeling tools in climate economics (cf. Farmer et al., 2015; Pindyck, 2013; Stern, 2016) and facilitated by methodological advances in computational economics, the field of agent-based climate economics was rapidly growing in recent years (e.g. Balbi and Giupponi, 2009; Balint et al., 2017; Ciarli and Savona, 2019; Lamperti et al., 2018b; Monasterolo and Raberto, 2019). The model developed in this thesis aligns with this research. It is a green technology extension of the macroeconomic ABM *Eurace@unibi* (Dawid et al., 2019b).

One distinctive feature of the *Eurace@unibi* model is the explicit representation of technological skills. Skills and technological learning are key drivers of the dynamics of technological change. In this thesis, I extended the representation of technology in the baseline model by a module that allows studying the evolution of heterogeneous, competing technologies and technology-specific learning processes at the level of heterogeneous, technology-adopting firms.

The extended model, called *Eurace@unibi-eco*, and the analyses made with this model are conceptually different from other (agent-based) approaches to climate economics. It is not aimed to study mutual climate-economy feedbacks or (at least not primarily) to evaluate the cost-effectiveness of different climate policies. Instead, it is aimed to open the "black box of technology" a little bit further and to understand how emerging patterns of transitions unfold.

The macroeconomic structure of the modeling approach allows studying the technological evolution and associated economic side effects reflected in the aggregate output, productivity, market structure and the distributional outcome. These side effects are important to evaluate the degree of disruptiveness of technological change.

1.1.3 How does this thesis embed in the literature?

Before outlining the content of this thesis in detail, it is worth acknowledging the theoretical and methodological antecedents of this work. The research question and the methodology in this thesis are different from the neoclassical, equilibrium-based studies in climate economics and directed technological change, but this thesis does also have many overlaps. This thesis is inspired by and builds on theories and thoughts of past and ongoing research on endogenous growth, technological change, innovation and technological learning.

Debates on the role of technology for future resource dynamics date back to the early days of system dynamics. In the 1972s, Meadows et al.'s *Limits to growth* was the first systematic, computational approach to analyze the dynamic interplay between growth and resource exploitation trajectories. The authors showed that their scenarios are very sensitive to the assumptions of technological progress.

Early attempts to take account of technology in simulation and climate assessment models included technological improvements as quasi-autonomous processes or exogenous backstop technology shocks (see for an overview Löschel, 2002; Sarr and Noailly, 2017). This is a useful simplification to improve the predictions of climate-economic models, but this approach presumes that future technological pathways can be reliably estimated. Moreover, these approaches do not explain the *sources* of technological change and help to identify the scope for policy to influence the pace and direction of technological development (Köhler et al., 2006).

In this context, the distinction between different types of technology is critical. Theories of directed technological change are based on the idea of induced innovation acknowledging that relative prices may influence the allocation of R&D efforts and steer the direction of research (Popp et al., 2010).

A major research gap, that was addressed in the early 2000s, is the lack of micro-foundations that link the activities of individuals to the process of technological development. A major contribution was Acemoglu's (2002) model of directed technical change that built the foundation of a series of follow-up works that incorporated endogenous directed technological change into the macroeconomic analysis of climate policy (e.g. Acemoglu et al., 2012; Hart, 2019; Lemoine, 2018). These theoretical refinements were addressed in a surge of empirical studies aimed to gain a deeper understanding of the nexus of climate policy and innovation (Popp, 2019).

These theories search for explanations of the origins of technological development. But technological innovations are only one side of the coin. Technologies do not only need to be developed. Technologies also need to diffuse to have an impact. A second stream of research on the nexus of technology and climate change has elaborated the reasons why diffusion can be sluggish and how this might be stimulated by policy. Typical reasons for sluggish diffusion are, for example, investment cycles, the imperfect spread of information and/or heterogeneous benefits of adoption. An overview of theoretical approaches and empirical approaches to the study of green technology diffusion and its relation to climate policy is provided by Allan et al. (2014).

Technology development and technology diffusion are inherently linked. Technology diffusion increases the market size of a technology and the amount of R&D resources available. Higher R&D investments stimulate innovation and technical improvements. On the side of technology users, learning effects may improve the effective usability of a technology. Both may stimulate the demand further. These self-reinforcing dynamics are difficult to capture analytically. Small events may have extreme effects. Heterogeneity and interactions at the mirco-level need to be understood to explain how emergent patterns in the technological evolution (Dawid, 2006). Mutual feedbacks may also have a qualitative dimension. Feedback from technology users influences the direction and type of improvement that is pursued by developers. Innovations may alter user practices and the meaning of technology in users' everyday life (Di Stefano et al., 2012; Geels, 2004; Safarzyńska et al., 2012). In this thesis, I will not address this qualitative dimension of mutual feedback. However, this is partly a matter of interpretation.[6]

The methodological basis of this dissertation was laid by a whole generation of computational economists. Their seminal work created a new powerful toolbox for economic analysis that enables and supports new and more heterodox ways of economic reasoning. Methodological improvements in model calibration, validation and technical tools of simulation and analysis contributed to the wider acceptance of ACE as a new paradigm in economic theory. Good overviews of the methodological debates, developments and foundations of ACE are provided by the Handbooks of Computational Economics Volume 2 and 4 (Hommes and LeBaron, 2018; Tesfatsion and Judd, 2006). This thesis benefited substantially from these early contributions, particularly those in agent-based macroeconomics (Dawid and Gatti, 2018).

Within the broad field of ACE, this thesis profited particularly from the achievements of a large-scale European research project with the name *EURACE - 'An Agent-based Software Platform for European Policy Design with Heterogeneous Interacting Agents: New Insights from a Bottom-Up Approach to Economic Modeling and Simulation'*. Within this project (2006-2009), a group of economists and computer scientists developed an agent-based macroeconomic simulation toolbox consisting of software, programming environments and a large-scale, empirically calibrated macroeconomic simulation model that can be used for different types of economic policy analysis (Deissenberg et al., 2008).

[6]But it becomes critical if the theoretical concepts used in this thesis are brought to empirical data. The eco-innovation concept might be a useful approach to reducing the definition of a green technology to its environmental performance compared to the status quo (cf. Rennings, 2000). However, this is an intrinsically dynamic definition that is not easy to bring to data across a longer time horizon.

The *Eurace@unibi* model, that is the methodological basis of this dissertation, is one of the outcomes of this project. It provides a macroeconomic environment that is constructed from the bottom-up. Macroeconomic aggregate variables and dynamics are explicitly deduced from the interactive and adaptive behavior of heterogeneous agents. This provides a modeling environment that is well suited to study processes of learning, adaptation to change but also macroeconomic, distributional and structural consequences associated with technological change (Dawid et al., 2019b).

1.2 Outlook on this thesis

A transition to climate-friendly technology can be thought as a large scale substitution process in which an incumbent technology is replaced by a new one. The aim of this thesis is to understand the mechanisms that drive the process of technology substitution and its macroeconomic side effects. This understanding is crucial for the development of political instruments that accelerate the transition to green technologies and smoothen disruptive consequences.

1.2.1 Major contributions

The general contributions of this thesis can be grouped into a methodological and theoretical part. Methodologically, I contribute an agent-based evolutionary approach to study technology transitions at the macroeconomic level. The potential of evolutionary, economic ABMs in the nexus of climate and innovation economics has been extensively discussed in recent years (Balint et al., 2017; Ciarli and Savona, 2019; Farmer et al., 2015; Safarzyńska et al., 2012; Stern, 2016) and an increasing number of climate-economic ABM became available (see Balint et al., 2017; Ciarli and Savona, 2019, for a review). But the full potential of the flexible and microeconomically granulate modeling framework of ABMs to address the complex nexus of socio-technical transitions and the economic implications of climate change is still far from being exploited. The approach introduced in this thesis addresses one particular aspect of climate economics. That is technological change.

Technological change is studied with a green technology extension of the *Eurace@unibi* model that forms a major methodological contribution of this thesis. I extended the original model in mainly five dimensions. (1) I introduced two heterogeneous types of production technology. One of them is interpreted as a *green* technology, the other is called *conventional*. Firms' production technology is two-dimensional. A *tangible* dimension is embodied in physical capital goods that are traded on a market. A second *intangible* dimension is embodied in the technological capabilities of firms. These capabilities are not tradable. (2) Technological capabilities are modeled as the aggregate of firm's employees who are endowed with evolving technology-specific skills. These skills are needed to work effectively with a specific type of capital goods. Skills are learned during work. The pace of learning is dependent on the type of physical capital that is used by the firm where the household is working. (3) Firms decide whether to invest in green or conventional capital dependent on the technological capabilities of employees, available technology options and the market environment. (4) An environmental accounting keeps track of the environmental impact of final goods sector. (5) A policy module allows to investigate the impact of different diffusion policies.[7]

The key difference compared to the original model is the heterogeneity of technology and the associated amendments in the type-dependent process of learning and investment. The model extension allows to study topics of directed technological change, innovation diffusion and technology substitution processes. A key feature of the model is endogenous, technology-specific absorptive capacity of heterogeneous technology adopters that evolves through learning.

The comprehensive, macroeconomic framework of the *Eurace@unibi-eco* model introduced in this thesis is well suited for transition studies for mainly two reasons. First, the granulate nature of agents' decision making routines allows a detailed view of individual adoption behavior of heterogeneous agents. Technology-adopting firms are differently endowed with technology-specific skills. These skills are learned over time and enable firms to make effective use of new technology. This explicit representation of technological capabilities allows investigating sluggish processes of green technology diffusion and evolving heterogeneity of firms' capacities to cope with changing technological environments.

Second, the comprehensive and consistent link between the behavior of individual agents and emergent patterns at the macroeconomic level allows investigating the economic consequences of transitions. For example, it is possible to study the impact of different transition patterns on aggregate output, productivity growth, market structure and even the distributional consequences. This allows developing consistent explanations for the emergence of new technology, agents' responses and macroeconomic evolution.

The second major contribution of this thesis is a theoretical one. The time for effective climate change mitigation is short. In this thesis, I study and evaluate pathways along which a technology transition might evolve. Recent studies in climate science are sufficiently alarming to justify the urgent need for radically transforming patterns of consumption and production (Steffen et al., 2018). The need is widely recognized by policymakers, but adopted measures are insufficient (Hagedorn et al., 2019; Rogelj et al., 2016).

[7] A comprehensive documentation of the model extension is available in the supplementary material I. A summarized comparison of the extended model to the original version can be found in table 2.A.1.

This thesis searches for explanations why the transition appears to be so difficult. It focuses on aspects of *feasibility, acceleration and governance* of a transition from an economic perspective. This perspective raises different questions compared to the theoretical contributions that search for optimal policy. Given the deep uncertainty about climate change effects and the dynamics of socio-technical change, this is a pragmatic approach that seeks to improve the understanding of socio-technical abatement pathways and their technical and societal feasibility.

In this thesis, I do not study mutual climate-economy feedbacks but use the climate-induced need for technological change to motivate the research questions and to reject the assumption of technological neutrality. However, the proposed theory of technological change and the model are general and can be straightforwardly applied to other topics of directed technological change, e.g. digitization, economic development and convergence.

1.2.2 Structure and outlook

This thesis is composed of this general introduction, three main chapters and a short conclusion. The three main chapters focus on different aspects of socio-technical transitions. The series of chapters incrementally generalizes the theoretical perspective on technological knowledge and its relevance for transition dynamics.

Each of the chapters is a self-contained research article that consists of a theory part and a simulation study using *Eurace@unibi-eco*. Each chapter has a separate appendix that includes all necessary information to ensure the self-containedness. The model descriptions in the chapters are kept as short as possible. In addition to the main chapters, this thesis contains two sections with supplementary material (SM) that provides a more comprehensive, self-contained model documentation (SM I) and some technical detail about the statistical analyses in chapter 3 and 4 (SM II). The documentation has been published as an independent working paper (Hötte, 2019d). It explains the full model and elucidates in detail the link of the model extension to the underlying baseline model *Eurace@unibi* (Dawid et al., 2019b).

As a stylized model, the process of a technology transition can be thought as a dynamical system composed of two interdependent dynamical functions, ν^g and π^g with ν^g having values in $[0, 1]$. A diffusion curve, represented by ν^g, describes the share of green technology use in relation to a conventional incumbent. If the green technology g is not used, $\nu^g = 0$. This is the initial state when the green technology is not yet available, but this may also describe a situation in which the economy is locked in the incumbent technology. A green transition has occurred, if $\nu^g = 1$, i.e. if only the green technology is used. The diffusion curve

$$\nu^g = f(\pi^g, t)$$

is a function of time t and the relative superiority of the green technology π^g.

The relative use of a technology in the economy changes over time when depreciating physical artifacts are replaced by newer versions or if the economy grows and new capacities are installed. When agents are faced with investment decisions, they may choose between different technology options. Their choice is dependent on the relative superiority of a technology type, i.e.

$$\frac{\partial \nu^g}{\partial t} = g(\pi^g)$$

where π^g as relative superiority of the green technology.[8] If the green technology is superior compared to the incumbent, it is adopted and the share of green technology use increases, i.e. $\frac{\partial \nu^g}{\partial \pi^g} > 0$ if $\nu^g < 1$ and π^g is sufficiently high.

The relative superiority π^g is a bundle of features that determine the relative profitability of using green technology. For example, π^g may reflect the relative productivity of green machinery. It can also capture input costs required to use or produce green or conventional machinery, regulatory compliance costs or consumer preferences for products produced with green machinery. In this thesis, I study the determinants that influence the evolution of the relative superiority. Throughout the chapters, I incrementally introduce different groups of variables that matter. These groups of variables can be used to describe competing technologies.

In chapter 2, I introduce a first group represented by relative, *cumulative* endowments with technology-specific knowledge κ^g. Technology-specific knowledge is embodied in technical innovations, physical installments and productivity but also in technology users' skills. These skills are learned by using a specific technology and allow to make effective use of a technology type. Relative knowledge is one determinant of π^g with $\frac{\partial \pi^g}{\partial \kappa^g} > 0$. For example, if the technical productivity of green capital or if users' relative skill endowments are high, the realized *relative* performance of green capital is also high. The evolution of κ^g over time t is dependent on the market share of green technology ν^g, i.e. $\frac{\partial \kappa^g}{\partial t} = \ell(\nu^g, \cdot)$. The higher the market share, the faster is the pace of relative knowledge accumulation. If a technology is used intensively, its users learn how to use it. A higher market share does also coincide with a higher availability of financial resources that are invested in R&D that contributes to the technical improvement of a technology. In chapter 2, I study the role of initial endowments with κ^g for the process of technology diffusion. Lower endowments with cumulative knowledge stocks may be a barrier to diffusion for new technologies.

The evolution of relative technological knowledge $\frac{\partial \kappa^g}{\partial t} = \ell(\nu^g, \chi)$ is also dependent on the properties χ of competing technologies. These properties χ affect the pace at which relative technological knowledge is accumulated.

[8] Note that many relevant aspects, e.g. depreciation rates and stochasticity, are neglected in this stylized model for the sake of a simpler representation.

For example, some technologies are easy to learn and knowledge is accumulated fast. Technologies may be also described by the similarity to their competitors. If technologies are similar, accumulated technological knowledge is applicable to both technology types. These properties moderate the influence of ν^g on the pace of relative knowledge accumulation. If the similarity is high, both knowledge stocks grow if one technology is used and the *relative* endowment with knowledge κ^g changes only slowly. These properties describe cross-technology interactions in the learning process and are studied in chapter 3. This second group of variables, called *interactive* properties χ, determines the pace at which relative endowments with technological knowledge diverges. The divergence coincides with a divergence in the relative superiority of competing technologies. This is a driver of technological specialization in the economy.

Taking chapter 2 and 3 together, the evolution of technological knowledge can be described by a dynamic function

$$\frac{\partial \kappa^g}{\partial t} = \ell(\nu^g(\pi^g, t), \chi).$$

Relative technological knowledge κ^g is not the only determinant of the relative superiority π^g. Technologies are used in a specific economic and societal context that determines the value of specific properties of a technology. For example, an environmentally friendly technology is only more valuable than a conventional one, if the society has a preference for a sound environmental quality. A technology, that saves material input requirements, is only valuable if material inputs are costly. Preferences and input costs can not be influenced directly by technology users and developers. These exogenous properties ξ, introduced in chapter 4, make up the third group of variables that influence the dynamics of transition.

The dynamical system composed of these three groups of properties can be described by

$$\nu^g = f(\pi^g, t) \quad \text{and} \quad \pi^g = h(\kappa^g(\nu^g, \chi, t), \xi, t)$$

and the differential equations introduced above.

This is a deterministic representation that is aimed to introduce the main concepts but neglects stochasticity. In reality and throughout the analyses in this thesis, the dynamical system entails stochastic elements at the microeconomic level which may tip the technological evolution into one or the other direction. In the following, I explain how the conceptual aspects are operationalized in the three main chapters of this dissertation.

Chapter 2: ***How to accelerate green technology diffusion? Directed technological change in the presence of coevolving absorptive capacity***

In this chapter, I study the evolution of technological knowledge and investigate the role of different types of diffusion barriers. In the terminology of the framework above, I study $\frac{\partial \nu^g}{\partial \kappa^g}$ and the feedback effects of ν^g on the evolution of κ^g as source of path dependence of technological change.

Path dependence is one explanation for the sluggish diffusion of green technologies. Heterogeneous firms acquire capital that differs by technology type and build up type-specific technological know-how needed to use capital efficiently. Type-specific know-how can not be bought on the market but needs to be learned. The learning process is dependent on the intensity to which a firm is using a specific type of technology. It is a source of heterogeneous benefits of technology adoption at the firm level.

Path dependence emerges from cumulative stocks of technological knowledge manifested in the productivity of supplied capital and firms' capabilities. Increasing returns arise from induced innovation and learning by doing. Relatively lower endowments of technological knowledge are a barrier to diffusion for new technologies. This chapter gives a short introduction to the implementation of these mechanisms as a green technology extension in the *Eurace@unibi* model.

The model is used to generate a sample of simulated diffusion curves. I show how the evolution of relative stocks of technological knowledge can explain the shape of these curves. Over time, the economy converges to one of two possible technological regimes in which only one of the two technologies is used. Technological uncertainty is macroeconomically costly if learning and R&D resources are wasted for a technology that is obsolete in the long run.

In an experiment, I analyze how the effectiveness of diffusion policies depends on the type and strength of barriers. Environmental taxes can outweigh lower productivity and subsidies perform better if lacking capabilities hinder firms to adopt a sufficiently mature technology.

This paper contributes a theory of coevolving absorptive capacity to the literature on directed technological change. The problem of sustainability transitions is reframed as a coordination problem among heterogeneous adopters. This is a methodologically and theoretically new approach in climate economics.

Chapter 3: ***Skill transferability and the stability of transition pathways - A learning-based explanation for patterns of diffusion***

In the first paper, I have shown that the accumulation of technology-specific know-how at the firm-level drives the stabilization of a diffusion process and reduces uncertainty about the future technological state. Learning is one key mechanism of the technological specialization process. In this chapter, I study the determinants of technological learning that were called *interactive* properties χ in the conceptual model above.

More specifically, I address the effects of skill transferability for technology adoption behavior at the firm-level. Technological know-how is necessary to make effective use of new machinery. Firms accumulate know-how when working with specific machinery. Technological know-how can be transferable across technology types if competing technology types are sufficiently similar. Radical innovation differs by technology type and the transferability of knowledge is low.

Based on the empirical and theoretical innovation literature, I introduce the microfoundations of technological learning in the *Eurace@unibi-eco* model. In a simulation study, I show that a high transferability of skills has ambiguous effects. It accelerates the diffusion process initially but comes with the cost of technological uncertainty and retarded specialization in the long run. For firms, it is easy to adopt new technology, but it is also easy to switch back to the incumbent type.

In the existing literature, microeconomic models of technological learning at the firm-level are scarce. This paper introduces a formal theory of learning and shows its implications for emerging, macroeconomic patterns of diffusion. This type of analysis and the results are a novelty in the literature on macroeconomic technological change.

Chapter 4: ***Pathways of transition and the characteristics of competing technology: A taxonomy of technologies and a policy experiment***

In the first papers, I have shown that the characteristics of competing technologies and external conditions help to explain the shape of diffusion curves. Diffusion curves are a formal representation of transition pathways. Empirically, pathways of transition differ across countries and technologies. Sometimes, new technologies are rapidly taken up, sometimes these processes are very unstable and associated with disruptions in the market structure. In other cases, economies or industries are locked in the incumbent technology.

Technology diffusion is not only dependent on the relative endowment with technological knowledge κ^g and its accumulation. The relative performance of a specific technology option also depends on external conditions ξ. Understanding the reasons for observed differences in transition patterns can be important to develop effective transition policies and to gain an intuition for the macroeconomic side effects.

In the this chapter, I propose a unifying framework that reconciles the different concepts introduced in the preceding chapters and develop a taxonomy to characterize technologies. The taxonomy is linked to the multi-level perspective (MLP) of transition theory which is a widely used conceptual framework for historical and empirical transition studies (cf. Köhler et al., 2019; Lachman, 2013). This framework conceptualizes transitions as dynamic coevolutionary processes in which emergent niche technologies possibly replace an incumbent socio-technical regime. External conditions of the so-called socio-technical landscape operate in favor of or against entrant technologies.

The typology, introduced in this chapter, reflects the properties of technology in a landscape and the relative maturity of an emergent niche technology. Interactions in the process of technological specialization depend on the transferability of accumulated complementary skills and infrastructure. This is a generalization of the technology concept of the *Eurace@unibi-eco* model and an economic interpretation of the MLP. I illustrate how the characteristics of competing technologies can explain emergent transition pathways and discuss empirical examples.

Policies may alter the external landscape conditions of the technology race. In a policy experiment, I demonstrate how different market-based instruments can be used to speed up and stabilize a transition pathway. Taxes and subsidies perform differently conditional on the characteristics of competing technologies.

The simulation results help understanding why transition pathways and the effectiveness of policies differ across countries and technology groups. These insights are crucial for policy design. The lack of formalization and vagueness is a weakness in existing approaches to transition studies (Lachman, 2013). This paper adds a theoretical framework for transition studies that can be used to systematize and formalize empirical data and to think about technology transitions in economic termini.

1.2.3 Associated publications

At the time of writing this thesis, a slightly different version of chapter 2 has been (online) published by *Energy Economics* (Hötte, 2019e). Chapter 3 and 4 have been submitted to journals and the decisions are pending. Comprehensive versions of the results presented in the chapters are published in two working papers (Hötte, 2019b,f), in one technical paper, that documents the model (Hötte, 2019d), and three data publications to ensure transparency and reproducibility of the analyses (Hötte, 2019a,c,g).

Chapter 2

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

2.1 Introduction

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

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

In this paper, path dependence at the microeconomic level is integrated into a macroeconomic model of directed technological change. This systematic approach helps to understand how green transitions can be accelerated.

Based on empirical and theoretical insights of the evolutionary innovation and macroeconomic directed technological change literature, a microeconomic model of technological learning is developed. Capabilities of firms are accumulated over time during production. The model is implemented as an eco-technology extension of the macroeconomic agent-based model (ABM) *Eurace@unibi* (Dawid et al., 2019b; Hötte, 2019d). Evolving capabilities of heterogeneous firms determine whether firms can profitably adopt clean technologies.

Path dependence is decomposed into supply- and demand-side diffusion barriers embodied in the productivity of supplied capital goods and absorptive capacity of heterogeneous adopters. Absorptive capacity is the capability to make effective use of a specific technology.

Technology is heterogeneous by type (green or brown). Firms choose between types when acquiring capital goods and build up type-specific technological know-how needed to exploit the productive potential of capital. Path dependence arises from cumulative knowledge stocks manifested in the productivity of supplied capital and firms' capabilities. Increasing returns in knowledge accumulation arise from positive feedback loops of market-induced innovation and learning by doing.

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

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

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

Four key results are derived from this first analysis:

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

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

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

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

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

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

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

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

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

The remainder of the paper is structured as follows: In section 2.2, the paper is motivated by a survey of the related literature. In section 2.3, the main features of the eco-technology extension of the *Eurace@unibi* model and the design of experiments are introduced. The results of the baseline simulation and a series of experiments on the technological starting conditions of the entrant technology are presented in section 2.4. It is discussed how the mechanisms underlying the simulated diffusion curves can explain diverse empirically observed patterns of diffusion. Section 2.5 is dedicated to the policy experiments. Section 2.6 concludes.

2.2 Background

On the theoretical level, this paper links the macroeconomic literature on endogenous and directed technological change with evolutionary, microeconomic studies of technological learning. It focuses on the interplay between technological change and the effectiveness of climate policy.

Methodologically, the paper belongs to the field of evolutionary, agent-based macroeconomic analyses of climate policy.

2.2.1 Directed technological change as evolutionary process

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

In the evolutionary literature of innovation and technological change, adaptive behavior and interactions at the microeconomic level are a source of emerging patterns of innovation, diffusion and technological change at the macro level (Balint et al., 2017; Farmer et al., 2015).

Technological change is driven by the coevolution technological development and learning of interacting agents subject to bounded rationality and group dynamics. Path dependence and lock-in effects may occur (Safarzyńska et al., 2012).

The economic environment influences the decisions of investors whether an invention is introduced on the market (Dosi, 1991; Foxon and Andersen,

2009) and captures regulatory, infrastructural, technological and behavioral aspects (Safarzyńska et al., 2012).

In this study, the economic environment is understood as all factors that enable or hinder firms to adopt climate-friendly production techniques. Potential adopters are faced with firm-, industry- or region-specific challenges that arise from accumulated infrastructures, technological capabilities and behavioral routines (Arundel and Kemp, 2009). *Absorptive capacity* describes firms' ability to make use of specific technological novelties (Cohen and Levinthal, 1990). It influences the perception and value of a technological solution, and may be a source of heterogeneous adoption patterns (Allan et al., 2014).

Here, absorptive capacity is interpreted as firms' *tacit* knowledge required to use a specific technology effectively. These capabilities are tacit because they can not be traded on the market (Cowan et al., 2000). Tacit knowledge is heterogeneous across firms. Insufficient capabilities and limited transferability of capabilities across technology types can be a barrier to adoption (Arundel and Kemp, 2009).

The decisive property of absorptive capacity and addoption barriers is the cumulative nature, not the conceptual coverage. The accumulation of technology-specific capabilities depends on the extent to which a specific technology type is used. This is a microeconomic source of increasing returns to adoption (Arthur, 1989; Dosi and Nelson, 2010).

2.2.2 Technological change in macroeconomic models of climate change

The dynamics of technological change are critical for the effectiveness and costs of climate policy. A comprehensive overview of early approaches to incorporate directed technological change into climate economics and simulation models is provided by Grübler et al. (2002) and Löschel (2002). In early approaches, directed technological change is quasi-autonomous and explanations about the origins of green technology development was lacking.

Acemoglu (2002) closed this gap and integrated a microeconomically founded theory of the R&D market into an analytical, macroeconomic general equilibrium framework. This work built the basis for a subsequent climate-economic applications and studies of innovation-led transitions to green technology (Acemoglu et al., 2012; Lamperti et al., n.d.; Lemoine, 2018).

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

Seminal approaches in macroeconomic agent-based climate policy modeling were made by Gerst et al. (2013); Lamperti et al. (2018b); Rengs et al. (2015); Wolf et al. (2013). Their models focus on different aspects related to the nexus of climate, the economy and policy. Haas and Jaeger (2005) and Wolf et al. (2013) modeled technological change as a process of imitation and mutation which is interpreted as innovation, and endogenous dynamics of differential R&D investments.

The ENGAGE model, proposed by Gerst et al. (2013), focuses on the energy sector. Technological change from learning by doing and accumulated R&D efforts is manifested in energy efficiency and productivity improvements of capital goods.

Rengs et al. (2015) focuses on the evolution of consumer behavior and the interplay of Veblen- and snob-effects steering the development of consumers' preferences for sustainable products.

A very recent contribution is the integrated assessment approach introduced by Lamperti et al. (2018a). It captures coevolutionary features of the economy and potential feedbacks from climate change. Endogenous growth emerges from different types of incremental innovation. The authors analyzed how different policies affect the probability of a green transition (Lamperti et al., 2018b).

Monasterolo and Raberto (2019) extended a behavioral Stock-Flow consistent model by an energy module to study the effect of phasing out of fossil fuel subsidies on energy transition dynamics.

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

2.3 The model

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

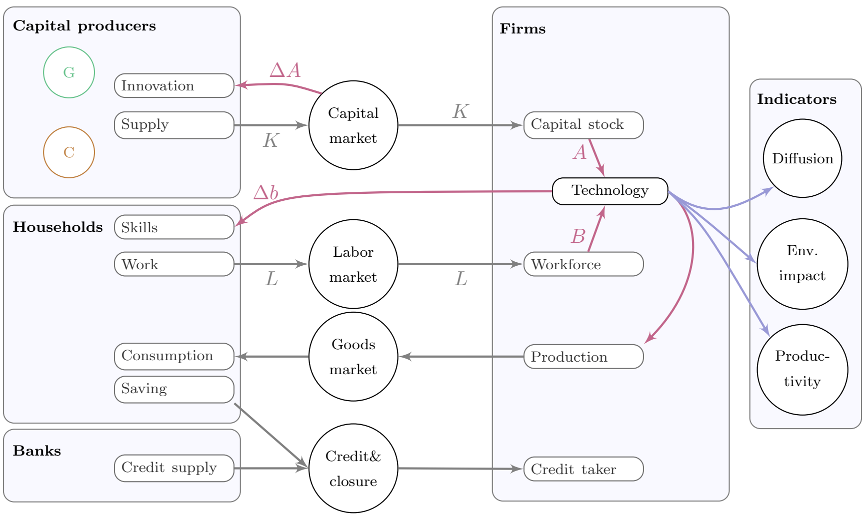
In the following subsections, I sketch the main structure of *Eurace@unibi* and introduce the eco-technology extension of the model schematically. A concise technical introduction to the model extension including the relevant equations is available in the appendix 2.A.

The *Eurace@unibi* baseline model is extensively documented in Dawid et al. (2019b). A self-contained description of the eco-technology extension and its linkage to the baseline model is available in the supplementary material (SM) I. The full code of the model is available in a data publication (Hötte, 2019a).

2.3.1 Overview of the macroeconomic structure

The *Eurace@unibi* model represents a macroeconomy composed of different groups of heterogeneous agents that are linked by their trans- and interactions on different markets and by mutual flows of information. The most relevant agents are depicted in figure 2.1. Heterogeneous households supply labor on the labor market to consumption goods (CG) producing firms. They spend their income for consumption and savings. Households differ by income and skill endowment b. CG firms use labor L and capital K to produce a homogeneous consumption good. Employees of a firm need to know-how to use capital goods for production. This know-how is captured by employees' specific skill level. The average skill level of a firm's workforce is a proxy for the technological capabilities B of the firm. Capital or investment goods (IG) are supplied by two heterogeneous IG firms, each representing a specific technology type. Each of them supplies a range of vintages with different productivity levels A. Probabilistic, incremental innovation enables IG firms to bring more productive capital goods to the market.

FIGURE 2.1: Macroeconomic structure of *Eurace@unibi-eco*



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

Capital goods differ by productivity and technology type. One of the two IG producers supplies a climate-friendly, *green* technology, the other supplies an environmentally harmful, *conventional* alternative. Both IG producers invest part of their revenue in R&D activities. Monthly R&D spendings positively affect the probability of innovation success. Successful innovation is associated with an upwards shift of the IG producer-specific technological frontier.

If an IG producer successfully innovates, the productivity of supplied capital is multiplied by a factor of $(1 + \Delta A)$.

Dependent on the productive properties of capital and firms' technological capabilities, CG firms make investment decisions and buy capital goods on the capital market.

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

Firms can apply for credit from banks to cover current expenditures and to finance investment if their own financial means are insufficient. The financial market is used as a technical tool to ensure the macroeconomic and financial closure of the model.

A government (not shown in figure 2.1) has a re-distributive and regulatory function. It collects income from taxes and pays unemployment benefits. The government may also impose different (climate) policies.

Firms' market exit is endogenous. Firms that are unable to repay loans go bankrupt and exit the market. New firms are founded at random and build up production capacities out of an initial monetary budget (see Harting (2019)).

The transactions between the agents are stock-flow consistent. Agents behave boundedly rational, have limited foresight and incomplete information. Decision making, information updating processes and routines are asynchronous. This is a source of stickiness of prices, wages and production decisions.

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

2.3.2 The eco-technology extension of *Eurace@unibi*

The model extension focuses on endogenous innovation dynamics of competing technologies supplied by two representative capital good producers.

Competitive innovation dynamics are modeled as a technology race between an incumbent, *conventional* technology c and an entrant, *green* technology g. The use of the conventional technology is environmentally harmful and requires costly material and energy inputs.

The green technology is environmentally neutral and allows adopters to reduce material input costs. It is potentially technologically superior in the long run. More generally, technological superiority is a reduction in unit production costs. This reduction is enabled by radical innovation and not achievable by the incumbent technology.[1]

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

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

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

Tacit knowledge is represented by technological capabilities $B^{ig}_{i,t} = \sum_{h \in L_{i,t}} b^{ig}_{h,t}$ of CG firm i where $b^{ig}_{h,t}$ are the technology-specific skills of employees $h \in L_{i,t}$ in time t. Technology-specific skills are needed to make effective use of the

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

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

[3]$K^{ig}_{i,t}$ is the *used* capital stock of type ig. The total used capital stock $K_{i,t} = \sum_v k^v_{i,t}$ is composed of different vintages and different technology types $ig = c, g$. Firms do not necessarily produce at full capacity. If estimated demand is insufficient, firms use only the most cost-effective capital stock items. Learning and the environmental impact are dependent on the *used* capital stock. More technical detail is available in the appendix 2.A.

productivity embodied in a capital good A^v. Employees need to know-how to use a specific type of capital efficiently.

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

The codified knowledge embodied in a capital vintage is uniform for all firms, but the tacit knowledge is firm-specific. It is interpreted as a firm's absorptive capacity for a specific technology. Henceforth, the bundle of codified and tacit technological knowledge of firms is referred as to *effective* productivity $A^{Eff_v}_{i,t}$.

The effective productivity is bounded above by the availability of matching technological capabilities, hence $A^{Eff_v}_{i,t} = \min[A^v, B^{ig}_{i,t}]$ with index v as pointer to a specific vintage in the firm's capital stock.

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

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

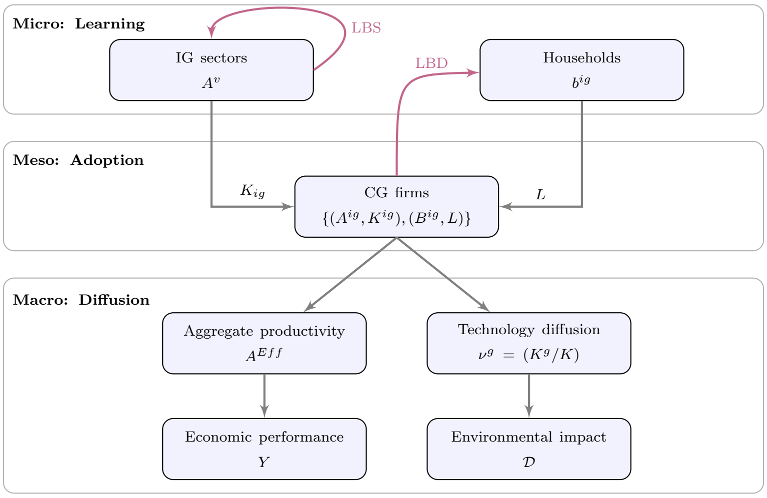
These barriers are stylized aggregates of different types of diffusion barriers documented in the empirical literature on eco-innovation (cf. Arundel and Kemp, 2009; Carlsson and Stankiewicz, 1991; Triguero et al., 2013). Diffusion barriers can be the source of a *technological lock-in* in the conventional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

Two types of learning dynamics influence the evolution of diffusion barriers.

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

Second, IG firms are *learning by searching*. Endogenous innovation in the IG sector affects the codified part of technological knowledge embodied in the productivity level of supplied capital. IG firms invest a fraction of monthly

FIGURE 2.2: Innovation, learning and diffusion schematically



profits in R&D. Monthly R&D spendings positively affect the probability to innovate successfully and launch a new, more productive capital vintage on the market. Higher profits in sector ig are associated with a faster pace of technological progress in this sector.

A stylized representation of technology, the learning mechanism and the role of technology for the macroeconomic outcome is shown in figure 2.2. The formal implementation including equations is explained in more detail in the appendix 2.A.

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

The entrant technology is subject to diffusion barriers. These barriers are effective in two ways. At the day of market entry t_0, the entrant IG firm g produces at a lower technological frontier A^V_{g,t_0} where V indicates the most productive vintage supplied by an IG firm. Vintages supplied by the green entrant have lower productivity than those supplied by the incumbent.

Further, the green technology is new to firms and employees have not yet learned how to use the new technology. They have a relatively lower endowment with technology-specific know-how b^g_{h,t_0} for green capital utilization.

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

$$A^V_{g,t_0} = (1 - \beta^A) \cdot A^V_{c,t_0} \tag{2.1}$$

where $\beta^A \in [0,1)$ is the percentage technological disadvantage of green technology at the day of market entry.

It is assumed, that the market entry of the green technology was associated with a technological breakthrough that enables the rapid development of a full range of varieties of green capital that differ by productivity (cf. appendix 2.A.4).

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

The green capital is supplied at the same prices as incumbent capital in t_0, but the price *per productivity unit* is higher due to the assumed technological disadvantage.

The initialization of technology-specific skills for green capital utilization is similar. Households' endowment with green skills is scaled in relation to its skills for conventional technology use, i.e.

$$b^g_{h,t_0} = (1-\beta^b) \cdot b^c_{h,t_0}. \tag{2.2}$$

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

2.3.3 Simulation settings and experiments

The simulations are run with $H = 1600$ households, two IG firms, two private banks and up to $I = 120$ CG firms. Because CG firms can enter or exit the market, the number of CG firms can vary over time. At the initialization period, the number of active CG firms was determined by the calibration process and is 74.[5] The simulations are run for $T = 15000$ iterations corresponding to approximately 62.5 years interpreting one iteration as a working day and a year to consist of 240 working days.

The runs were repeated 210 times to generate a sufficiently large sample of simulated economic data that can be analyzed. At the beginning of the simulations, the conventional technology is incumbent. After $t_0 = 600$ iterations,

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

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

TABLE 2.1: Empirical stylized facts for model design and validation

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

The macroeconomic validation scenario are a selection of criteria used and described in more detail in Dawid et al. (2018b). More information about the validation procedure and a demonstration how the criteria are matched by the model is provided in the appendix 2.B.

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

Later, these assumptions are relaxed in a series of experiments about drivers and barriers to diffusion, and their interplay with innovation oriented climate policy. In this analysis, it is assumed that there are moderate cross-technology spillovers in the learning process. Part of the knowledge that is learned during the utilization of a technology type is transferable to the use of other technology. Transferable skills are those that coevolve with technological progress, but are independent of the technology type, for example, computer skills. An in-depth analysis of the role of learning spillovers for technology choice and the evolution of market structure is subject to the analysis in chapter 3.

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

An overview of the macroeconomic patterns that are matched by the model is provided in table 2.1. A more detailed explanation of these criteria, technical details and test results is provided in 2.B. Most of the parameter values are taken from the original *Eurace@unibi* model. More detail on the calibration of the original model can be found in Dawid et al. (2018b).

Table 2.1 also provides an overview of stylized facts of innovation that have been used for the *technological* conceptualization of the model. It is briefly mentioned how the model satisfies these criteria. More comprehensive information can be found in Hötte (2019b) and the SM I.

2.4 Results

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

In this section, I describe the core features of the baseline scenario. Subsequently, I present the results of an experiment on the strength of barriers and explain how the observed patterns coincide with empirical observations.

In the next section, it is analyzed how market-based policies can accelerate the process of a green transition.

2.4.1 The baseline scenario: Two possible technological regimes

In the simulations, entry barriers are sufficiently low such that the green technology outperforms the conventional in terms of effective using costs. Initial adoption rates are high and the green technology incrementally diffuses.

Technology diffusion is measured by the aggregate share of conventional capital that is used in t. It is given by $\nu_t^c = \frac{\sum_i K_{i,t}^c}{\sum_i K_{i,t}}$ with $K_{i,t}^{ig}$ as amount of capital of type $ig = c, g$ that *used* by firm i in t and $K_{i,t} = K_{i,t}^c + K_{i,t}^g$.[6] By design, the share of conventional technology use is 100% on the day of market entry, i.e. $\nu_{t_0}^c = 1$.

Figure 2.3 illustrates the evolution ν_t^c. On the left-hand side, ν_t^c is shown as an average across runs. On the right-hand side, it is shown for single simulation runs. It can be seen that the average across runs hides a pattern of divergence and uncertainty in the technology choice.

The disaggregated plot illustrates that the phase of initial green technology uptake is not necessarily sustainable. In the beginning, in almost all runs, the ν_t^c decreases, but in roughly half (49%) of the considered cases initial diffusion reverses after some time and ν_t^c converges to a lock-in state with roughly 100% utilization of conventional capital.

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

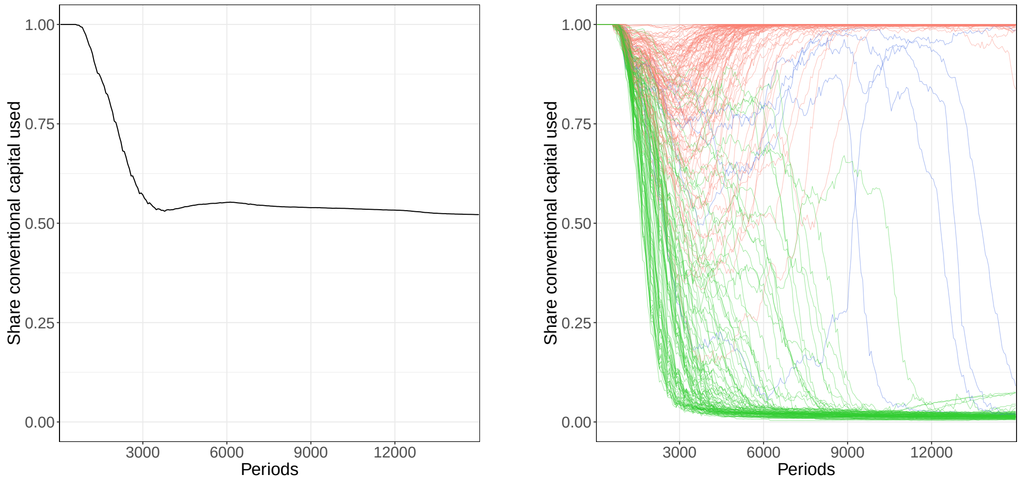
The final technological state is interpreted as "technological regime" defined by the dominance of a technology type measured at the *intensive margin*.

Definition
*A **technological regime** is defined as set of runs that match the threshold condition of* 50%, *i.e.* $r^{eco} = \{r \in R/\{r^{switch}\}|\nu_{T,r}^c < .5\}$ *and* $r^{conv} = \{r \in R/\{r^{switch}\}|\nu_{T,r}^c \geq .5\}$. *$r$ is a single run out of the full set of runs R and r^{switch} is a special case introduced below. A **regime shift** or* green transition *is defined as situation where the incumbent conventional technology is replaced by the entrant green until the end of simulation time, i.e.* $\nu_T^g = \frac{\sum_i K_{i,T}^g}{\sum_i K_{i,T}} > .5$.

The diffusion curves reveal that the divergence is even stronger and a more rigorous definition could be applied since the technology share converges to one of the extreme values of 100% or 0%. Using these definitions, 98 (107)

[6] An alternative indicator is the productivity weighted share of green capital in production. Which indicator to use is a matter of priority setting in the analysis. Given the type of production technology (Leontief) and assumptions about the learning process, the unweighted measure is more informative about the environmental performance of the economy, about employees exposure to a specific technology type and its implications for learning.

FIGURE 2.3: Diffusion curves



(A) Batch

(B) Disaggregation

2.3a shows the average ν_t^c of all simulation runs, 2.3b shows $\nu_{r,t}^c$ for each single run r.

out of 210 runs are defined as *eco* (*conv*) regimes. The remaining 5 runs are classified as *switch* scenarios that are discussed in further detail below.

The disaggregated diffusion curves (2.3) reveal that initial adoption is not necessarily stable. In some cases, the fallback towards conventional technology is subject to a second reversal towards green technology.

Four questions arise from these observations:

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

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

Definition

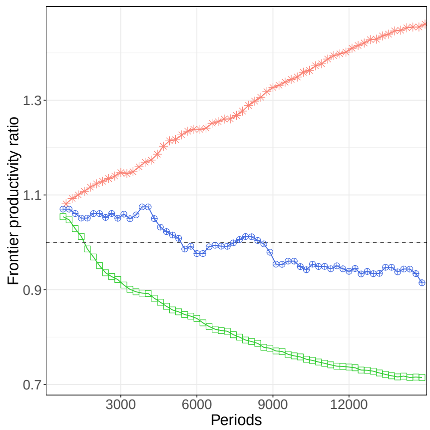
Switch regimes *are identified by two criteria: (a) The level of conventional (green) technology utilization did not converge, i.e. it is less than 90% in* T*, i.e.* $a := (\nu_{T,r}^{ig} < 90\%), ig \in \{c, g\}$*. (b) The final level of* $\nu_{T,r}^{ig}$ *is higher or equal 90%, but its minimum level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

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

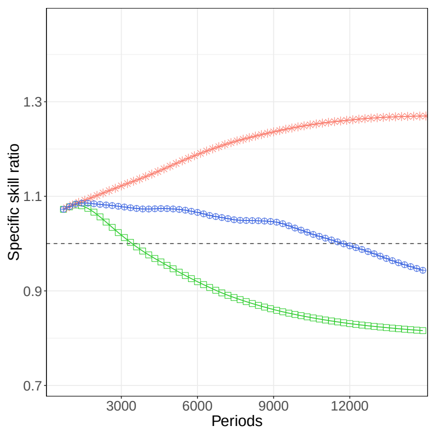
The technological evolution The stabilization of final states is reflected in the bifurcation-like pattern that is observable in the diffusion curve and in the evolution of relative knowledge shown in figure 2.4. Relative knowledge stocks are measured as ratio of the average level of green over conventional technology-specific skills $\beta_t = b_t^g / b_t^c$ and the ratio of the frontier productivity of the two technologies $\alpha_t = A^V_{g,t}/A^V_{c,t}$. The divergence is driven by endogenous learning dynamics.

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

FIGURE 2.4: Relative technological knowledge



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



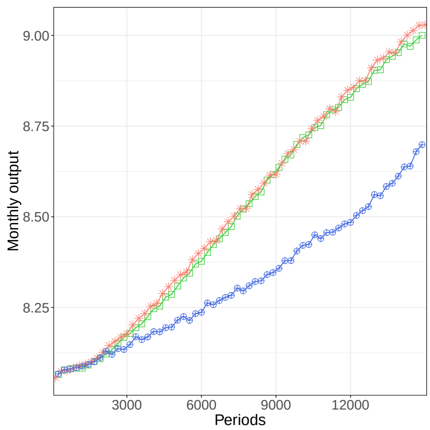
(B) $\beta_t = \frac{b_t^c}{b_t^g}$

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

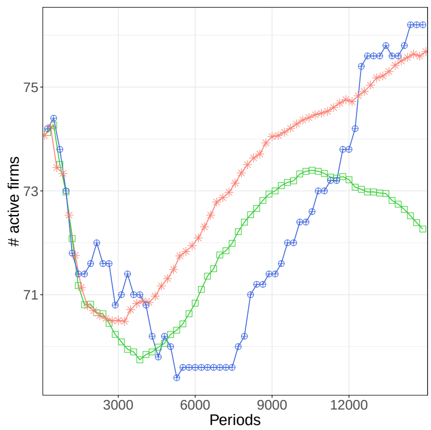
The role of relative knowledge stocks dominates the evolution of relative nominal capital prices. The relative, nominal price for capital of the dominant technology increases which is a result of adaptive mark-up pricing. More demanded technology becomes nominally more expensive. However, technical progress in the dominant sector is relatively faster as a result of endogenous R&D investments. The relative price per productivity unit decreases for the dominant technology. Faster progress offsets the increase in relative nominal prices (see figure in the appendix 2.C.2).

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

FIGURE 2.5: Output and number of firms



(A) Monthly output



(B) #active firms

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

A comparison time series of macroeconomic indicators exhibit differences across technological regimes. In figure 2.5, the time series of log aggregate output and the number of active firms are shown. The significance of differences across scenario types is confirmed by series of Wilcoxon rank sum tests comparing the outcome within subsets for different phases of the diffusion process (cf. table 2.C.1 and Hötte (2019b)).

As illustrated in figure 2.5a, the green and conventional regimes do not exhibit remarkable differences in aggregate output in the long run. This does not hold in the initial phase, defined as the first 10 years after market entry. The green regimes are characterized by significantly lower output, which is not visible in the time series plot but indicated by the Wilcoxon test (available in Hötte, 2019b). This is interpreted as *learning costs*. Firms have a lower productivity when they have to learn how to use new technology. This is only a temporary effect that diminishes by the end of the simulation time. Learning costs are an evolutionary interpretation of abatement costs. These costs arise during the switch to an alternative, less mature and less routinized technology.

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

$$g_t^{output} = \underset{(.0397)}{1.7614^{***}} \quad \underset{(.0066)}{-.0640^{***}} \cdot \sigma_t^{\nu} \quad + \epsilon_t \tag{2.3}$$

The volatility is associated with lower economic growth. This finding is robust across different model configurations including different sets of control variables. Additional analyses are available in the data publication. In capter 3 and chapter 4, it is shown that the volatility of the diffusion process depends on the characteristics of the competing technology. The macroeconomic side effects depend on the types of technologies that compete.

The time series of the number of active firms indicates intensified competition after the green technology entered the market (cf. figure 2.5b). This leads to a series of market exits. After some time, the situation stabilizes and new firms incrementally enter the market. The market entries are a probabilistic process with an exogenously determined entry probability and should not be over-interpreted. But the exit dynamics are fully endogenized and informative about firms' ability to adapt (cf. I). In the green regimes, a second surge of market exits is observable. When the economy stabilizes at the green regime, those firms that were not able to adapt to the changing technological environment are not any longer competitive and exit the market.

The lack of specialization in the switch regimes allows a larger variety of firms to co-exist. Additional macroeconomic indicators and a short discussion of these indicators can be found in figure 2.C.3 in the appendix. Further discussion and additional test statistics and figures can found in the accompanying working paper Hötte (2019b).

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

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

2. Some of the economic processes in the model are probabilistic. This affects firms' investment behavior and the productivity of supplied technology. In the presence of increasing returns to diffusion, "small

events” do not necessarily average out and have a lasting impact on the technological trajectory (cf. Arthur, 1989).

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

4. Both stable regimes perform similarly in the long run. This is partly due to the parametrization. In the early diffusion phase, the green regimes are subject to learning costs in terms of lower productivity and output. This difference vanishes in the long run if the regime converges to a stable state. Learning costs are more pronounced if the technological pathway is uncertain and producers enduringly switch between technology types. Technological uncertainty is costly because learning resources are misallocated and the specialization is retarded. The initial surge of green technology diffusion is associated with stronger competition among CG firms. This leads to a series of market exits. The exit dynamics are stronger if the economy converges to the green regime because a second market cleansing occurs. Firms that failed to adopt the new technology go bankrupt.

Is the transition to green technology costly? The answer developed in this study is: It depends on the pathway of transition and the type of technology.

A controversy in studies on green directed technological change is the existence and extent of macroeconomic abatement costs. The arguments range from distortions in the technology choice (Popp et al., 2010), the incorporation of damage functions (Stern, 2008) to innovative dynamics triggered by environmental regulation (Ambec et al., 2013). This study does *not* address the question whether the transition to green technologies is economically superior in the long run.[7]

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

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

2.4.2 Barriers to diffusion

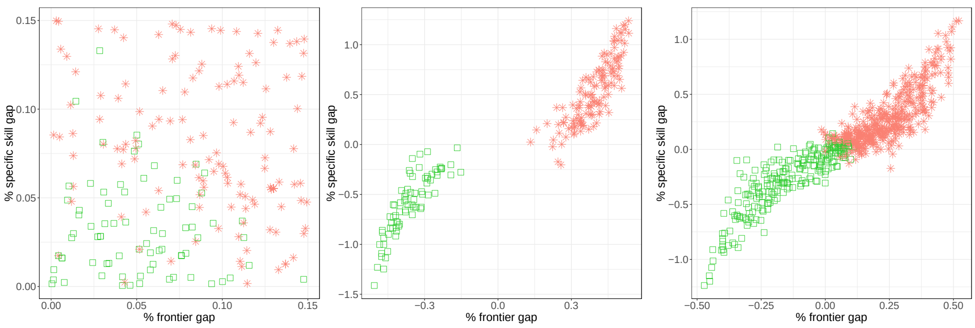
What is *marginal* impact of barriers on the transition probability? To address this question, a series of Monte Carlo (MC) experiments with randomly drawn levels of β^A and β^b is run.

The strength of diffusion barriers

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

The distribution of the random draws in t_0 is shown in figure 2.6 on the left-hand side. In the middle figure, it is shown how the endogenously evolving difference in technological knowledge has emerged until the end of the simulation time T. Two clusters in the opposite corners of the plot have formed.

FIGURE 2.6: Distribution of β^A and β^b at different times



(A) $t_0 = 600$ (B) $T = 15000$ (C) All periods

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

Compared to the baseline scenario, the diffusion barriers are higher on average. This reduces the frequency of observed transitions to 37%. A Wilcoxon test confirms that the transition occurs more frequently if initial diffusion barriers are low (cf. 2.C.2). Observations about the macroeconomic and technological time series patterns are qualitatively similar to those of the baseline scenario. The divergence of relative technological knowledge stabilizes the transition process and technological uncertainty is costly. Time series plots and a short discussion can be found in the SM of (Hötte, 2019b).

The MC setting allows studying the role of entry barriers by a regression analysis. The results of an OLS and binary Probit model are shown in table 2.2. The aggregate ν^c_T is regressed on initial conditions and a set of controls.[8]

[8]The binary specification captures the binary nature of the response variable. The share of conventional capital that is used in the last period is roughly 100% or 0%, but there is

TABLE 2.2: Regression of the transition probability on diffusion barriers

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

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

The barriers β^A and β^b both enter with positive coefficients and are economically and statistically significant across different model specifications. Positive coefficients indicate a higher share of conventional capital in T and a negative association with the transition probability.

Robustness tests using the percentage difference in skill and productivity levels measured at later snapshots in time and more disaggregated firm data confirm that these relationships hold at different aggregations and across time.

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

The coefficients of the linear OLS model can be interpreted as marginal effect on the probability of technological lock-in. In the linear model, a change by one percentage point in β^A (β^b) is associated with a 5% (3.8%) higher share of conventional capital utilization.

little variation between them. The variation in the control variables beyond the randomized entry conditions arises from the period until the day of market entry $t \in [0, 600]$. The initial population in $t = 0$ is identical in all 210 simulation runs. In all specifications, smoothed values of the dependent variables are used, i.e. one-year averages.

But the relationship between the barriers and the transition likelihood is non-linear. The value range used in this experiment is truncated and barriers can be prohibitively high to prevent a transition. In columns (4) and (5), the results of a regression model that includes quadratic and interaction terms of β^A and β^b.[9]

The effectiveness of β^A as a barrier to diffusion is diminishing. The opposite is found for β^b.[10] The macroeconomic controls are not significant. This is not surprising because the variation between the simulation runs is low. The simulations are initialized with identical populations and the variation in the controls stems from the first 600 iterations until the day of market entry.

Which firms are early adopters?

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

The results reveal insights into the macroeconomic diffusion process and into the relationship between firm characteristics and early green technology uptake at the micro level. The regression results are shown in table 2.3.

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

Compared to the previous regression on the emerging regime, lacking skills have higher relative explanatory power for early green technology uptake. In relation to β^A, the economic significance of β^b and its explanatory power captured by the R^2 in column (1) is higher compared to the previous regression. This is reflected in the relative coefficients compared to β^A and the higher R^2 in column (2). The interaction term $(\beta^A\beta^b)$ is statistically significant and has a negative coefficient.

[9] I refrain from an in-depth study of the functional form of the relationship between different barriers and diffusion for mainly two reasons. First, the effect of the barriers on the pattern of diffusion is sensitive to the assumptions on the shape of the endogenous innovation and learning function. These functions are set in a plausible, but stylized way and the outcome should not be over-interpreted in quantitative terms. In economic reality, the mechanisms that determine technological learning and the success of innovation are likely to vary strongly across different technological fields due to different patterns of innovation, learning and cross-technology spillovers. Second, the better fit of more complex functional forms comes at the cost of lower ease of interpretation and expected lower generalizability, also referred as to *bias-variance trade-off* (cf. Bishop, 2006). The regressions should underline the qualitative insights derived of this study.

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

TABLE 2.3: Firm-level egression to identify early adopters

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

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

Firms with a high general endowment of tacit knowledge B^c_{i,t_0} on the day of market entry, tend to adopt earlier. Above average B^c_{i,t_0} is an indicator for a high-skilled workforce at the firm. High skilled employees are assumed to have higher ability and to learn faster in the *Eurace@unibi* economy irrespective of the type of skills that needs to be learned.[11]

The stock variables reflect the general, but not technology-specific endowment of a firm with human capital and technology. The stock of codified knowledge is negatively associated with the likelihood to be an early adopter. On the day of market entry, firms do only have conventional capital and a high level of $A^c_{i,t}$ indicates that a firm is operating at a high productivity level.

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

It may also indicate investments in new machines shortly before the green technology becomes available. Both are impediments to early green technology uptake. The negative association with diffusion suggests that firms with more productive capital stock are less likely to be early adopters.

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

2.4.3 The empirical content of the model

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

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

The authors argue the different patterns to be (partly) explainable by the types of technologies under consideration and by the circumstances of adoption. Inverted U-forms are observed when a technology initially diffuses but is driven out of the market by a competing alternative in the long run (Geels and Schot, 2007).

The proposed model sheds light on the dynamic interplay of learning and endogenous innovation of two competing alternatives. Learning and innovation are key to understand the evolution of substitutability and superiority of competing technologies.

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

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

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

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

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

2.5 What is the scope for green technology diffusion policies?

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

To answer these questions, an experiment on different market-based policies is run. The considered policy instruments are a tax on the resource input and two types of subsidies. The tax θ is imposed as value added tax on material inputs making the use of conventional capital more costly. An investment subsidy ς^i reduces the price for green capital goods by a fixed factor. A consumption subsidy ς^c is implemented as firm-specific price support for eco-friendly produced final goods. The level of support is linearly scaled by the relative amount of green capital goods $\nu^g_{i,t}$ that is used by the firm. The government seeks to balance its budget. If expenditures for subsidies exceed the tax revenue, other taxes e.g. on income are increased such that the budget is balanced in the long run. The formal implementation of policies is documented in the appendix 2.A.5.

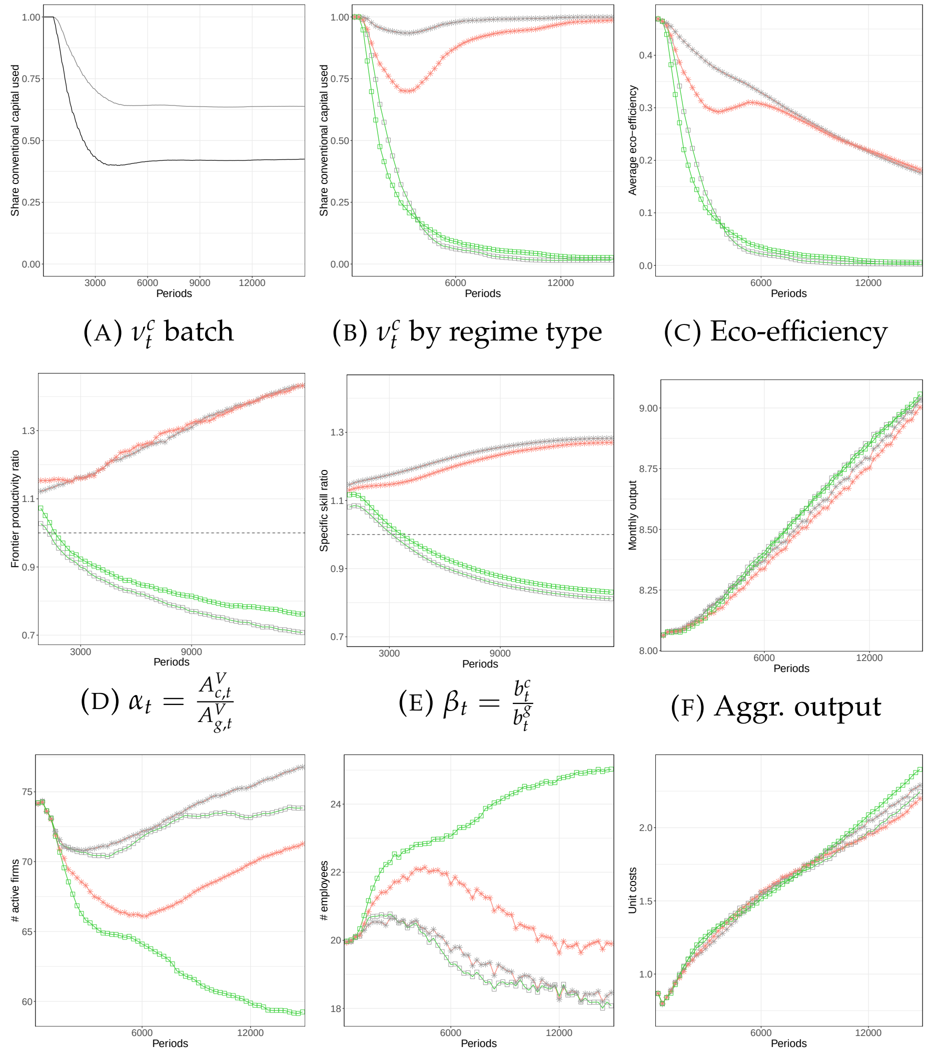
2.5.1 The impact of policies on the technological evolution

To explore the interplay of policy and barriers, a set of MC simulations is run with randomly drawn levels of β^A, β^b, and policies. The diffusion barriers are drawn from the same interval ($\beta^A, \beta^b \in [0, .15]$) as above (see 2.4.2). The intervals for the subsidies and the eco-tax had been set such that the average levels of the different subsidies are similarly effective as diffusion stimulus.[12] The intervals are $\theta \in [0, 1]$, $\varsigma^i \in [0, 1]$ and $\varsigma^c \in [0, .025]$. The initial conditions are summarized in table 2.C.4 in the appendix 2.C.3. 210 simulations are run à 15000 iterations. The simulation results of the MC experiment above (2.4.2) serve as no-policy baseline. In figure 2.7, time series of technological and macroeconomic core indicators are shown. The colored (gray) lines represent the policy experiment (baseline scenario). The time series are disaggregated by the type of technological regime without the additional distinction of switch-regimes. Measuring diffusion at the extensive margin the presence of policy exhibits a strong effect. The relative frequency of observed technological transitions is increased from 27% to 59%, i.e. 123 out of 210 simulation runs. The effect of the policy on diffusion appears to be strongest in the beginning. Even if path dependence leads to a reversal to conventional technology, the share of green technology utilization is significantly higher in an early phase of diffusion (cf. figure 2.7a and 2.7b and appendix 2.C.3).

The time series of relative productivity α_t and relative skill endowments β_t are shown in figure 2.7d and 2.7e. In comparison to the benchmark scenario, the divergence between different regimes is less pronounced. Moreover, a descriptive comparison of the average initial diffusion barriers computed

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

FIGURE 2.7: Technological and macroeconomic time series



(A) ν_t^c batch

(B) ν_t^c by regime type

(C) Eco-efficiency

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

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

(F) Aggr. output

(G) # active firms

(H) # employees

(I) Unit costs

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

within green (conventional) runs shows that, on average, the diffusion barriers in the policy scenario are higher (lower) (cf. 2.C.4). This can be interpreted as an upwards shift of the threshold level of diffusion barriers that is prohibitively high and prevents green transitions. Diffusion barriers and policies operate in opposite directions. Barriers inhibit and policies stimulate the diffusion of green technology. The diffusion policy increases the intensity of competition in situations where the green technology is only competitive with policy support. This might result in increased technological uncertainty with negative effects on productivity growth in the short run.[13]

[13] A longer discussion can be found in Hötte (2019b).

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

To shed light on the relationship between the transition probability and the interplay of barriers and policy, a regression analysis of $\nu^c_{i,T}$ is run. The explanatory variables are β^A, β^b, the policies θ, ς^i, ς^c and firm-specific controls. The results are shown in table 2.4. Columns (1)-(5) show the coefficients of different model specifications in an OLS model. Column (6) shows additionally the results of a binary Probit model.[14]

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

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

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

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

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

2.5.3 How can the differential effectiveness of policies be explained?

The effects of the political instruments on the relative superiority of a technology type and on the investment decision of firms differ over time. The tax θ imposes an additional cost burden on firms that are using conventional capital. It is proportional to the price of the environmental resource. Early

[14] Explanatory notes can be found in 2.C.4.

TABLE 2.4: Regression of the transition probability on diffusion policies

Dependent variable: $\nu^c_{i,T}$ at firm level in $T = 15000$						
	OLS					Probit
	(1)	(2)	(3)	(4)	(5)	(6)
(Intercept)	.7522***	.0025	.2553***	-.0463	1.572***	2.496
	(.01490)	(.0181)	(.0198)	(.0298)	(.4231)	(1.6710)
θ	-.0019***		-0.0027***	-.0005	-.0006	.0027.
	(.0002)		(.0001)	(.0004)	(.0004)	(.0015)
ς^c	-0.1426***		-0.1337***	-.0498***	-.0533***	-.1592**
	(.0063)		(.0054)	(.0140)	(.0140)	(.0582)
ς^i	.0006		-0.0041**	.0262***	.0259***	.1753***
	(.0017)		(.0014)	(.0039)	(.0039)	(.0160)
β^A		.0224***	.0228***	.0478***	.0507***	.1797***
		(.0028)	(.0027)	(.0035)	(.0036)	(.0142)
$(\beta^A)^2$		.0010***	.0015***	.0015***	.0014***	.0067***
		(.0002)	(.0002)	(.0002)	(.0002)	(.0007)
β^b		.0371***	.0524***	.0592***	.0598***	.1879***
		(.0037)	(.0035)	(.0042)	(.0042)	(.0162)
$(\beta^b)^2$		-.0026***	-0.0030***	-.0031***	-.0031***	-.0098***
		(.0002)	(.0002)	(.0002)	(.0002)	(.0008)
$(\beta^b\beta^A)$		.0015***	.0006***	.0013***	.0012***	.0097***
		(.0002)	(.0002)	(.0002)	(.0002)	(.0008)
$(\beta^b\theta)$				7e-05*	7e-05*	.0001
				(3e-05)	(3e-05)	(.0001)
$(\beta^b\varsigma^c)$				-.0090***	-.0086***	-.0462***
				(.0012)	(.0012)	(.0049)
$(\beta^b\varsigma^i)$				-.0007*	-.0008*	-.0061***
				(.0003)	(.0003)	(.0012)
$(\beta^A\theta)$				-.0003***	-.0003***	-.0017***
				(3e-05)	(3e-05)	(.0001)
$(\beta^A\varsigma^c)$				-.0017	-.0023*	-.0084.
				(.0010)	(.0010)	(.0047)
$(\beta^A\varsigma^i)$				-.0026***	-.0027***	-.0184***
				(.0003)	(.0003)	(.0013)
Adj./ps.R^2	.0568	.2994	.3596	.3828	.3851	.3433
AIC	15172	11896	10907	10506	10470	10020
Significance codes: 0 '***' .001 '**' .01 '*' .05 '.' .1 ' ' 1.						

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

after market entry, it increases marginal production costs because the share of conventional capital use is high. Firms that incrementally switch to green technology reduce the tax burden and costs for the natural resource input. This effectively compensates for the incurred disadvantage if firms adopt less productive green capital. This type of production-cost balancing is permanent.

In contrast, the investment subsidy ς^i operates through the channel of one-time investment costs. It reduces the price for green capital but does not provide a permanent compensation for higher production costs that arise from an inferior productivity performance. Its effectiveness is not sensitive to the composition of the capital stock. The other two instruments (relatively) reward firms that switch to green technology with lower input costs or higher mark-ups. In chapter 3 and 4, it was shown that this can be associated with delayed technological convergence and higher technological uncertainty.

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

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

2.5.4 How do different policies affect the firm population?

The policies operate through different channels that are differently important at different stages of the diffusion process. This does not only affect the diffusion process but may also have an impact for the characteristics of the firm population. Figure 2.7f-2.7i shows the time series of the number of active firms, monthly aggregate output, firm size and unit costs.

The first years after t_0 are characterized by a surge of market exits (cf. figure 2.7g). The policies cause a downward shift in the threshold level of diffusion barriers that prevent a transition. Hence, in the presence of policy, a transition may occur even if the conditions are unfavorable. This is associated with technological uncertainty, learning costs and slow down in output growth during the first $5-10$ years (cf. figure 2.7f).

After some time, the technological regime stabilizes and the surge of market exits stops. This effect is stronger in the policy experiment. The exits are followed by an increase in the firm size (cf. 2.7h). Hence, the market becomes more concentrated with fewer, but larger firms. In the benchmark scenario and in the lock-in regime, the growth of the average firm size is stopped. In the policy experiment, the concentration process continues.

Additional regression analyses of the firm size as a measure for firm size and unit costs as a proxy for production efficiency reveal that the effects of policy differ across instruments, time and indicator variables. The results and additional explanations are provided in the appendix 2.C.3.

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

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

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

2.5.5 Summary and discussion

Three core insights can be derived from the policy experiment:

1. The policy can increase the transition probability. Policies stimulate the initial green technology uptake. If initial uptake is sufficiently high, path dependence embodied in relative technological knowledge is overcome and the green technology permanent diffuses.

The effect of the policy as diffusion stimulus may come with the cost of higher technological uncertainty. If policies are not sufficiently strict to trigger a permanent transition, it retards specialization effects in conventional technology when the economy relapses to the conventional regime. Retarded specialization has a negative effect on productivity and economic performance. When using relative indicators for the environmental performance measure, an insufficiently strict policy may be detrimental because lower production efficiency is associated with a worse environmental performance per unit of output.[15]

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

   The effectiveness of the consumption subsidy is increasing in the strength of both types of barriers. This effect is stronger if the barrier is demand-sided, i.e. when lacking skills hinder firms to adopt green technology. It is an instrument that stabilizes an ongoing diffusion process and is not distorting if the economy is locked in. An investment subsidy operates via an instantaneous price mechanism in firms' investment decisions. Its effectiveness is independent of the type of barriers.

3. Policies affect firms asymmetrically. The initial phase after the market entry of the green capital producer is characterized by strengthened competition and a surge of market exits. This effect is more pronounced in the policy experiment. The policy countervails the effect of diffusion barriers which intensifies the technology race in situations where the green technology would not sustain without policy support.

   If the green technology wins the race, firms that successfully adopt green capital benefit most from the subsidies. If a transition occurs late adopters have difficulties to survive on the market. They do not only technologically have to catch up, but also take less advantage of the consumption subsidy. The investment subsidy provides an incentive to build up capacity. This effect is independent of the success of a technological regime shift.

[15]The environmental effect in absolute terms compared to the baseline is a matter of calibration. The worse economic performance in uncertain environments may offset the efficiency effect. Here, the calibration is chosen such that the economic performance across different regimes in the policy and benchmark scenario does not substantially differ but this is also a matter of the choice of other characteristics of the competing technologies. More information is available in chapter 3 and 4 and in the comprehensive working paper (Hötte, 2019f).

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

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

It was also shown that the performance of different market-based climate policies is conditional on the type and strength of barriers. Taxes help to overcome supply-sided diffusion barriers that are embodied in the productivity of capital goods. Tradable, innovation-induced knowledge embedded in productivity is typically the way how directed technological change is modeled in innovation and climate economics (cf. Löschel, 2002; Popp et al., 2010).[16]

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

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

2.6 Concluding remarks

In this article, a microeconomic model of technological learning of heterogeneous firms as a driver of directed technological change is introduced. The

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

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

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

Market-based policies can help to overcome diffusion barriers but, dependent on the type of diffusion barriers, different instruments perform differently well. Taxes effectively compensate disadvantages related to the productivity of the green alternative. Subsidies help if lacking non-tradable capabilities at the firm level impede the diffusion process.

For the design of policy, the heterogeneous nature of diffusion barriers is important. Conditional on the strength of barriers, policies need to be sufficiently strict to provide an effective mechanism of coordination. Lack of coordination causes technological uncertainty. This is economically unfavorable because learning and R&D resources are possibly wasted for the development of a technology type that is obsolete in the long run.

One core limitation of the model are the assumptions about cross-sectoral knowledge spillovers in the learning process. The assumptions about learning spillovers are justified by qualitative insights from the literature. Here, spillovers only exist in the learning by doing process, but spillovers may be also relevant in the R&D sector. Empirical studies on innovation networks and spillovers confirm the importance of technological similarity for diffusion (cf. Acemoglu et al., 2016; Carvalho and Voigtländer, 2014). Spillovers may affect the process of relative knowledge accumulation. This is the topic of the subsequent chapter 3.

Qualitative case studies and sector-based quantitative insights (cf. 2.4.3) support the model's validity. It is challenging to find robust quantitative and cross-technology sector consistent measures for the concepts of technological knowledge introduced in this paper, and for the clear distinction between different types of technologies. These measures would be required for a general empirical validation of this model. This work is left for future research.

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2.A Model documentation

In this section, the formal implementation of the eco-technology extension of the *Eurace@unibi* model is introduced. For an introduction to the baseline model itself, its calibration and applications in economic policy analysis, the interested reader is referred to articles of the original developers of the model (e.g. Dawid et al., 2019b; Harting, 2019). A concise but self-contained introduction to the eco-technology extension of the model is available in the SM I. The most relevant changes and extensions compared to the baseline model are summarized in table 2.A.1.

TABLE 2.A.1: Overview of the eco-technology extension of *Eurace@unibi*.

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

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

2.A.1 Consumption goods firms' production technology

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

The variable $K_{i,t}^v$ indicates the quantity of capital goods of type v with the characteristics $(A^v, \mathbb{1}(v))$ within the firm's current capital stock $K_{i,t}$. Formally, the amount of capital of type v is given by $K_{i,t}^v := \{k \in K_{i,t} | A^v(k) = A^v, \mathbb{1}(k) = \mathbb{1}(v)\}$. Further, I use the notation $K_{i,t}^{ig}$ when referring to the part of the capital stock that is composed of vintages of technology type ig, i.e. $K_{i,t}^c = \sum_v \mathbb{1}(v) \cdot K_{i,t}^v$ and $K_{i,t}^g = \sum_v (1 - \mathbb{1}(v)) \cdot K_{i,t}^v = K_{i,t} - K_{i,t}^c$ where $\mathbb{1}(v)$ is the technology type identifier taking the value one (zero) if the vintage v is of conventional (green) type.

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

$$A_{i,t}^{Eff_v} = \min\left[A^v, B_{i,t}^{ig}\right] \tag{2.4}$$

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

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

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

$$Q_{i,t} = \sum_{v=1}^{V} \left(\min\left[K_{i,t}^v, \max\left[0, L_{i,t} - \sum_{k=v+1}^{V} K_{i,t}^k\right]\right] \cdot A_{i,t}^{Eff_v} \right) \tag{2.5}$$

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

Firms can only use as much capital as workers are available in the firm to operate the machines. This is captured by the term $\max\left[0, L_{i,t} - \sum_{k=v+1}^{V} K_{i,t}^{k}\right]$.[17]

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

$$\zeta_{i,t}^{v} = \frac{A_{i,t}^{Eff_v}}{w_{i,t} + \mathbb{1}(v) \cdot c_t^{eco}} \tag{2.6}$$

where $\mathbb{1}(v)$ indicates the capital type.[18]

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

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

$$C_{i,t}^{eco} = c_t^{eco} \cdot \sum_{v=1}^{V} \mathbb{1}(v) \cdot K_{i,t}^{v}. \tag{2.7}$$

with V as the set of vintages that are actually utilized for production in t. The natural resource input costs $c_t^{eco} = e \cdot \tilde{p}_t^{eco}$ are composed of the user price $\tilde{p}_t^{eco}$ for the input multiplied with an efficiency parameter e.[19]

The utilization of conventional capital is associated with the degradation of an environmental resource. The damage is proportional to the number of conventional capital units that are used in production. If conventional capital becomes more productive, a relative decoupling takes place. The environmental damage per unit of output decreases.

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

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

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

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

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

2.A.2 Employees' technological learning

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

Technological learning is embedded in the evolution of households' technology-specific skills. Technology-specific skills $b^{ig}_{h,t}$ of employee h are learned during work. The speed of learning depends on the technological properties of the capital stock that is used by the employer and h's learning ability. The ability depends on the household's (fix) general skills χ_h. It moderates the speed of learning. This is explained in more detail in chapter 3 and in the SM I.

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

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

$$b^{ig}_{h,t+1} = b^{ig}_{h,t} + \chi_h \cdot \max\left[(\chi^{spill} \cdot \psi^{-ig}_{h,t}), \psi^{ig}_{h,t}\right] \tag{2.8}$$

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

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

$$\psi^{ig}_{h,t} = \max\left[\chi^{int}, \nu^{ig}_{h,t}\right] \cdot \Delta b^{ig}_{h,t}. \tag{2.9}$$

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

This is interpreted as *intensity of effort* or time invested in learning a specific type of skills (cf. Cohen and Levinthal, 1990). Learning skills of technology type ig is faster if the relative amount of this type in the used capital stock is higher. The relative amount is assumed to reflect which relative time the employee is working with a technology type and learning by doing. The fixed parameter $\chi^{int} \in [0,1]$ imposes a minimum level on the sensitivity of learning progress to the intensity of effort.[20]

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

$A^{ig}_{h,t}$ is the average productivity of vintages of type ig in the capital stock of h's employer. $A^{ig}_{h,t}$ imposes an upper bound on learning by doing. However, the skill level $b^{ig}_{h,t}$ may exceed $A^{ig}_{h,}$ if $\chi^{spill} \cdot \phi^{-ig}_{h,t}$ is sufficiently high and the employee learns from spillovers.

2.A.3 Capital goods and innovation

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

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

$$A^V_{ig,t+1} = (1 + \Delta A) \cdot A^V_{ig,t}. \tag{2.10}$$

[20]Note that this representation slightly differs from the model version introduced in the SM I.

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

The success of innovation is probabilistic and IG firms are able to influence the probability of success by investment in R&D. The probability of success $\mathbb{P}_{ig,t}$ is given by

$$\mathbb{P}_{ig,t}[\text{success}] = \bar{p} \cdot (1 + \widehat{R\&D}_{ig,t})^{\eta} \tag{2.11}$$

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

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

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

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

2.A.4 Green technology producer's market entry

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

The market entry was associated with a technological breakthrough that enables the rapid development of further varieties of green capital. A whole supply array becomes successively available. Half a year after the day of market entry, the next and incrementally more productive vintage is added to the array of available vintages. It has the productivity level $A^2_{g,t} = (1 + \Delta A) \cdot A^1_{g,t} = (1 - \beta^A) \cdot A^2_{c,t_0}$.[21]

This procedure repeats every sixth month until the maximum number of the supplied vintages is reached. Thereafter, additional technological progress happens through the innovation procedure as introduced above (see 2.A.3).

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

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

2.A.5 Policy

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

The policy instruments are implemented as follows:

- An **environmental tax** θ is imposed as a value added tax on material inputs. This makes the use of conventional capital relatively more costly for CG firms,
$$\tilde{p}^{eco}_{i,t} = (1+\theta) \cdot p^{eco}_t. \tag{2.12}$$
Because the environmental impact of production is proportional to the use of material inputs, this tax can also be seen as a tax on the environmental externality. Alternatively, different levels of the tax can interpreted as different degrees of technological superiority of the entrant technology.
- An **investment subsidy** ς^i reduces the the price for green capital goods,
$$\tilde{p}^v_t = (1-\varsigma^i) \cdot p^v_t. \tag{2.13}$$
- The government may also pay a **green consumption price support** ς^c for environmentally sound produced CG, i.e.
$$\tilde{p}_{i,t} = \left(1 - \nu^g_{i,t} \cdot \varsigma^c\right) \cdot p_{i,t} \tag{2.14}$$
This subsidy is directly paid to firms and is proportional to the share of green capital used in current production $\nu^g_{i,t} = \frac{K^g_{i,t}}{K_{i,t}}$. The price support allows CG firms to achieve a higher mark-ups when producing in an environmentally friendly way.[22]

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

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

2.A.6 Additional notes on the parameter settings

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

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

Initial conditions are determined in a series of *training simulations*. The model is based on a calibrated version of the *Eurace@unibi* model and an initial population is taken from previous applications. The initial population reflects the initial distribution of skills and wealth across households and firms and the firm size distribution. However, the introduction of the additional module made a partial recalibration of the model necessary. Starting with an initial population, the model was run for different parameter settings until stable economic processes have emerged. At that time, the population was saved and used as initial input to the model. This explains, for example, the arbitrarily seeming number of 74 firms.[23]

[23] The number of periods until the day of market entry was set such that the economy is on a stable path of development, but sufficiently small that the divergence across runs is not too large. The deviations across different runs that emerge during this time are of minor importance. The number of 210 simulation runs was chosen such that it factorizes with the number of available cores of the computer that was used for the simulations.

2.B Stylized facts and empirical calibration

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

2.B.1 Economic stylized facts for model validation

In this subsection, an overview of micro- and macroeconomic stylized facts that are reproduced by the model is provided. The selection of validation criteria follows the approach used in Dawid et al. (2018b). The authors discuss and motivate the use of specific stylized facts more comprehensively pointing to their counterparts in the empirical literature. Here, I give only a short overview and show a subset of validation criteria to demonstrate the models ability to reproduce empirically observed economic regularities and is expected to provide an appropriate tool for economic scenario exploration and policy analysis. All data and the corresponding R code is provided in the online documentation to allow the reader to reproduce the results. The results presented below refer to the simulation results of the baseline scenario (cf. section 2.4.1). The references to the empirical counterparts of the stylized facts are discussed in more detail in Dawid et al. (2018b). Here, I demonstrate that extended model behaves in a similar way as the original *Eurace@unibi* model.

1. The model is able to reproduce **growth rates, business cycle volatility and persistence patterns** similar to those documented in the empirical literature (cf. Dawid et al., 2018b). The average growth rate of the 210 simulation runs accounts for .0156 and an average standard deviation of .0011.[24] The average growth rate is slightly lower than empirically documented values, but this is merely a matter of scaling of productivity progress parameters in the model, but does not qualitatively change the results. The variation across different simulation runs is low and indicates robustness of the model simulations.

2. **Business cycle volatility** is evaluated by the size of the cyclical component. It is measured as average of the absolute size of the percentage deviation of the time series from its bandpass filtered trend data. The

[24]These values are the arithmetic mean of 210 run specific average growth rates computed as geometric mean in bandpass filtered time series across 15000 iterations representing roughly 60 years. The standard deviation is the average standard deviation of run specific deviations over time. The variation across runs in means (standard deviations) accounts for .0010 (.0011).

average size of a business cycle accounts for .0013, i.e. aggregate output variates on average by 0.1 percent. The standard deviation of the variation accounts for .0017. Again, the variation across runs, i.e. the standard deviation of per-run average size of the business cycle (standard deviation) is low accounting for .0004 (.0005). The model reproduces slightly less volatile patterns than the original model. As discussed in the text, this is intended and caused by the design of functions that have a smoothing effect. These are, for example, routines that refuel residual financial flows back to the economy through lump-sum payments implemented via dividends, R&D budgets or governmental budget allocation and allow to smoothen effects of cyclical volatility. The aim of this study is the understanding of the relevance of knowledge accumulation processes for technology diffusion. Stronger cyclical dynamics would make this analysis more difficult and are left for future investigations.

3. **Co-movement of key variables with the business cycle** is shown in table 2.B.1 by a representation of the cross correlation structure of macroeconomic key variables and business cycle dynamics. The values in the table indicate the correlation of the cyclical part of bandpass filtered time series data with the business cycle measured as output fluctuations for different time lags. The table confirms the pro-cyclical behavior consumption, investment, employment and vacancies. Anti-cyclical behavior is observed for wages, mark-ups and unemployment.

4. The **relative magnitude of fluctuations** of macroeconomic variables differs in their extent. In figure 2.B.1a, I show the relative magnitude of the percentage variation in the cyclical argument of the bandpass filtered time series of output, consumption and investment. The plot covers a 10-year time period close to the end of simulation time and shows the time series of a randomly drawn single simulation run.[25] In line with the empirical literature, investment exhibits a higher volatility than consumption and output. Moreover, the figure reveals the lag structure of the three variables, i.e. production responds to a positive consumption shock with a time lag and an output shock precedes a boom in investment. In figure 2.B.1b, an analogous plot is shown for the relative magnitude of variations in output, vacancies and unemployment.

5. **Labor market properties** can be summarized by a Beveridge and Phillips curve. The model reproduces a Beveridge curve (figure 2.B.2b) which illustrates the relationship between unemployment and vacancies, i.e. higher unemployment is associated with a lower vacancy rate. The Phillips curve shown in figure 2.B.2a shows the relationship between unemployment and inflation. The figures on show these curves

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

for a single randomly selected run for a 20 year snapshot in the first and second half of the simulation horizon.

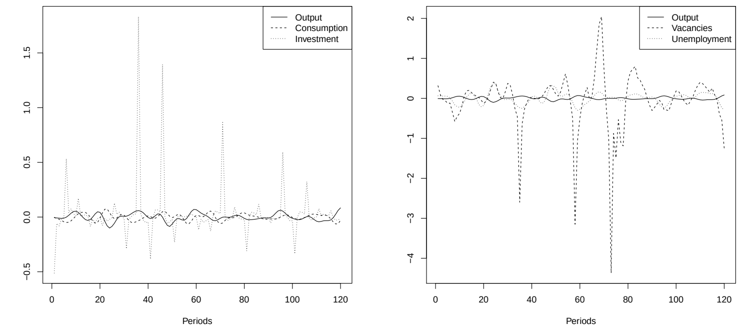
TABLE 2.B.1: Simulated cross correlation patterns

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

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

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

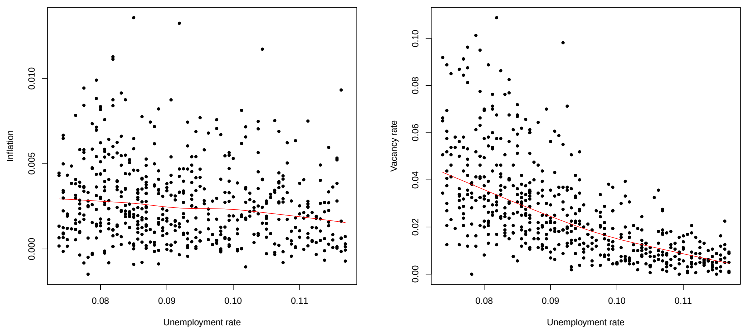
FIGURE 2.B.1: Relative volatility of macroeconomic indicators



(A) Output, consumption, investment (B) Output, vacancies, unemployment

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

FIGURE 2.B.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 unsmoothed time series data covering the whole simulation period of roughly 60 years. Outliers are removed from the data.

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

The *Eurace@unibi-eco* model is designed and validated along a number of stylized facts that can be derived from the empirical insights discussed above.

It can be distinguished between characteristics of (eco-)innovation that served as priors for the model design and observed patterns that are used for validation. In this subsection, an overview stylized facts of (eco-)innovation is given and it is briefly explained how these aspects are incorporated in the

Eurace@unibi-eco model. The observed patterns related to ex-post model validation are discussed in the main article (esp. 2.4.3).

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

2. **Incremental nature of innovation:**
   "Standing on the shoulders of giants", inventors build on previous knowledge when researching for technological novelties (cf. Dosi, 1988). In *Eurace@unibi*, IG firms *incrementally* shift upwards their technological frontier through innovation.

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

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

5. **Heterogeneity of innovation adopters:** Costs and benefits of innovation adoption can be heterogeneous. This can be due to heterogeneous

preferences and experiences, different adoption costs dependent on capabilities and the compatibility with current endowments (Allan et al., 2014; Nelson and Winter, 1977). In the model, this is captured by the heterogeneity of CG firms in terms of capabilities, expectations, capital endowments and financial capacities.

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

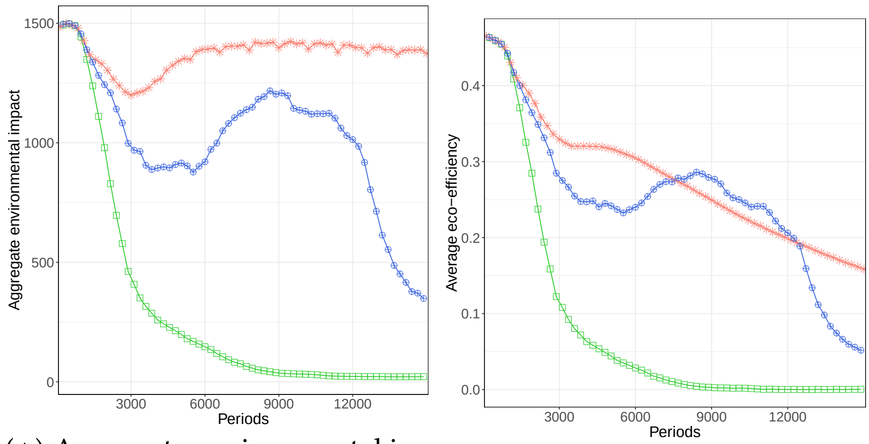
7. **Creative destruction and technological obsolescence:** Creative destruction and/ or technological obsolescence refer to the phenomenon of replacement of an incumbent technology by a new one. This process is associated with a loss in the value of the old technology, equipment and skills that are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

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

2.C Simulation results

2.C.1 Baseline scenario

FIGURE 2.C.1: Environmental performance indicators



(A) Aggregate environmental impact

(B) Average ecoefficiency

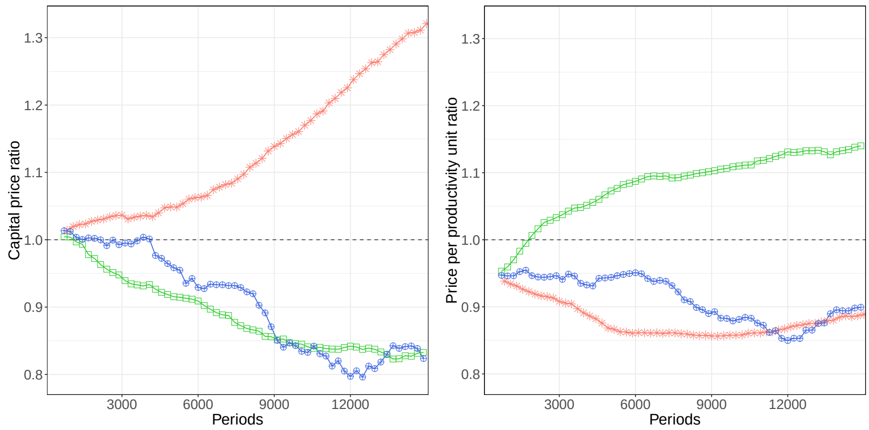
These figures show the evolution of the aggregate environmental impact and ecoefficiency as environmental impact per unit of output. The line types indicate different scenario types (□: eco, $*$: conv, ⊕: switch).

The figures on the aggregate environmental impact and eco-efficiency reveal that there is a relative decoupling of environmental damage and production activities. The level in figure 2.C.1a stabilizes even if no transition to the green technology takes place. This is due to improved production efficiency and in consequence a reduction of emissions per unit of output (cf. figure 2.C.1b). However, the improvement in terms of eco-efficiency is fully outweighed by an increase in the total quantity of output. This phenomenon is also known as *rebound effect* (cf. Arundel and Kemp, 2009).

Figure 2.C.2 shows the evolution of relative nominal prices for capital goods and prices that are normalized by the supplied productivity level. Nominal prices evolve as expected, i.e. the more demanded technology becomes relatively more expensive which is a result of the adaptive pricing mechanism in the capital goods market. When considering not nominal prices normalized by the offered productivity level the pattern is reversed. In this setting the growth in the productivity performance outweighs the demand induced price increase of the more demanded technology. These plots confirm that the endogenous technological evolution dominates the market demand induced scarcity effect that underlies the upward trend of the nominal price ratio in favor of the more demanded technology.

The divergence between green and conventional technological regimes is not only reflected in technology utilization, but also in capital prices, skills and

FIGURE 2.C.2: Capital price indicators



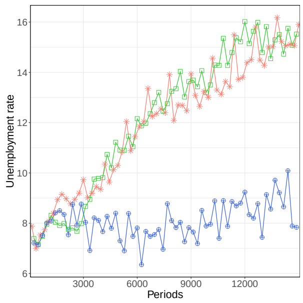
(A) $\frac{p_t^c}{p_t^g}$ (B) $\frac{p_t^c / A_t^c}{p_t^g / A_t^g}$

The different line shapes indicate the scenario type (i.e. □: eco, *: conv, ⊕: switch). Figure 2.C.2a shows the evolution of the ratio of prices paid for the most productive vintages supplied by the conventional and green producer. Figure 2.C.2b shows the evolution of the price-per-productivity-unit ratio.

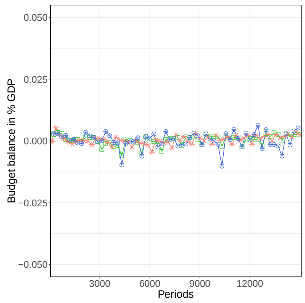
technological development. The endogenous nature of technological innovation is the dominating force that governs the process of divergence of the two technological regimes. A more detailed discussion of price indicators and the relative pace of learning and technological innovation is provided in the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

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

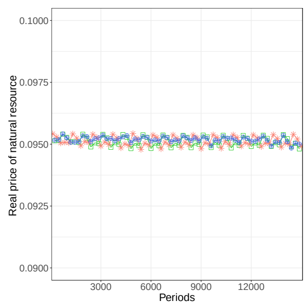
FIGURE 2.C.3: Macroeconomic and technological indicators



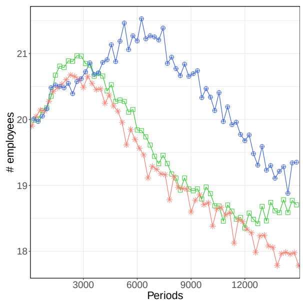
(A) Unemployment rate



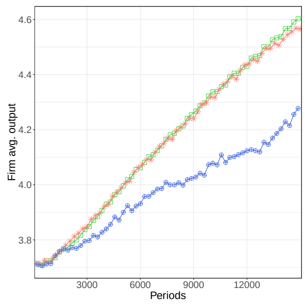
(B) Gov. budget balance (% GDP)



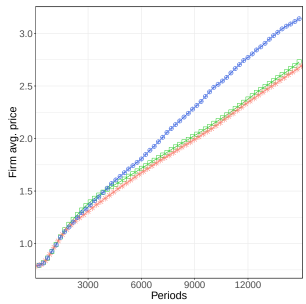
(C) $c^{eco_t} / \bar{w}_t$



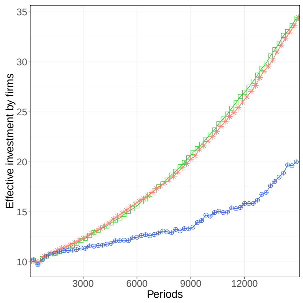
(D) Avg. # employees



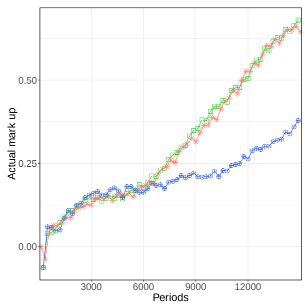
(E) Avg. output



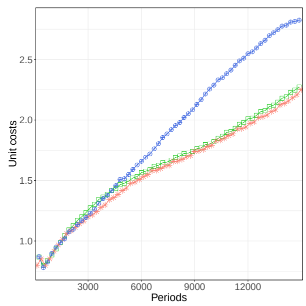
(F) Avg. price by firms



(G) Avg. effective investment



(H) Avg. mark up



(I) Avg. unit costs

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

TABLE 2.C.1: Wilcoxon test on equality of means comparing regimes (baseline)

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

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

2.C.2 Random barrier experiment

TABLE 2.C.2: Initialization of diffusion barriers

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

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

TABLE 2.C.3: Wilcoxon test on equality of means comparing regimes

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

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

2.C.3 Policy experiment

Initialization

The initializations of the random parameters are summarized in table 2.C.4. On the left-hand side, the initial conditions for the full set of simulations are shown. The remaining columns represent the initializations of the runs within the subsets of ex-post classified technological regimes. The p-value in the last column indicates whether the difference in initial conditions between conventional and green regimes is significant tested by a two-sided Wilcoxon test. On average, β^A (ς^c) is significantly lower (higher) in the subset of green regimes. This is an indication that the interactions among policies and barriers might be important to understand the effectiveness of the other political instruments.

TABLE 2.C.4: Initialization of policies and diffusion barriers

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

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

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

Additional information about the evolution of policy effects over time

An evaluation of policy effects over time is made by a regression analysis of the diffusion measure and other firm-level variables on policy instruments, barriers and firm-level controls. To capture systematic differences across different technological regimes, a dummy variable $\mathbb{1}^{eco}$ and its policy interaction terms are included in the regression.[26]

Table 2.C.5 shows the results of a regression analysis of the $\nu^c_{i,t}$ measured 5, 10 and 35 years after market entry ($t \in \{1800, 3000, 9000\}$) on the different policies, barriers and firm-level controls. The table has to be read as follows. The coefficient of $\mathbb{1}^{eco}$ shows fix differences between the different technological regimes. To get the marginal impact of a tax on $\nu^c_{i,t}$ in the transition regime, the coefficient of θ and $\mathbb{1}^{eco}\theta$ have to be added. Five years after market entry, all instruments are associated with a significantly lower share of conventional capital utilization.

The different instruments have different impacts on the shape of the diffusion curve and the impact differs depending on the type of the emerging regime. Ten years after market entry in $t = 3000$, all instruments still have a net negative association with $\nu^c_{i,t}$. In the transition regimes, the effect of θ is stronger, but the effect of the subsidies is weaker. 35 years after market

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

TABLE 2.C.5: Regression of dynamic and conditional side effects of policy

Dep. var: $\nu^c_{i,t}$, $\#employees_{i,t}$, $UnitCosts_{i,t}$									
		$\nu^c_{i,t}$			$\#employees_{i,t}$			$UnitCosts_{i,t}$	
t	1,800	3,000	9,000	1,800	3,000	9,000	1,800	3,000	9,000
$\mathbb{1}^{eco}$	-.0281*	-.3125***	-.8967***	1.483***	2.400***	-.2193	-.0483***	.0486***	.1709***
	(.0136)	(.0157)	(.0106)	(.2982)	(.3836)	(.4530)	(.0050)	(.0059)	(.0147)
θ	-.0010***	-.0015***	.0003**	.0004	.0058.	.0111**	-2e-5	-3e-5	5e-5
	(.0001)	(.00012)	(8e-5)	(.0023)	(.0030)	(.0035)	(4e-5)	(5e-5)	(.0001)
ς^i	-.0093***	-.0165***	-.0056***	.0153	.0037	.1083***	-.0015***	.0019***	-.0071***
	(.0010)	(.0011)	(.0008)	(.0215)	(.0277)	(.0327)	(.0004)	(.0004)	(.0011)
ς^c	-.0477***	-.0743***	.0054	.2661	.3676	-.0536	-.0027.	.0270***	-.0112*
	(.0041)	(.0047)	(.0032)	(.0897)	(.1153)	(.1362)	(.0015)	(.0018)	(.0044)
$\mathbb{1}^{eco}\theta$	-.0014***	-.0011***	-.0005***	-.0027	-.0104**	-.0055	.0004***	.0003***	-.0002
	(.0001)	(.0002)	(.0001)	(.0030)	(.0039)	(.0046)	(5e-5)	(6e-5)	(.0002)
$\mathbb{1}^{eco}\varsigma^i$	-.0063***	.0069***	.0089***	-.1445***	-.2515***	.4090***	.0011*	-.0048***	-.0307***
	(.0014)	(.0017)	(.0011)	(.0316)	(.0406)	(.0479)	(.0005)	(.0006)	(.0016)
$\mathbb{1}^{eco}\varsigma^c$	-.0012	.0468***	.0106*	-.3515**	-.4362**	.9063***	.0228***	-.0154***	.0121*
	(.0056)	(.0065)	(.0044)	(.1222)	(.1572)	(.1857)	(.0020)	(.0024)	(.0060)
R^2	.6795	.6738	.8987	.6413	.5316	.2039	.4137	.3664	.1757
AIC	-4124	-961.3	-9609	63870	69421	73091	-26497	-22569	-2478
Mean	.6011	.4582	.4722	22.98	23.25	23.04	1.075	1.252	1.785
Std.	(.0034)	(.0039)	(.0047)	(.0695)	(.0783)	(.0709)	(.0009)	(.0010)	(.0023)
Significance codes: 0 '***' .001 '**' .01 '*' .05 '.' .1 ' ' 1. R^2: for OLS heterosked. adjusted.									

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

entry, the θ has a net positive coefficient in the conventional, and negative in the green regimes. More conventional (green) capital is used in the conventional (green) regimes. Hence, both instruments have contributed to the technological divergence. The opposite is true for ς^i.

In another series of regressions, it is analyzed how the different policy instruments affect the firm size measured as the number of employees and production efficiency of firms captured by unit costs. The same model configuration is used as introduced above. The dependent variable is evaluated 5, 10 and 35 years after the day of market entry. The coefficients of the policy instruments and their interaction with the type dummy $\mathbb{1}^{eco}$ are summarized in table 2.C.5.

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

In $t = 3000$, i.e. ten years after market entry, this situation has stabilized. In the lock-in regimes, a positive association between both subsidies and unit production costs is observed (cf. 2.C.5). The subsidies have stimulated the initial uptake of green technology. If firms switch back to conventional capital, they have the burden of green capital that undermines their speed of specialization in the conventional technology. The opposite effect is observed in the eco-regimes where the higher green capital penetration, in the beginning, accelerates the technological specialization.

2.C.4 Technical notes on statistical procedures

Data preprocessing and controls

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

The firm level controls that are included in the regression analyses, but are not explicitly shown in table 2.4 and 2.C.5 are the level of skills and productivity of the conventional technology, firm output, age and the price. ν^c_{i,t_0}, $\#employees_{i,t_0}$ and $UnitCosts_{i,t_0}$. In table 2.C.5 also barriers to diffusion are included in the model but not shown. Further, the number of employees and unit costs are also used as dependent variables. In this case, all controls are used except the dependent variable itself. All controls are measured in t_0. For all variables in the regression model, one-year average data is used.

Model selection

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

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

Effectiveness of policies over time

In section 2.5.1 and 2.5.4, the results of a regression of $\nu^c_{i,t}$, $\#employees_{i,t}$ and $UnitCosts_{i,t}$ at different snapshot in time are introduced.

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

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

Chapter 3

Skill transferability and the stability of transition pathways: A learning-based explanation for patterns of diffusion

3.1 Introduction

Two major technological challenges characterize the dawn of the 21st century, climate change and digitization. To reduce the existential risk of triggering irreversible dynamics of a self-reinforcing climate change, the transition to green technology needs to be accelerated (IPCC, 2018; Rogelj et al., 2016; Steffen et al., 2018). Digitization has the potential to alter established modes of production and occupations obsolete (Brynjolfsson and McAfee, 2012). Both technology trends are large scale substitution processes in which an incumbent technology is replaced by a new one. Both trends are likely to be associated with disruptive consequences in terms of distribution at the level of individual households, firms, regional and national economies.

Disruption is caused when occupational skill requirements and the valuation of tangible and intangible assets change in a short time (Grübler, 1991). 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).

These topics are addressed in this study. 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).

This study builds on a model of two competing technologies (green and brown) with endogenous learning dynamics. Technology diffusion is studied as a co-evolutionary transition process where 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 introduced in the first chapter 2.

In the macroeconomic simulation model, 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 capabilities, learning, and technological change. The *relative* pace of accumulation of technology-specific skills depends on the technological similarity and difficulty of competing technologies.

An important output of the model is a sample of simulated diffusion curves that is statistically analyzed. Endogenous learning and endogenous innovation influence the evolution of substitutability in the long run.

If the accumulation of technology-specific skills and supplied productivity sufficiently diverges, 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. Arthur, 1989; Dosi, 1982). In the long run, technological change may dominate the role of relative prices in input substitution decisions. Delayed technological convergence is associated with technological uncertainty. It 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 can be an adoption barrier that might be prohibitively high such that it prevents the diffusion of the entrant technology. It can be a source of path dependence in the process of knowledge accumulation. The macroeconomic coordination among heterogeneous agents in the process of technological learning is important for the stability and pace of technology transitions. It is also shown that the stability has an effect on the macroeconomic outcome.

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

In contrast, a low transferability of skills across technology types reinforces path dependence rooted in cumulative knowledge stocks.

(2) The transferability of technological knowledge may have implications for the disruptiveness of technological change and the emerging market structure. If knowledge is easily transferable, large incumbent firms can incrementally replace parts of their technology with the green alternative without having struggle with the incompatibility of systems.

In contrast, technologies that require radically different capabilities make it difficult to incrementally switch to an alternative technological system. The insights of this study improve the understanding of transition processes. This might be valuable for the design of effective diffusion policies that are responsive to the pecularities of specific technologies, markets and user populations.

This study contributes to 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 directed technological change.

Second, this study is a bottom-up approach to study technology transitions. It is shown, how different pathways of transition can be explained on the basis of technological characteristics and their implications for the process of technological 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 on directed technological change and technology transitions. The modeling framework allows to evaluate the reationship between learning pathways and the macroeconomic performance.

In the next section, an overview of the related literature on the nature of technological capabilities and its link to the transition literature is provided. In section 3.3, the model of technological learning and the mechanisms of technological competition are introduced. In section 3.4, it is shown how the shape of the pathway of transition and its macroeconomic side effects depend on the properties of competing technologies. In section 3.5, it is discussed how the simulation results can be integrated into a general characterization of technologies and how this relates to the transition literature. Section 3.6 concludes.

3.2 Related literature

The microfoundations of technological learning are based on insights from management literature on the acquisition of technological capabilities to absorb technological novelties. In this section, an overview of this literature is given. The model is embedded in a broader concept of macroeconomic, directed technological change.

3.2.1 Technological knowledge and learning in the literature

Technological knowledge and human capital as enabling factors to adopt new technology and sources of endogenous growth have a long tradition in economics (e.g. Nelson and Phelps, 1966; Romer, 1990). Motivated by increasing concerns about climate change and the distributional consequences of skill-biased technical development, the interest in the directional nature of technological change became increasingly important (e.g. Acemoglu, 2002; Löschel, 2002). Different types of technology are modeled as different types of knowledge that are required to develop and use different types of capital goods.

Technological knowledge can be acquired via type-specific R&D investments or learning by doing (Löschel, 2002; Popp et al., 2010). The majority of macroeconomic studies on directed technological change in the endogenous growth literature focus on technology suppliers and the allocation of R&D investments across different technology types. Changing resource endowments and factor prices, possibly manipulated by policy, are the mechanism that determines the allocation of R&D and the direction of technological change. These models are used to study distributional consequences if changes in the relative endowment with skilled and unskilled labor alter relative factor prices and the expected profits of R&D investments in specific types of technology (Acemoglu, 2002). In climate economics, the effect of climate policy or resource scarcity on relative factor prices and the associated effects on relative profitability of R&D in climate-friendly technology (Acemoglu et al., 2012; Löschel, 2002; Popp et al., 2010).

In this paper, the dimension of co-evolving absorptive capacity is added acknowledging that technology diffusion may be sluggish. Sluggishness and adoption lags are major topics in the diffusion literature (e.g. Kemp and Volpi, 2008; Metcalfe, 1988; Pizer and Popp, 2008). Micro-level reasons for sluggish diffusion range from incomplete information, to heterogeneous benefits of adoption, investment cycles and learning-by-doing effects on the side of suppliers and adopters (Allan et al., 2014).

An aggregate approach to explain initially slow technology uptake is based on learning curves. In learning curves, 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 of a specific technology. However, learning curves of single technologies say little about initial technology selection, substitution dynamics and possible interdependencies among competing alternatives. McNerney et al. (2011) consider technologies as composites of different components. They find that similarities of different technologies in the process of technological development can be important to explain the pace of learning.

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

Analogous observations have been made on the basis of overlapping citation links in patent documents. The portfolio of cited patents reveals qualitative information about the technological knowledge of the patent owner (Jaffe and De Rassenfosse, 2017). Acemoglu (2002) and Huang (2017) have used patent similarity metrics to predict the direction of future research. Antony and Grebel (2012) used patent portfolios at the firm-level to derive measures for the absorptive capacity of technological knowledge that is developed in other technological sectors.

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

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

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

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

Four stylized facts on technological learning can be derived from these insights:

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

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

3.2.2 Technology transitions

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

[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.

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

A common approach to study transitions is the multi-level perspective. A socio-technical system is composed of three levels, i.e. the niche-, regime- and landscape level. Incumbent technologies dominate at the regime level. New technologies are developed at the niche-level. Niches are markets with specialized needs and provide a protected space for experimentation and learning. Technologies are developed and used within the context of a landscape layer that represents external forces (e.g. customer needs, natural resource availability, regulations, complementary technologies). These forces are external to technology users and developers.

If the landscape changes and the dominant technology at the regime level is not able to adapt to new circumstances, a niche technology may enter the regime level. It possibly replaces the incumbent alternative if it outperforms the incumbent alternative within the new environment (Geels, 2002). A prominent example are energy transitions in the context of climate change. Fossil fuel energy determines the technological regime and is challenged by different types of renewables originally developed in protected market niches (Safarzyńska et al., 2012; Unruh, 2000).

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

The analysis in this paper is based on a macroeconomic agent-based simulation model. Agent-based models offer an analytical and methodological framework that allows simulating the co-evolutionary nature of technology transitions and their underlying dynamics (Dawid, 2006; Farmer et al., 2015).

Sustainability transitions within agent-based macroeconomic frameworks had been studied by Gerst et al. (2013); Hötte (2019b); Lamperti et al. (2018b); Rengs et al. (2015); Wolf et al. (2013). Acemoglu et al. (2012); Lemoine (2018) have studied (climate-friendly) directed technological change within an analytical framework. This study differs from previous studies by its explicit focus on learning dynamics in the presence of heterogeneous absorptive capacity.

Aim of this paper is to improve the qualitative understanding of the conditions of transition success

3.3 The Model

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

3.3.1 The concept of technology

Technology is the ability of producers to combine inputs such that an economically valuable output is produced. In this paper, 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 that is equally valued by consumers but requires different types of inputs. In figure 3.1, the concept of technology and learning is shown as a flowchart for the two-technology case of a climate-friendly, green g that competes with an incumbent conventional c alternative. The framework is not restricted to this example and can straightforwardly be applied to other examples of competing 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 embodied in physical production inputs labor L and capital K and accumulated by different mechanisms.

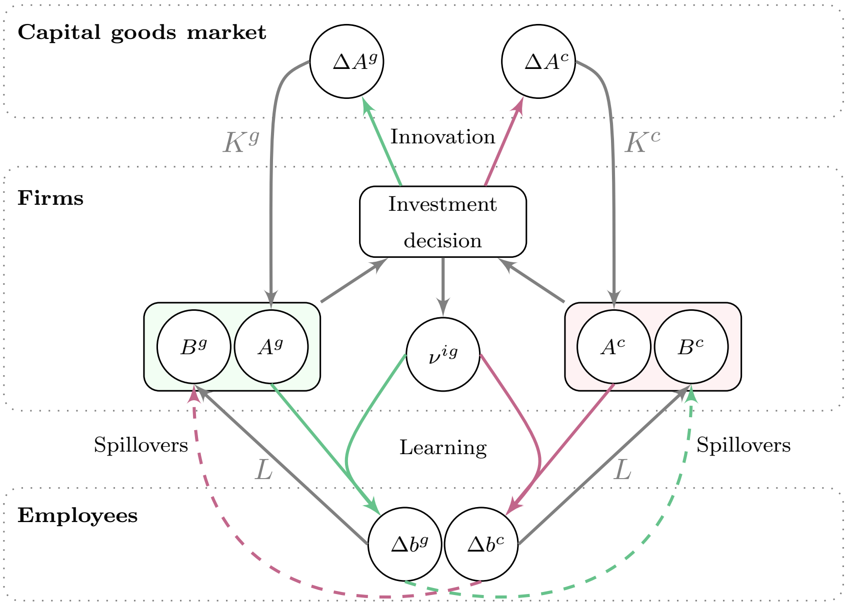
Codified technological knowledge is embodied in the technical properties of the capital stock and is acquired on the capital goods market by investments. Innovation and technical progress in the capital goods market are driven by endogenous innovation. The productive properties are called *theoretical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

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

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

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

FIGURE 3.1: Illustration of the learning mechanism



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 two technology race between one incumbent and one entrant technology is considered. A static property of the entrant technology is its technical superiority. It allows the adopter to save a fraction of variable input costs. In the case of green technologies, this is interpreted as natural resource input that is required to operate conventional capital. One unit of the resource is needed to use one unit of conventional capital. The conceptual framework can be generalized to other types and a larger number of competing technological alternatives.

A key assumption is that the cost savings cannot be achieved in the same way by the incumbent alternative. The green entrant is technically superior in terms of resource efficiency but suffers from lower cumulative stocks of tacit and codified "green" technological knowledge. At the time of market entry t_0, the green alternative is technologically less productive, i.e. $A^g_{t_0} < A^c_{t_0}$. Firms and employees have, compared to the incumbent technology, not yet developed the capabilities to use the green technology efficiently, i.e. $B^g_{t_0} < B^c_{t_0}$.

Firms can acquire different types of capital and substitute them for each other. Substitutability between technology types is limited by the transferability of tacit technological knowledge across types. Hence, employees who know how to make productive use of conventional capital do not necessarily know how to use the climate-friendly alternative. The cross-technology transferability is higher if the two technologies are similar.

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

3.3.2 Technological learning and spillovers

Technological learning at the macroeconomic level is the aggregate of learning by individual employees working in heterogeneous firms. Firms' learning is reflected in the improvements of firms' *effective* productivity in using technology type $\tau = c, g$. This is embodied in 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 represented as average productivity of the firm's capital stock items of technology type τ. Tacit knowledge is given by the average technology-specific skill level of the firm's employees.

Consumption goods firms' production technology

The effective productivity of firms determines how effectively a firm can transform inputs into final consumption goods $Q_{i,t}$. Production inputs are a stock of capital $K_{i,t}$, a stock of employees $L_{i,t}$ and, in case of conventional capital, natural resource inputs. Inputs are combined in a constant returns to scale Leontief production function. The adjustment of labor and capital is sluggish. Capital stepwise depreciates and is stepwise expanded by investment. Similarly, a firm can dismiss only a given fraction of employees and if hiring new employees (in discrete units) it is not certain whether the firm is able to fill all vacancies immediately (see for more detail Dawid et al., 2019b).

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

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

$$A^{Eff_v}_{i,t} = \min\left[A^v, B^\tau_{i,t}\right]. \tag{3.1}$$

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

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

$$Q_{i,t} = \sum_{v=1}^{V} \left(A^{Eff_v}_{i,t} \cdot \min\left[K^v_{i,t}, \max\left[0, L_{i,t} - \sum_{k=v+1}^{V} K^k_{i,t}\right]\right] \right) \tag{3.2}$$

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 $\max\left[0, L_{i,t} - \sum_{k=v+1}^{V} K^k_{i,t}\right]$ 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 use the full capacity or expected demand is lower than the maximal output and using costs of capital exceed the expected revenue. In such a case, 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 energy and material costs c_t^{eco}.[2] Formally, this can be written as

$$\zeta_{i,t}^{v} = \frac{A_{i,t}^{Eff_v}}{w_{i,t} + \mathbb{1}(v) \cdot c_t^{eco}}. \tag{3.3}$$

The decision of firms about the quantity to produce is dependent on demand estimations and inventory stocks. Based on estimated demand curves, firms determine the profit-maximizing price-quantity combination. Because the estimation is imperfect in most cases and prices cannot be immediately adjusted, the consumption goods market does not necessarily clear. Further information on the production decision and market environment can be found in Dawid et al. (2019b).

Accumulation of tacit and codified knowledge

Codified knowledge at the firm-level is acquired by investments in capital goods. The productive properties A^v of capital contribute to the firm's stock of codified knowledge $A_{i,t}^{\tau}$ of type τ. It is given by the average productivity of used capital goods of type τ, i.e. $A_{i,t}^{\tau} = \frac{1}{K_{i,t}^{\tau}} \sum_{v \in K_{i,t}^{\tau}} (K_{i,t}^{v} \cdot A^v)$ where $K_{i,t}^{\tau}$ 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 has to choose the optimal combination of the investment quantity, productivity level and technology type. This decision is based on the firms' expectations about the marginal profit of the different options. The firm computes and compares the net present values of different quantity-productivity-type combinations taking account of expected demand, prices, costs, skill developments and financial constraints.[3] More detail on the investment decision and capital supply is provided in the SM I.

Tacit knowledge $B_{i,t}^{\tau} = \frac{1}{L_{i,t}} \sum_{l \in L_{i,t}} b_{l,t}^{\tau}$ is embodied in the capabilities of the firm's employees. Employees $l \in L_{i,t}$ are characterized by their learning ability and two types of technology-specific skills. Workers' ability to learn is captured by a time-invariant general skill level b_l^{gen} of employees. 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.

The two types of technology-specific skills $b_{l,t}^{\tau}$ represent the employee's capability to work productively with a specific type of capital $\tau \in \{c, g\}$. These skills are stock variables that increase by stepwise updates that represent a learning process. The learning process is dependent on the learning ability

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

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

χ_l^{gen} and the technological properties of the capital stock used in firm i where the employee is working. There are two sources of learning. Employees are learning by doing when working with a specific technology type and they can learn via cross-technology spillovers.

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

$$\Delta b_{l,t+1}^{\tau} = \chi_l^{gen} \cdot \left(\left[\left(\psi_{l,t}^{\tau}\right)^{(1+\chi^{dist})} \left(\psi_{l,t}^{-\tau}\right)^{(1-\chi^{dist})} \right]^{1/2} - 1 \right). \tag{3.4}$$

$\psi_{l,t}^{\tau} \geq 1$ represents "amount" of knowledge learned in one period during the utilization of technology type τ. Part of this knowledge is transferable across technologies. It contributes to the accumulation of skills of the alternative technology 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 which is a source of state dependence. The functional form is inspired by models on state-dependent technological change (cf. Acemoglu, 2002).

The skill update by learning by doing $\psi_{l,t}^{\tau}$ is dependent on the technical difficulty of the technologies χ^{int}, the relative amount of effort $\nu_{l,t}^{\tau}$ 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 $\max[0, (A_{i,t}^{\tau} - b_{l,t}^{\tau})]$ of capital τ which reflects the potential amount of knowledge an employee l can learn. The updating step is given by

$$\psi_{l,t}^{\tau} = 1 + \left(\nu_{l,t}^{\tau}\right)^{\chi^{int}} \cdot \max[0, (A_{i,t}^{\tau} - b_{l,t}^{\tau})]. \tag{3.5}$$

The relative intensity of learning in a specific technology category τ is dependent on the relative amount of technology τ that is used $\nu_{i,t}^{\tau} = (K_{i,t}^{\tau}/K_{i,t})$ in the firm. This can be understood as a proxy for the amount of time invested in the learning to use a specific type of machinery (cf. Cohen and Levinthal, 1990). Learning in category τ is faster if the relative amount of this type in the used capital stock higher.

The parameter χ^{int} captures marginal returns. In the baseline scenario, I assume weakly decreasing marginal returns in the learning process, i.e. the first hour of learning is more effective than the last one. A conceptual interpretation of χ^{int} is the *difficulty of learning*. If χ^{int} is close to zero, employees learn how to use the machinery irrespectively of the time invested in working with the machine. If technologies are more difficult to learn, the learning progress is more sensitive to the amount of time invested in learning.

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

Firms cannot observe the skill endowment of individual employees, but observe the effectiveness of the production process. They know the amount of inputs and the amount of output and draw conclusions about their aggregate stock of tacit knowledge $B^{\tau}_{i,t}$.

Learning in a nutshell

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

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

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

Three factors determine the speed of learning by doing:

1. The learning intensity $v^{\tau}_{i,t} = K^{\tau}_{i,t}/K_{i,t}$ determines how intensively employees are working with a specific type of technology. Increasing returns in the learning process χ^{int} are related to the difficulty of learning. If $\chi^{int} = 0$, workers learn independently of the extent to which they are using a certain type of capital. If $\chi^{int} > 1$, returns to learning are increasing in the relative extent to which employees are working with a technology type.
2. The quality of the learning environment is captured by the *technical novelty* $\max[0, A^{\tau}_{l,t} - b^{\tau}_{l,t}]$ of individual workers l. Employees learn faster if capital goods are technically new to them.
3. Spillovers or the *transferability of technological knowledge* are negatively dependent on the technological distance χ^{dist}. If the distance is low, technologies are similar and knowledge is transferable across technology types. Learning in one technology class contributes to the stock of know-how in the other class.

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

3.3.3 Simulations and experiments

A technology race between an incumbent conventional and green entrant technology is simulated. The two technologies are characterized by initial diffusion barriers, technical superiority and interactive properties of the learning process χ^{int} and χ^{dist}. The simulations allow isolating the influence of technological distances χ^{dist} and difficulty in learning χ^{int} on individual technology adoption and the emerging pathways of transition.

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

The simulations are subject to stochasticity. For example, capital producers' innovation success, the matching mechanism at the labor market and consumers' consumption decision are probabilistic (see Dawid et al., 2019b) and the SM I. In the experiments presented below, sets of 210 simulation runs are generated and the simulated time series data are statistically analyzed. One simulation run consists of 15000 iterations which corresponds to a time horizon of approximately 60 years. One iteration represents to 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*.

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

Which of the two technologies succeeds depends on the type and strength of diffusion barriers in relation to the technical superiority of the entrant and the characteristics of the learning process. If barriers are sufficiently strong, path dependence in technological learning may reverse the process of initial green technology diffusion that is triggered by its input-cost superiority. The economy is locked in the incumbent technological regime. If barriers are weak, firms incrementally substitute conventional for green capital. A *technological transition* takes place. A more detailed discussion of the role of diffusion barriers and diffusion policies can be found in chapter 2 and a more comprehensive discussion is provided in Hötte (2019b).

Two different types of experiments are run.

1. To compare the effects of different degrees of state dependence, time series simulated with different discrete levels of the learning parameters $\chi^{dist} \in \{0, .5, 1\}$ and $\chi^{int} \in \{0, .5, 2\}$ are compared.
2. To make a statistical analysis of the effect of the learning parameters on the micro- and macroeconomic outcome, a Monte Carlo analysis drawing random values of the learning parameters from a uniform distribution on the interval $\chi^{dist} \in [0, 1]$ and $\chi^{int} \in [0, 2]$ is done.

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.

3.4 Results

Three major questions are addressed in this analysis.

- How does the success and pattern of diffusion depend on the technological similarity and on the ease of learning?
- What are the drivers of technological convergence and how do these relate to the stability of the diffusion process?
- Which macroeconomic side effects occur and can the effects be attributed to the characteristics of competing technologies?

These questions are addressed by an analysis of simulated time series data. The core indicator to evaluate the diffusion success is the share of conventional technology utilization at the firm-level $\nu^c_{i,t} = K^c_{i,t}/K_{i,t}$. It describes the share of conventional capital that is used for production in t by firm i. It measures diffusion at the intensive margin. It can be aggregated across firms to obtain a macroeconomic diffusion curve ν^c_t. The stability of the diffusion process is evaluated by the standard deviation $\sigma^{\nu}_{i,t}$ of the diffusion measure in percentage points. It is calculated over a moving time window of 2.5 years.[4] A diffusion process is called *unstable* if firms switch between the two technology types.

In the preceding chapter 2 on barriers to technology diffusion it was found that relative stocks of technological knowledge $\alpha_t = A^c_t/A^g_t$ and $\beta_t = B^c_t/B^g_t$ represent a source of path dependence in technological change. Both stocks are endogenously accumulated dependent on the relative profits in the IG sector and relative intensity of technology use. If knowledge stocks diverge, the economy becomes increasingly locked in the relatively more productive

[4]Further information about its computation and relation to other measures of convergence is available in SM II.

technology irrespective of relative factor input costs. Relative knowledge stocks help to describe the technological state of the economy.

3.4.1 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. It is briefly described to give an overview of the typical processes that occur during the simulation horizon.

The simulated diffusion curves show a pattern of technological divergence. The economy converges to one of two possible technological states, either with almost 100% or 0% green technology utilization at the end of simulation time. The final states are called *technological regimes* and are classified by the share of conventional technology used ν_T^c in $T = 15000$. A regime is called *green* (*conventional*) if $\nu_T^c < .5$ ($\nu_T^c \geq .5$). This is illustrated in the time series of the diffusion curves for each single run in the appendix 3.A.1b. In 142 out of 200 simulation runs the economy converges to a green technological regime corresponding to a transition probability of 71%.

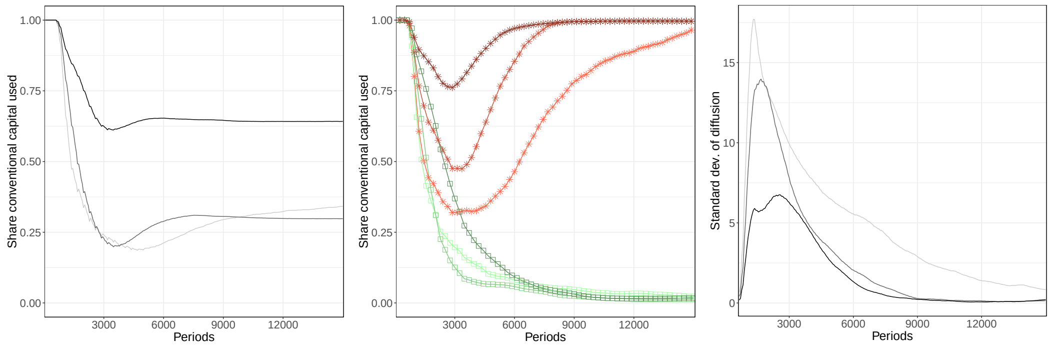
Independent of the resulting technological state, the curves exhibit a phase of initial technology uptake triggered by the technical superiority of the green technology. The initial uptake is not necessarily permanent. In some of the simulation runs, initial diffusion is reversed by the effects of path 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 IG market and the stochastic elements in the innovation process. Further information about the main technological and macroeconomic properties of the simulations and the empirical model validation criteria is provided in the appendix 3.A.1 and Hötte (2019f), respectively.

3.4.2 The technological distance

In this experiment, the relationship between the technological distance and the stability of the diffusion process is illustrated and the macroeconomic side effects are briefly discussed. 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 $\chi^{int} = .5$.

FIGURE 3.1: Diffusion curves (baseline)



(A) ν_t^c batch (B) ν_t^c by regime type (C) $\sigma_{i,t}^{\nu}$ batch

These figures show the diffusion process measured by the share of conventional capital used ν_t^c. The time series in the middle are disaggregated by the type of technological regime. Different line shapes indicate regime types (□: eco, $*$: conv). Darker color indicates a higher distance $\chi^{dist} \in \{0, .5, 1\}$.

Patterns of diffusion

In figure 3.1, the time series of different diffusion indicators for the different spillover levels are shown. The lines are disaggregated by parameter value and in figure 3.1b by the technological regime. Throughout this article, different line shapes and colors indicate different technological regimes. Darker color indicates a higher technological distance.

Figure 3.1a shows the evolution of the diffusion measure for different parameter levels without a disaggregation by the technological regime. This aggregate measure is informative about the relationship between the level of spillovers and the probability of a technological regime shift.

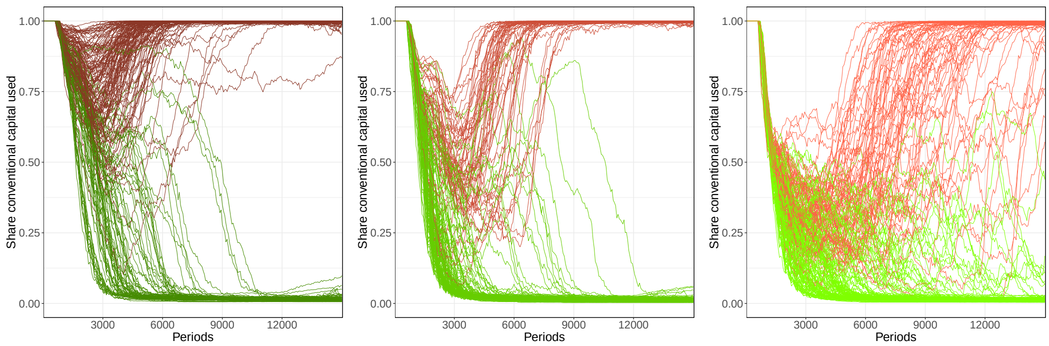
The relationship between the χ^{dist} and the transition frequency has an inverted u-shape. The observed frequency of transition accounts for 36% if $\chi^{dist} = 1$ and 66% if spillovers are perfect, i.e. $\chi^{dist} = 0$. With 71%, the transition frequency is highest for the intermediate level of spillovers, i.e. $\chi^{dist} = .5$.

Figure 3.1b shows the time series of ν_t^c for two different subsets of simulation runs that are classified by the final technological regime. Green color indicates the subset of transition regimes identified by $\nu_T^g > .5$. The darkness of color indicates the parameter value. The distinction between the different regimes shows that initial green technology adoption, irrespectively of the final regime, is highest if spillovers are perfect. But this initial adoption lead in the case of perfect spillovers 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 relapses back to conventional technology despite the average ν_t^c fell below 32% around $t = 3000$, i.e. roughly 10 years after market entry. In some cases, path dependence dominates and the economy relapses into the conventional regime. 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. The statistics are available in the appendix of Hötte (2019f).

In figure 3.2, the time series of ν_t^c for the single simulation runs within the aggregated subsets of green and conventional regimes are shown. Comparing the plot for the highest distance level (3.2a) with the figure for the case of perfect spillovers (3.2c), 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.

FIGURE 3.2: Diffusion curves by spillover intensity



(A) $\chi^{dist} = 1.0$ (B) $\chi^{dist} = 0.5$ (C) $\chi^{dist} = 0.0$

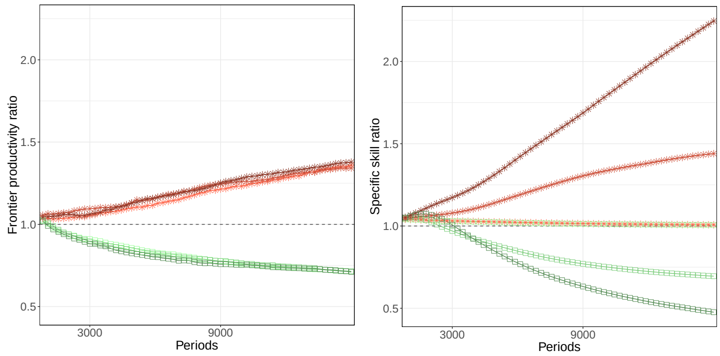
These figures illustrate show diffusion curves ν_t^c of all 210 single simulation runs within the different parameter subsets with $\chi^{dist} = \{.0, .5, 1\}$.

A measure for the pace of convergence and the diffusion volatility is the standard deviation $\sigma_{i,t}^{\nu}$ of the diffusion measure $\nu_{i,t}^c$ (figure 3.1c). A high deviance is an indicator of technological uncertainty and a high number of changes in the direction of diffusion. It is a measure of the pace of convergence. 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 it remains highest for the case of perfect spillovers. This is an indication of technological instability.

If the technological distance is small it is easy to adopt new technology, but it is also easy to switch back to the incumbent technology type.

Previous analyses have shown that the relative technological performance is decisive for the stabilization of the technological evolution (cf. chapter 2 and (Hötte, 2019b)). The convergence to a stable technological state with one clearly dominating technology is accompanied by the divergence of relative stocks of technological knowledge measured as ratio of the technological

FIGURE 3.3: Relative technological knowledge by spillover intensity



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

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 figure 3.3. The evolution of β_t reveals the mechanism through which the distance parameter operates. The divergence of the curves between the two technological regimes is stronger if the distance is high.

If spillovers are perfect, the curve of relative tacit knowledge β_t does not diverge because learning in one technology category equally contributes to the stocks of tacit knowledge of both technology types. In this case, the convergence to a stable technological state is mainly driven by market induced innovation if the frontier of the dominant technology type grows relatively faster.

Other technological indicators on relative real and nominal capital prices, the degree of technological novelty reflect the same pattern. An overview of these indicators is available in the appendix of Hötte (2019f) and comprehensively discussed in Hötte (2019b).

Macroeconomic effects

Spillovers and the stability of the diffusion process have implications for the market structure and the macroeconomic performance. In table 3.1 the results of a pooled OLS regression analysis of different macroeconomic indicators are shown. To take account of the panel-like structure of the data, two-way clustered standard errors on run-time are used. This analysis illustrates the relationship between the diffusion volatility, the different assumptions about the technological distance and the regime shift.

Row 3 of the table shows that technological uncertainty is costly in terms of aggregate log output, but lower unemployment. It is associated with a smaller number of firms, but lower market concentration measured by the

Herfindahl-index. The effect of the uncertainty dominates the influence of the parameter dummies on the market structure and unemployment.

A higher distance has ambiguous effects. Its effect is dependent on the occurrence of a transition. If the transition occurs, it facilitates the specialization in the new technology and has a positive association with output. In the transition regimes, it has a statistically weak positive association with market concentration and a negative with the number of active firms. A higher distance reinforces path dependence. This makes it difficult for late adopters to catch up.

TABLE 3.1: Regression to explain macroeconomic side effects

	Output	# firms	Herfindahl	Unempl.
(Intercept)	8.619***	72.66***	159.9***	11.42***
	(.0141)	(.2382)	(.4990)	(.3572)
$\mathbb{I}(eco)$	.0058	.4936.	-.0213	.4215
	(.0108)	(.2673)	(.5854)	(.4195)
σ_t^ν	-.0686***	-.3178***	-.3517***	-.6036***
	(.0026)	(.0274)	(.0389)	(.0389)
$\mathbb{I}(0.5)$	-.0338*	.2637	-.4736	-.2593
	(.0134)	(.3464)	(.7489)	(.4884)
$\mathbb{I}(1.0)$	-.0592***	.2363	.3808	.1745
	(.0115)	(.2984)	(.7312)	(.4872)
$\mathbb{I}(eco) \cdot \mathbb{I}(0.5)$	.0403*	-.4813	1.955.	1.182
	(.0169)	(.4364)	(1.013)	(.7277)
$\mathbb{I}(eco) \cdot \mathbb{I}(1.0)$	.0532**	-.8698.	2.766*	1.452
	(.0174)	(.4714)	(1.330)	(.9674)
R^2	.29	.0476	.0165	.0647

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

This table shows the results of a pooled OLS regression with two-way clustered standard errors. Dependent variables: log monthly output, the number of active firms, the Herfindahl-Index (multiplied by 10,000) and the unemployment rate. Explanatory variables: dummy for the regime type $\mathbb{I}(eco)$, dummies for the different parameter settings $\mathbb{I}(\chi^{dist})$, the standard deviation of the diffusion measure σ_t^ν and regime-parameter interaction terms. More information is available in the appendix 3.B.

If the transition does not occur, the distance has a negative association with output. Reinforced path dependence operates in the opposite direction. Triggered by the initial superiority of the green technology, diffusion in the first 10 years after market entry is high (cf. figure 3.1). Path dependence 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, conventional technology. This is associated with lower productivity. No significant relationships between χ^{dist} and the market concentration are observed.

These observations are also reflected in a set of time series figures. The regression results are qualitatively and quantitatively robust across different model specifications. The figures and a short discussion, and further information about robustness checks and alternative model specifications are available in SM II.

Note that the comparison of transition and lock-in regimes is sensitive to the assumptions about initial diffusion barriers. In this experiment, diffusion barriers are relatively low. Higher diffusion barriers tend to be associated with higher transition costs but reduce uncertainty if the economy is locked in.

3.4.3 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. The more difficult a technology is, the more sensitive is the progress to the relative time invested in learning. In an additional experiment that is not presented here, it was shown that the difficulty is only of minor importance in the presence of cross-technology spillovers (cf. Hötte, 2019f).

The impact of difficulty on 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. 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. This is discussed in more detail in (Hötte, 2019f).

3.4.4 Interactions of spillovers and the ease of learning

The interaction effect of spillovers and the difficulty of learning on the transition probability is illustrated as a transition boundary shown in figure 3.4a. A transition boundary can be understood as 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 $\chi^{int} \in \{0, 2\}$.[5] 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.[6] 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 technological distance and moderate difficulty to learn. This pattern can be explained by the transition dynamics and the influence of the parameters on the knowledge accumulation process.

In all simulation runs, the green technology initially diffuses. This is triggered by its technical superiority of the green technology. Whether the diffusion is permanent is dependent on the degree of state dependence of the learning process. In the initial phase, the incumbent technology has a dominant position in the capital stock of firms. Employees continue to accumulate conventional skills. If technologies are similar, this also contributes to the stock of green skills.

The decision region for green regimes has an ambiguous relationship with technological difficulty. If the technology is very easy to learn, i.e. learning is independent of ν^c, a transition is more likely. On the other hand, increasing returns in the learning function also have a positive association with the transition probability. In this case, increasing returns strengthen the specialization in green technology during the initial surge of green technology diffusion. This makes a relapse into the conventional regime less likely. This effect is conditional on a sufficiently high green-technology uptake in the beginning.

The transition probability

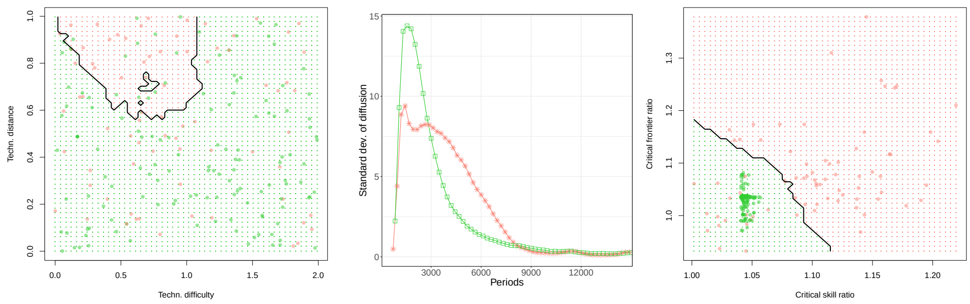
A regression analysis of the diffusion measure ν_i^c evaluated at firm-level at the end of the simulation horizon T on the learning parameters and a set of micro- and macroeconomic controls confirms the observations made before. The data of control variables is demeaned and scaled to facilitate the comparison of coefficients. ν_i^c is almost binary in T taking the values zero or one. It is interpreted as measure for the inverse of the transition probability.[7] A higher

[5] A technical explanation of this experiment is available in the appendix 3.4.4 and a short discussion of the results can be found in Hötte (2019f).

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

[7] This interpretation of the diffusion measure and the association of other micro- and macroeconomic control variables with the transition probability is discussed chapter 2 and more comprehensively in Hötte (2019b).

FIGURE 3.4: Transition patterns and technological learning



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

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

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

Figure 3.4a and 3.4c 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 stocks of technological knowledge α^*, β^*. Further information about the clustering and the derivation of critical knowledge stocks is available in SM II.

technological distance χ^{dist} is associated with a lower transition probability $(1 - \nu^c_i)$.

In contrast, returns to scale in the learning process χ^{int} are positively related to the transition probability. The relationship is quantitatively weaker than the technological distance. The role of the other control variables is explained in Hötte (2019f) and a more comprehensive discussion of their role for the diffusion process can be found in Hötte (2019b). Additional information about the data preprocessing, the model specification and model selection is available in the technical notes in SM II. The coefficient of the interaction term $(\chi^{int} \cdot \chi^{dist})$ is negative, but quantitatively small. This indicates that the negative association of the distance with technology diffusion is weaker if returns to learning are high.

The positive effect of χ^{int} on technology diffusion might be conditional on the strength of diffusion barriers. Increasing returns in the learning process favor the dominant technology. If entry barriers for the green technology are sufficiently low, the green technology rapidly achieves a sufficiently high diffusion level to benefit from increasing returns.

The pace of convergence

To study is the relationship between state dependence in technological learning and the stability of the diffusion process, a set of additional indicators is introduced. The volatility is measured by the variance $(\sigma^{\nu}_i)^2$ of $\nu^c_{i,t}$ computed over the full time horizon. In addition, the duration t^*_i until the diffusion process becomes stable is measured. t^*_i is defined as the point in time when the last change of the sign of the slope of the diffusion curve $\nu^c_{i,t}$ is observed.

TABLE 3.2: Firm-level regression analysis of transition pattern

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

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

The first two columns show the diffusion measure ν_i^c evaluated at the end of simulation. Column 3 illustrates a regression of the duration t_i^* until the firm-level adoption curve stabilizes. The results in column 3-6 are the results of an instrumental variable regression with the type dummy $\mathbb{I}(eco)$ as endogenous variable. Further info is provided in the main text and appendix A of Hötte (2019f).

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. at an early point in time the technological trajectory is clarified and a process of stabilization and specialization begins.

These indicators are used in a regression analysis similar to the analysis above. A dummy variable for the type of the technological regime $\mathbb{I}(eco)$ is included to capture fix differences and differences in the interaction patterns across the two technological regimes. It takes the value 1 if a transition took place. To rule out possible endogeneity of the type dummy, i.e. possible correlatedness of the error term and the regime type, the type dummy is included through an instrumental variable regression.[8]

State dependence in learning has an ambiguous relationship with the time until technological stabilization t_i^*. Whether the association is positive or negative is conditional on the transition. In general, the stabilization is earlier if a transition occurs. This is in line with figure 3.4b showing that the diffusion volatility in the subset of green regimes is high in the beginning, but rapidly diminishes in the later phase. In contrast, in the subset of lock-in regimes, the volatility decreases more slowly. A Wilcoxon test confirms the significance of the difference (cf. Hötte (2019f)).

If a transition occurs, a higher distance retards the technological specialization. The distance increases the strength of path dependence. If the distance is high, it is more difficult for firms to overcome the relative disadvantage in terms of lower knowledge stocks when beginning to use green technology. This is associated with a higher diffusion volatility in the transition regimes.

In contrast, the distance has an accelerating effect on the time of convergence if the economy is locked in. χ^{dist} exacerbates the effect of initial diffusion barriers. The opposite holds true for the difficulty of learning χ^{int}. The retarding effect in the lock-in case can be (again) explained by the high technology uptake in the early diffusion phase. This retards the relapse into the conventional regime.

Sources of stability

The divergence of relative knowledge stocks is a driver of technological convergence. To understand the link between relative performance measured by relative knowledge stocks and state dependence in learning, I introduce a measure for *technological thresholds*.

The threshold levels are illustrated in figure 3.4c. The black line in the figure is interpreted as transition boundary beyond which the technological path has stabilized. The vertical (horizontal) axis represents the relative technological frontier $A^V_{c,t^*}/A^V_{g,t^*}$ (skill endowment $B^c_{t^*}/B^g_{t^*}$) evaluated in the aggregate t^*. In this figure, relative knowledge stocks are used as training input for a k-nearest neighbors clustering algorithm to derive a transition boundary. The boundary serves only for the purpose of illustration here.[9] Apparently, relative knowledge stocks have a high explanatory power for the resulting technological regime because the number of mis-classified simulation runs is low.

The relationship between these performance thresholds and state dependence in technological learning is illustrated by a regression analysis shown

[8]Technical and explanatory detail about the IV approach and alternative model specifications can be found in SM II. Test statistics and the results of alternative model specifications are available online in Hötte (2019g).

[9]Technical detail can found in SM II.

in columns (4) and (5) in table 3.2. These are levels of relative technological performance evaluated at t_i^*. $\left(A_i^+/A_i^-\right)^*$ $\left(\left(B_i^+/B_i^-\right)^*\right)$ measure the relative stock of codified (tacit) knowledge at firm-level in time t_i^*. $+$ $(-)$ indicates the technology type that is dominant in T. The regression indicates that the divergence in the relative technological performance is less (more) pronounced in the presence of state dependence of learning in transition (lock-in) regimes. This makes the technology race for the green technology more difficult. It might be an explanation why the diffusion volatility measured by $(\sigma_i^\nu)^2$ is increasing in the distance if a transition occurs. A short discussion of these findings can be found in Hötte (2019f).

The variance $(\sigma_i^\nu)^2$ is an indicator for technological stability. The variance $(\sigma_i^\nu)^2$ is a measure for the volatility of the diffusion process computed over the whole simulation horizon. It is an indicator of firms' switching behavior between green and conventional technologies. In the lock-in regimes, the regression indicates that a higher distance is associated with higher stability. In the case of a transition, it may increase technological uncertainty. A higher distance exacerbates the effect of barriers. This retards the technological specialization in the transition process.

The qualitative findings are robust across a large variety of alternative model specifications. The results of some of these alternative specifications are available in the accompanying data publication (Hötte, 2019g) and a longer discussion can be found in the accompanying working paper (Hötte, 2019f).

3.5 Discussion

The three questions formulated in section 3.4 can be answered as follows:

How does the success and pattern of diffusion depend on state dependence of technological learning? The transition probability is ambiguously related to the state dependence of learning. A high transferability of knowledge reduces state dependence and facilitates the adoption of new technology. But it may also operate in the opposite direction. If relative performance changes, firms may easily switch back to the conventional technology if spillovers are high. A higher the degree of state dependence is associated with less volatile diffusion curves.

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 technological knowledge contribute to the convergence to a stable technological state. A higher technological distance is associated with a more pronounced divergence. If the divergence in relative stocks of knowledge is sufficiently high, the economy is locked-in in a stable technological regime.

Which macroeconomic 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.

Technological distances and the difficulty of learning can be used to characterize competing technologies. This characterization is dependent on the economic context given by an industry, region, etc. and the incumbent type of technology therein. The technological distance can be interpreted as a measure for the disruptiveness of the market entering technology in relation to the incumbent technology. 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).

It is also a way how theories about the task-content of technological change can be linked to patterns of diffusion (e.g. Autor et al., 2003). The technological knowledge embodied in non-routine can be transferred across technology types. For example, Vona et al. (2015) have shown that firms that have a high share of occupations characterized by non-routine tasks do less struggle to cope with technological change.

An alternative approach to link the proposed characterization to economic data is the concept of technological distances (cf. Boehm et al., 2016; Carvalho and Voigtländer, 2014; 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, the switch to an new, market entering technology might become superior. Switching to new technology is easier if the transferability of skills is high. But this may come with the cost of stability and specialization. This can be also interpreted as trade-off between exploitation and exploration.

The divergence in the endowments with technology-specific knowledge stabilizes the process of technology diffusion. Relatively higher endowments with technology-specific skills are a barrier to diffusion for market entering technologies. Accumulated skills reflect the experience and maturity of a technology. This barrier is easier to be overcome if technologies are sufficiently similar and if accumulated knowledge (but also infrastructure etc.) can be transfered to the utilization of the new technology type.

This analysis was applied to the case of green technology diffusion but the framework and the simulation model can be straightforwardly applied to other technologies.

3.6 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. Based on a synthesis of the theoretical and empirical literature of economics, management and technology studies, a microeconomic model of technological learning is developed. It is implemented in the Eurace@unibi-eco model and describes the accumulation of technology-specific absorptive capacity at the firm-level. Competing technologies are characterized by their technological similarity and difficulty. It is shown that the characteristics of the two 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 undermines the pace of specialization and stabilization within a technological regime. 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 of supplied technology change. An enduring phase of switching between two technologies is interpreted as *technological uncertainty*. It is macroeconomically costly because learning and R&D resources are wasted if they are invested in a technology that is obsolete in the long run. Increasing returns in the learning process are interpreted as a measure for technological difficulty 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 reflected in lower stocks of technological 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 green technology successfully penetrates the market, it is difficult for late adopters to catch up. This may be associated with a higher market concentration.

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 reduced to a minimum. It will 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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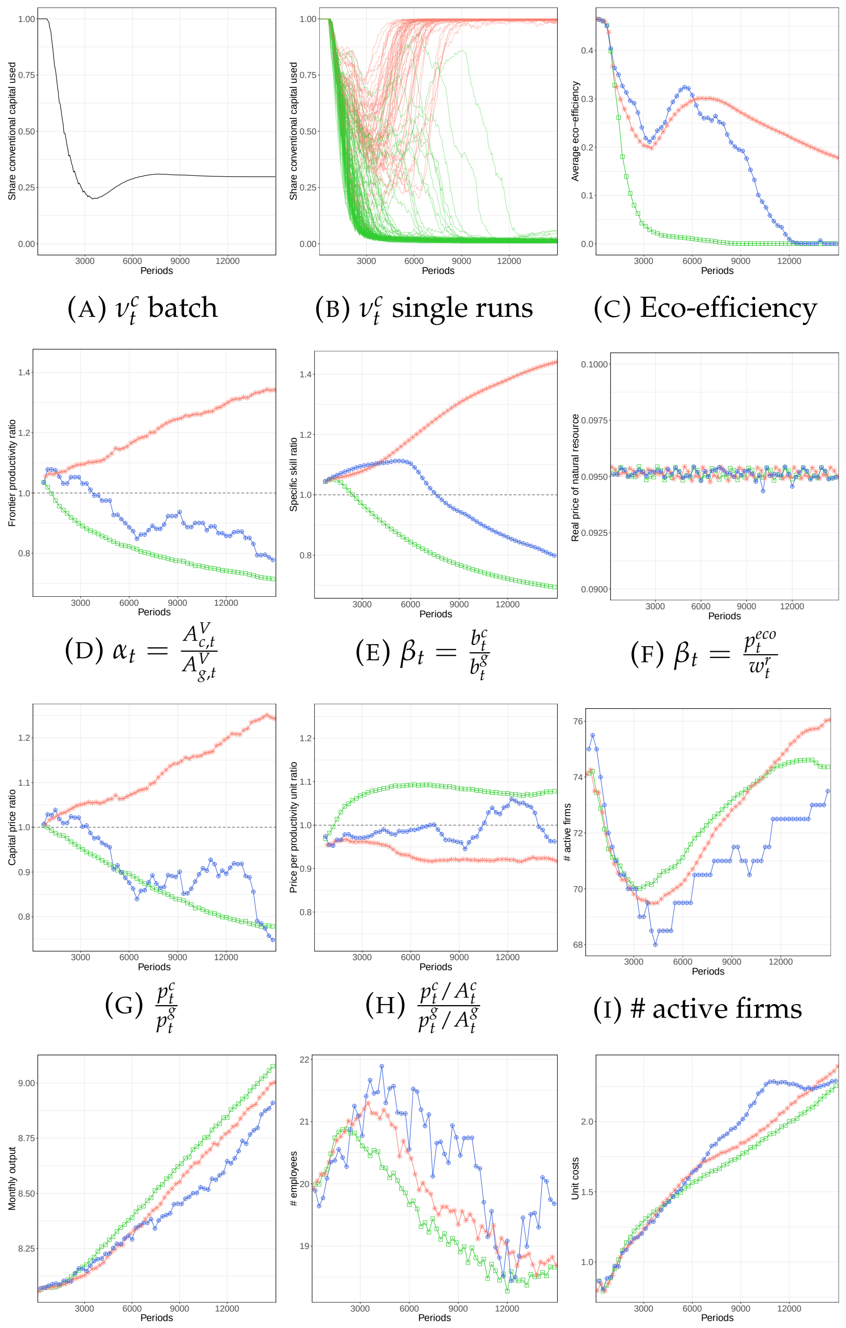
3.A Simulation results

3.A.1 Baseline

Here, only some general features of the simulated time series data are shown. Information about the empirical validation and more detail on this baseline simulations is available in the appendix A I and appendix A of Hötte (2019f). A longer discussion of a similar simulation is provided in Hötte (2019b). A difference to the simuations in chapter 2 and Hötte (2019b) 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, 2019g).

In figure 3.A.1, the time series are disaggregated into green, conventional and so-called *switching regimes*. A simulation run is classified as *switching regime* if the diffusion process is characterized by multiple reversions of its direction. This is associated with uncertainty about the final technological state. The time series data illustrate that *"technological uncertainty"* is costly. 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, lower productivity and lower aggregate output compared to the green or conventional regimes with a more clear-cut technological path selection (cf. figure 3.A.1). A two sided Wilcoxon test indicates that the differences between green and conventional regimes are significant (see appendix A of Hötte (2019f).

FIGURE 3.A.1: 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) $\beta_t = \frac{p^{eco}_t}{w^r_t}$

(G) $\frac{p^c_t}{p^g_t}$ (H) $\frac{p^c_t / A^c_t}{p^g_t / A^g_t}$ (I) # active firms

(J) Monthly output (K) Avg. # employees (L) Unit costs

Different line shapes indicate different regime types (□: eco, ∗: conv, ⊕: switch).

3.A.2 Interactions between spillovers and the ease of learning

TABLE 3.A.1: Initialization of learning parameters

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

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

In the Monte-Carlo experiment in section , 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. 135 out of 210 simulation runs converge to a green regime, corresponding to a transition probability of 64%.

In table 3.A.1, means and standard deviation of the initialization are summarized as aggregate and disaggregated 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 the appendix of Hötte (2019f).

3.B Technical notes on statistical procedures

In section 3.4.2, the results of a regression of macroeconomic indicators on χ^{dist}-dummy variables, a regime type dummy and the standard deviation of the diffusion measure σ_t^ν 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 instable 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, 2019g).

Chapter 4

Pathways of transition and the characteristics of competing technologies: A taxonomy and a policy experiment

4.1 Introduction

To reduce the risk of crossing irreversible tipping points in the climate system, the transition to carbon-neutral technologies needs to be accelerated (cf. IPCC, 2018; Steffen et al., 2018). Technology transitions are processes in which an emergent, entrant technology diffuses and replaces the prevalent technological solution (Geels, 2002). Empirically observed diffusion and transition patterns are diverse and differ across technology types (Adner and Kapoor, 2016; Comin et al., 2006; Geels and Schot, 2007) and across countries, sectors and firms (Geels et al., 2016; Vona et al., 2015). The purpose of this paper is to explain these differences based on a characterization of competing technologies and a simulation experiment using the macroeconomic, agent-based model (ABM) *Eurace@unibi-eco*.

The characterization is based on a typology to classify different transition patterns proposed by Geels and Schot (2007). This typology is derived from the multi-level perspective (MLP) which is a common methodological framework in transition studies (Köhler et al., 2019; Lachman, 2013). MLP decomposes a socio-technical system into a landscape, regime and niche level. The landscape captures external conditions such as resource prices, regulation or consumer preferences. A technological regime is determined by the dominant technological solution to fulfill a societal function. It is stabilized by norms, institutions, infrastructures and technological know-how that are built up over time. If the socio-technical landscape changes, the regime may come under pressure. This opens a window of opportunity for emergent niche technologies to challenge the regime if they are sufficiently superior given the new landscape conditions (Geels and Schot, 2007).

In this paper, I propose an economic operationalization of the concepts of MLP. Competing technologies are characterized by cumulative *stock* variables, *exogenous* and *interactive* properties. The entrant technology is a radical innovation that is technically superior because it allows its users to overcome a technical limitation of the incumbent technology. The economic valuation of the technical superiority is an *exogenous property* because it is beyond the direct influence of technology adopters and users. It is an inherent feature of a specific technology type but whether this feature is economically valuable depends on the socio-technical landscape (reflecting e.g. resource endowments, oil prices, cultural values, etc.).

Stock variables reflect the relative maturity of a technology. The incumbent technology benefits from larger experience and endowments with supporting factors accumulated by intended research, learning-by-doing, investments and routinization. In transition terminology, the accumulation is called *"endogenous renewal"* and stabilizes the incumbent regime (Geels and Schot, 2007).

If technologies are similar, part of the accumulated technological knowledge and supporting factors required to operate the incumbent are transferable to the utilization of the entrant technology (cf. Boehm et al., 2016; Jaffe and De Rassenfosse, 2017). Transferability is an *interactive* property because it affects the *relative* pace of technological specialization. It may also explain the disruptiveness of technological change.

This conceptual framework is motivated by empirical and theoretical stylized facts from the literature. It is a first step to write the concepts of MLP in analytical economic terms. The characterization is reflected in the formal implementation of technology in the macroeconomic ABM *Eurace@unibi-eco* introduced in the preceding chapters. The formalization of a technology race in the model shows how these groups of properties can be presented in the analytical terms of a macroeconomic model.

The model is used to simulate a technology race between an incumbent conventional technology and an emergent, green market entrant. One outcome of the simulations is a sample of transition curves and macroeconomic time series that are statistically analyzed. In the simulations, transitions are studied from the bottom-up perspective of heterogeneous, technology adopting firms and their learning abilities as explained in the chapters before. The simulations allow disentangling the interplay of single drivers and barriers of transition at the micro- and macroeconomic level. It is shown that the shape of transition pathways can be explained by the characteristics of competing technologies. Macroeconomic side effects and disruptions in the market structure differ across pathways of transition.

Policy can change the external conditions of the socio-technical landscape in favor of the entrant technology. In an experiment, three different market-based policies are tested. A tax on the use of conventional technology (e.g. a carbon tax) makes the utilization of the entrant technology relatively cheaper.

An investment subsidy reduces the price for green capital goods. Both capital and resource prices are exogenous to users and reflect the availability of resources. A price support reduces the price for consumer goods produced with green machinery. It is analog to a higher willingness to pay for green products.

It is shown that these policies may reinforce and stabilize an ongoing diffusion process, but increase technological uncertainty if the economy is locked in the incumbent regime.

Interactions between diffusion policies and technological characteristics reveal qualitative differences in the way how different market-based policies operate. For example, the consumption subsidy is only effective if the two competing technologies are sufficiently similar. In contrast, a tax that makes the utilization of the incumbent technology more expensive works well for dissimilar technologies.

The insights of this study help to understand the reasons for the heterogeneity of diffusion patterns. This understanding is crucial for the development of appropriate and effective transition policies conditional on the properties of available technology options. The evaluation of economic side effects may bring clarity about future technological pathways and facilitates an informed debate about sustainability transitions (Rosenbloom, 2017). This is important for policymakers and might help addressing socio-psychological resistance to change (Watson, 1971). Moreover, the characterization of competing technologies may also provide a theoretical basis for empirical work.

This study focuses on technology diffusion at the production side. The theoretical concepts are generalizable to the consumer side but this is beyond the scope of this study.

This work contributes mainly to three branches of literature. First, it is a theoretical approach to formalize concepts used in MLP. It draws a link between transition research and macroeconomic theory (Köhler et al., 2019). MLP had been criticized for its vagueness of the concepts that lack unambiguous empirical counterparts. Its complexity makes it difficult to disentangle single drivers of interactive dynamics of transition (Köhler et al., 2019; Lachman, 2013). The proposed characterization is an economic operationalization of multi-level interactions that are introduced by Geels and Schot (2007) to explain different shapes of transition pathways.

Second, the macroeconomic ABM approach allows to differentiate systematically between different types of technology and processes of learning. This granulate view is, to the best of my knowledge, a novelty in the literature on climate economics. It is an approach to formalize the technological challenges of a sustainability transition that differ across economic systems (e.g. industries or countries).

Third, it contributes methodologically and theoretically a new perspective to the branch of macroeconomic literature on directed technological change. It is a methodologically new approach to distinguish different technology types systematically and to link this distinction to microeconomic behavior of technology substitution. Assumptions about the substitutability of technologies are critical for the pace, costs and distributional consequences of directed technological change (cf. Acemoglu, 2002; Lemoine, 2018; Nijkamp et al., 2005). In the majority of existing studies, substitution elasticities are estimated or taken from the literature but a consistent microeconomic explanation based on observable properties of technologies and absorbing firms is yet to come. Moreover, the agent-based framework allows studying the importance of coordination for processes of learning in a population of heterogeneous adopters (cf. Jaeger, 2013). This deviates from aggregate approaches (e.g. Acemoglu et al., 2012; Lemoine, 2018) and allows a more granulate view on coevolving market structures, patterns of redistribution and the costs of coordination failures.

This paper is structured as follows. First, on the basis of a literature review, empirical stylized facts of transition and technology diffusion patterns are elaborated and linked to transition theory. In section 4.3, these insights are synthesized as dynamic characterization of competing technologies. The link to the formalization of technology in *Eurace@unibi-eco* is explained in section 3.3. In section 4.5, a simulation experiment is used to study the interplay between the characteristics of technology and emerging pathways of transition and the results of a policy experiment are discussed. Section 4.6 concludes.

4.2 Diverse pathways of transition - empirical stylized facts

Processes of sustainable transitions and (clean) technology diffusion differ across countries, sectors and firms and across technology types. Here, I will provide a short selection of empirical observations to derive four stylized facts (SF) of transitions.

The conceptual difference between technology diffusion and transition processes is the substitutive nature of a transition. A transition is a large-scale substitution process in which an incumbent, dominant technological solution to fulfill a societal function is replaced by an emergent alternative (Geels, 2002). In contrast, diffusion does - at least theoretically - not necessarily involve an incumbent that is replaced. Often, diffusion studies seek to explain aggregate or firm-level productivity growth, technological catch-up or product diffusion in consumer markets.[1]

[1]This conceptual distinction is not always clearly articulated in the existing literature and the terms are used interchangeably. But it is empirically questionable whether the term diffusion makes sense without consideration of an incumbent even if it is ignored in the majority theoretical models of technology diffusion (cf. Allan et al., 2014).

TABLE 4.1: Empirical stylized facts of technology transitions

	Stylized fact	Key references
1	The relative endowment ("relative maturity") with technology-specific knowledge and tangible assets influences individual adoption behavior.	Aghion et al. (2016); Dechezleprêtre et al. (2011); Geels (2005); Jiang and Lu (2018); Lema and Lema (2012); Wells and Nieuwenhuis (2012)
2	Cross-technology interactions in the accumulation of supporting factors (e.g. complementary skills, infrastructures, technologies) influence the pace of technological specialization reflected in the *realized* relative performance of competing technologies.	Adner and Kapoor (2016); Aghion et al. (2016); Carvalho and Voigtländer (2014); Wesseling et al. (2015)
3	External shocks (e.g. regulation, preference shifts, input price shocks, technological breakthroughs) may trigger the market entry of a technology that competes to replace the incumbent.	Belz (2004); Høyer (2008); Jones and Bouamane (2011, 2012); Ma and Sauerborn (2006); Popp (2019); Popp et al. (2010)
4	The characteristics of competing technologies determine the degree of disruption which is reflected in economic and distributional side effects of the transition process e.g. in the market structure and reallocation of income and wealth.	Consoli et al. (2016); Tushman and Anderson (1986); Vona et al. (2015); Wesseling et al. (2015)

At the country-level, Dechezleprêtre et al. (2011) illustrated differences in the cross-country diffusion of environmentally friendly innovations measured by patent applications. Comin et al. (2006) have shown that historical technology diffusion rates differ considerably across adopting countries and technology types. They disproved the general validity of the s-shaped pattern of diffusion (cf. Allan et al., 2014) and identified country-specific aggregate indicators for the stage of technological development as a potential explanation for cross-country differences. Adner and Kapoor (2016) have shown that the characteristics of both the entrant and incumbent and dynamic cross-technology interactions in the innovation process need to be considered to understand the heterogeneity of diffusion patterns.

The adoption of electric vehicles (EV) and renewable energy technologies (RET) is a further example of country-level heterogeneity. For example, the energy sector and automotive industry in India and China are rapid adopters of green technology (Fu and Zhang, 2011; Jiang and Lu, 2018; Lema and Lema, 2012). Firms and the government, are aware that it is more difficult to compete with Western market leaders in mature, highly specialized incumbent technologies (Jiang and Lu, 2018). Supported by national policy, Indian and Chinese car manufacturers began early to switch to EV and stopped the built-up of a conventional car industry (Lema and Lema, 2012; Tyfield and Zuev, 2018). Another example is RET in South Asia and Africa. The lacking availability and reliability of fossil-fuel-based electricity systems are positively associated with the diffusion of (decentralized) RET (Lema and Lema, 2012; Pfeiffer and Mulder, 2013). In both examples, the low maturity of the incumbent technology is part of the explanation for the rapid take-off of clean entrant technologies.

In contrast, major developed countries struggle with path dependence. Much of the accumulated infrastructure and technological knowledge base is built upon a fossil-fuel dominated technological paradigm (Unruh, 2000). Driven by effective policies, Germany became one of the technological leaders in the development solar PV and wind technologies (Pan et al., 2017; Quitzow, 2015) but a profound transition of the energy sector is long in coming (Geels et al., 2016; Kemfert et al., 2018). The reasons can be found in accumulated infrastructure but also cultural rules, societal resistance and inappropriate institutional frameworks to integrate renewable energies into the market (Geels et al., 2016; Nordensvärd and Urban, 2015; Pahle, 2010).

The German automobile industry is highly competitive, innovative and deeply entrenched in the production network. German manufacturers built up a competitive specialization in the production of vehicles with internal combustion engines (ICE) and dominate global export markets. But both the industry and the government failed to initiate the transition to low carbon technologies in time (Altenburg et al., 2015). These observations indicate that the transition to green technologies is challenging if firms accumulated high technological expertise in carbon-intensive incumbent technologies. Wells and Nieuwenhuis (2012) and Wesseling et al. (2015) considered firm-level strategies in the automobile sector and showed that the compatibility with the pre-existing specialization may also influence the choice across different types of low carbon propulsion technologies in response to regulation.

These observations motivate stylized fact number one:

Stylized fact 1
The relative endowment ("relative maturity") with technology-specific knowledge and tangible assets influences individual adoption behavior.

This stylized fact is also reflected in the history of EV and renewable energy technologies RET. During the formative phase of the current transportation and energy system, RET and EV were fair competitors, but cumulative learning, innovation, infrastructural and regulatory adjustments and the evolution of consumer habits and norms contributed to the emergence of fossil-fuel energy and ICE vehicles as a dominant technological regime (e.g. Geels, 2005; Høyer, 2008; Jones and Bouamane, 2011, 2012). Spillovers between the electricity generation and transportation sector mutually contributed to the realized cost-effectiveness in the two sectors and reinforced the fossil fossil-fuel-based trajectory of technological development (Unruh, 2000).[2]

The relative endowment with technology-specific knowledge is a property that relates to both the diffusing technology (and its suppliers) and the absorbing market. That is one explanation why the pattern of diffusion of

[2]Unruh (2000) and Grübler (1991) elaborate these spillovers further. Spillovers arise from overlaps in supply chains and networks, applications and endogenous innovation in complementary industries (e.g. in the petrochemical industry), institutional and political support and societal interest groups that contribute to the formation of norms and values, and from education systems that shape the type of available skills at the labor market.

the same technology may differ across industries and firms. Marimon et al. (2011) studied the adoption behavior of environmental management systems and observed considerable differences in the adoption rate across different sectors of economic activity. Oliveira and Martins (2010) make a comparison of e-business adoption behavior across industries. They find that the pace of adoption but also the relative importance of drivers of adoption differ significantly across industrial sectors.

At the level of individual firms within the same sector and the same regional market, Aghion et al. (2016) documented path dependence in the automobile sector. The authors have shown that the composition of accumulated technological knowledge embodied in firms' patents can explain the type of subsequent innovation. Firms with a higher share of patents for environmentally friendly technologies are more likely to carry out green innovation. Similarly, Wesseling et al. (2015) showed that type of pre-existing technological expertise affects the future technology choice of automobile producers in the US in response to regulation. Firms followed technological pathways that are similar to their pre-existing type of technological capabilities.

Firm-level relative endowment with technology-specific knowledge may explain the direction of future technological specialization. Using input-output data, Carvalho and Voigtländer (2014) has shown that the adoption of production inputs adoption is positively dependent on the technological similarity between the input producing sector and absorbing firms. Acemoglu et al. (2016); Boehm et al. (2016); Huang et al. (2018); Oikawa (2017) made conceptually similar observations. The similarity is positively related to knowledge spillovers across sectors and technology fields in learning processes (Jaffe and De Rassenfosse, 2017).

Adner and Kapoor (2016) re-examined the s-shaped pattern of diffusion curves in the semiconductor industry. The authors considered interactions between the incumbent and entrant technology in the innovation process. They focus on the characteristics of a technological novelty and its interaction with pre-existing technology and the (co)evolution complementary factors. They illustrated that the pace of diffusion is retarded if an innovation is competence-destroying, if technological bottlenecks in the supportive innovation system arise or if external developments improve the realized, firm-specific performance of the incumbent. The authors emphasize the importance of interactions between both the entrant and the incumbent technology. This leads to stylized fact number two:

Stylized fact 2
Cross-technology interactions in the accumulation of supporting factors (e.g. complementary skills, infrastructures, technologies) influence the pace of technological specialization reflected in the realized *relative performance of competing technologies.*

Many basic (green) technologies have their origins in the late 19th century. Examples are the emergence of RET, EVs and organic food (Behera et al., 2012; Belz, 2004; Høyer, 2008; Jones and Bouamane, 2011, 2012; Ma and Sauerborn, 2006; Neukirch, 2009).[3] Early deployment took place in niche markets characterized by very specific consumer preferences or governmental procurement programs. These niches provided a protected space that allowed these technologies to mature free from the pressure of price and performance competition with conventional technologies that provide a similar output (e.g. electricity, propulsion technology, food in the examples above). External shocks (e.g. preference shifts, regulation, price shocks) allowed these innovations to challenge the dominant position of the incumbent. The interest of entrepreneurs and policymakers to commercialize RET and EV at the mass market rose in the aftermath of the oil price shock in the 70s. The oil price shock coincided with an increasing awareness for the finiteness of resources and the environmental issues, that became part of the political agenda. Prices, political support and regulation were key drivers of a new surge of entrepreneurial and innovative activities in RET and EV technology (Geels et al., 2011, 2016; Høyer, 2008; Jones and Bouamane, 2011, 2012; Popp, 2019; Popp et al., 2010). Parallels can be found in the history of organic farming but the dynamics were to a larger extent driven by changing consumer preferences reflected in a higher willingness to pay and incrementally in regulations, support policies, labels and standardization (Behera et al., 2012; Belz, 2004; Lockeretz, 2007; Ma and Sauerborn, 2006; Reganold and Wachter, 2016).

These observations from different technology histories lead to stylized fact number three:

Stylized fact 3
External shocks (e.g. regulation, preference shifts, input price shocks, technological breakthroughs) may trigger the market entry of a technology that competes to replace the incumbent.

Other technologies gained *momentum* through a technological breakthrough even though it took time until the incumbent was replaced. Prominent historical examples are the transition from sailing to steamships (Geels and Schot, 2007) or the transition from mainframe to integrated circuit computers (Malerba et al., 1999).

Transitions and technological change can be accompanied by changes in the market structure and the redistribution of income and wealth. These effects are observable at the labor market, across firms within the same industry and across industries. Whether and to which extent these side effects occur is dependent on the capacity of employees, firms and industries to cope with new technology.

[3] Here, I refer to *organic* food as a product innovation that is explicitly labeled in distinction to *conventional* agriculture. In fact, at the turn of the 20th century, the majority of food production was organic. And also today, many farms in developed and developing countries, rely on practices of organic farming without being certified and selling their products as *organic* food (Reganold and Wachter, 2016).

Vona et al. (2015) and Consoli et al. (2016) have empirically documented that the adoption and effective utilization of green technologies is associated with structural changes at the labor market. Occupations and skills needed for the adoption and operation of green technologies differ from those demanded for the incumbent. Following the propositions of the literature on skill-biased technological change (esp. Acemoglu, 2002; Autor et al., 2003), the authors argue that this might be associated with a redistribution of income. Relative wages for green skills and occupations increase at the expense of the incumbent. Vona et al. (2015) did also find that the pre-existing "skill-profile" of industries determines the pace and ease to which industries adopt green technologies in response to environmental regulations. Industries that are characterized by a high share of employees with green skills adopt green technologies more effectively.

Tushman and Anderson (1986) have shown that the compatibility of pre-existing knowledge with the utilization of new technologies can explain changes in the market structure. Competence destroying innovations, i.e. those that require radically different types of knowledge, tend to be introduced to the market by entrant and not by incumbent firms. This leads to a reallocation of market shares within the same product group. Wesseling et al. (2015) adopted the framework of competence-destroying innovations and investigated responses of automobile firms to the technology-forcing *Zero Emission Vehicle* mandate in California. They illustrated a systematic relationship between the strategic response of firms and the compatibility of firms' pre-existing competences with the technical requirements needed to meet the mandate. Firms' whose pre-existing knowledge appears to be least compatible with the new standards exhibited the most opposing behavior and missed the entry to the low-emission vehicle market.

These observations lead to stylized fact number four:

Stylized fact 4
The characteristics of competing technologies determine the degree of disruption which is reflected in economic and distributional side effects of the transition process e.g. in the market structure and reallocation of income and wealth.

The four stylized facts are summarized in table 4.1.

4.3 MLP and a dynamic characterization of competing technologies

4.3.1 Pathways of transition - theory

A common theoretical framework to study technology transitions is the multi-level perspective (MLP) (Köhler et al., 2019; Lachman, 2013; Smith et al., 2010). In MLP, socio-technical systems are decomposed into three interacting levels, called landscape, regime and niche.

The *regime* describes a dominant technical solution to fulfill a societal function (Geels, 2002; Geels and Schot, 2007; Kemp, 1994). It is associated with a technological paradigm that determines how technology users and developers define technological problems and search for solutions (Dosi, 1982; Nelson and Winter, 1977). A regime is dynamically stabilized by incremental technical improvements, the accumulation of experience, the built-up of supporting infrastructure, regulation and the deepening societal and economic entrenchment.

The *landscape*-level reflects external conditions into which a technological regime is embedded. These conditions are e.g. consumer preferences, regulations, resource endowments, prices and general technology trends. These conditions are beyond the influence of technology developers and users.

Internal problems of the *regime* or changes in the *landscape* may put the regime under pressure. This creates a window of opportunity for alternative technologies to replace the existing regime. The alternative technology emerges from a market *niche* with specific demand characteristics or governmental procurement that protect the technological development in the niche from competitive forces at the regime level. Transitions from niche to the regime are driven by the enactment of different societal groups and interactions among different levels (Geels, 2002).

MLP provides a framework for the systematic, empirical and theoretical study of technology transitions. It was used to study historical and current transitions in different technology fields (e.g. Berkeley et al., 2017; Geels, 2002; Geels et al., 2011; Kemp, 1994; Köhler et al., 2019; Safarzyńska et al., 2012; Wells and Nieuwenhuis, 2012; Yuan et al., 2012) and also for cross-country comparisons (Geels et al., 2016).

The transition from one socio-technical regime to another evolves along a technological trajectory (Dosi, 1982). Geels and Schot (2007) proposed a typology to distinguish different transition *pathways*. Their typology is dependent on the timing and nature of multi-level interaction.

Different pathways have implications for the power relations and degree of disruption of technological change. In this paper, I abstract from the role of societal groups and actors and focus on technology users. It is an economic approach to study technology transitions. Users are neutral with regard to the type of technology but have endogenously, accumulated vested interests that are embodied in physical capital and intangible knowledge. The technology choice is conditional on the relative, effective performance of a technology given the existing stock of physical and intangible assets.

4.3.2 A characterization of competing technologies

Based on the empirical stylized facts and the MLP, competing technologies can be described by three groups of properties. These properties have different implications for the evolutionary dynamics of a transition process.

Exogenous properties reflect the landscape conditions that surround an evolutionary process of technological competition. Exogenous properties are, for example, prices of input requirements for the utilization of a technology, consumers' willingness to pay for specific output characteristics, production and provision costs of the technology of broader landscape conditions. These conditions determine the economic valuation of specific properties of a technology.

For example, a fuel-saving technology is not valuable if fuel is for free. Organic food is not superior in the market if consumers do not have a specific preference or if the production process is not regulated.

These conditions are beyond the control of technology developers and follow dynamics that are independent of technology race. They are considered as given in daily decision making of technology users and developers (Geels, 2002).

Stock variables are stocks of technological knowledge and supporting factors. They are accumulated by intended research and investment and as a byproduct of learning by using. Stock variables contribute to the *dynamic stabilization* of the dominant technology (Geels, 2002). The ratio of stocks accumulated in the different sectors describes the relative maturity of the entrant compared to the incumbent.

For example, the stabilization of automobility based on ICE vehicles as dominant technological regime in passenger transportation arose from the accumulation of supporting factors such as regulatory adjustments, complementary infrastructures, incremental technical performance improvements and technical skills of manufacturers (Geels, 2005). Alternative transportation technologies that might possibly replace ICE mobility have to compete with this ongoingly evolving stock of technological knowledge. After the oil price shock in the 70s, the low initial technical maturity and lack of supporting infrastructures combined with adaptive innovations in fuel efficiency and exhaust filters of conventional cars dampened the optimism to launch EV as an alternative (Geels et al., 2011; Høyer, 2008; Wells and Nieuwenhuis, 2012).

Interactive properties influence the accumulation process of *relative* stock variables and the pace of technological divergence. Technological pathways diverge if the relative technological maturity diverges. This occurs if the accumulation of stock variables is faster in one technology compared to the other. Interactive properties can be operationalized as technological similarity between the niche and incumbent and as technological difficulty. The similarity has implications for the transferability of accumulated stock variables to the utilization of the emergent niche technology. The higher the technological difficulty, the more difficult is the accumulation of technological knowledge and the more difficult is the catch-up for technological latecomers (Cohen and Levinthal, 1990; Lema and Lema, 2012). A higher difficulty is associated with higher returns to specialization.[4]

For example, the production of both electric and ICE vehicles is very complex. It requires a high level of technology-specific capabilities and a large number of technology-specific intermediate inputs. At the same time, both propulsion technologies are very dissimilar. For example, the production and maintenance of batteries for EV and combustion engines require different technological skill-sets and different material inputs (Høyer, 2008; Wells and Nieuwenhuis, 2012). This makes it difficult for companies to specialize in both technologies simultaneously. Empirically, it was observed that the technological frontrunners in the ICE sector struggle with the adoption of EV technology and explored (with limited success) fuel cells or biofuels as climate-friendly alternative. Fuel cells and biofuels are technologically much more compatible with the pre-existing ICE specialization. Early adopters of EV technologies are either market entrants or not operating at the technological performance frontier of ICE technology (Altenburg et al., 2015; Berkeley et al., 2017; Ehret and Dignum, 2012; Wells and Nieuwenhuis, 2012; Wesseling et al., 2015).

Geels and Schot (2007) discussed how the nature of multi-level interaction, i.e. the type of pressure from the landscape and the interaction between the entrant and incumbent technology are related to observed pathways of transition. Whether an emergent entrant technology can successfully replace the incumbent depends on the timing, i.e. relative maturity of the entrant and the pressure on the incumbent caused by a changing landscape.[5] These concepts are embodied in the *Eurace@unibi-eco* model.

[4]In the terminology of Geels and Schot (2007), these properties describe the *nature* of interaction between the regime and niche level, i.e. whether the new technology is symbiotic, substitutive, disruptive or reinforcing (cf. Geels and Schot, 2007).

[5]The characteristics are not independent of the landscape. For example, the metrics imposed on exogenous properties of technologies are a question of valuation that is dependent on consumer preferences and resource endowments. A technology is only valuable if it fulfills a societal purpose (cf. Geels, 2002).

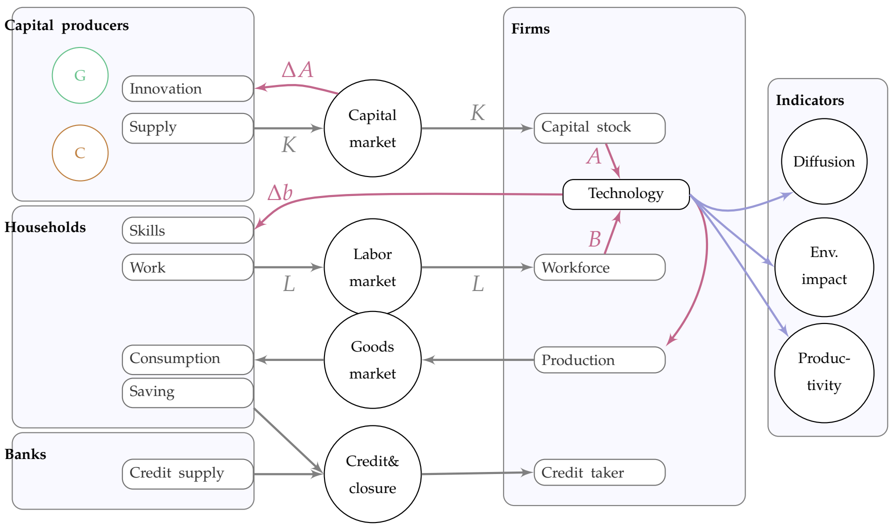
4.4 A macroeconomic ABM of technology transitions

In this section, I give a concise conceptual introduction to the macroeconomic ABM *Eurace@unibi-eco* and the representation of technology. A comprehensive and formal documentation of the model is available in the supplementary material (SM) I.

4.4.1 The model

The model is an extended version of the macroeconomic ABM *Eurace@unibi* (Dawid et al., 2019b). The extended model is illustrated in figure 4.1. It can be used to simulate a whole closed macroeconomy covering markets for consumption and capital goods, labor, credit and finance. Heterogeneous agents interact on these markets and exchange goods, labor and information.

FIGURE 4.1: Macroeconomic structure of *Eurace@unibi-eco*



Blocks represent a group of agents and their role in the economy. Circles in the middle between show the markets as places where agents interact. Gray (magenta) arrays indicate monetary or physical (immaterial) flows. The block on the right-hand side contains the main macroeconomic indicators that have been studied. This flowchart is the same as in the previeous chapters. It is based on Dawid et al. (2011).

Heterogeneous firms produce a final consumption good that is offered at the goods market. Households act as consumers and supply labor to firms. Their wage income is spent for consumption and saving at private banks or it is invested in an index fund at the financial market. Capital producers offer capital goods to firms and invest in R&D to increase the productivity of supplied capital. The model is financially stock-flow consistent, i.e. each agent has a bank account and financial flows between agents are mutually settled. Private banks manage the bank accounts and give credit to firms if firms' own financial means are insufficient to finance current expenditures and investment. The model also has a central bank that can influence the economy through monetary policy.

The routines of the agents in the economy are executed stepwise and follow different time schedules. One iteration in the model corresponds to one working day. Some routines are executed on a regular frequency, e.g. daily, weekly or monthly, others are event-based. For example, firms only demand credit if their financial means are insufficient and households' labor market routines are only executed when they are unemployed. The model is empirically validated, i.e. it is able to reproduce a number of micro- and macroeconomic empirical stylized facts. In previous studies, the baseline model had been used in different policy studies focusing on different aspects of economic policy, e.g. labor markets, economic cohesion, monetary policy or economic stimuli (e.g. Dawid and Gemkow, 2013; Dawid et al., 2018b, 2019a,b; Harting, 2019; van der Hoog and Dawid, 2017).

The most relevant agents for this study are firms, capital good producers and households. Firms produce final goods using capital K and labor L as inputs. Capital is heterogeneous by technology type ig and supplied by two competing capital producers $ig = c, g$. One of the producers c is incumbent in the market and offers conventional capital goods. Their use is environmentally harmful and requires natural resource inputs. The other producer g is a green entrant that offers a climate-friendly alternative.

Consumption goods-producing firms invest in capital goods that are accumulated as a stock at the firm-level. Firms' capital stock is composed of a range of (possibly) different capital goods. It depreciates over time and is maintained or expanded through investments. Single capital goods ("vintages" v) do not only differ by technology type ig but also by productivity level A^v. Each capital producer offers a range of different vintages that differ by A^v. If the capital producer in sector ig successfully innovates, it brings a new and more productive vintage to the market. The sectoral productivity frontier $A^V_{ig,t}$ is shifted upwards. t is the time index. The probability of innovation success is positively dependent on R&D expenditures. Capital producers invest a fraction of profits in R&D. This is a source of increasing returns in sectoral innovation. The capital producer that performs better on the market innovates relatively faster. Capital producers set prices according to an adaptive pricing rule. This reflects the market response and scarcity in the supply of capital. It partly counterbalances increasing returns.[6]

Labor $L_{i,t}$ is required by firm i to operate capital. It is hired at the labor market. Heterogeneous employees $l \in L_{i,t}$ are endowed with technology-specific skills $b^ig_{l,t}$. These skills are needed to exploit the productivity of capital of

[6]For example, if a producer increased prices in the previous periods and if this was associated with increasing profits the producer continues to increase prices. If profits and market share were decreasing, the producer does the opposite.

type $ig = c, g$. In other words, employees need to know how to work with green or conventional machinery effectively. Employees learn technology-specific know-how when working with a specific capital type ig ("learning by doing", LBD). If employees of a given firm work only with green (conventional) capital, they accumulate green (conventional) skills relatively faster.

Technology-specific skills $B_{i,t}^{ig} = \frac{1}{L_{i,t}} \sum_{l \in L_{i,t}} b_{l,t}^{ig}$ accumulated across the whole workforce $L_{i,t}$ determine the firm's *effective*, technology-specific productivity. This is a source of evolving, heterogeneity across firms in green and conventional technology adoption benefits. In their investment decision, firms estimate and compare the net present value (NPV) of different investment options. They have to decide about the quantity, the technology type ig and productivity level A^v. They form expectations about future prices, wages, demand and the evolution of their employees' technology-specific skills.

The process of LBD is conditional on the interactive properties of competing technologies. The technological distance $\chi^{dist} \in [0, 1]$ is an inverse measure for the cross-technology transferability of knowledge. If the distance is small, technologies are similar. Skills that are useful to operate conventional technology are also useful for the operation of green capital, and vice versa.[7]

The second interactive property is the technological difficulty $\chi^{int} \in \mathbb{R}$. It describes the effectiveness of relative effort in LBD. If χ^{int} is high, the technology is difficult to learn and LBD is inefficient if both technologies are used at the same time. χ^{int} is a measure for the returns to technological specialization. If $\chi^{int} = 0$, both technologies are very easy to learn. LBD is independent of the capital share of each technology type $\nu_{i,t}^{ig}$ that is used in the firm i.[8] This may reduce the costs of transition because two technology types can be used simultaneously.

If $\chi^{int} > 1$, returns to specialization are increasing in $\nu_{i,t}^{ig}$. The formal implementation is outlined in 4.A. More detail about the empirical motivation of the learning function is provided in chapter 3 and Hötte (2019f).

Macroeconomically, the technological evolution over time t is driven by two processes of learning. The productivity of supplied capital $A_{ig,t}^{V}$ is interpreted as *codified* knowledge. Its evolution is driven by a process of intended "learning by (re-)searching" reflected in R&D investments. Technology-specific skills of employees $B_{i,t}^{ig}$ are interpreted as *tacit* knowledge (cf. Cowan et al., 2000). In contrast to codified knowledge, tacit knowledge is not explicitly traded on the market and needs to be learned at the firm level i. LBD is a byproduct of everyday production routines.

[7]Note that skills can be more generally interpreted as site-specific supporting factors. This is discussed in more detail in chapter 2 and (Hötte, 2019b).

[8]The share of capital of type ig is given by $\nu_{i,t}^{ig} = K_{i,t}^{ig}/K_{i,t}$ where $K_{i,t}^{ig}$ is the amount of capital of type $ig = c, g$ that is used by firm i in time t and $K_{i,t} = K_{i,t}^{c} + K_{i,t}^{g}$ is the total amount of capital used in t.

Both learning processes are subject to increasing returns dependent on the technological state of the economy and stabilize the incumbent regime. The technological state at the macroeconomic level is evaluated by the relative market penetration of green and conventional capital. It is measured by the share of conventional capital ν_t^c that is used in the economy in current production. If $\nu_t^c \to 0$, a transition to green technology has occurred.

The aggregate technological evolution is driven by the technology adoption behavior and learning processes at the level of heterogeneous firms and by endogenous innovation in the capital sector.

4.4.2 The characteristics of competing technologies in *Eurace@unibi-eco*

The model is used to simulate a competitive race between an incumbent conventional and a market entering green technology. The competitive dynamics are dependent on the characteristics of the technologies. The green, entrant technology has the chance to diffuse only if it is sufficiently superior given the properties of the socio-technical landscape and given its relative maturity. Interactions in the process of learning affect the pace of convergence to the final technological regime. The characteristics and its link to the *Eurace@unibi-eco* model are summarized in table 4.1.

Exogenous properties are conditional on the socio-technical landscape, reflected in e.g. resource endowments and consumer preferences. In the model, resource endowments are reflected in the price of natural resource inputs that are required to operate conventional capital and in relative production costs of capital goods. Consumer preferences are reflected in households' relative willingness to pay for final goods produced with a specific technology type. These properties determine the relative, technical superiority of the green technology in the landscape context.

In a baseline simulation, landscape pressure on the incumbent comes from the costs of resource inputs. A technological breakthrough enables the production of green capital that allows adopters to save input costs. The price for the natural resource is sufficiently high that the green technology is sufficiently superior to challenge the incumbent technological regime. In a policy experiment in section 4.5.2, I show how market-based policies may influence the type and strength of landscape pressure.

Stock variables are embodied in the accumulated codified (productivity) and tacit knowledge. Firms accumulate technology-specific tacit knowledge $B_{i,t}^{ig}$ that is needed to operate a technology. Capital producers incrementally innovate and increase the productivity of supplied capital goods $A_{ig,t}^{V}$. Tacit knowledge has a similar effect as supportive infrastructure or learned routines and habits. It is a supporting factor

TABLE 4.1: Characterization of competing technologies

	Exogenous landscape	Stock variables	Interactive properties	Pathways of transition
Concept	· Value of technology in given context.	· Accumulated over time by intended investment and as byproduct of doing.	· Degree of spillover in accumulation process. · Degree of complexity and returns to specialization.	· Process of technological substitution of incumbent by emergent entrant.
Impact	· Determines the relative technical superiority dependent on external conditions.	· Stabilize the dominant technology. · Source of path-dependence and barrier to diffusion for the entrant.	· Strength of path dependence, degree of disruptiveness in pre-existing distribution of power and wealth.	· Economic and distributional outcome dependent on pathway.
Economic indicators/ empirical concepts	· Resource endowments reflected in prices, · Consumer norms and attitudes reflected in willingness to pay, stated and revealed preferences. · Relative policy support.	· Codified knowledge (R&D, publications, education systems and occupations). · Tacit knowledge proxied by embeddedness in production network, employment shares (assumed to be correlated with infrastructure, routines, regulation etc.).	· Technological distances in patent and IO data (e.g. via citation overlaps, commodity flows, labor mobility). · Substitution elasticies. · Complexity measured by number of links in production and innovation networks.	· State of transition: Market share, use rate. · Stability: Variance of diffusion measure, market share across time, relative pace of accumulation (e.g. sectoral growth rates, growth of patent counts). · Depth of transition/ disruptiveness: Market exits, reallocation across industries and occupations.
Variables in *Eurace@unibi-eco*	· Resource price: p_t^{eco}, · Policies: θ, ς^{inv}, ς^{cons}. · Consumer preference parameter γ (not used).	· Productivity of supplied capital A_t^c, A_t^g. · Tacit knowledge of firms $B_{i,t}^c$, $B_{i,t}^g$.	· Spillovers in the learning process χ^{dist}, · Technological difficulty/ returns to specialization χ^{int}.	· Penetration rate of conventional capital ν_t^c, its variance σ_t^ν, · Relative technological divergence α_t^*, β_t^*, · Duration until convergence t^*. · Evolution of market structure.

This table summarizes the characterization of competing technologies, economic indicators, that can be used to measure these concepts and shows the link to the *Eurace@unibi-eco* model.

that facilitates the effective use of a technology. Tacit knowledge is reflected in the skills embodied in labor, local infrastructures, standards and consumer habits. Its accumulation is the outcome of learning by using.

The ratio between the technology-specific stock variables $\alpha_t = \frac{A^V_{g,t}}{A^V_{c,t}}$ and $\beta_t = \frac{B^g_t}{B^c_t}$ determines the relative maturity of the niche technology. Increasing divergence in the relative endowment with technology-specific stocks drives a process of convergence to a dominant technological regime.

Interactive properties describe interactions in the accumulation of knowledge and infrastructures. They influence the pace of divergence of relative stock variables and the pace of technological convergence.

In the model, interactive variables are given by the spillover intensity χ^{dist} and returns to specialization χ^{int} in LBD.

4.5 Simulations and experiments

The model is used to simulate a competitive race between an incumbent, conventional technology established at the regime level and a green market entrant. The simulations are run over a time horizon of $15,000$ iterations that correspond to roughly 60 years. More detail about simulations with *Eurace@unibi-eco* can be found in the SM I.

At the beginning of the simulations, the conventional technology dominates the market and is entrenched in the production system. The capital stock of firms consists only of conventional capital. Firms and employees have accumulated the matching skill type $B^c_{i,t}$ needed to operate conventional machines. The conventional capital producer invests a fraction of profits to improve the productivity performance of supplied capital incrementally. Learning and innovation dynamics are *"aligned"* (cf. Geels and Schot, 2007), i.e. both are directed to the improvement of conventional capital. This stabilizes the regime. Permanent pressure from the landscape is reflected in the price of the natural resource that is required to operate conventional capital. But a sufficiently mature alternative technology to challenge the regime is lacking.[9]

After some time, the market entry of the green capital producer is enabled by a technological breakthrough. In the simulations, the day of market entry is set to $t_0 = 600$ which corresponds to roughly 2.5 years. The green technology is technically superior because it allows firms to get rid of the costly

[9] In the simulations, the price for the resource input is set to 10% of labor costs. Over time, this cost-share is held constant, i.e. the price evolves proportionally to average wages.

requirement of resource inputs.[10] But it suffers from barriers to diffusion that are operationalized as lower endowments with accumulated knowledge. Employees have not yet worked with green capital and the technical maturity, reflected in the productivity of supplied capital, is lower. This is in line with the empirical literature that has documented that insufficient skills and supporting infrastructures and an inferior technical performance may hinder firms to adopt new technologies (cf. Arundel and Kemp, 2009; Triguero et al., 2013). Lower initial endowments with accumulated codified and tacit knowledge represent two different types of *diffusion barriers*. These diffusion barriers are implemented as a factor β^A (β^b) that scales down the initial productivity (skill level) of the entrant technology, i.e. $A^V_{g,t_0} = (1-\beta^A)A^V_{c,t_0}$ ($b^g_{h,t_0} = (1-\beta^b)b^c_{h,t_0}$) with $\beta^A, \beta^b \in [0,1)$. β^A (β^b) is a supply-sided (demand-sided) diffusion barrier because it refers to technological knowledge that is (not) traded on the market (cf. chapter 2 and Hötte (2019b)).

The dynamics of the competitive race depend on the ratio between technical superiority (resource cost savings) and the technological disadvantage (lower maturity). The green technology has the chance to diffuse only if it is sufficiently superior given its relative maturity. Otherwise, the regime can preserve itself. In the simulations, the entry conditions are sufficiently balanced such that both technologies have the chance to win the technology race. Further explanations of simulation settings, the calibration and validation of this baseline scenario are explained in further detail in the comprehensive working paper Hötte (2019f).

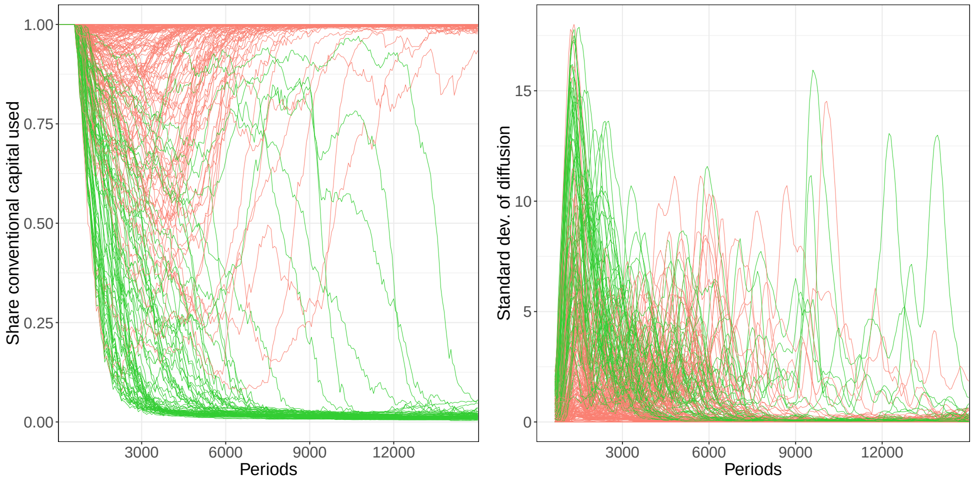
The outcome of the technology race is uncertain. It depends on the competitive dynamics and on the stochastic elements of the model. For example, innovative success is probabilistic and may shift the relative productivity critically in favor of one technology. Further, households' purchasing behavior and matching processes on the labor market have stochastic elements. This may critically affect the performance and investment behavior of individual firms. These small events may tip the technological evolution into one direction that is stabilized by increasing returns.

In figure 4.1a, an exemplary sample of 210 simulated transition curves is shown. Transition curves are measured as the time series of the share of conventional capital $\nu^c_t = K^c_t/K_t$ that is used in the economy. Single curves in figure 4.1a exhibit very diverse patterns.

In some cases, the economy is locked in and the green technology does not diffuse at all. In other cases, the green technology is quickly taken up and the green regime stabilizes. The process can be very unstable. This occurs if the green technology is initially taken up, but path dependence in the accumulation process of knowledge is high. The initial diffusion process is reversed. Sometimes, a change in the direction of the transition process occurs multiple times and the economy switches between lock-in and green transition.

[10]Resource input requirements can be alternatively interpreted as compliance costs with environmental regulations or other inputs that are relatively more costly than those required to operate the entrant technology.

FIGURE 4.1: Simulated patterns of transition



(A) ν_t^c per run

(B) σ_t^ν per run

These figures show the characteristics of simulated transition pathways. Each line represents a single simulation run r out of a set of 210 runs.

The standard deviation σ_t^ν of ν_t^c is a measure to operationalize the volatility of the transition process. It is computed run-wise over a moving time window of 600 periods and illustrated in figure 4.1b. This volatility measure is negatively associated with aggregate economic output.[11] The switching behavior is costly because learning and R&D resources are wasted for a technology type that is obsolete in the long run.

In capter 2, I have discussed how initial diffusion barriers may prevent a green transition (see also Hötte, 2019b). In the subsequent chapter 3, I studied knowledge transferability in more detail (see also Hötte, 2019f). In this paper, I focus on the interactions between the characteristics of competing technologies and market-based transition policy.

4.5.1 Market-based diffusion policies

The acceleration of a sustainable transition is one of the most pressing societal and economic challenges in the coming years. Political instruments can be used to accelerate a transition. In a policy experiment, I evaluate the effect of three market-based policies that alter the market conditions for the

[11]The coefficient of correlation between annual output growth and σ_t^ν is -4.466%. An OLS regression using two-way clustered standard errors on run-time confirms a significant negative relationship between annual output growth and the diffusion volatility measured by σ_t^ν. This relationship is consistent across different model specifications and aggregations.

$$\%growth_t = 1.89^{***} - .0085 \cdot \sigma_t^{\nu***} + \epsilon_t.$$

Additional detail about this analysis is available in the appendices 4.B.1 and 4.C.

green technology in different regards. These instruments are (1) a resource tax that penalizes the use of conventional capital, (2) an investment subsidy that makes investments in green capital cheaper and (3) a price support for green products that stimulates the creation of green product markets. I study the effect of these policies on the transition pathway and the macroeconomic outcome. It will be shown below that the effect of different market-based instruments depends on the relative maturity of the green technology and the transferability of knowledge.

The policies are operationalized as follows:

1. The eco-tax θ is imposed on the material resource input, i.e. its price p_t^{eco} is multiplied by the factor $\tilde{p}_t^{eco} = (1+\theta) \cdot p_t^{eco}$.
2. The investment subsidy ς^{inv} reduces the price of green capital goods p_t^g, i.e. the price is multiplied by $\tilde{p}_t^g = (1-\varsigma^{inv}) \cdot p_t^g$.
3. ς^{cons} is a price support that reduces consumer prices $p_{i,t}$ for eco-friendly produced final goods. The level of support is proportional to the share of green capital goods $\nu_{i,t}^g$ that is used in production. The supply price of final goods offered by firm i is multiplied by $\tilde{p}_{i,t} = p_{i,t} \cdot (1 - (\nu_{i,t}^g \cdot \varsigma^{cons}))$. Firms with a higher $\nu_{i,t}^g$ receive a relatively higher subsidy on product sales.

The implementation is explained in more detail in the SM I. The budget of the government is balanced in the long run. Net expenditures for diffusion subsidies and the income of the eco-tax are settled by adaptive income and corporate taxes. Taxes are increased (decreased) if the smoothed net financial inflows of the government are negative (positive).

More generally, these three instruments reflect the characteristics of the technological landscape when ignoring the budgetary implications of the policies. The eco-tax is analog to the price for the natural resource input. The investment subsidy reflects the availability of resources required for the production and installment of green capital goods. The consumption subsidy is analog to a shift in consumer attitudes that results in a higher willingness to pay. This yields a price premium for green products.

In the following, I describe first the impact of different political instruments on the emerging technological pathway and discuss the interactions between the instruments and the characteristics of competing technologies. Thereafter, I illustrate the effects of the policies on the macroeconomic outcome and market structure within the *Eurace@unibi-eco* economy.

4.5.2 Technological learning and the effectiveness of diffusion policy

To analyze the effectiveness of policies conditionally on the characteristics of competing technologies, a Monte-Carlo experiment is run. In this experiment, diffusion barriers β^A and β^b, learning parameters χ^{dist} and χ^{int} and policy parameters are drawn at random from uniform distributions of predetermined intervals. All three policy instruments are used simultaneously but at different levels that are drawn independently at random. The impact of single instruments can be isolated through statistical analysis. The intervals are determined such that trivial patterns of monotone diffusion or lock-in are avoided and a well-mixed sample of transition and lock-in regimes is obtained.[12]

The outcome of the policy experiment is descriptively compared to a benchmark scenario with the same average levels of relative maturity and learning parameters. Some general properties of the simulated time series of the benchmark are summarized in appendix 4.B.1.

The impact on the technological evolution

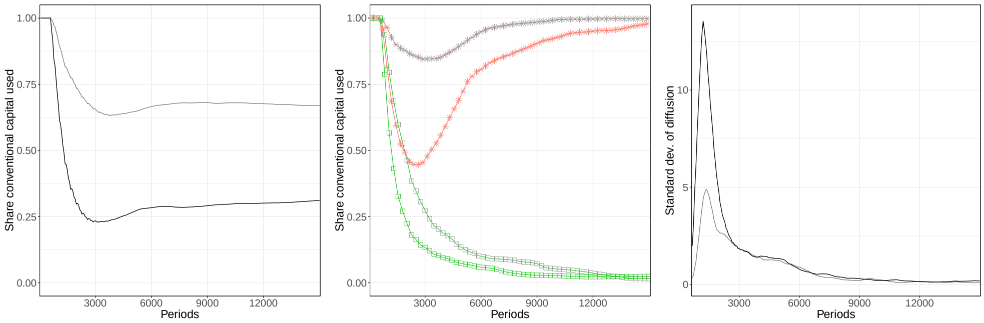
A descriptive comparison of the diffusion outcome suggests that the policies stimulate a transition. In the benchmark scenario without policy, the economy converges to a green technological regime in 30% of the simulation runs. This is much lower compared to the policy experiment with a transition frequency of 70%. This is reflected in the diffusion curve shown in figure 4.2a that is aggregated across all 210 simulation runs.[13] The black (gray) line indicates the policy experiment (benchmark). Figure 4.2b shows the diffusion curve disaggregated by regime (green transition or lock-in). In the lock-in regimes, green technology take-up is higher until the reversal to conventional technology occurs. This suggests that the policies accelerate the diffusion of green technology, independently of the emerging regime. The higher uptake of green technology is reflected in higher volatility σ_t^{ν} in the early phase after the day of market entry. It jumps up early after the day of market entry and approaches to zero when the economy converges to one of the two technological regimes (cf. figure 4.2c).

The impact of the policies on the transition probability can be presented as a shift in the transition boundary. The probability of a green transition is dependent on the initial maturity of market-entering green technology. The transition boundary is a dividing line in the two-dimensional space of initial relative knowledge stocks α_{t_0} and β_{t_0}. Higher levels of α_{t_0} and β_{t_0} indicate

[12]More information on the initialization is available in the appendix 4.B.2.

[13]An aggregate value of 0.30 means that, on average, 30% of capital goods that are used for production at time t are conventional and the remaining 70% are green. Due to the convergence to a value between 0 and 1, the rounded $\nu_T^g = 1 - \nu_T^c$ measured at the end of the simulation horizon T and aggregated across runs can be interpreted as transition probability.

FIGURE 4.2: Transition patterns in policy experiment



(A) Aggregate ν_t^c (B) ν_t^c by regime (C) Volatility σ_t^ν

These figures show time series patterns of the diffusion curve and its volatility over time. Gray curves represent the experiment without policy. In figure 4.2b, the red (green) curve represents the aggregate diffusion curve within the subset of runs that converge to the conventional (green) technological regime. In figure 4.2c, σ_t^ν is the standard deviation of the diffusion measure ν_t^c computed over 2.5 years.

less favorable starting conditions for the green technology, i.e. a lower relative maturity of the entrant technology in t_0. Figure 4.3a (4.3b) shows the transition boundary in the benchmark (policy) scenario. An upward shift of the transition boundary is observed. This indicates that the policies effectively compensate for initial technological disadvantages.

Regression analyses reveal the structural relationships between different political instruments, initial maturity of the entrant, learning interactions and their impact on the transition probability and its pathway. The transition probability is approximated by the diffusion measure $\nu_{i,T}^c$ at the firm level in $T = 15,000$. Until T, $\nu_{i,t}^c$ has converged to one (zero) if the economy is locked in (a transition occurred). Its rounded inverse aggregated across firms and simulation runs is a measure of the transition probability.[14]

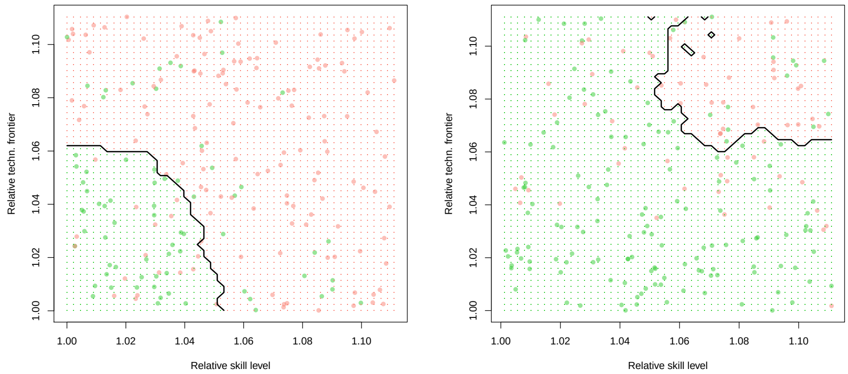
The shape of the transition pathway is described by a set of different indicators, that measure the time until technological stabilization, the degree of technological divergence and the stability of the transition pathway. The time until stabilization t_i^* measures the period when the last switch between different technology types was observed. After t_i^*, the adoption behavior becomes monotone and firm i invests in only one technology type.

Long-lasting switching behavior between technology types is associated with higher diffusion volatility. The volatility is measured by the variance $(\sigma_i^\nu)^2$ of $\nu_{i,t}^c$ computed across the whole simulation horizon.[15] A high value

[14]Until T, the economy has converged to one of the two technological states and the variation of $\nu_{i,T}^c$ across firms is negligibly small. Across runs, the average standard deviation of $\nu_{i,T}^c$ across firms in T accounts for .0064.

[15]The variance is computed firm-wise across the full time horizon, i.e. $(\sigma_i^\nu)^2 = \frac{1}{T}\sum_{t=0}^{T}(\nu_{i,t}^c - \bar{\nu}_i^c)^2$ with $\bar{\nu}_i^c = \frac{1}{T}\sum_{t=0}^{T}\nu_{i,t}^c$.

FIGURE 4.3: Policy-induced shift in the transition boundary



(A) No policy (B) Policy experiment

These figures illustrate the shift in the transition boundary. The vertical (horizontal) axis represent the relative technological frontier $\alpha_{t_0} = A^c_{t_0}/A^g_{t_0} = 1/1-\beta^A$ (relative skill level $\beta_{t_0} = b^c_{t_0}/b^g_{t_0} = 1/1-\beta^b$) at the day of market entry t_0. Each dot represents a simulation run, its color indicates the resulting technological regime and the position the barrier combination at the day of market entry. The boundary separates green from conventional regimes. The transition boundary is derived with a k-nearest neighbors clustering algorithm that is trained to predict the emerging regime using α_{t_0} and β_{t_0} as input. Technical detail on the algorithm is available in the appendix I.

of $(\sigma^\nu_i)^2$ indicates a very unstable transition curve. The degree of technological divergence is described by relative knowledge stocks $\alpha^*_i = \left(A^+_i/A^-_i\right)^*$, $\beta^*_i = \left(B^+_i/B^-_i\right)^*$ evaluated in t^*_i. The superscript $+$ $(-)$ indicates the technology type that wins (loses) the technology race. A high value of α^*_i and β^*_i indicates a high degree of divergence in t^*_i.

These indicators are used as dependent variables and are regressed on the policy instruments (θ, ς^{inv}, ς^{cons}), initial diffusion barriers (β^A, β^b), learning conditions (χ^{int}, χ^{dist}), interaction terms of these parameters and a set of micro- and macroeconomic controls. A binary Probit regression is used to explain the transition probability. The other regressions are OLS.

The shape of the transition pathway and its interaction with explanatory variables may exhibit systematic differences across technological regimes. These differences are captured by the inclusion of an interaction term of a regime-dummy $\mathbb{1}(eco)$ that equals one if the emerging regime is green. An extract of the regression results is shown in table 4.1.[16]

[16]To take account of possible endogeneity, the dummies are included through an instrumental variable regression. All explanatory variables are scaled and demeaned to ensure the comparability of coefficients. Technical details about the data processing, the model selection procedure, robustness checks and alternative model specifications are provided in the SM II. In the subsequent part, I discuss only those effects that are significant at a $<$ .1% level if not explicitly mentioned differently.

The regressions allow disentangling the relationship between market-based diffusion policies, different groups of technology characteristics and their interactions and emerging pathways of transition. Column (1) and (2) represent the results of the transition probability. Column (3) illustrates the effect on the duration until stabilization. Column (4) and (5) describe the technological divergence. The last column (6) shows the association of policies with the diffusion volatility.

The core observations are the following:

All policy instruments are effective and are associated with a higher transition probability. The effect on the diffusion volatility and the time until stabilization t^* differs across instruments $(\theta, \varsigma^{inv}, \varsigma^{cons})$.[17]

The effectiveness of the consumption subsidy ς^{cons} to increase the transition probability is undermined by a high distance and increasing returns to specialization (see column (1) and (2) in table 4.1). Its effect can be even reversed if χ^{dist} and/ or χ^{int} are large. In contrast, the effectiveness of the tax θ is reinforced by χ^{dist} and weakened by χ^{int}. The investment subsidy ς^{inv} is least sensitive to cross-technology interactions in LBD.

The distance χ^{dist} increases the diffusion volatility $(\sigma_i^{\nu})^2$ and the duration until stabilization t_i^* if a transition occurs, i.e. if $\mathbb{1}(eco) = 1$. If the economy is locked in, it has the opposite effect and stabilizes the technological evolution because it reinforces the specialization in the conventional technology (cf. row (2) and (17) in table 4.1).

The duration until stabilization t_i^* is differently affected and the direction of the policy effect differs across technological regimes. If the economy is locked in, t_i^* is increasing in the level of θ but decreasing in the level of subsidies (row (4)-(6)). The opposite is true if a transition is successful. Taxes accelerate (subsidies postpone) t_i^* (row (18)-(20)).

The diffusion volatility in the last column is negatively associated with θ and ς^{inv} if a transition occurs, i.e. $\mathbb{1}(eco) = 1$. Both instruments stabilize a successful diffusion process but increase uncertainty if the economy is locked in. In contrast, ς^{cons} has a negative association with the volatility in the lock-in case and is neutral in the transition. The subsidy ς^{cons} is paid proportionally to the amount of green capital that is used in production. Hence, the strength of support is dependent on $\nu_{i,t}^g$. This stabilizes an ongoing diffusion process but diminishes if green technology is not used. It does not destabilize the technological evolution. In contrast, the strength of support of ς^{inv} is constant.

[17] With some limitations, quantitative inference about the effectiveness can be drawn. The effect of the ς^{cons} on $\nu_{i,T}^c$ is quantitatively the strongest when neglecting the interaction effects. If interactions with diffusion barriers and learning parameters are absent, an increase of ς^{cons} (θ, ς^{inv}) is associated with a 4 (3, 2) % higher transition probability (column (1) in table 4.1). All explanatory variables were scaled and normalized to allow a comparison of coefficients. But the size of the intervals from which the parameters are drawn is not entirely comparable because of the non-linear effects of interaction terms. A longer discussion of the possibility to draw *quantitative* inference is available in the SM II.

The strength of the relationship between the volatility and the policies is conditional on the technological distance. The interaction of χ^{dist} with all policy instruments increases the volatility. The policies and χ^{dist} operate in opposite directions. Policies favor green technology uptake and stimulate initial diffusion. Lacking spillovers associated with a high distance reinforces path dependence arising from pre-existing knowledge stocks. This operates in favor of the incumbent if initial green technology use is not yet sufficiently high.[18]

The technological divergence and the volatility tend to be negatively correlated. Explanatory variables that lead to a stronger technological divergence, i.e. higher $(A_i^+/A_i^-)^*$ and $(B_i^+/B_i^-)^*$, tend to be associated with lower volatility. This qualifies relative technological knowledge as a driver of the direction of technological change and technological stabilization.[19]

Diffusion barriers may be prohibitively high and prevent the diffusion of green technology. The strength of barriers is associated with a lower technological divergence in case of a transition. The negative effect of the technical barrier β^A, i.e. a lower initial productivity of green capital goods, is decreasing in χ^{dist}. If the competing technologies are sufficiently distant, productivity performance becomes relatively less important for diffusion compared to other factors.

In contrast, the inhibiting effect of β^b is stronger if χ^{dist} is large. Lacking spillovers in LBD make it more challenging to overcome the disadvantage of lower endowments with technology-specific know-how $B_{i,t}^{ig}$. If χ^{dist} is high, firms are challenged by the incompatibility of pre-existing know-how when adopting green technology. External factors that are not related to productivity, e.g. variable input costs, become more important. This is also visible in the increasing effectiveness of the tax reflected in the negative coefficient of $\chi^{dist} \cdot \theta$ in the regression of $\nu_{i,T}^c$.[20]

The different policies operate through different channels. The tax and the investment subsidy have an instantaneous effect on the relative cost-effectiveness of a technology. The tax compensates permanently for the technical disadvantage if adopting a less productive technology (reflected in β^A). It operates through the channel of relative utilization costs. A less productive capital good that is bought remains in the capital stock until it is depreciated or taken out of use. The tax compensates for this disadvantage over the full

[18]This is also visible in the opposite coefficients of χ^{dist}, ς^{inv} and θ and their regime-type interaction terms.

[19]In the long run, the higher effective productivity embedded in cumulative knowledge may offset the role of relative prices and marginal using costs. This is an explanation for long-term upwards sloping factor demand curves discussed by Acemoglu (2002) and Hanlon (2015).

[20]Keep in mind that this finding might be specific to the assumptions in the model. χ^{dist} is related to spillovers in the evolution of relative, technology-specific absorptive capacity on the technology demand side. Spillovers in the innovation process are not considered, but might have an analogous effect.

life time of a green capital good. This trade-off is taken into consideration in firms' investment decisions. The permanent compensation explains why the tax may reduce the duration until stabilization if $\mathbb{1}(eco) = 1$.

The investment subsidy ς^{inv} is neutral with regard to the relative technological performance over time. It has an instantaneous effect on relative investment costs. Relative investment costs per productivity unit are sensitive to the dynamics of innovation success and price competition on the capital market (cf. 4.A). This explains why ς^{inv} is associated with lower stability.

In contrast to the other instruments, the effectiveness of the consumption subsidy is sensitive to the current technological state. The strength of support is *proportional* to $\nu^{c}_{i,t}$. In the beginning, when a firm adopts green capital but has a high share of pre-existing conventional capital, the level of support of the subsidy is relatively weak. The adoption decision is stronger influenced by the relative endowment with technological know-how and the relative performance of the technologies. ς^{cons} is a stabilizing policy instrument because it reinforces ongoing transition processes but diminishes if the green technology is not used. It is asymmetric across firms depending on the type of technology that is used by firms. This may have side effects on the market structure.

TABLE 4.1: Regression of transition pathways on technology characteristics

	Dependent variable	ν_i^c OLS	ν_i^c Probit	t_i^* IV	$\left(A_i^+ / A_i^-\right)^*$ IV	$\left(B_i^+ / B_i^-\right)^*$ IV	$(\sigma_i^\nu)^2$ IV
(1)	(Intercept)	.3381***	-.4684***	3794***	1.099***	1.097***	6.548***
		(.0043)	(.0144)	(70.63)	(.0031)	(.0029)	(.1399)
(2)	χ^{dist}	-.0130**	-.0898***	-471.0***	.0141***	.0213***	-.9603***
		(.0044)	(.0151)	(65.99)	(.0041)	(.0031)	(.1172)
(3)	χ^{int}	.0081.	-.0161	-117.2***	.0085***	.0078***	-.0240
		(.0043)	(.0145)	(31.42)	(.0017)	(.0012)	(.0535)
(4)	θ	-.0300***	-.1119***	788.9***	-.0297***	-.0296***	2.267***
		(.0043)	(.0145)	(70.37)	(.0037)	(.0029)	(.1218)
(5)	ς^{cons}	-.0401***	-.1730***	-318.1***	.0085***	-.0065*	-.1806***
		(.0044)	(.0151)	(77.99)	(.0018)	(.0032)	(.0536)
(6)	ς^{inv}	-.0205***	-.0763***	-310.8***	-.0369***	-.0286***	1.506***
		(.0045)	(.0149)	(58.73)	(.0037)	(.0030)	(.1090)
(7)	β^A	.1139***	.4650***	8.747	.0395***	.0069***	-.3212***
		(.0046)	(.0196)	(27.75)	(.0049)	(.0016)	(.0482)
(8)	β^b	.0946***	.2974***	-501.0***	.0478***	.0519***	-2.894***
		(.0044)	(.0149)	(65.63)	(.0040)	(.0035)	(.1436)
(9)	$\chi^{dist} \cdot \theta$	-.0504***	-.1177***	-119.3***	-.0110***	-.0063***	.4541***
		(.0044)	(.0149)	(28.46)	(.0019)	(.0014)	(.0609)
(10)	$\chi^{int} \cdot \theta$	.0460***	.1706***	-143.2***			
		(.0040)	(.0137)	(28.06)			
(11)	$\chi^{dist} \cdot \varsigma^{cons}$	.0289***	.0972***			-.0070***	.4550***
		(.0044)	(.0156)			(.0016)	(.0601)
(12)	$\chi^{int} \cdot \varsigma^{cons}$	.0163***	.0466***				
		(.0042)	(.0139)				
(13)	$\chi^{dist} \cdot \varsigma^{inv}$		.0522**	140.0***	-.0099***	-.0073***	.4853***
			(.0160)	(25.38)	(.0018)	(.0013)	(.0561)
(14)	$\chi^{int} \cdot \varsigma^{inv}$				.0049***		-.7356***
					(.0015)		(.0552)
(15)	$\chi^{dist} \cdot \beta^A$	-.0378***	-.1738***	195.1***			.5285***
		(.0044)	(.0199)	(23.1)			(.0442)
(16)	$\chi^{dist} \cdot \beta^b$	.0447***	.1624***	301.8***		.0092***	.2984***
		(.0046)	(.0163)	(37.7)		(.0015)	(.0711)
(17)	$\mathbb{1}(eco) \cdot \chi^{dist}$			1144***	-.0222*	-.0213***	2.658***
				(146.8)	(.0089)	(.0064)	(.2647)
(18)	$\mathbb{1}(eco) \cdot \theta$			-1070***	.0540***	.0532***	-3.919***
				(135.8)	(.0076)	(.0059)	(.2298)
(19)	$\mathbb{1}(eco) \cdot \varsigma^{cons}$			671.4***		.0239***	
				(149.1)		(.0066)	
(20)	$\mathbb{1}(eco) \cdot \varsigma^{inv}$			843.7***	.0952***	.0772***	-2.392***
				(140.9)	(.0090)	(.0075)	(.2719)
(21)	$\mathbb{1}(eco) \cdot \beta^A$				-.0413***		
					(.0060)		
(22)	$\mathbb{1}(eco) \cdot \beta^b$			786.3***	-.0908***	-.1064***	4.706***
				(137.2)	(.0084)	(.0074)	(.31)
	R^2	.1868	.266✐	.2071	.2483	.2699	.315

Significance codes: 0 '***' .001 '**' .01 '*' .05 '.' .1 ' ' 1. ✐ Pseudo R^2.

This table shows an excerpt of the results of a regression analysis of different technological indicators on a initial conditions and control variables. For the sake of readability, only the coefficients are shown that are discussed in the text. The full model is shown in the appendix (table 4.B.4).

Pathways of transition and macroeconomic side-effects

The macroeconomic side effects of policies differ across instruments. The policies reinforce the initial surge of green technology uptake independently of the emerging regime and weaken the competitive pressure for the entrant. This initial surge can be undesirable if the economy is locked in. AF higher initial adoption of green technology is associated with an allocation of learning resources in favor of green technology. If the transition is not successful, the green technology type is obsolete in the long run. The misallocation of learning resources retards the specialization in conventional technology and may have negative consequences for the macroeconomic performance (cf. chapter 2 and Hötte (2019b)).

For the sake of simpler representation, I consider only regimes with a successful transition.[21] I focus on the effects of different policy measures on macroeconomic performance, market concentration and unemployment. To evaluate these effects, a regression analysis is run using macroeconomic data of the first 30 years after market entry in the subset of green technological regimes.

Economic implications depend on the choice of policy instruments. The most decisive factor of influence is the volatility of the diffusion process σ_t^ν. The first column in the table shows the association of the policies, the technological characteristics and σ_t^ν with aggregate output. The analysis indicates a negative relationship between aggregate output and σ_t^ν. Also the investment subsidy ς^{inv} and a lower entrant productivity β^A exhibit a negative relationship. ς^{inv} distorts instantaneous investment decisions through the capital price channel. It reduces total investment costs while the other two instruments influence the relative cash-flow of using green capital. This might distort firms' choice about the investment quantity, i.e. how many capital goods to buy (cf. Hötte, 2019b). This can be a source of inefficiency.

ς^{inv} is associated with higher unemployment. This contrasts with the observation that technological uncertainty σ_t^ν tends to have a job-preserving effect. The negative effect of σ_t^ν on unemployment is a general property of the simulations. Stable technological pathways are associated with higher labor-saving productivity growth. This coincides with an increase in aggregate output and consumption but also with a moderate increase in unemployment.[22] Technological uncertainty, reflected in σ_t^ν, undermines the pace

[21] Moreover, one might argue that policies would be adjusted if a lock-in becomes apparent. The study of insufficiently stringent policy would be an analysis of policy failure which is not in the focus of this study.

[22] Recall the time horizon of several decades that is considered in the simulations. The consideration of the unemployment rate is an insufficient indicator to evaluate labor market effects. Labor supply in the model is inelastic which assumes away possible income effects and adjustments of supplied working hours at the intensive margin. Reductions in working hours per household have been empirically observed over the course of the 20th century and are visible in cross-country comparisons (e.g. Bick et al., 2018; Messenger et al., 2007). Macroeconomic gains of productivity growth are reflected in an increasing level of wealth and a higher demand for leisure.

TABLE 4.2: Regression of macroeconomic side effects

Dependent variable	Output	# firms	Herfindahl	Unempl.
Intercept	8.333***	64.49***	176.1***	7.707***
	(.0097)	(.2360)	(.5364)	(.0926)
σ_t^ν	-.0232***	.5106***	-1.192***	-0.1335***
	(.0013)	(.0255)	(.0571)	(.0117)
θ	.0067	-.0380	.0200	.1623*
	(.0046)	(.1628)	(.3525)	(.0661)
ς^{cons}	-.0045	-.5934***	1.288**	.0966
	(.0053)	(.1801)	(.4063)	(.0811)
ς^{inv}	-.0170**	-0.0777	-.0995	.7740***
	(.0060)	(.1985)	(.4506)	(.0974)
β^b	-.0032	-.1399	.4983	-.0670
	(.0050)	(.1624)	(.3686)	(.0736)
β^A	-.0193***	.1828*	-.4089*	-.0822*
	(.0035)	(.0858)	(.2052)	(.0396)
χ^{int}	.0026	-0.1588	.2881	.1413.
	(.0054)	(.1650)	(.3549)	(.0850)
χ^{dist}	.0013	-.2443	.3788	-.0138
	(.0046)	(.1613)	(.3501)	(.0576)
R^2	.3640	.2778	.2723	.2341

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

In parentheses, two-way clustered standard errors are shown. The results are consistent across alternative panel model specification (random effects, between). Variables are measured at the macroeconomic level.

of productivity improvements. This has a job-preserving effect.

ς^{inv} is associated with higher unemployment which indicates a qualitative difference to the uncertainty-employment trade-off mentioned above. Technological uncertainty is a coordination failure. It undermines productivity growth at the aggregate but individual investment decisions of firms are efficient. The investment subsidy distorts investment decisions at the micro-level.

The negative effect of β^A on aggregate output is expected. β^A is similar to a downward shift in aggregate productivity. A higher β^A indicates lower productivity of green capital goods on the day of market entry that persists over time. Similarly as σ_t^ν, β^A has a negative association with unemployment.[23] β^b is not significant. Lacking skills to operate the green technology have an impact on the transition probability, technological uncertainty and the macroeconomic performance in the short run, but this initial disadvantage is quickly

[23]This can be explained by the same argument as before. β^A scales the productivity of green capital down and reduces (or retards) the effect of labor-saving technological progress compared to simulation runs with lower β^A.

overcome when the economy converges. This is longer discussed in chapter 2 and more comprehensively in Hötte (2019b).

Technological uncertainty and less productive green capital goods (given that a transition occurs) allow less efficient firms to survive on the market. A high β^A forces most productive firms to operate at a lower frontier if they adopt green technology because the maximal productivity of capital goods on the market is lower. This reduces the productivity gap between more and less productive firms and weakens competitive pressure. These effects are reflected in a lower market concentration measured by the Herfindahl-index and a higher number of active firms.

The consumption subsidy ς^{cons} is an effective transition stimulus that has a smoothening effect on the technological evolution, even if the economy is locked in. Its impact vanishes if none of the firms uses green capital. However, ς^{cons} can be a driver of market concentration. It rewards firms most that adopted green technology early. If the transition is successful, these firms benefit twice. On the one hand, they have early specialized on the "right" technology type. This is associated with a competitive advantage if late adopters still have to catch up. Further, they benefit from higher subsidy support which is proportional to $\nu^g_{i,t}$. This support allows to achieve higher mark-ups or to reduce prices. This double advantage makes it difficult for late adopters to sustain on the market.

This analysis illustrates a trade-off between technological specialization and economic variety. Technological uncertainty undermines technological specialization which is a driver of productivity and output growth. At the same time, specialization may affect the market structure if it is difficult for weaker firms to survive.

4.5.3 Discussion

Market-based diffusion policies alter the conditions of the socio-technical landscape. The tax and the investment subsidy reflect relative costs for the inputs required to produce and use the green technology. The consumption subsidy operates through the same channel as consumer preferences and a higher willingness to pay for green products. Using Geels and Schot's terminology to describe different types of landscape pressure in transition theory, the tax exerts constant pressure. The investment subsidy exerts abrupt, but not permanent pressure. The consumption subsidy is *avalanche like* because its strength is endogenously increasing.

The analysis shows that each type of landscape pressure has its own idiosyncratic effect on the technological evolution. Landscape pressure is not necessarily sufficient to trigger a transition to green technology. It was seen that preferences for green products are only effective as diffusion stimulus if it is easy for producers to adopt and learn to use the green technology. The consumption subsidy performs better if the green technology is similar to the incumbent and easy to learn.

The parameters χ^{dist} and χ^{int} can be interpreted as a measure for the disruptiveness of innovation and the *nature of interaction* between the entrant and incumbent technology. If the distance and returns to specialization are small, firms can gradually switch to the green technology without incurring high learning costs during the transition phase.

These costs can be effectively compensated by price-dependent policies like an investment subsidy or a penalty on the utilization of the incumbent technology. In contrast, the returns from a price surplus arising from a higher willingness to pay are realized in a more distant future. Their full realization is uncertain if the type of the emerging regime is not yet clear.

4.6 Concluding remarks

In this paper, a conceptual framework for the characterization of competing technologies is introduced. This framework builds the basis for the technology-concept in the macroeconomic ABM *Eurace@unibi-eco* that is used to study transition pathways. It is an economic approach to the MLP in transition theory.

Relative endowments of codified and tacit technological knowledge are embodied in the productivity performance of supplied capital and adopters' absorptive capacity. Diffusion barriers for the entrant are reflected in the relative maturity of the entrant technology and are formalized as lower stocks of technological knowledge. The productivity-related diffusion barrier is less important if technologies are dissimilar and spillovers in the evolution of adopters' absorptive capacity are low. 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). Other factors, for example, resource prices become increasingly important.

Three market-based diffusion policies are analyzed, i.e. a consumption subsidy for green products, a green investment subsidy and a tax imposed on the environmental resource. These policies reflect the characteristics of the socio-technical landscape.

All political instruments are effective as diffusion stimuli but have different effects on the stability of the diffusion process. The consumption subsidy reinforces ongoing transition dynamics but is neutralized if the economy is locked in. This stabilizes the diffusion process and reduces uncertainty. The consumption subsidy (eco-tax) is less (more) effective if technologies are dissimilar.

The insights of this study are helpful to understand the empirically observed variety of transition pathways. This understanding is critical for the development of appropriate policy measures to accelerate a (sustainable) transition process and to understand macroeconomic side effects and disruptions in the market structure. The proposed taxonomy links concepts of transition theory systematically to micro- and macroeconomic termini.

It is an economic interpretation of the drivers of transition and transition pathways. Rosenbloom (2017) proposes to use the concept of pathways to bridge the insights from different scientific disciplines. This may facilitate a political and societal discourse about different ways to achieve a transition to a carbon neutral economy. This study adds an economic perspective. It aggregates the multi-dimensional nature of socio-technical systems into economic categories. This aggregation procedure may overlook the granular nature of single processes, e.g. the role of agency and the heterogeneous nature of single drivers of change and their interaction (Geels, 2011). These processes are indirectly reflected in the proposed indicators. The coarseness of aggregation should be seen as motivation for the elaboration of more detailed microfoundations. Linking the characterization of competing technologies to empirical concepts and data is left as an agenda for future work.

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4.A Formal description of the model

This description is an extract of the more comprehensive model documentation available in the SM I. The most relevant parts of the model are production and learning processes at the firm-level and competition on the capital goods market.

4.A.1 Production of consumption goods

Heterogeneous firms produce a homogeneous consumption good that is offered at firm-specific prices. Households are consumers. Their consumption decision is based on a multinomial logit function. Households' purchasing decision is probabilistic, but influenced by the price. Firms are heterogeneous by demand expectations, production efficiency and capacity. Their individual pricing and production decisions are based on a firm's estimations about future demand and conditioned on the firm's production capacity and efficiency.

The production efficiency is determined by the bundle of the productivity of the firm's physical capital stock and technology-specific skills of the firm's employees.

The productivity of physical capital is interpreted as codified knowledge. The capital stock is composed of a range of different vintages v of capital that differ (possibly) by technology-type $\mathbb{1}(v)$ and productivity level A^v. Each vintage of capital is characterized by the bundle of properties $(\mathbb{1}(v), A^v)$ where $\mathbb{1}(v)$ is the indicator for the technology type. It takes the value 1 if the technology-type ig is conventional c and zero if it is green g.

Employees work with capital goods in a Leontief fashion. To make effective use of the theoretical productivity A^v of a specific vintage, employees l need to know how to operate the machine. This know-how is called technology-specific skills $b^{ig}_{l,t}$ that are acquired in a learning process. t is the time index. Technology-specific skills averaged at the firm-level $B^{ig}_{i,t} = \frac{1}{L_{i,t}} \sum_{l \in L_{i,t}} b^{ig}_{l,t}$ is interpreted as the firm's stock of tacit knowledge with $L_{i,t}$ as number of employees of firm i. The bundle of $B^{ig}_{i,t}$ and theoretical productivity A^v determine the firm's effective productivity $A^{Eff_v}_{i,t} = \min[A^v, B^{ig}_{i,t}]$ for a given vintage v characterized by $(\mathbb{1}(v), A^v)$.

Firm i's production in t given by

$$Q_{i,t} = \sum_{v=1}^{V} \left(A^{Eff_v}_{i,t} \cdot \min\Big[K^v_{i,t}, \max\big[0, L_{i,t} - \sum_{k=v+1}^{V} K^k_{i,t}\big]\Big] \right) \tag{4.1}$$

where $\sum_{v=1}^{V} K^v_{i,t}$ 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 invest in new capital goods to replace depreciated units or to expand their production capacity. Employees are hired on the labor market.

4.A.2 Capital goods market

Capital goods are offered by two competing capital goods producers. Both producers are in price-per-productivity-unit competition. Each producer offers a range of different vintages that differ by productivity. Older vintages are less productive than newer vintages. Prices of capital goods are set adaptively taking account of the evolution of relative demand and profits. A fraction of profits is re-invested in R&D that contributes positively to the probability of innovative success. Successful innovation shifts the frontier of the producer upward in discrete steps, i.e. $A^V_{ig,t+1} = (1 + \Delta A) \cdot A^V_{ig,t}$. It enables the successful producer $ig = c, g$ to bring a new and more productive vintage to the market while input requirements per produced vintage are constant. The producer can supply more productivity units using the same amount of inputs. Further detail is available in the SM I.

4.A.3 Learning by employees

Employees learn over time how to use capital goods efficiently. The pace of relative learning depends on $\nu^{ig}_{l,t} = \frac{K^{ig}_{l,t}}{K^c_{l,t}+K^g_{l,t}}$ the share of capital of type ig that is used in current production. $K^{ig}_{l,t}$ is the amount of capital goods of type $ig = c, g$ that is used by the firm where l is working.

Technology-specific skills $b^{ig}_{l,t}$ are updated in discrete steps. The step size $\Delta b^{ig}_{l,t+1} = b^{ig}_{l,t+1} - b^{ig}_{l,t}$ is given by

$$\Delta b^{ig}_{l,t+1} = \chi^{gen}_l \cdot \left(\left[\left(\psi^{ig}_{l,t}\right)^{(1+\chi^{dist})} \left(\psi^{-ig}_{l,t}\right)^{(1-\chi^{dist})} \right]^{1/2} - 1 \right). \quad (4.2)$$

The pace of learning is scaled by l's learning ability χ^{gen}_l. Technological knowledge may be transferable across technology types and contribute to the stock of skills of the alternative technology type $-ig$ with $ig \neq -ig$ and $ig, -ig \in \{c, g\}$. $\chi^{dist} \in [0, 1]$ is a measure for the technological distance. A smaller distance is associated with a higher degree of cross-technology transferability of skills.

$\psi_{l,t}^{ig} \geq 1$ is the amount of knowledge learned in one period when working with technology type ig. It is given by

$$\psi_{l,t}^{ig} = 1 + \left(\nu_{l,t}^{ig}\right)^{\chi^{int}} \cdot \max[0, (A_{l,t}^{ig} - b_{l,t}^{ig})]. \tag{4.3}$$

It is dependent on the parameter χ^{int} which is a measure for the technological difficulty and returns to specialization. $\nu_{l,t}^{ig}$ is a proxy for the amount of effort invested in learning by doing with capital type ig. It captures the degree of technological specialization of the employer. The updating step is also dependent on the technical novelty $\max[0, (A_{l,t}^{ig} - b_{l,t}^{ig})]$ where $A_{l,t}^{ig}$ is the average productivity of capital goods of type ig in the employer's capital stock, i.e. $A_{l,t}^{ig} = \frac{1}{K_{l,t}^{ig}} \sum_{v \in K_{l,t}^{ig}} k_{l,t}^{v}$. This reflects the potential amount of knowledge that is new to the employee. An employee can only learn if there is something new to learn. The endowment of technology-specific skills of individual employees is not observable by the firm. Firms can only estimate the average skill endowment $B_{i,t}^{ig}$. Firms observe the amount of inputs and the amount of output. This allows to estimate the effective productivity given by $A_{i,t}^{Eff_v}$.

4.B Additional information on the simulation results

4.B.1 Barriers to diffusion and learning

TABLE 4.B.1: Initialization of barriers and learning parameters (baseline)

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

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

A Monte-Carlo experiment with randomly drawn levels of learning parameters (χ^{dist}, χ^{int}) and diffusion barriers (β^A, β^b) serves as benchmark scenario for the policy experiment. This baseline scenario is not a *true* counterfactual. Initial conditions are drawn uniformly at random from the same interval, but are not identical. However, the sample size of both experiments is supposed to be sufficiently large to draw descriptive inference.

Barriers to diffusion measured as percentage difference β^A, β^B in the initial frontier $A^V_{g,t_0} = (1-\beta^A) \cdot A^V_{c,t_0}$ and initial endowments of employees with tacit knowledge $b^g_{l,t_0} = (1-\beta^b) \cdot b^c_{l,t_0}$ are drawn at random from the interval $[0, .1]$. The learning conditions are drawn from uniform intervals. The interval of $\chi^{dist} \in [0,1]$ ranges from perfect spillovers and the absence of learning spillovers. $\chi^{int} \in [0,2]$ covers the extreme cases of increasing returns to specialization ($\chi^{int} = 2$) and a pace of learning that is independent of degree of specialization at the firm level ($\chi^{int} = 0$). A comprehensive discussion and conceptual motivation of these parameters can be found in chapter 3.

In this benchmark scenario, the transition probability accounts for 30%, i.e. 70 out of 210 simulation runs converge to a green technological state. An overview of different macroeconomic time series plots is provided in the supplementary material 4.B.1. In table 4.B.1, the initial conditions of the experiment are summarized. Descriptively, it can be seen that lower diffusion barriers seem to be positively associated with the transition probability. In the subset of green regimes, initial barriers are on average lower compared to the average initial conditions in the subset of conventional regimes. A Wilcoxon test confirms that these differences are significant.

A similar observation can be made for the role of state dependence in learning. The differences across regimes are significant for the technological distance, but not for the difficulty. On average, the distance is lower in the subset of transition regimes. A longer discussion can be found in chapter 3.

The transition probability, its volatility and measures for the pace and degree of technological divergence can be used to describe the pathway of transition. These indicators are introduced in section 4.5.

A regression analysis of these indicators illustrates the relation between the relative pace of learning embodied in χ^{dist} and χ^{int} and the relative maturity of the entrant technology. The model selection procedure is described in SM II.

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

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

A lower initial maturity has, in general, a postponing effect on t^*. Previous analyses have shown that β^A and β^b are decisive for the emerging technological regime. Their effect on the diffusion volatility is ambiguous. Both very

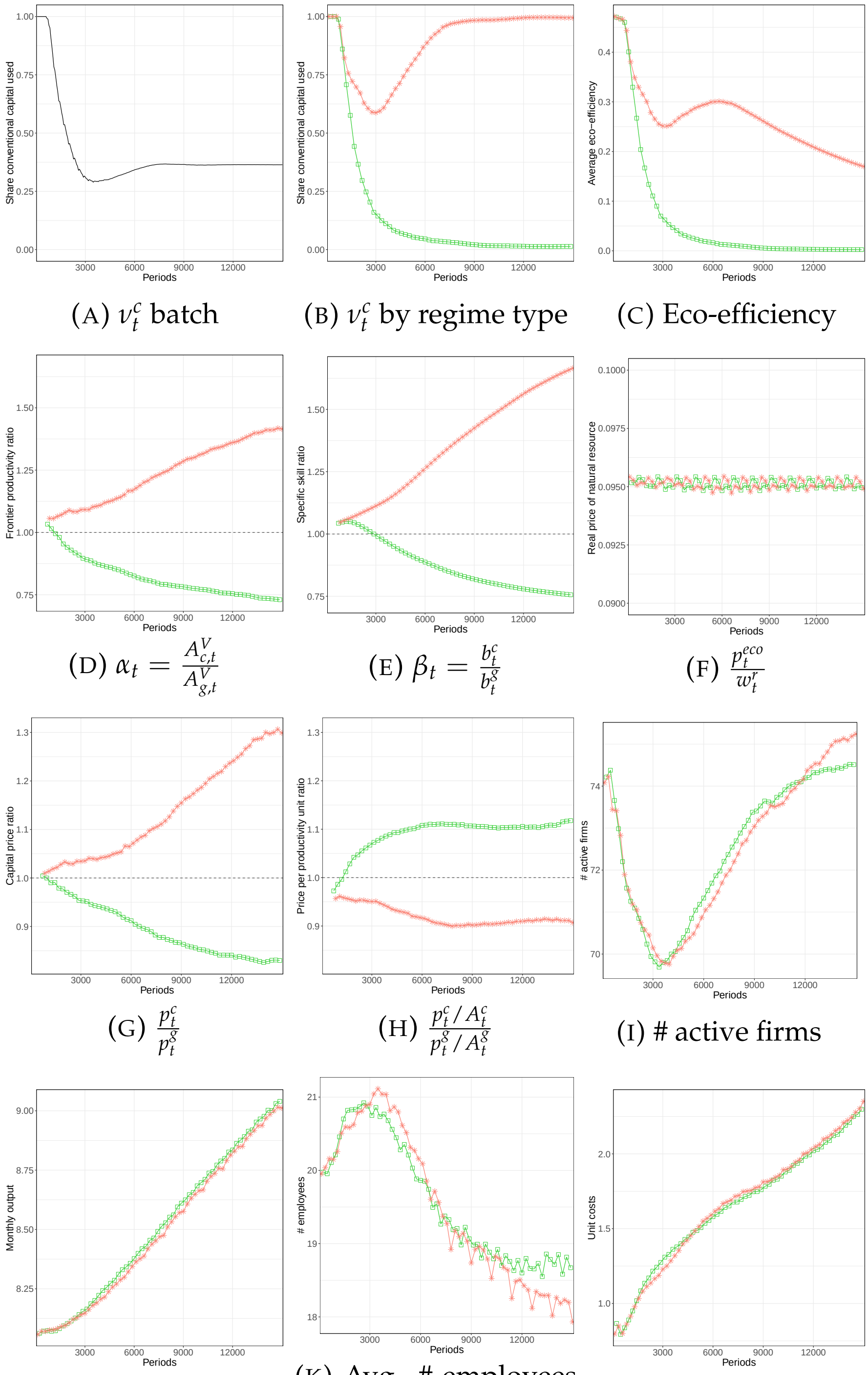
TABLE 4.B.2: Regression of transition patterns on barriers and learning

	ν_i^c OLS	ν_i^c Probit	t_i^* IV	$\left(A_i^+/A_i^-\right)^*$ IV	$\left(B_i^+/B_i^-\right)^*$ IV	$(\sigma_i^\nu)^2$ IV
(Intercept)	.6599***	.8293***	3519***	1.112***	1.07***	2.569***
	(.0033)	(.0203)	(183.3)	(.0178)	(.0138)	(.3278)
χ^{dist}	.0934***	.6556***	1220***	.075***	.0955***	-.698***
	(.0037)	(.0238)	(120.5)	(.0106)	(.0079)	(.1326)
χ^{int}	-.0027	-.028.	492.9***	.0176*	.0086	-.4932***
	(.0034)	(.0145)	(110.1)	(.0087)	(.0063)	(.1009)
$\chi^{dist} \cdot \chi^{int}$						-.8477***
						(.0493)
β^A	.1532***	.7162***	1168***	.0487***	.0437***	-.454**
	(.0038)	(.0218)	(111.3)	(.0057)	(.0056)	(.1491)
β^b	.1871***	.8811***	368.6***	.0987***	.0915***	-1.654***
	(.0034)	(.0194)	(81.76)	(.0091)	(.007)	(.1448)
$\chi^{dist} \cdot \beta^A$	-.0209***	.1041***		.0221***	.0155***	
	(.0034)	(.016)		(.0046)	(.0033)	
$\chi^{dist} \cdot \beta^b$	.0328***	.4102***		.0311***	.0222***	-.0574
	(.0033)	(.0191)		(.0082)	(.0062)	(.0872)
$\chi^{int} \cdot \beta^A$	-.0542***	-.1541***				.1126
	(.0033)	(.0141)				(.0747)
$\chi^{int} \cdot \beta^b$			-305.5***	-.0109***	-.0069**	
			(44.51)	(.0032)	(.0023)	
$\mathbb{1}(eco)$			-699.8	-.1107*	-.0499	9.839***
			(449.1)	(.0497)	(.0384)	(.889)
$\mathbb{1}(eco) \cdot \chi^{dist}$			-2428***	-.0541.	-.0974***	1.203***
			(198.4)	(.0282)	(.0209)	(.3091)
$\mathbb{1}(eco) \cdot \chi^{int}$			-1305***	-.0579**	-.0295*	2.158***
			(236.1)	(.0188)	(.0134)	(.2425)
$\mathbb{1}(eco) \cdot \beta^A$			-929.1***			-.4974.
			(198.5)			(.2705)
$\mathbb{1}(eco) \cdot \beta^b$				-.1210***	-.1156***	3.997***
				(.0111)	(.0075)	(.2980)
A_c^V		.1455***		.0171***	.0225***	-.3407***
		(.0232)		(.0020)	(.0031)	(.0789)
B_i^c			-151.4***	-.0061***	-.0054***	
			(31.66)	(.0018)	(.0013)	
$\#employees_i$			-263.7***	-.0111***	-.0097***	
			(31.96)	(.0022)	(.0024)	
$output_i$	.0159***					
	(.0046)					
$price_i$	.0251***	.049***			-.0039*	.0682
	(.0047)	(.0142)			(.0018)	(.0418)
$\#firms$	-.0105**	-.0720***				-.3611***
	(.0033)	(.0137)				(.0429)
p^{eco}/w^r	-.0167***	.1000***			.0149***	-.3424***
	(.0043)	(.0294)			(.0035)	(.0919)
R^2	.3417	.4952	.1626	.3436	.4168	.2759

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

The first two columns show the diffusion measure ν_i^c evaluated at the end of simulation. The third column illustrates the relationship between initial conditions and the duration t^* until the diffusion process stabilizes. $\left(A_i^+/A_i^-\right)^*$ ($\left(B_i^+/B_i^-\right)^*$) are measures for the relative stock of codified (tacit) knowledge at firm-level in time t_i^*. The variance $(\sigma_i^\nu)^2$ is a measure for the volatility of the diffusion process. The results in column 3-6 are the results of an instrumental variable regression taking account of the potential endogeneity of the type dummy $\mathbb{1}(eco)$. Further info is available in SM II.

FIGURE 4.B.1: Macroeconomic and technological indicators (baseline)



(A) ν_t^c batch (B) ν_t^c by regime type (C) Eco-efficiency

(D) $\alpha_t = \frac{A^V_{c,t}}{A^V_{g,t}}$ (E) $\beta_t = \frac{b_t^c}{b_t^g}$ (F) $\frac{p_t^{eco}}{w_t^r}$

(G) $\frac{p_t^c}{p_t^g}$ (H) $\frac{p_t^c / A_t^c}{p_t^g / A_t^g}$ (I) # active firms

(J) Monthly output (K) Avg. # employees per firm (L) Unit costs

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

high and very low barriers have a negative effect on t^*. Sufficiently high barriers prevent the diffusion process very early and the lock-in regime is stable. Very low barriers do not represent a burden for the entrant technology and the transition may be fast and stable. The role of barriers was more comprehensively discussed in chapter 2.

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

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

Additional discussion about the interplay of barriers and learning parameters can be found in the description of the policy experiment in section 4.5.1. For the sake of completeness, in figure 4.B.1 , some time series figure of macroeconomic core indicators are shown. A longer discussion of these simulation results can be found in (Hötte, 2019f).

4.B.2 Policy experiment

TABLE 4.B.3: Initialization of the policy experiment

		eco	*conv*	
	Mean (Std)	Mean (Std)	Mean (Std)	p-value
θ	.4927 (.2853)	.5087 (.2847)	.4553 (.2852)	.2346
ς^{inv}	.0565 (.0279)	.0584 (.0263)	.0521 (.0309)	.2246
ς^{cons}	.0129 (.0073)	.0133 (.0073)	.0121 (.0071)	.2788
β^A	.0472 (.0287)	.0394 (.0279)	.0655 (.0212)	6.9e-10
β^b	.0524 (.0280)	.0488 (.0276)	.0609 (.0272)	.0033
χ^{int}	.9923 (.5687)	.9934 (.5741)	.9899 (.5605)	.9624
χ^{dist}	.4868 (.2873)	.4903 (.2849)	.4784 (.295)	.8429

The columns show mean (standard deviation) of the initial conditions for the aggregate set of simulation runs and the subsets of green and conventional regimes. The p-value indicates whether the difference of the means across the regime subsets is significant. The parameters are drawn from the intervals: $\theta \in [0,1]$, $\varsigma^{inv} \in [0,.1]$, $\varsigma^{cons} \in [0,.025]$, $\beta^A, \beta^b \in [0,.1]$, $\chi^{int}, \chi^{dist} \in [0,.5]$.

The entries in table 4.B.3 show the mean (standard deviation) of the initial conditions for the full set of simulation runs and the subsets of green and conventional regimes. The last column indicates the p-value of a two-sided Wilcoxon test. Within the policy simulations, only the difference in the initial level of the barriers exhibits a significant difference when comparing the subset of green and conventional regimes. The initial policy parameters are on average slightly higher in the subset of transition regimes, but the difference is not significant using the Wilcoxon test as a test criterion.

The intervals from which the policy parameters are drawn were determined in a series of preceding analyses. Holding the other parameters fixed, the mean values of the two subsidies perform similarly well in their diffusion effectiveness. The modeling framework prevents an analytical derivation of exactly equally performing instruments. Additional discussion of this issue can be found in (Hötte, 2019b).

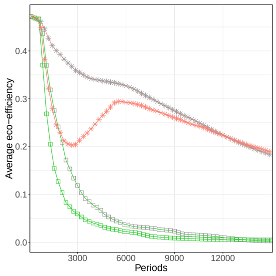
The intervals from which the diffusion barriers are drawn are determined such that a balanced sample of green and lock-in regimes is obtained. The levels are the same as used in the benchmark scenario introduced above 4.B.1.

In this section, some additional information about the macroeconomic and technological side effects of policy are illustrated by time series plots and briefly explained. In figures 4.B.2a to 4.B.2e the evolution of technological indicators is shown comparing the aggregate outcome of the policy simulations with the baseline. The difference in the subset of conventional regimes between the policy and business as usual case is remarkable. In the early simulation phase, policies trigger a higher green technology uptake, independently of the resulting regime. This has positive effects on the environmental performance in the short run. The environmental impact per output unit ("eco-efficiency") is lower in the beginning, but not necessarily in the long run. If the economy is locked in and does not switch to the green regime, eco-policies cause a distortion in the allocation of learning and R&D resources. The specialization in the conventional technology is retarded which has a negative effect on productivity compared to the baseline scenario without policy. This is also visible in the evolution of relative knowledge stocks α_t and β_t.

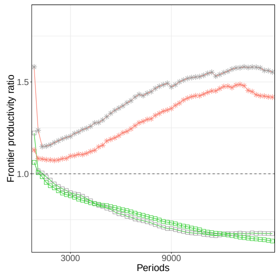
In figure 4.B.2f the budget balance measured as percentage GDP is shown. It fluctuates around zero which confirms that the budget is balanced on average. The fluctuations are largest for the green transition regimes in the policy scenario. This is largely explainable by the pro-cyclical behavior of the subsidy payments which are correlated with sold quantity of green goods and investment dynamics in green capital. If green capital is not adopted, subsidies are not paid. Figure 4.B.2g illustrates the functioning of the budget balancing mechanism. The base income tax is incrementally adapted such that the budget is balanced in the long run. It is not only responsive to the expenditures and income of green policies, but also to the payment of unemployment benefits, corporate tax rates and government's involvement in the financial sector, i.e. via the government's interest income and payment.

The day of market entry causes severe distortions in the economic system. It is associated with increased competition and a series of market exits independent of the resulting technological regime and independent of the policy as shown in figure 4.B.2h. The series of market exits is associated with a growth of the firm size. Note that the market entry dynamics in this model

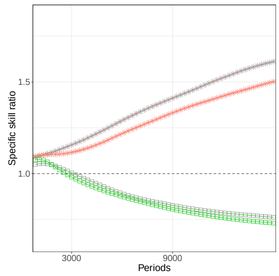
FIGURE 4.B.2: Macroeconomic and technological indicators (experiment)



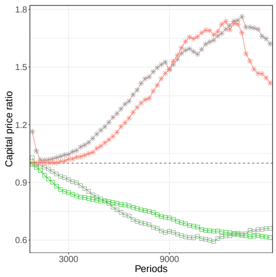
(A) Eco-efficiency



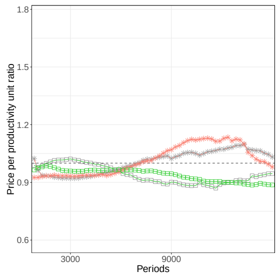
(B) $\alpha_t = \frac{A^V_{c,t}}{A^V_{g,t}}$



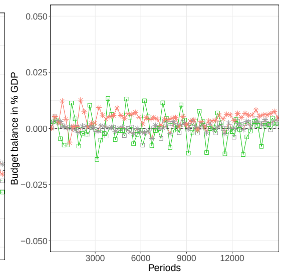
(C) $\beta_t = \frac{b^c_t}{b^g_t}$



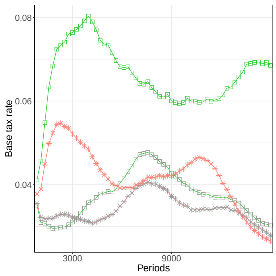
(D) $\frac{p^c_t}{p^g_t}$



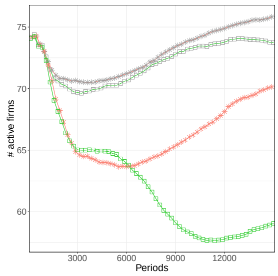
(E) $\frac{p^c_t / A^c_t}{p^g_t / A^g_t}$



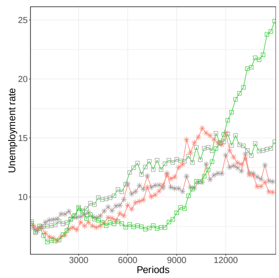
(F) Budget balance (%GDP)



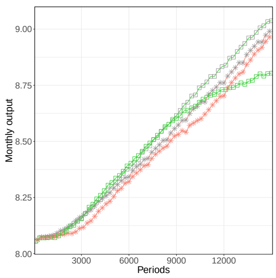
(G) Base tax



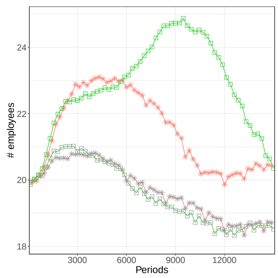
(H) # active firms



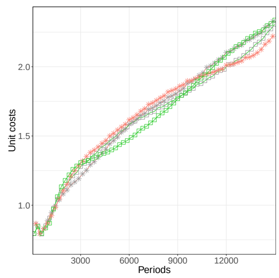
(I) Unemployment rate



(J) Monthly output



(K) Avg. # employees per firm



(L) Unit costs

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

are highly stylized and probabilistic. Only the survival rate of entrants and the number of exits is endogenous and responsive to the technological evolution and policies.

In the policy scenario, the distortions are stronger and seem to be a side effect of relatively higher green technology adoption rates. This is partly reflected in monthly output with a short phase of stagnation that can be explained by learning costs incurred in the beginning. Recall that also in the lock-in regimes, inefficiencies arise because some firms take up the green technology. This is observable in the rise of unit costs in figure 4.B.2l. Unit costs steeply increase immediately after the day of market entry.

The simulations in the model tend to exhibit "technological unemployment" that is not compensated by consumption growth. If productivity grows, firms dismiss labor, but the dismissal rates are low. In the baseline case, the unemployment rate increases over a horizon of roughly 60 yeas from 5 to 12.5%. In the presence of policy, this behavior is different and largely explainable by the consumption subsidy. The consumption subsidy makes green consumption goods cheaper. Hence, it is only paid if green technology is used. In the case green policy regimes, this price support is sufficient to stimulate demand such that the tendency of "technological unemployment" is overcome. But this effect is not permanent and conditional on the subsidy.

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

TABLE 4.B.4: Full list of regression results of policy experiment

	ν_i^c OLS	ν_i^c Probit	t_i^* IV	$\left(A_i^+ / A_i^-\right)^*$ IV	$\left(B_i^+ / B_i^-\right)^*$ IV	$(\sigma_i^\nu)^2$ IV
(Intercept)	.3381***	-.4684***	3794***	1.099***	1.097***	6.548***
	(.0043)	(.0144)	(70.63)	(.0031)	(.0029)	(.1399)
χ^{dist}	-.013**	-.0898***	-471***	.0141***	.0213***	-.9603***
	(.0044)	(.0151)	(65.99)	(.0041)	(.0031)	(.1172)
χ^{int}	.0081.	-.0161	-117.2***	.0085***	.0078***	-.024
	(.0043)	(.0145)	(31.42)	(.0017)	(.0012)	(.0535)
$\chi^{dist} \cdot \chi^{int}$	-.0291***	-.0701***				
	(.0045)	(.0158)				
θ	-.03***	-.1119***	788.9***	-.0297***	-.0296***	2.267***
	(.0043)	(.0145)	(70.37)	(.0037)	(.0029)	(.1218)
ς^{cons}	-.0401***	-.173***	-318.1***	.0085***	-.0065*	-.1806***
	(.0044)	(.0151)	(77.99)	(.0018)	(.0032)	(.0536)
ς^{inv}	-.0205***	-.0763***	-310.8***	-.0369***	-.0286***	1.506***
	(.0045)	(.0149)	(58.73)	(.0037)	(.003)	(.109)
β^A	.1139***	.465***	8.747	.0395***	.0069***	-.3212***
	(.0046)	(.0196)	(27.75)	(.0049)	(.0016)	(.0482)
β^b	.0946***	.2974***	-501***	.0478***	.0519***	-2.894***
	(.0044)	(.0149)	(65.63)	(.004)	(.0035)	(.1436)
$\chi^{dist} \cdot \theta$	-.0504***	-.1177***	-119.3***	-.011***	-.0063***	.4541***
	(.0044)	(.0149)	(28.46)	(.0019)	(.0014)	(.0609)
$\chi^{int} \cdot \theta$	.046***	.1706***	-143.2***			
	(.004)	(.0137)	(28.06)			
$\chi^{dist} \cdot \varsigma^{cons}$	.0289***	.0972***			-.0070***	.4550***
	(.0044)	(.0156)			(.0016)	(.0601)
$\chi^{int} \cdot \varsigma^{cons}$	.0163***	.0466***				
	(.0042)	(.0139)				
$\chi^{dist} \cdot \varsigma^{inv}$		.0522**	140***	-.0099***	-.0073***	.4853***
		(.016)	(25.38)	(.0018)	(.0013)	(.0561)
$\chi^{int} \cdot \varsigma^{inv}$				.0049***		-.7356***
				(.0015)		(.0552)
$\chi^{dist} \cdot \beta^A$	-.0378***	-.1738***	195.1***			.5285***
	(.0044)	(.0199)	(23.1)			(.0442)
$\chi^{dist} \cdot \beta^b$	.0447***	.1624***	301.8***		.0092***	.2984***
	(.0046)	(.0163)	(37.7)		(.0015)	(.0711)
$\chi^{int} \cdot \beta^A$	-.0171***	-.1635***				
	(.0044)	(.0199)				
$\chi^{int} \cdot \beta^b$	.0301***	.0975***				-.2552***
	(.0044)	(.0149)				(.0485)
$\mathbb{1}(eco)$			-2718***	-.1695***	-.1753***	2.874***
			(144.4)	(.0071)	(.0061)	(.3324)
$\mathbb{1}(eco) \cdot \chi^{dist}$			1144***	-.0222*	-.0213***	2.658***
			(146.8)	(.0089)	(.0064)	(.2647)
$\mathbb{1}(eco) \cdot \theta$			-1070***	.054***	.0532***	-3.919***
			(135.8)	(.0076)	(.0059)	(.2298)
$\mathbb{1}(eco) \cdot \varsigma^{cons}$			671.4***		.0239***	
			(149.1)		(.0066)	
$\mathbb{1}(eco) \cdot \varsigma^{inv}$			843.7***	.0952***	.0772***	-2.392***
			(140.9)	(.009)	(.0075)	(.2719)
$\mathbb{1}(eco) \cdot \beta^A$				-.0413***		
				(.006)		
$\mathbb{1}(eco) \cdot \beta^b$			786.3***	-.0908***	-.1064***	4.706***
			(137.2)	(.0084)	(.0074)	(.31)
A_c^V	-.017***		102.9***	.0066***	.0072***	-.2764***
	(.0044)		(26.88)	(.0018)	(.0012)	(.0548)
B_i^c						-.2179***
						(.0569)
$\#employees_i$	-.143***	-.4386***				.3848***
	(.0257)	(.0873)				(.0562)
$output_i$	.1674***	.5116***				
	(.0259)	(.0886)				
$price_i$	.0254***	.0634***				
	(.0057)	(.0191)				
$\#firms$	.0272***	.0988***	-120***		-.0035***	
	(.0043)	(.0142)	(25)		(8e-04)	
R^2	.1868	.266	.2071	.2483	.2699	.315

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

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

4.C Technical notes on statistical procedures

Relationship between aggregate growth and the transition stability In section 4.5, the negative relationship between aggregate growth and the diffusion volatility is mentioned. This finding is robust across different model specifications and levels of aggregation.

It was evaluated at an aggregate and at the run-specific level. At the aggregate level, it the correlation between the aggregate volatility computed as variance $(\sigma^{\nu}_{T})^2$ of ν^c_t across the whole simulation horizon and the average growth rate within a single simulation run. The correlation between both measures is negative and a simple regression analysis including a type-dummy confirms the significance of this relationship.

At the run-specific level, this relationship is investigated through a series of panel data methods. The data is indexed by time and run identity. I tested an fixed effects, a between , a first differences (FD) and a random effects estimator. The results of the between and FD estimator are not significant. The other estimators confirm the negative relationship at a $< 0.1\%$ level. Likely, the FD estimator is not significant due to the data types that are used. The variance is computed as running average across a 2.5 year window and the variation between individual two time steps is small. The results mentioned in the text are the estimates of a pooled regression analysis using two-way clustered standard errors on run-time.

This relationship was confirmed and more comprehensively discussed in previous studies within slightly different settings (cf. chapter 2, 3 and (Hötte, 2019b,d,f). The volatility of the diffusion measure is dependent on the conditions of technological learning and the strength of initial diffusion barriers. Both are drawn at random in this example and are fixed within a single simulation run. A more comprehensive discussion of the relationship between these properties and the transition stability can be found in Hötte (2019f).

Chapter 5

Conclusion

A state without the means of some change is without the means of its conservation. *(Edmund Burke)*

The world is changing. Climate change, digitization, but also globalization and the emergence of new powerful players in the geopolitical sphere will likely disrupt the established routines in economic and social systems. For individuals, firms and whole economies, it is a challenge to adapt to new circumstances. But this adaptation requires the willingness and capacity to change. Empirically, resistance to change is well-documented in the literature on social psychology, sociology, political science and organizations (Feygina et al., 2010; Pardo del Val and Martínez Fuentes, 2003; Watson, 1971; Wells and Nieuwenhuis, 2012).

It is an essential question how adaptation and active change can be managed. In the context of climate change, change in established modes of production and consumption is urgently needed to reduce existential risks and this needs to be realized as rapid as possible (Steffen et al., 2018).[1] In the context of digitization, but also globalization, change is on the course of happening. Change and its economic, political and societal side effects can be governed and the pathway of change can be pro-actively shaped. It is unlikely that an "ostrich-strategy" of ignorance and continuation will be the best choice in the long run.

In this thesis, I studied processes of sustainability transition in search for levers and barriers of change. I introduced a theory of directed technological change in the presence of heterogeneous, coevolving absorptive capacity. The theoretical framework is implemented in a large scale macroeconomic agent-based model. This approach helps to identify potential reasons for the empirically observed heterogeneity of pathways of transition and to study the relationship between different pathways and economic side effects. The conceptual framework can be generalized as an economic approach to the multi-level perspective in transition theory (cf. Geels and Schot, 2007).

[1]The term *possible* acknowledges the endogenous resistance that imposes constraints to the political and technical feasibility.

The approach is not aimed at searching for optimal pathways. Real-world transitions are subject to a high degree of uncertainty that makes ex-ante statements about optimal pathways very vulnerable to contentions about the technical, ethical and empirical assumptions. These controversies might be useful to advance the scientific debate but it makes statements about optimality unreliable in the political and societal discourse when it is not feasible to communicate the underlying assumptions in detail. In this thesis, I have descriptively highlighted that patterns of transitions are sensitive to the characteristics of competing technologies and the characteristics of the absorbing economic environment. It is one step towards gaining a better intuition for the economic drivers and barriers to change. It may help reducing uncertainty about the consequences of change.

The reduction of uncertainty helps to translate the abstract claim for sustainability transitions into well (or at least better) defined pathways of transition that can serve as an informative tool for political debate and communication (Rosenbloom, 2017). Research in social psychology has shown that both, the reduction of uncertainty and a higher transparency in the debate, may help overcome resistance to change at the individual and societal level (Watson, 1971). People are more reluctant to change if the pathway and its consequences are unclear.

However, translating the complex multi-level nature of socio-technical transitions into economic termini should not invite to overlook the co-evolutionary dynamics in other societal domains such as culture, social values and policy. It should also not invite to understate the role of *agency*, i.e. the capacity of individuals to act independently of structural restrictions (Geels, 2011). Agency is essential to understand the origins of novelty and intervention points for policy.

Joseph Schumpeter described the problem of dealing scientifically with radical change very aptly. If change is radical, established norms, means of measurement and thinking may be rendered inappropriate if systems of valuation change (Knudsen, 2005). This is true for economic analyses of social welfare where the metrics of measurement are *values* that are sensitive to change. But it is also true for other disciplines.

Transition research is an interdisciplinary project characterized by mutual, adaptive learning (Köhler et al., 2019). Economic side effects of transitions affect the evolution of the distribution power, societal debates, cultural norms and values. Insights from anthropology, political science, sociology and history are valuable to understand the multi-dimensional feedbacks. Rosenbloom (2017) proposed to use the concept of transition pathways as a *bridging concept* that facilitates communication across disciplines. This thesis delivers an economic conceptualization of transition pathways.

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Supplementary material I

Eurace@unibi-eco: A model of technology transitions Model documentation v1.1

I Motivation and overview

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

The underlying baseline model is the agent-based macroeconomic model *Eurace@unibi* that is comprehensively described in Dawid et al. (2019b). Throughout the paper, many explicit references to the descriptive article of the baseline model are made for readers who are interested in technical details of specific modules. This paper is aimed to be self-contained and the description provided here should be sufficient to understand the functioning of the model. Routines that are newly added to the baseline model are explained in more detail.

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

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

The model is simulated multiple times and the set of multiple simulated time series can be statistically analyzed.

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

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

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

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

1. Agents are heterogeneous. Their behavior and interaction is described by adaptive functions.
2. Decision making is asynchronous which is a source of frictions and uncleared markets.
3. Processes are subject to stochasticity and non-determinacy arising from non-linear, self-enforcing dynamics.

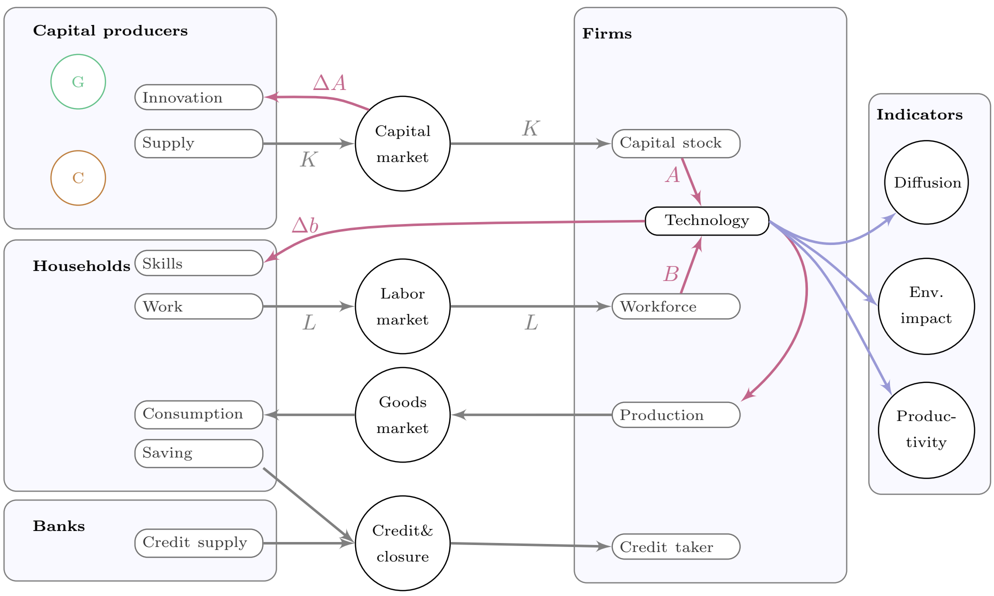
These features have been insightful to build theories of macroeconomic technological transitions driven by interaction and adaptation at the microeconomic level.

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

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

II The model

FIGURE II.1: Macroeconomic structure of *Eurace@unibi-eco*



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

The *Eurace@unibi* model is a macroeconomic agent-based model that simulates an economy composed of various groups of individual agents that are linked by economic trans- and interactions. The most important links and groups of agents are sketched in figure II.1. The main activities of the agents that are relevant for the technological evolution are summarized in

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

TABLE II.1: Overview of agents and their main activities

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

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

table II.1. The structure of the simulated economy resembles the structure of other macroeconomic models. Households (HH) supply labor and earn wages. Households' income is either spend for consumption or can be saved. Households are heterogeneous. They differ by skill level and wealth which has implications for their consumption and saving behavior. Skill and wealth differences may be the source of emerging inequality if relative wages for different skill groups or the ratio between financial and wage income diverge. Households' consumption choice is not deterministic and has probabilistic elements, but it is influenced by relative supply prices.

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

Capital or investment goods (IG) are supplied by an investment goods sector that is composed of firms that produce different types of capital. In the eco-technology version, the IG sector is composed of two representative producers. One of them is incumbent in the market and offers a conventional type of capital goods. The other firm is a market entrant and offers a green alternative.[2] The two technologies are qualitatively different by technology type. It is assumed that the entrant technology is superior because it allows its adopters to save variable input costs. In the case of green technologies, this is interpreted as costly natural resource input. In other contexts, it can be interpreted differently, for example as labor that is replaceable by machines (Goldin and Katz, 1998). Even though the entrant technology is superior in terms of variable input cost savings, it does not necessarily diffuse because it is subject to entry barriers. Diffusion barriers are measured as lower supplied productivity and lower technology-specific skills of employees that are needed to work effectively with green machinery. Skills B and supplied productivity A are stock variables that are accumulated over time in a process of learning and innovation.

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

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

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

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

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

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

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

In its *technical* features that concern the execution of routines, the *Eurace@unibi-eco* model coincides with the baseline model. A detailed description of the technical features of the model and issues of implementation can be found in section 2-3.1 of Dawid et al. (2019b).

CG firms, IG firms and households are the main agents that are involved in the technological transformation. Further, the government may intervene and implement policies to stimulate the diffusion of (green) technology. Their behavioral routines and the policy module are explained in the subsequent sections. Banks have an intermediary function managing the supply of credit. Their behavior is only briefly sketched in this article and the reader is referred to section 3.4 in Dawid et al. (2019b) for more detail.[3]

II.1 Consumption goods sector

CG firms are the key agents involved in technology diffusion. Technological knowledge is developed by innovation in the IG sector and embodied in the productive properties of available capital goods. To have an economic impact, technological knowledge does not only need to be invented, it also needs to be used. In this model, CG firms decide whether to adopt a specific technology when making their investment decisions. Skills of households and the quality of supplied capital goods of IG firms are complementary factors that facilitate or impede the adoption of new technology, but are exogenous from the firm perspective. Households' technology-specific skills are needed at work. IG firms supply capital goods of different productivity levels and technology type. An incumbent (entrant) IG producer supplies capital goods of the conventional (green) type. Productivity embodied in physical capital and skills of employees are aggregated as firm specific stocks of codified and tacit technological knowledge as a consequence to firms' investment and production decisions. In their investment decision, CG firms decide upon the technology type that is used and have an influence on the

[3]For reasons of simplification and differently from the model discussed in Dawid et al. (2019b), only 2 not 20 private banks are active in the *Eurace@unibi-eco* economy.

skills that are learned by employees. The investment decision influences indirectly the allocation of profit-oriented R&D investments and the direction of research in the IG sector. Conditional on the type of capital that is used by a firm, employees learn during work. The type of machinery that is used at their workplace determines the type of know-how that is accumulated over time. Technological change manifests in the way how final consumption goods are produced. At the same time, the way how goods are produced influences which type of technological knowledge is accumulated throughout the economy.

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

II.1.1 Production

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

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

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

[4]The mall represents a regional market and allows to introduce a spatial dimension of the model. Households and firms may have a regional identity and households are assumed to purchase goods only locally (cf. Dawid et al., 2019b, section 4.3).

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

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

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

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

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

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

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

where $L_{i,t}$ is the number of employees, and $\sum_{v=1}^{V_{i,t}} K_{i,t}^v$ is the firm's *ordered* capital stock composed of $V_{i,t}$ different capital stock items. *Ordered* refers to the running order of capital that is determined by the cost-effectiveness of capital goods. Feasible output does not necessarily coincide with the output that is actually produced. It can happen, that firms do not utilize their full capacity. This may occur because of an insufficient availability of labor, insufficient expected demand or because of prohibitively high using costs of capital goods. In such case, most cost-effective capital goods are used first. Firms can use only as much capital as workers are available in the firm to operate the machines. This is captured by the term $\max\left[0, L_{i,t} - \sum_{k=v+1}^{V} K_{i,t}^k\right]$. An additional capital stock item is only used as long as there are workers in the firm who are not intended to work with more productive machines summed up in $\sum_{k=v+1}^{V} K_{i,t}^{k}$. Therefore, the running order of machines is decisive whether a capital stock item is used or not. The cost effectiveness determines the running order and is given by the amount of output per capital unit $A_{i,t}^{Eff_v}$ divided by vintage using costs. Using costs are given by the average wage payment for a worker $w_{i,t}$ and, if it is a conventional capital good, costs for the environmental resource input c_t^{eco}. Formally, this is written as

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

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

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

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

The $*$ is a marker that indicates that the capital stock items are used for production in t. The resource input costs $c_t^{eco} = e \cdot \tilde{p}_t^{eco}$ are composed of the user price $\tilde{p}_t^{eco}$ for the input multiplied with an efficiency parameter e. The price for the environmental resource $\tilde{p}_t^{eco}$ grows at the same rate as the average wage in the economy. Hence, the cost share for the resource in variable using costs of conventional capital is held constant for an average firm. The user price includes potential environmental taxes (see II.5.1). The parameter e is fix. Efficiency improvements in the conventional sector occur only indirectly through productivity enhancements.

The decision of firms about the quantity to produce is based on their demand estimations and their inventory stocks. Once a year, firms apply a market research routine to estimate their demand potential for the coming year. In monthly frequency, based on these estimated demand curves and taking account of current inventory stocks at the "shopping mall", they determine the profit maximizing price-quantity combination to make their production decision. Newly produced goods are delivered to the mall where households purchase goods in a weekly frequency. Delivery of goods to the market and

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

purchasing decisions are asynchronous in time. Because the estimated demand and resulting production decision do not necessarily coincide with the real demand and prices can not be immediately adjusted, the consumption goods market does not necessarily clear. Firms' hold inventory stocks at the mall being composed of a buffer for the case of unpredicted demand overshoot and goods that are remaining at the end of the month if the demand potential was overestimated. These routines are explained in more detail in Dawid et al. (2019b, section 3.2.1-2).

Firms' adjustments of labor and capital stock are sluggish and occur in discrete steps. Firms buy units of capital and hire single employees. The wage paid for an employee is firm-specific. If the workforce of the firm is not sufficient to produce the desired quantity, firms post vacancies with an offered wage at the labor market. Unemployed households send applications if the posted wage satisfies their expectations. If the firm accepts the application, the matching occurs. If the vacancies are not filled, firms adjust their wage upwards. It may occur that even after the wage adjustment the job is left vacant. In such case, firms have to adjust their production decision and produce with reduced capacity. If more than one household apply for a vacancy, the firm's hiring decision is probabilistic but positively influenced by the educational attainment of the applicant. It is assumed that technology-specific skills $b_{h,t}^{ig}$ are not observable for the firm during the application process. In contrast, general skills of applicants interpreted as educational attainment as proxy for ability are observable. Further information about the households' endowment with general and technology-specific skills is provided below in section II.3. More detailed information about the labor market and the matching process can be found in section 4.2 in Dawid et al. (2019b).

II.1.2 Investment decision

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

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

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

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

where $\tilde{p}^v_t$ is the unit price of a certain vintage and I^v_t the amount of capital items to be bought. It may include subsidies if subsidies are used by the government (see II.5.1). $\hat{\pi}^v_{i,t+\tau}$ is the expected net of revenue and costs in period $t+\tau$ conditional on the investment quantity I^v_t in investment option v. Different investment options have different implication for the expected feasible production quantity, labor and resource input requirements and financial costs. Financial costs are interest payments, dividends and annuities of outstanding and, possibly, interest and annuities of new loans if own financial means are insufficient to finance investment. Firms form expectations about the development of wages and the skills of newly hired employees, prices, inflation, future interest rates and the market size on the basis of past observations. Own potential prices in the NPV calculation are computed on the basis of estimated demand curves in search for the profit maximizing price-quantity combination (cf. Dawid et al., 2019b; Harting, 2019, section 3.2.10). Firms do also anticipate learning of employees based on past observations.

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

Investment and production expenditures have to be financed in advance. If the firm's own financial means on the bank account are insufficient, it applies for a credit from private banks (cf. Dawid et al., 2019b, section 3.2.8).

II.1.3 Environmental impact

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

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

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

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

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

where the asterisk $*$ again indicates that a capital stock item is actually used. The share of green capital used in current production determines the environmental quality of a consumption good which is not observable for consumers. In the policy experiments, the government can pay a price support for environmentally sound products which allows firms to achieve a higher profit margin on green product sales (see II.5.1). The share ν^g_t aggregated across firms is used to evaluate green technology diffusion at the macroeconomic level at the intensive margin, i.e. it measures the intensity of green technology utilization in current production.

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

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

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

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

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

[7] This is a strong assumption that is mainly made for simplification reasons. It implies that scarcity in the supply of resources is assumed away. It can be justified through the very aggregate interpretation of resource inputs where a large number of substitutes is available. This deviates from other resource economic models in which scarcity plays an important part and price induced substitution between different types of resource inputs is key mechanism for the reduction of carbon emissions (Gerst et al., 2013; Nijkamp et al., 2005). In such models, price interactions across different resources represent a decisive mechanism to

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

II.2 Investment goods sector

The technological evolution in the simulated economy is embodied in the evolution of the stocks of codified A and tacit technological knowledge B. Codified knowledge is developed in the investment goods (IG) sector. If IG firms successfully innovate, they shift the productivity frontier $A^V_{ig,t}$ upwards which is a measure for the available stock of codified technological knowledge in sector ig in t. The investment goods sector is composed of two IG firms $ig \in \{c, g\}$ that offer different types of capital goods.[8] The firm c produces a conventional, the other firm g produces green capital goods. Each IG firm offers a range of vintages that are indexed by $v = \{1, ..., V\}$ that differ by productivity. The parameter V indicates the fix maximal number of vintages that can be supplied by a capital goods producer. The index $v = 1$ refers to the least productive vintage supplied by IG firm ig and $v = V$ to the most productive. If a producer invents a new vintage, the least productive vintage is assumed to be technologically obsolete and is removed from the supply array.[9]

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

How to interpret "green" and "conventional" capital goods? The distinction between green and conventional capital follows the eco-innovation concept (Arundel and Kemp, 2009). Eco-innovations are defined in relation to the incumbent and refer to any production practices that are environmentally more benign than the incumbent solution and save material and energy input costs. For example, these technologies can be different kinds of renewable energy and energy efficiency measures, but also re-using and recycling technologies and organizational methods and systems that allow to

achieve emission reductions. Here, a shift between two technologies and learning dynamics are studied but not incremental adjustments in the composite of intermediate inputs.

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

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

produce any final good or service without the dependency on material or fossil fuel energy inputs. In short, green capital is interpreted as productive capacity of the firm that enables employees to produce a final consumption good using relatively less (natural) resource inputs compared the incumbent, conventional production technique. The model may be extended to a multi-technology case where the indicator $\mathbb{1}(v)$ is not binary but ranges in the interval $\mathbb{1}(v) \in [0,1]$. In such case it represents different degrees of eco-performance. Technology-specific skills of both types are proportionally applicable.

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

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

II.2.1 Production

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

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

where α^v_t is a scaling factor determining the amount of labor $l_{ig,t}$ needed to produce one unit of capital. The scaling factor $\alpha^v_t = \alpha \cdot (\frac{A^v}{A^1})$ depends on the ratio of the productivity of the least productive vintage $v = 1$ in the current supply array to the vintage v. Hence, more productive vintages are more labor intensive and as a consequence more expensive to produce (see II.2.3). The indexation of vintages v is time dependent. Successful innovation shifts the ratio. Production costs per supplied productivity unit decrease because the least productive vintage becomes obsolete and all supplied vintages are re-indexed (see II.2.2). The parameter α is homogeneous across different vintages and IG firms.

The total amount of labor used by ig is given by $L_{ig,t} = \sum_{v=1}^{V} K^v_{ig,t} \cdot \alpha^v_t$ where $K^v_{ig,t}$ is the total, demanded quantity of vintage v in t. To ensure the model's closure, the costs for labor inputs $C^{lab}_{ig,t} = p^{lab}_t \cdot L_{ig,t}$ are recycled back to the economy as a transfer to households. Unit labor costs in the IG sector p^{lab}_t

co-evolve with average wages in the economy. This assumption can be interpreted as a separated labor market. Hence, there are some invisible households who work in the capital goods sector and consume in the same proportions as households working in the CG sector. The use of *virtual* labor as input implies that capacity constraints are assumed away.

II.2.2 Innovation

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

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

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

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

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

II.2.3 Pricing

IG firms impose an adaptive mark-up over unit production costs captured by the wage proxy mentioned above (II.2.1). Adaptive pricing rules are a common approach for heuristic pricing rules in agent-based models (e.g. Assenza et al., 2015). The price $p^v_{ig,t}$ of vintage v is given by

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

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

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

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

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

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

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

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

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

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

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

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

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

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

II.2.4 Revenue allocation

IG firms' revenue is composed of two parts. The first part accounts for *virtual* wage payments for labor inputs to IG production. The amount is channeled back into the economy as a lump-sum transfer that is uniformly allocated across households (see II.2.1). The remaining part of IG firms' revenue accounts for profits $\pi_{ig,t}$ stemming from the mark-up pricing. A given fraction $\lambda \in (0,1)$ is reinvested in R&D. The remaining share $(1-\lambda)$ of profits is paid as dividends to shareholders. They invest part of their income in a risky index fonds. IG firms are part of the index fonds. This is a simplifying assumption to ensure the financial closure of the model. The financial market is explained briefly in II.3.2 and more detailed in Dawid et al. (2019b, section 3.6.4 and 4.4.1-2).

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

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

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

II.2.5 Technological competition

Technological competition is a race between the incumbent conventional and entering green technology. It is assumed that the incumbent conventional technology is established on the market. Hence, the capital stock of CG firms is composed of merely conventional capital. At a given time, the eco-IG firm enters the market. At this point of time, the entrant firm suffers from different entry barriers. These barriers are explained below (II.6).

II.3 Households

Households (HH) act as consumers, savers and investors, and employees in the CG sector. Most important for this model extension is the role of households as employees and how employees learn at work. The other activities of households are only briefly sketched in this paper. Additional detail is available in Dawid et al. (2019b, section 3.6).

II.3.1 Learning employees

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

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

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

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

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

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

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

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

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

$\tilde{b}^{ig}_{h,t} = \max[0, (A^{ig}_{i,t} - b^{ig}_{h,t})]$ is a measure for the *technical novelty* and represents the learning potential of employee $h \in L_{i,t}$. It is given by the gap between the codified technological knowledge of the employer $A^{ig}_{i,t}$ and the employee's

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

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

current skill level $b^{ig}_{h,t}$. The larger the gap is, the larger is the potential technological knowledge the employee can learn and the faster is the pace of learning. This accounts for the fact that employees only learn if they are exposed to (codified) technological knowledge they that is new to them, i.e. employees learn only if there is something new to learn.

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

Households are matched to CG firms on the labor market as it was mentioned above (II.1.1). An employed households h works at the same firm until she is dismissed or leaves the firm deliberately. Unemployed household receive an unemployment benefit from the government. If a household does not find a job for a longer duration, she incrementally revises its reservation wage downwards. Further detail is provided in section 4.2 in Dawid et al. (2019b).

II.3.2 Consumption and saving

Beyond their involvement in the labor market and production process, households consume and save. Before households make their consumption decision and after receiving their monthly income, they compute the planned consumption budget for each week of a month. Households' income is composed of wage and financial income from savings and investments. After the payment of taxes, households allocate the disposable income on saving and consumption taking account of current income, current and desired financial wealth (cf. Dawid et al., 2019b, section 3.6.2).

Households purchase goods in a weekly frequency at the mall which serves as intermediary between CG firms and households and as inventory holder. The decision which good to buy is computed by a multinomial logit function where the probability to buy goods produced by firm i depends on the price of the good $\tilde{p}_{i,t}$ and the prices of other goods available at the mall G_t. Goods available G_t are equally valued by consumers, but are produced by different firms and offered at different prices. The supply price of CG firms is subsidy inclusive if a consumption subsidy is paid by the government (see II.5.1). The probability that household h selects the product of firm i is given by

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

The parameter γ^C is a constant that measures the consumers' price responsiveness and is a proxy for the degree of competition on the market. The consumption quantity is determined by the weekly consumption budget of the household, i.e. the full budget is spent if a sufficient amount of goods of the selected producer is available. If the quantity is not available, the household makes a second choice. If it is again not sufficient, the household is rationed. The remaining budget is added to the consumption budget for the subsequent week. More detail is available in Dawid et al. (2019b, section 4.3).

Households' total wealth consists of deposits at their bank account and financial assets invested in a risky index fonds. Once a month and after the subtraction of planned consumption expenditures and taxes, households make a revision of financial asset allocation. For reasons of simplification, there is only one risky asset available that consists of an index of shares issued by CG firms and "virtual shares" of the IG firm and its R&D activities. The portfolio revision consists of the decision whether to buy or sell shares of the risky index fonds (cf. Dawid et al., 2019b, section 6.4.2). The decision is modeled in a very stylized way and is not responsive to changes in the interest rate. This might be a severe restriction, but facilitates the tractability of the model. Economic effects channeled through portfolio revisions on the financial market are beyond the scope of the current model. Changes in the interest rate affect firms' investment decision through the accessibility and affordability of loans at private banks.

II.4 Banks

Banks serve as financial intermediaries and bookkeepers keeping track of all financial flows and stocks of agents' deposits and liabilities. Agents receive interest income paid for their deposits. Banks do also supply credit to the CG production sector. The supplied interest rate $r^b_{i,t}$ is firm-specific and depends on the volume of the requested credit, its probability of default and the interest rate of money supplied by the central bank. The default probability is computed on the basis of the firm's debt-equity ratio and the credit volume. Banks have to fulfill reserve requirements. This may constrain their capability to grant credit. This module is explained in more detail in Dawid et al. (2019b, section 3.4.2-7)

II.5 Government

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

The replacement of the incumbent by the green entrant is interpreted as sustainability transition (Safarzyńska et al., 2012).

II.5.1 Policies

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

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

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

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

- The government can use an **investment subsidy** ς^i that reduces the price for green capital goods,

$$\tilde{p}_{g,t}^{v} = (1-\varsigma^i) \cdot p_{g,t}^{v}. \tag{I.19}$$

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

$$\tilde{p}_{i,t} = \left(1 - \nu_{i,t}^{g} \cdot \varsigma^c\right) \cdot p_{i,t} \tag{I.20}$$

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

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

The tax and the subsidy rates are initialized at a given level at the beginning of the policy horizon and remain constant during the whole horizon. Before the horizon ends, taxes and subsidies are phased out to avoid disruption.[12]

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

The government may freely combine taxes and subsidies and the assumptions about the fix or adaptive rates are a matter of the policy experiment of interest.

II.5.2 Budget balancing

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

II.6 Market entry & barriers to diffusion

At the day of market entry t_0, the green technology becomes available as investment possibility for CG firms. At this time, the incumbent technology is established on the market. All firms produce only with conventional technology and workers have only worked with conventional capital. Market entering (green) technologies may suffer from different types of barriers to diffusion. Barriers emphasized in the literature are for example technological disadvantages, infrastructural and network effects in favor of the incumbent technology, or labor related factors that concern the insufficient availability of sufficiently skilled employees. Other barriers to technology adoption are effective at the microeconomic firm level such as financial constraints or the vintage structure of the capital stock (Arundel and Kemp, 2009; Carlsson and Stankiewicz, 1991; Triguero et al., 2013). This analysis focuses on the two broad categories of labor and technology related barriers. Many of the adoption barriers mentioned in the (eco-)innovation literature can be subsumed within the two categories concerning the availability of technology-specific skills and the technological performance of capital supplied by the entrant. The market entry conditions of the green IG firm are given by households' relative endowment with technology-specific skills required to use the entrant technology type and by the relative productivity of supplied green capital goods.

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

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

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

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

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

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

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

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

II.7 Simulation settings and calibration

The simulation model is run for a given number of simulation runs R and for a given number of iterations T. The model is run multiple times because it has stochastic elements, for example in the innovation process, the labor market matching and consumption decision. The outcome of a single run is not necessarily representative. The number of R is set such that a sufficiently large sample of simulated time series data is generated that can be studied

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

with statistical tools. A typical number of R ranges between 50 and 200. Its choice is dependent on the variation across runs and whether additional randomness, for example as Monte Carlo analysis on initial conditions, is introduced.

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

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

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

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

FIGURE II.2: Pseudocode of routines executed during one iteration

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

This pseudocode sketches a selection of routines executed during each iteration. The routines executed by the government and financial intermediaries are not shown here. Interaction between agents is organized via a so-called "message board" that stores information sent by an active agent until the addressee is activated again and can update its memory. See for further detail Dawid et al. (2019b).

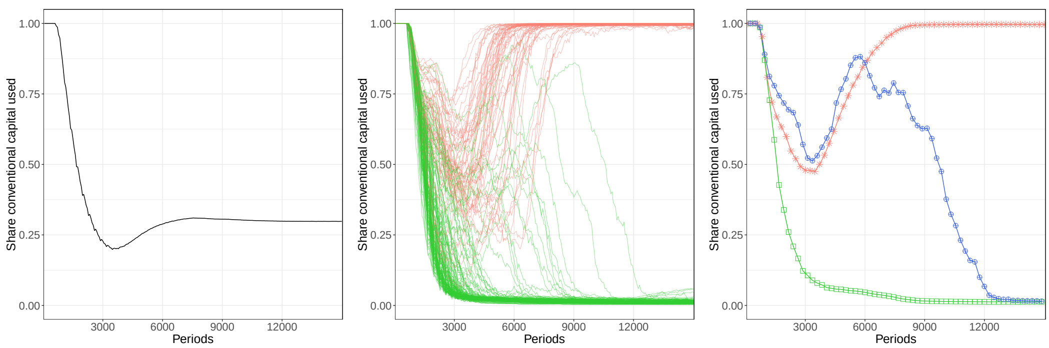
III Illustrative simulation results

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

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

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

FIGURE III.1: Simulated diffusion curves



(A) Aggregate across runs (B) Single runs (C) Aggregate by regime

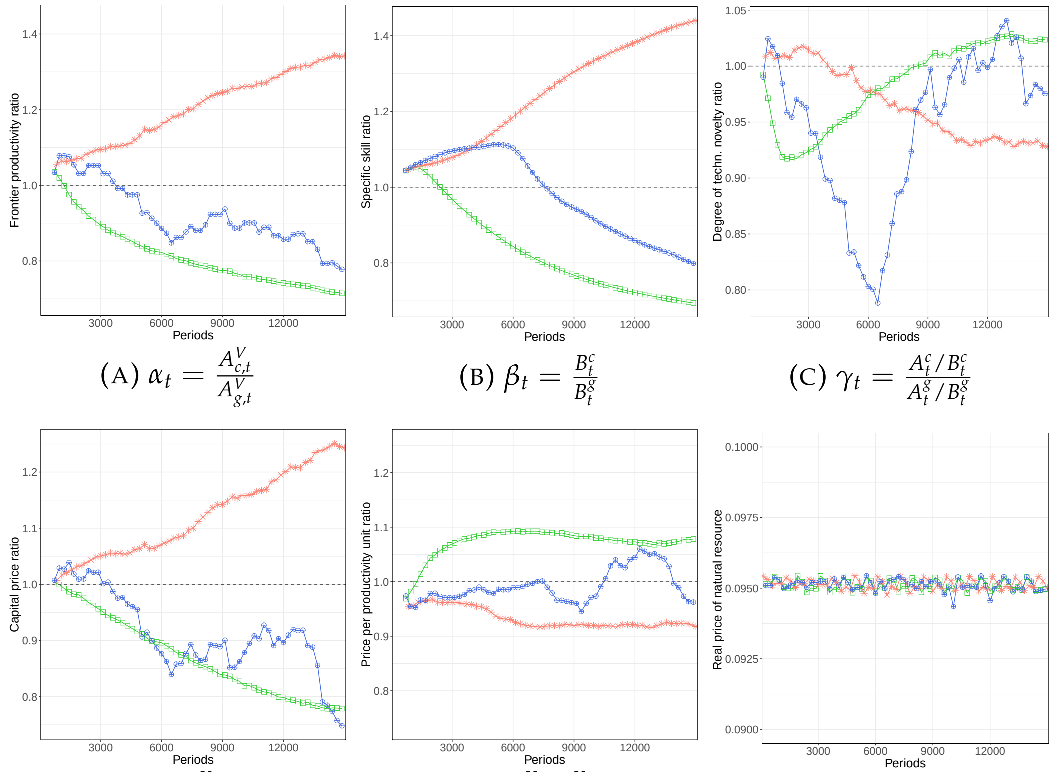
One core indicator to study diffusion processes is the share of conventional capital ν_t^c that is used for production in time t. In figure III.1, the time series of this diffusion measure is shown in three different representations. Figure III.1a shows an aggregate diffusion curve given by the average computed across 200 simulation runs. The average share of conventional technology use at the end of the simulation horizon accounts for roughly 30% corresponding to a green technology diffusion rate of 70%. Though, the aggregate curve hides an important pattern. In figure III.1b, the diffusion curves of each single simulation run are shown. Within a single simulation run, the economy converges typically to one of two possible technological states with roughly 100% or 0% conventional technology utilization. The diffusion process in the model is subject to increasing returns that arise from learning dynamics and endogenous innovation. Relative R&D investments in technology type *ig* are positively dependent on relative profit made in sector *ig*. Employees learn relatively faster skills of type *ig* if they are working relatively more with capital goods of technology type *ig*. Increasing returns lead to the convergence to one of the two states. The dominance of the green (conventional) technology is interpreted as green (conventional) technological regime (cf. Dosi, 1982). A heuristic definition of a technological regime of type *ig* is given by a share of technology use ν_T^{ig} at the end of the simulation horizon T that is larger than 50%.

The relative frequency of green regimes in T is interpreted as transition probability for a given set of initial conditions. In the example shown in figure III.1, in 142 out of 200 simulation runs a transition is observed which corresponds to a transition probability of 71%. This roughly coincides with the average share of green technology use shown in figure III.1a. Though, it should be noted that the pace of convergence and the stability of the regime depends on the characteristics of the two technologies and initial conditions. Initial conditions and technology characteristics are for example initial diffusion barriers (β^A, β^b), the properties of the learning function $(\chi^{int}, \chi^{dist})$, policies $(\theta, \varsigma^i, \varsigma^c)$ and the macroeconomic environment.[14] In a forthcoming study it is shown that the stability of the diffusion process is sensitive to knowledge spillovers in technological learning (Hötte, 2019f). If the technological distance χ^{dist} is small, knowledge is easily transferable across technology types. Hence, for firms it is easy to switch to the green technology but it is also easy to switch back to the incumbent type. In such case, the divergence of ν_t^c is less pronounced and ν_t^c may range well between 0 and 100%.

Figure III.1b reveals another important property of the diffusion process. In some of the simulation runs, the transition to one of the two regimes is clear cut. The initial surge of green technology diffusion is triggered by the technical superiority of the entrant. Though, initial diffusion is not necessarily permanent. In some of the runs path dependence in the process of knowledge accumulation outweighs the technical advantage and the economy quickly relapses into the conventional regime. In other cases, path dependence is

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

FIGURE III.2: Technological indicators



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

(D) $\frac{p^V_{c,t}}{p^V_{g,t}}$ (E) $\frac{p^V_{c,t}/A^V_{c,t}}{p^V_{g,t}/A^V_{g,t}}$ (F) $\frac{p^{eco}_t}{w^r_t}$

overcome and the economy rapidly converges to the green state. Most interesting, some of the diffusion curves are characterized by multiple local extrema. This is an indicator for long enduring technological uncertainty, i.e. firms switch between two different technology types. It is uncertain which technology will dominate at the end of the simulation time.

To illustrate the drivers of technological convergence and the macroeconomic effects of technological uncertainty, the set of simulation runs is split into three subsets that are illustrated by three different lines in the time series plots shown in III.1c. The green (red) curves represent the green (conventional) the subset of runs whose technological evolution was relatively stable. The blue curve represents the subset of so-called *switching regimes* that are characterized by a long lasting technological uncertainty.[15]

[15] The formal definition is the same as used in Hötte (2019b). A technological regime is defined by the set of runs that exceed the 50% threshold, i.e. $r^{eco} = \{r \in R/\{r^{switch}\} | \nu^c_{T,r} < .5\}$ and $r^{conv} = \{r \in R/\{r^{switch}\} | \nu^c_{T,r} \geq .5\}$ where r is a single run out of the set of runs R excluding the switching regimes. A switching regime r^{switch} is characterized by two criteria: (a) The level of conventional (green) technology utilization in T is less than 90%: $a := (\nu^{ig}_{T,r} < 90\%), ig \in \{c, g\}$. (b) The final level of conventional (green) capital utilization is higher than 50%, but the minimum level of conventional (green) technology utilization within the second half of simulation time had been fallen below 25%, i.e. $b := (\nu^{ig}_{T,r} > .5 \wedge \min_{t \in [t_{half}, T]} \nu^{ig}_{t,r} <$

This differentiation helps identifying the core mechanisms that drive the technological divergence. In figure III.2a and III.2b, increasing returns to diffusion are illustrated in terms of relative knowledge stocks. Figure III.2a and III.2b show the ratio of the frontier productivity supplied in the two IG sectors $\alpha_t = (A^V_{c,t}/A^V_{g,t})$ and the ratio of technology-specific skill endowments $\beta_t = (B^c_t/B^g_t)$. A level > 1 (< 1) indicates an advantage for the conventional (green) technology. These figures illustrate path dependence of the diffusion process. The relative advantage of the conventional (green) technology becomes stronger in the conventional (green) regime. A shift to the alternative technology type becomes increasingly difficult.

The delayed divergence of the skill ratio (figure III.2b) is a result of technological legacy path dependence in the learning process during the early diffusion phase. In the early phase after market entry, firms still have a large share of conventional capital in their capital stock. The relative pace of learning is dependent on the relative amount of capital that is used in a firm. This explains why the skill related disadvantage of the entrant β_t initially increases, independently of the emerging technological regime.

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

Figure III.2c illustrates the relative degree of technological novelty. The degree of novelty of a technology is given by the ratio of supplied productivity and the level of the corresponding skill level. If this ratio is high, the technology is relatively new to employees and the know-how is not yet sufficiently high to exploit the full productivity. This has a positive effect on the pace of learning, but only if firms invest in the corresponding technology type.

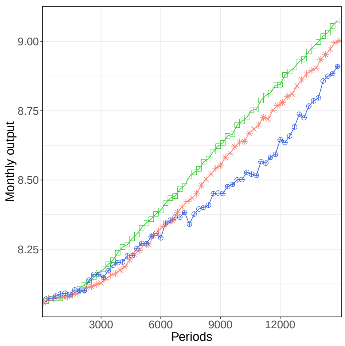
Figure III.2d confirms the functioning of the adaptive capital pricing mechanism. It shows the price ratio for the most productive vintage offered by the IG producers. In the subset of green (conventional) regimes, the green (conventional) technology is relatively more expensive in nominal terms. The relative price of the relatively more demanded capital type increases. Though, in real terms defined by the IG price per supplied productivity unit, the dominant technology is relatively cheaper. Hence, improvements in the productive quality of the dominant technology outweigh the relative increase in nominal prices.

.25), $ig \in \{c, g\}$. Criterion (b) indicates large fluctuations at a relatively late point in time. In this exemplary set of simulation runs, only 2 out of 200 runs are classified as switching regimes. Note that this is a heuristic definition without any formal justification, but serves well for the purpose of illustration.

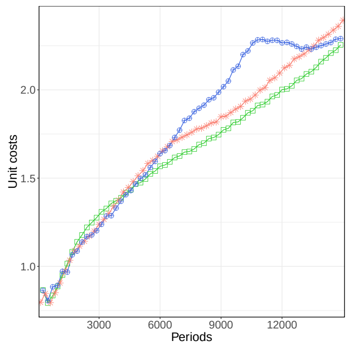
[16] The jumpy behavior of the blue curve is due to the small number (2) of simulation runs classified as *switching regimes*. Discrete adjustments as e.g. in the innovation or market entry function (see below III.3c) are not smoothed by aggregation over a larger number of runs.

The green entrant technology is interpreted as technically superior because it allows its users to save material input costs. By the design of the model, this relative advantage is stable over time. Hence, the price of the natural resource is assumed to grow by the same rate as wages. Wages and the natural resource are variable input costs in production. The share of variable input costs to be paid for the natural resource is constant as shown in figure III.2f. Small fluctuations are due to delayed smoothing routines in the model.

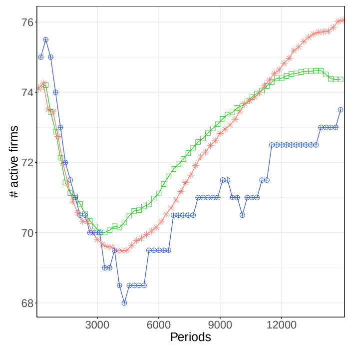
FIGURE III.3: Macroeconomic indicators



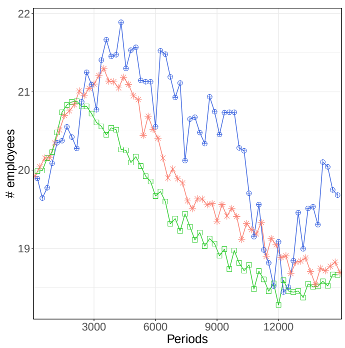
(A) Aggr. output (log)



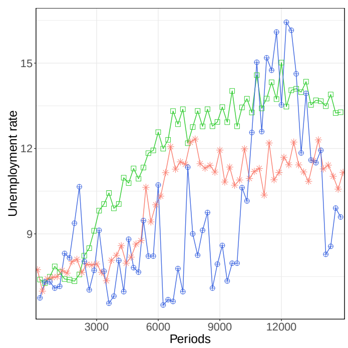
(B) Unit costs



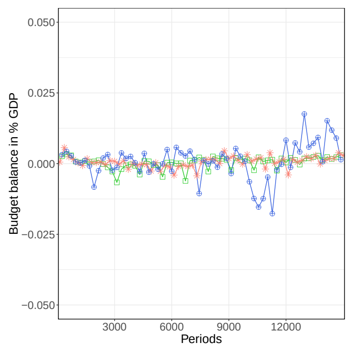
(C) # firms



(D) # employees



(E) Unemployment



(F) Gov. budget balance

Uncertainty about the allocation of R&D and learning resources in the switching regime has macroeconomic side effects in the long run. In figure III.3 a selection of macroeconomic time series is shown. In the long run, aggregate output (figure III.3a) is significantly lower in the switching regimes and unit costs (figure III.3b) are higher. Technological uncertainty is associated with a waste of R&D and learning resources. These resources are partly invested in a technology type that is obsolete in the long run. This undermines productivity improvements compared to a regime where the economy specializes in only one technology type. If the divergence between both possible technological trajectories is clear-cut, all resources are invested in learning and R&D to improve only one technology type.

The other figures in III.3 illustrate some general properties of the simulation model. Figure III.3c shows the evolution of the number of active firms. The initial surge of green technology adoption is associated with an increase in competition among CG firms. Some firms are not able to sustain and leave the market. Note that the subsequent growth of the number of active firms is mechanically driven by the design of the model. The probability that a new firm is founded is given and only the number of market exits is fully endogenized.[17] Similarly, the evolution of the average number of employees as measure for the firm size reflects partly the evolution of the number of firms. The market exits in the early diffusion phase lead to an expansion of capacity of surviving firms and the average number of employees increases.

The unemployment rate increases on average some years after the market entry at the time when the technological specialization begins and stabilizes after some time. Figure III.3f confirms the balancing of the governmental budget. The differences between the green and conventional regime that are visible in the figures are significant for the later phases of the diffusion process tested by a Wilcoxon signed rank test available (cf. supplementary material of Hötte, 2019f). Note that these differences should not be over-interpreted. Monthly output in the green regimes is higher because the conventional regimes are characterized by a higher technological uncertainty than green runs. The green technology is initially taken up independently of the resulting technology type. Learning and R&D invested in the green technology during the initial uptake are wasted if the economy is transition is permanently reversed. This would be different in a situation with prohibitively high barriers in comparison to the technical superiority of the entrant such that diffusion does effectively not take place.

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

IV Outlook

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

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

The framework of the model leaves room for numerous extensions which might be relevant in the context of diffusion and transition. Potential fields for the future application of the model are an extension to a multi-technology

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

case, R&D spillovers in the accumulation of codified knowledge, the role of regulation and non-market based political instruments, green finance, heterogeneous and evolving consumer preferences, the responsiveness of labor demand for specific skills and the spatial dimension of technological change.

V Additional information about model validation

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

Average growth rates and the size of business cycle variation are summarized in table V.1. The average growth rate of aggregate output accounts for 1.6% and the business cylcle volatility for 0.13%.

TABLE V.1: Growth rate and business cycle

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

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

Cross- and autocorrelation patterns of macro- and microeconomic time series data are shown in table V.2. The cross correlation is the correlation between business cycle dynamics and lagged macroeconomic indicators as e.g. consumption, unemployment, prices or investment. Business cylce dynamics are measured as cyclical deviation of aggregate output from its long term trend. The correlation patterns confirm procyclical patterns of consumption, prices and investment and a countercyclical pattern of unemployment.

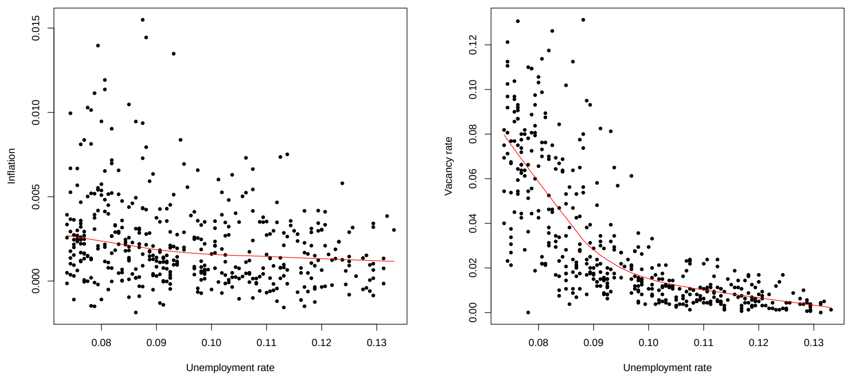
In figure V.1 plots of a Phillips and Beveridge curve using the simulated data are shown. The Phillips curve exhibits a slightly negative relationship between inflation and unemployment. The Bereridge curve illustrates the negative association between the unemployment rate and the vacancy rate. Figure V.2 shows the relative volatility of output, consumption and investment and output, vacancies and unemployment. It confirms that investment is more volatile than consumption and output.

TABLE V.2: Simulated cross correlation patterns

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

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

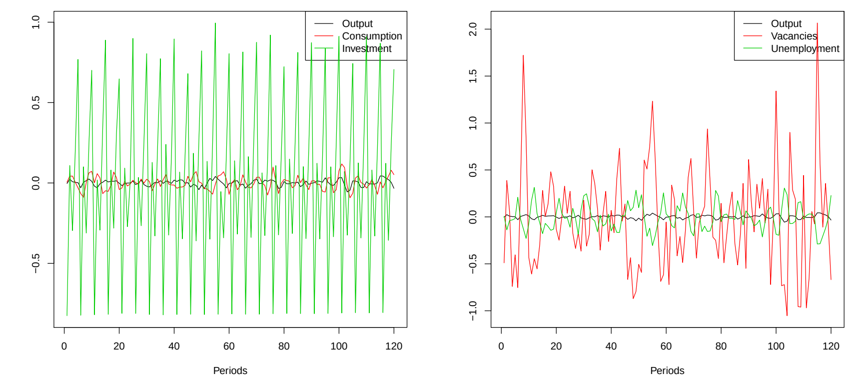
FIGURE V.1: Beveridge and Phillips curve.



(A) Phillips (B) Beveridge

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

FIGURE V.2: Relative volatility of macroeconomic indicators



(A) Output, consumption, investment (B) Output, vacancies, unemployment

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

Supplementary material II

Technical notes

This supplementary material is kept as a separately from the chapter appendices because it contains information that applies to serveral chapters.

I General technical detail on statistical procedures

Data The data used in the regressions to explain transition patterns, for example in tables 2.4, 2.3, 3.2, 3.2, 4.1, is one year average smoothed data. Additional explanations about the analyses in chapter 2 are provided in the chapter appendix 2.C.4. Observations are monthly snapshots captured at different iterations representing initial conditions and the final state. The intervals used for smoothing range from $[600, 820]$ and $[14780, 15000]$ and cover 12 monthly snapshots. One month consists of $t = 20$ iterations interpreted as working days.

The set of firms used for the regression analysis shown in table 4.B.2 and 4.1 is truncated. The data of firms exhibits the structure of an unbalanced panel with entries and exits. The diffusion volatility is only meaningful if the full life time of a firm is considered. Here, only firms are considered that survive during the whole simulation horizon. For other dependent variables, the lack of completeness is ignored.

Explanatory variables Conceptually, it is distinguished between explanatory variables and controls. Explanatory variables capture the properties of competing technologies. Controls are not of major interest, but control for differences between simulation runs and firms.

Core explanatory variables in capter 4 are interactive properties χ^{int} and distance χ^{dist}, initial relative maturity of the entrant β^A, β^B and policy instruments θ, ς^{inv} and ς^{cons}. Policy instruments can be alternatively interpreted as features of the socio-technical landscape (see 4.5.1). In the analysis of the baseline scenario 4.B.1 and in chapter 3 the set of explanatory variables is restricted to those that are available. Explanatory 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 across the two technological regimes. It is included as identity capturing fix differences in the intercept and as interaction term with explanatory variables to capture differences in the slope of explanatory variables. In chapter 2 it is included as fix identity of the emerging regime. In the analyses in chapter 3 and 4, it is included through an instrumental variable approach (IV) explained below.

Explanatory variables and controls in chapter 3 and 4 are normalized to obtain quantitatively comparable coefficients. The data were demeaned and scaled by division by the standard deviation. Normalization was made using the R-function *scale()* (R Core Team, 2018). This facilitates the quantitative comparison of coefficients with some limitations that are due to the design of the experiment. A longer discussion is available in the technical appendix of (Hötte, 2019f).

Micro- and macroeconomic control variables The macroeconomic controls included in the regression analyses at the macroeconomic level are the aggregate stock of codified A_c^V in t_0 and the number of active firms as proxy for the competitive environment. A_c^V does not measure the difference in knowledge stocks, but captures 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 until $t_0 = 600$.

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, and the firm's price. B_i^c is a proxy for the firm's productivity and the price might be an indicator for the firm's future market performance and investment behavior. This is discussed in more detail in (Hötte, 2019b).

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 The share of conventional capital $\nu_{i,T}^c$ can be directly measured. Its rounded value is used in the Probit model.

The time until technological stabilization t_i^* is defined as the last local extremum in the smoothed diffusion curve measured by $\nu_{i,t}^c$. It is the last change in the direction of the firm-level adoption behavior within a single simulation run. After t_i^*, firm i does not any longer switch between green and conventional capital. At the macroeconomic level, the economy starts converging to one of the two possible technological states. Due to the possibly non-smooth behavior of the depreciation function at the firm-level, one-year average data of $\nu_{i,t}^c$ is used to identify t_i^*.

Technological indicators evaluated at t_i^* are interpreted as threshold levels in the relative performance. These are measures for degree of technological divergence beyond which the direction of technological change is trivial. The degree of divergence is measured by the ratio of productivity $\alpha_i^* = (A_{i,t^*}^{+}/A_{i,t^*}^{-})$ and skills $\beta_i^* = (B_{i,t^*}^{c}/B_{i,t^*}^{-})$ comparing the superior $+$ with the inferior $-$ technology. *Superior* is defined as the "winner" of the technology race. If the green (conventional) technology dominates in T, 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^* is truncated. In particular, all observations are removed in which t_i^* corresponds to the last or first observation. If t_i^* coincides with the day of market entry, 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. This may occur if barriers are prohibitively high that diffusion is prevented or such low that diffusion is straightforward. 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. Technological variables evaluated at this point in time cannot be interpreted as performance thresholds. Some additional discussion how about alternative procedures how to deal with these irregularities in the data can be found in (Hötte, 2019f).

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. The variance is scaled by 100 because otherwise, it is numerically to small for a proper computational analysis and subject to rounding errors. Note that $(\sigma_i^{\nu})^2$ is different from the standard deviation shown in the time series plots (e.g. figure 4.2c) which is computed over a 2.5 year window.

Model selection procedure In chapter 3 and 4, the specifications of the regression equations are chosen using a stepwise model selection procedure based on the Bayesian Information Criterion (BIC). This procedure is implemented in the R functions `stepAIC()` (`stepGAIC()` for Probit) (Stasinopoulos et al., 2017; Venables and Ripley, 2002). A full set of pairwise interaction terms for all explanatory variables (policy, barriers and spillovers) was included in the input term for the stepwise model selection functions. The functions return the model specification that is associated with minimum BIC.

The OLS and Probit functions 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 In some of the regression models, a dummy variable that indicates whether a transition took place $\mathbb{1}(eco)$ is included. Descriptive analysis of time series disaggregated by the type of regime exhibit very different patterns, not only with regard to the outcome, but also concerning the variation over time. This raises concerns about the possible endogeneity of emerging regime. The type dummy may be subject to reverse causation and may be correlated with the error term. In chapter 3 and 4, these concerns are addressed using an 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.

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. All variables that were excluded by the BIC on the second stage were included as instrument on the first stage. The selection procedure is rather a heuristic, but not analytically justified approach. It roughly ensures that the instrument is not or only weakly related to the dependent variable in the second stage regression. Additional information is available in (Hötte, 2019f).

Transition boundaries A K-nearest neighbors clustering algorithm with a given number of nearest neighbors was used to train the classification model that is used to draw the transition boundary. This was made by the use of the *knn3()* function of the R-package *caret* (Kuhn, 2018). The appropriate number of nearest neighbors depends on the sample size and affects the smoothness of the curve, but there is no analytical rule to determine the optimal number. Here, 25 neighbors were used for macroeconomic data. 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 chapter 3 and 4 show the transition boundaries in the space of initial diffusion barriers (figure 3.4 and 4.3). Colors indicate the final regime type. For the training of the classification algorithm, initial barriers were used to predict the type of the resulting technological regime.

Transparency and reproducibility The simulation model, all data and programming code that was used for the simulation and statistical evaluation of simulated data is available online as a separate data publication (Hötte, 2019g). The data publication also contains additional descriptive statistics, figures, and additional statistical tests using alternative model specifications and data processing procedures. The reader is also referred to the accompanying working paper (Hötte, 2019f). For chapter 4, some additional analyses were made that are not included in the data publication. These are available upon request.

Abstract

Climate change is an existential threat but mitigation action is slow. This thesis searches an economic explanation for the sluggishness of technological change and searches for strategies how the transition to low-carbon technologies can be facilitated.

Based on a theory of technological capabilities and learning, the thesis begins with an analysis of diffusion barriers. Using the agent-based macroeconomic model *Eurace@unibi-eco*, it is shown that the accumulation of technology-specific knowledge can be a source of path dependence. Technological uncertainty can be macroeconomically costly if learning and R&D resources are wasted for a technology type that is obsolete in the long run. I demonstrate that the effectiveness of diffusion policies is dependent on the type and strength of diffusion barriers.

In the next part, it is analyzed how the transferability of technological knowledge across technology types affects adoption decisions of individual firms. I introduce the microfoundations of a model of technological learning. In a simulation experiment, it is shown that the transferability may have ambiguous effects. A high transferability accelerates the diffusion in the beginning but it comes with the cost of technological uncertainty and retarded specialization in the long run.

Finally, these theoretical concepts are embedded in a general characterization of competing technologies. This characterization reflects the properties of technology in given socio-technical, external circumstances and the relative maturity of an emergent entrant technology. I show how the characteristics of competing technologies can explain the shape of emerging transition pathways and discuss empirical examples. Policy may change the external conditions of the technology race. In an experiment, it is shown that the performance of different policy instruments depends on the properties of competing technologies.

Keywords: Evolutionary macroeconomics; technology transition; green technology diffusion; agent-based model; absorptive capacity; technological knowledge.

Résumé court en français

La lutte contre le changement climatique nécessite d'accélérer la transformation durable de l'économie. Cette dissertation de thèse cherche une explication économique à la lenteur du changement technologique ainsi que des stratégies permettant de le faciliter.

Basée sur une théorie des capacités technologiques et de l'apprentissage, la thèse débute par une analyse des obstacles à la diffusion. Avec le modèle de simulation *Eurace@unibi-eco*, je montre dans un premier temps que l'accumulation des connaissances technologiques peut être source de dépendance au sentier, puis que l'incertitude technologique est économiquement coûteuse si les ressources d'apprentissage et de R&D sont gaspillées dans une technologie qui s'avère être obsolète à long terme. Enfin, je prouve que l'efficacité des politiques visant à propager une technologie dépend du type et de l'intensité des obstables à la diffusion.

Ensuite, j'examine les effets de la transférabilité des compétences d'une technologie à l'autre sur les décisions d'adoption de ces technologies par des entreprises individuelles. J'introduis un modèle d'apprentissage avec des fondations microéconomiques. Lors d'une expérience de simulation, je montre que la transférabilité a des effets ambigus. Une transférabilité forte accélère la diffusion initiale, mais elle est associée à une incertitude technologique et à un retard de spécialisation technologique à long terme.

Pour finir, je développe une taxonomie caractérisant des technologies concurrentes. Cette caractérisation reflète les particularités d'une technologie en prenant en compte le contexte sociotechnique, les circonstances extérieures ainsi que la maturité relative de la nouvelle technologie émergente. Je montre comment les caractéristiques de technologies concurrentes peuvent expliquer différentes trajectoires de transitions émergentes et je présente des exemples empiriques. Une mesure politique peut affecter ces circonstances extérieures. Lors d'une expérience de simulation, je montre comment l'efficacité de différents instruments politiques dépend des caractéristiques des différentes technologies concurrentes.

Mots clés: Macroéconomie évolutionniste; transition technologique; diffusion des technologies vertes; modèle multi-agent; capacité d'absorption de technologie; connaissances technologiques.