The transition to bioeconomy and its implications for sustainable development: The case of Germany

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Summary

Ensuring that climate neutrality, the bioeconomy, and economic competitiveness go hand in hand has become a key European goal for future sustainable development. Germany, as one of the leading countries in the modern bioeconomy, aims to boost its bioeconomy as a key strategy to achieve the Sustainable Development Goals (SDGs). The transition to bioeconomy depends not only on a sufficient biomass supply but also on supporting technological and institutional innovations. In Germany, the role that technological innovation can play in carbon emissions reduction in the agricultural system is far from clear. Currently, Germany has low R&D productivity due to a general production factor mismatch and low allocation efficiency. Additionally, little is currently known about the performance of institutional innovation in the bioeconomy. Therefore, a better understanding of the real impacts of technological and institutional innovation on sustainable development is critical for supporting policymaking and guiding the transition to bioeconomy.

This dissertation focuses on the bioeconomy in Germany, examining the mechanisms by which technological and institutional innovations influence, promote, and support its development. Specifically, this dissertation i) evaluates the potential impact of R&D investments on carbon emissions through the dynamic interactions among agricultural carbon subsystems using a system dynamics modelling approach based on sectoral data (Chapter II), ii) estimates the potential mitigation effects of technological innovation on carbon emissions using an extended Spatial Durbin Model based on 401 NUTS-3 level panel data (Chapter III), and iii) examines the impacts of bioclusters, representing regional institutional innovation in Germany, on sustainable performance through the use of a super slacks-based measure (super-efficiency SBM), a series of quasi-natural experiments, and a mediating model based on 401 NUTS-3 level panel data (Chapter IV).

Chapter II reports the modelling and analysis of various scenarios, where the simulations of the dynamic interactions in the agricultural carbon system from 2020 to 2050 suggest that R&D investments can have a mitigation effect on agricultural carbon emissions both directly and indirectly, with the direct effect being more significant. The result suggests that increasing the fallow land, improving the circular economy, and increasing R&D investment are effective strategies for reducing net carbon emissions. These strategies can provide an efficient and more sustainable pathway for the transition to bioeconomy in Germany.

In Chapter III, the results of the study regarding the implication of a forest-based bioeconomy on carbon emissions are presented and suggest that technological innovations in a forest-based bioeconomy can reduce carbon emissions through promoting industrial upgrading and creating job opportunities related to the bioeconomy in local areas. Additionally, it can lower carbon emissions indirectly in neighbouring areas through the spillover effects of industrial upgrading and the size of the bioeconomy. These findings highlight the need for a coordinated approach to align technological innovation (as indicated by the number and application of patents), employment population, and industrial transition strategies.

Chapter IV investigates the potential effects of bioclusters on green total factor productivity (GTFP), and the results indicate that developing bioclusters, including both Bioregions and green clusters, would have positive effects on GTFP, both directly and indirectly, essentially through technological innovation and market agglomeration. Furthermore, it reveals that different types of bioclusters have heterogeneous impacts on GTFP, with the greatest contribution arising from chemical green clusters.

By analysing various aspects of the bioeconomy development and its implications, the findings in this dissertation contribute to the field and provide insights that can inform and support ongoing and future scientific and policy actions that guide the transition to bioeconomy in Germany.

Keywords: Bioeconomy; Technological innovation; Institutional innovation; Bioclusters; Carbon emissions; Mitigation effects; Dynamic interactions; Spillover effects; GTFP; Germany

Zusammenfassung

Die Sicherstellung, dass Klimaneutralität, Bioökonomie und wirtschaftliche Wettbewerbsfähigkeit Hand in Hand gehen, ist zu einem zentralen europäischen Ziel für eine nachhaltige Zukunftsentwicklung geworden. Deutschland, als eines der führenden Länder in der modernen Bioökonomie, zielt darauf ab, seine Bioökonomie als Schlüsselstrategie zur Erreichung der Ziele für nachhaltige Entwicklung zu fördern. Der Übergang zur Bioökonomie hängt nicht nur von einer ausreichenden Biomasseversorgung ab, sondern auch von der Unterstützung technologischer und institutioneller Innovationen. In Deutschland ist die Rolle, die technologische Innovation bei der Reduzierung von landwirtschaftlichen Kohlenstoffemissionen spielen kann, noch unklar. Derzeit weist Deutschland eine geringe F&E-Produktivität aufgrund eines allgemeinen Missverhältnisses der Produktionsfaktoren und einer niedrigen Allokationseffizienz auf. Zudem ist wenig über die Leistungsfähigkeit institutioneller Innovationen in der Bioökonomie bekannt. Daher ist ein besseres Verständnis der tatsächlichen Auswirkungen von technologischen und institutionellen Innovationen auf die nachhaltige Entwicklung entscheidend für die Unterstützung der politischen Entscheidungsfindung und die Steuerung des Übergangs zur Bioökonomie.

Um die genannten Punkte zu adressieren, konzentriert sich diese Dissertation auf die Bioökonomie in Deutschland und untersucht die Einflussmechanismen technologischer und institutioneller Innovationen bei der Förderung und Unterstützung der Bioökonomie. Konkret bewertet diese Dissertation: (1) den potenziellen Einfluss von F&E-Investitionen auf die Kohlenstoffemissionen durch die dynamischen Interaktionen zwischen landwirtschaftlichen Kohlenstoffsubsystemen mithilfe eines Systemdynamik-Modellierungsansatzes auf Grundlage sektoraler Daten (Kapitel II), ii) die potenziellen Minderungseffekte technologischer Innovationen auf Kohlenstoffemissionen mithilfe eines erweiterten Spatial Durbin-Modells basierend auf Paneldaten auf NUTS-3-Ebene (Kapitel III); und iii) die Auswirkungen von Bioclustern, die regionale institutionelle Innovationen in Deutschland repräsentieren, auf die nachhaltige

Leistung durch den Einsatz eines Super Slacks-basierten Maßes (super-effizientes SBM), eine Reihe von quasi-natürlichen Experimenten und ein Mediationsmodell basierend auf Paneldaten auf NUTS-3-Ebene (Kapitel IV).

Kapitel II berichtet über die Modellierung und Analyse verschiedener Szenarien, bei denen die Simulationen der dynamischen Interaktionen im landwirtschaftlichen Kohlenstoffsystem von 2020 bis 2050 darauf hinweisen, dass F&E-Investitionen sowohl direkt als auch indirekt eine Minderung der landwirtschaftlichen Kohlenstoffemissionen bewirken können, wobei der direkte Effekt signifikanter ist. Das Ergebnis legt nahe, dass die Erhöhung der Brachfläche, die Verbesserung der Kreislaufwirtschaft und die Erhöhung der F&E-Investitionen wirksame Strategien zur Reduzierung der Netto-Kohlenstoffemissionen sind. Diese Strategien können einen effizienten und nachhaltigeren Weg für den Übergang zur Bioökonomie in Deutschland bieten.

In Kapitel III werden die Ergebnisse der Studie über die Auswirkungen einer wald-basierten Bioökonomie auf die Kohlenstoffemissionen präsentiert und legen nahe, dass technologische Innovationen in einer wald-basierten Bioökonomie die Kohlenstoffemissionen durch die Förderung der industriellen Aufwertung und die Schaffung von Arbeitsplätzen im Zusammenhang mit der Bioökonomie in lokalen Gebieten reduzieren können. Zudem können sie indirekt die Kohlenstoffemissionen in benachbarten Gebieten durch die Spillover-Effekte der industriellen Aufwertung und die Größe der Bioökonomie senken. Diese Erkenntnisse unterstreichen die Notwendigkeit eines koordinierten Ansatzes zur Abstimmung von technologischer Innovation (angezeigt durch die Anzahl und Anwendung von Patenten), Beschäftigung, Bevölkerung und industriellen Übergangsstrategien.

Kapitel IV untersucht die potenziellen Auswirkungen von Bioclustern auf die grüne totale Faktorproduktivität (GTFP) und die Ergebnisse zeigen, dass die Entwicklung von Bioclustern, einschließlich Bioregionen und grünen Clustern, positive Auswirkungen auf die GTFP sowohl direkt als auch indirekt haben würde, im Wesentlichen durch technologische Innovation und Marktagglomeration.

Ferner zeigt sich, dass verschiedene Arten von Bioclustern heterogene Auswirkungen auf die GTFP haben, wobei der größte Beitrag von chemischen grünen Clustern stammt.

Durch die Analyse verschiedener Aspekte der Bioökonomie-Entwicklung und deren Implikationen leisten die Ergebnisse dieser Dissertation einen Beitrag zum Fachgebiet und liefern Erkenntnisse, die laufende und zukünftige wissenschaftliche und politische Maßnahmen unterstützen können, die den Übergang zur Bioökonomie in Deutschland steuern.

Schlagwörter: Bioökonomie; Technologische Innovationen; Institutioneller Innovationen; Clustern; Kohlenstoffemissionen; Minderungseffekte; dynamischen Interaktionen; Spillover-Effekte; GTFP; Deutschland

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List of abbreviations

BMBF	German Federal Ministry of Education and Research
BMEL	German Federal Ministry of Food and Agriculture
BMELV	German Federal Ministry of Food, Agriculture and Consumer Protection
BMU	German Federal Ministry for the Environment, Nature Conservation and Nuclear Safety
CAP	Common Agricultural Policy
EC	European Commission
EFA	Ecological Focus Area
Eurostat	European Statistical Office
EEA	European Environment Agency
DEA	Data envelopment analysis
DDD	Difference in Difference in Differences
SDiD	Staggered Difference in Differences
PSM-SDiD	Propensity Score Matching- Staggered Difference in Differences
FAO	Food and Agriculture Organization
GHG	Greenhouse Gas
GTFP	Green total factor productivity
IPCC	Intergovernmental Panel on Climate Change
NCE	Net carbon emissions
NUTS	Nomenclature of territorial units for statistics
R&D	Research and Development
SD	System Dynamic
Sd	Standard deviation
SDG	Sustainable Development Goal
SDM	Spatial Durbin Model

1 Introduction

Developing the bioeconomy has become a key strategy for facilitating the transition towards sustainability in the European Union (EU) and in many other regions worldwide. Many countries have launched bioeconomy strategies, ranging from dedicated bioeconomy strategies to be-related strategies and dedicated be-strategies (see Figure 1.1). Figure 1.1 displays an overview of the distribution of bioeconomy strategies around the world, indicating countries where strategies are already in place or are under development. Germany is included in the figure as one of the countries that has already launched a dedicated bioeconomy strategy.

Figure 1.1: Bioeconomy strategies in place or under development around the world

Source: bioökonomierat (2018). "International bioökonomiestrategien".

https://bioökonomierat.de/bioökonomie/international.

Although the term "bioeconomy" first started to become popular in the early 2000s, the concept of the bioeconomy is still relatively new and it is considered to still be in its early growth stage. The concept of the bioeconomy has a multifaceted breadth and depth of meaning, varying across paradigms, disciplines, and countries. While definitions of the bioeconomy may differ, they typically share many similarities (Wesseler and von Braun, 2017). According to the United Nations Food and Agriculture Organisation (FAO), the bioeconomy refers to "the production, use, and conservation of biological resources, including related knowledge, science, technology, and innovation to provide information, products, processes, and services to all economic sectors with the aim of moving towards a sustainable economy" (FAO, 2018). The bioeconomy was defined by McCormick and Kautto (2013) as an economy where the basic building blocks for materials, chemicals, and energy are derived from renewable biological resources. In the policy framework of the European Union, the bioeconomy is regarded as a key component for attaining smart and green growth (EC, 2012). According to the European Commission, the bioeconomy "encompasses the production of renewable biological resources and their conversion into food, feed, bio-based products, and bioenergy. This includes agriculture, forestry, fisheries, food, pulp, and paper production, as well as parts of the chemical, biotechnological, and energy industries" (EC, 2012). This definition is widely accepted by academic and political communities all around the world. With the goals of ensuring food security, managing depleting natural resources sustainably, reducing the dependence on non-renewable resources, adapting to climate change, and creating job opportunities, the bioeconomy aims to contribute to intelligent, sustainable, and inclusive growth that will allow the transition towards a green economy (OECD, 2011a, b; 2016).

1.1 Background: The transition towards bioeconomy in Germany

1.1.1 The bioeconomy in Germany

The development of the bioeconomy in Germany is being driven by policy initiatives aimed at modernizing the economy in a sustainable, environmentally responsible and societally sensitive manner. With the aim to develop a cross-sectoral, knowledge and bio-based economy, the bioeconomy in Germany began with the establishment of the Bioeconomy Council in January 2009. The council was established by the Federal Ministry of Education and Research (BMBF) and the Federal Ministry of Food, Agriculture, and Consumer Protection (BMELV) and was regarded as an independent advisory board for the German Federal Government. In 2010, Germany published the National Research Strategy Bioeconomy 2030, which was designed by the Bioeconomy Council, becoming one of the first countries to outline its national bioeconomy strategy. In 2013, Germany implemented the National Policy Strategy Bioeconomy, setting another important milestone for the bioeconomy. In early 2020, Germany launched the new National Bioeconomy Strategy, which laid down guidelines for policies on the bioeconomy as well as the measures for implementation. With these and later initiatives, Germany has set a pioneering pace as one of the first countries to formally set out and pursue a bioeconomy strategy in line with the EU Framework Programme for Research and Innovation and later in 2012, the EU Bioeconomy Strategy.

Although revolutionary in their ambition to sustainably transform the entire society, these strategies started with a step backwards, namely by revisiting the potential of plant-based biomass. In April 2009, the National Biomass Action Plan was launched (BMELV/BMU, 2009; Goven and Pavone, 2015; Hagemann et al., 2016). Alongside 2009 amendments to the Renewable Energy Sources Act and a boom in renewable electricity uptake, this plan defined forest and agricultural biomass as one of the most promising domestic renewable energy sources that could significantly contribute to value creation, especially in rural areas (Troost et al., 2015). The plan envisaged a large-scale expansion of bio-based energy, including agricultural fuels. Recent European Union strategy papers on biodiversity (EC, 2020b) and food systems (EC, 2020c), along with recommendations by the National Academy of Sciences (Leopoldina, 2020), have further clarified the role of biomass in the bioeconomy.

Alarmed by the increasingly pessimistic projections for climate development, soil, water, and air quality, as well as by the noticeable consequences of unsuitable development paths, recent debate has begun to shift the focus from alternative models of economic growth to prioritizing environmental protection. The Biodiversity and Food to Fork strategies (EC, 2020b; 2020c), the core components of the European Green

Deal (EC, 2019), set time-bound targets for the expansion of nature conservation areas, with the aim of achieving farmland biodiversity and land degradation neutrality within a decade. The Leopoldina stresses the major role of agriculture in reducing carbon emissions and biodiversity loss and recommends even more profound and immediate actions are needed (Leopoldina, 2020). These recommendations, including minimizing the use of fertilizers, pesticides, and herbicides, a large-scale shift to organic farming, and limiting farmland for biofuels and animal feed production, have direct implications for non-food biomass production.

Despite the conflicting goals of sustainability and economic growth reflected in regional, national, and supranational agendas, the bioeconomy is gaining momentum along various dimensions (Bell et al., 2018). In 2005, the share of the bioeconomy in Germany accounted for 3.9% of gross value added and 5.2% of the labour force, while in 2019 these figures had risen to 19.9% and 13.5%, respectively (Bioeconomy Council, 2010; BMBF, 2020). This growth has been driven by significant research funding (EUR 20.3 billion in 2020, cf. BioStep (2016)), invested in "mapping and engineering the uncharted territories" of the technical and biotechnological knowledge and making them marketable (Aguilar et al., 2018). The transformation of the economy and especially of the chemical sector away from fossil-based resources (Schütte, 2018), along with the promotion of bioclusters and technology parks (Scarlat et al., 2015; BioSTEP, 2016), could accelerate this process by demanding more high-quality biomass (Budzinski et al., 2017; Efken et al., 2016). However, the envisaged production of high-value biomass-based goods and materials with economic and non-economic benefits may prove an unattainable vision (Brar et al., 2013), considering the already high imports of biomass for material and energy use (Leopoldina, 2012).

1.1.2 Technological innovation in the agricultural system in Germany

In the context of Germany, the role of technological innovation in reducing agricultural carbon emissions is still unclear, as the agricultural system is complex and the productivity of R&D is difficult to estimate. By comparison, while Germany's business R&D spending has increased by 3.3 % per year over the last decades, R&D productivity has fallen by an average of 5.2% per year (Boeing and Hünermund, 2020). This aligns with the findings that R&D productivity is decreasing in Germany, particularly outside the bioeconomy context (Schäfer, 2014; Ugur et al., 2016). In 2016, the total public R&D funding for the bioeconomy in Germany amounted to around EUR 120 million (Imbert et al., 2017). Through R&D investments, a number of local biotech innovation networks and bioeconomy clusters in Germany have integrated biomass producers within a circular economy to support innovation and coupled subsystems (Kaiser and Prange, 2004; Mennicken et al., 2016; Wilde and Hermans, 2021). This highlights the interaction between innovation and coupled subsystems in the German plant-based bioeconomy. In addition, Germany aims to fulfil all its electricity needs from renewable sources by 2035, with two-thirds expected to come from bioenergy (Frondel et al., 2010; Mohmmed et al., 2019). The projected decrease in energy-based emissions by 2030 with this energy transition due to the political incentives promoting renewable energy (754.883 Mt CO_2, cf. Mohmmed et al., 2019) underscores the relevance of coupled subsystem for renewable energy and the agricultural production subsystem in the plant-based bioeconomy.

1.1.3 Forest-based bioeconomy in Germany

The forest-based bioeconomy, encompassing the entire forest value chain, is considered to be a key player in the arena of promoting the bioeconomy for achieving decarbonization of the economy. In Germany, it has exhibited great potential for climate change mitigation by reducing carbon emissions (Hagemann et al., 2016; Purkus et al., 2018). Up to 2016, 570 policy documents linked to carbon-mitigation strategies, covering the whole value chain of the forest-based bioeconomy, have been launched at the EU level (Rivera León et al, 2016). It is argued that the forest-based bioeconomy can play both direct and indirect roles (e.g., carbon sequestration by the forest and soil, and substitution effects from bioenergy replacing fossil fuel, respectively) in carbon emission reduction (Seppälä et al., 2019; Jonsson et al., 2020; Kumeh et al., 2021).

Forests, a key resource input and support system for the forest-based bioeconomy, are a main source of carbon sinks. It has been reported that forests and harvested wood products together sequester the equivalent of circa 10% of the EU's greenhouse gas emissions (EU, 2022). Apart from forests and traditional wood products, the forest-based bioeconomy also covers efforts directed towards bioenergy, biochemicals, textiles, cellulose and lignocellulosic bioplastics, packaging products, etc. (Wolfslehner et al., 2016). It can also contribute to climate change mitigation by promoting the use of wood to substitute fossil fuels and other materials (EU, 2022). However, this substitution process occurs at the sacrifice of more forest biomass. It is evident that without sufficient afforestation and forest resources, the mitigation strategies focusing on enhanced carbon storage in wood products and the substitution of fossil fuels and energy-intensive materials require biomass removals; thereby, in most cases, decreasing the carbon sequestration potential of the forests (Lindner et al., 2017). Thus, the real mitigation effects of the forest-based bioeconomy on carbon emissions require a better understanding.

1.1.4 Bioclusters in Germany

Bioclusters are a special kind of clusters that operate with the explicit goal of promoting sustainable development by fostering the transition to a bioeconomy (Hermans, 2018). Bioclusters can play an important role in the sustainable transition to bioeconomy, especially in Germany. At the same time, bioclusters are characterized by coupled production systems, leading to stronger horizontal and vertical implications for industrial integration (Wesseler and von Braun, 2017). The circular production mode is prevalent in bioclusters carries a high expectation for linking innovation with climate neutrality (Biber - Freudenberger et al., 2020). This can help to tranform the prevalent linear production mode to a no-linear production mode for the whole of society as well. Furthermore, close cooperation among biotech companies, research institutes, technology parks, etc., can create sufficient scientific outputs and innovations to support the emerging bioeconomy. Especially for Germany, bioclusters, characterized by the heavy concentration of stakeholders and organizations, are proving to be important new technology impulse givers in this respect (Dorocki, 2014). The thriving bioclusters in Germany, with more than 770 biotechnology companies involved in 2021, have created substantial scientific outputs, offering opportunities to promote green efficiency and productivity at large (FMEACA, 2022).

1.2 Motivation and research gap

1.2.1 Carbon emissions in the plant-based bioeconomy

Agriculture is one of the backbones of the European Union (EU)'s bioeconomy, given its role as a key biomass supplier and a potential contributor to carbon emissions reduction (EC, 2018; Haddad, 2019). In 2018, emissions from the agriculture sector accounted for 17% of global anthropogenic greenhouse gas (GHG) emissions (FAO, 2020). Nonetheless, the sector has an immense potential to reduce these emissions following a transformative bioeconomy strategy (Koondhar et al., 2022). Germany, a leader in this endeavour, is championing the bioeconomy as a pathway towards achieving carbon neutrality by 2045 and meeting the Sustainable Development Goals (SDGs) (EC, 2020). The 2020 National Bioeconomy Strategy of Germany aspires to cultivate a knowledge-based, greener, more sustainable, and inclusive bioeconomy in the country (Hall and Zacune, 2012; EC, 2020). This strategy places significant emphasis on agriculture, highlighting the essential role it can play in the reduction of carbon emissions.

The agricultural carbon system within the framework of bioeconomy is intricately connected with ecosystem services and other industries. It encompasses carbon emissions from farming activities and industries, and carbon sequestration resulting from land-use changes and plant photosynthesis (Pataki et al., 2006; Wang et al., 2012; Gutzler et al., 2015). However, it is challenging to quantify the actual mitigation effects of a plant-based bioeconomy on carbon emissions. In addition, technological innovation intended to support the plant-based bioeconomy could inadvertently increase carbon emissions due to the rebound effect (Zhou et al., 2017; Li et al., 2022; Pahle et al., 2022). This introduces uncertainty regarding the role of technological innovation in reducing carbon emissions within the agricultural carbon system. Therefore, achieving a sustainable transition to a bioeconomy necessitates a deeper understanding of the carbon emissions in a plant-based bioeconomy and their connection to the agricultural carbon emission system.

Technological innovation, driven by scientific and technological knowledge and achieved through R&D investment, is a cornerstone of the bioeconomy (Schütte, 2018). Many studies hold the view that technological innovation has the potential to reduce carbon emissions by improving agricultural productivity, reducing cultivated land supply, raising innovation efficiency, and promoting the circular economy (Xiong et al., 2016; Frank et al., 2019; Balsalobre-Lorente et al., 2019; Nwakae et al., 2020). For example, Frank et al. (2019) showed that agriculture could significantly contribute to global carbon emission reductions, potentially achieving a reduction of 0.8–1.4 Gt of CO_2-equivalent by 2050 through applying emission-reducing technologies (e.g., new animal feed supplements, nitrification inhibitors, or anaerobic digesters) and making structural changes (e.g., changes to the crop and livestock production portfolio). Frank et al. (2019) studied the roles of technology and structural changes in carbon reduction measured and found that the innovation subsystem has become an integral part of the agricultural carbon emissions system. Additionally, increasing studies have found that R&D investments not only stimulate technological innovation but also foster the development of both the innovation subsystem and the coupled production subsystem within the plant-based bioeconomy as they also improve production efficiency through promoting the recycling and reuse of agricultural residues, e.g., biorefinery and renewable energy (Lebuhn et al., 2014; Gutzler et al., 2015). This also makes the innovation subsystem and coupled production subsystem more relevant.

However, some agricultural literature insists that the increase in carbon emissions caused by technological innovation is larger than the decrease in carbon emissions that such innovation enables. This is because, with the applications of technological innovation (e.g., new biotechnology and breeding technology), more biomass and energy are required to support the transition to bioeconomy (Henle et al., 2008; Fleiter et al., 2012; Iris and Lam, 2019). The increasing demand for biomass can lead to land use conflicts, biodiversity loss, and an overuse of chemicals and energy (Deininger, 2013; Liobikiene et al., 2020). In particular, land use conflicts and biodiversity loss can impair the ecological services previously provided by the land system, thereby diminishing its carbon absorption capacity, which can directly increase carbon emissions during productions. As technological innovation can also alter labour structures and promote a sustainable increase in gross domestic production in the socioeconomic subsystem, labour and capital inputs in agricultural production can be affected; thus, this results in higher carbon emissions as well as the need for increased capital investment in technological innovations (Tian et al., 2014; Xiong et al., 2020; Fu et al., 2021). Therefore, agricultural carbon emissions are closely linked to agricultural production, socioeconomic development, and land-use changes. Whether technological innovation can effectively reduce carbon emissions depends on the interactions among agricultural production, socioeconomic activities, and the environment's carrying capacity, which may be primarily represented by the carbon emissions from land-use changes or emissions per unit of GDP (Garrone and Grilli, 2010; Wen et al., 2021). These complex interactions within the agricultural carbon system and their effects on net carbon flow have recently attracted increasing academic attention (Fong et al., 2009; Fu et al., 2015; Zhao et al., 2018; Benbi, 2018; Ghiat et al., 2021).

1.2.2 Sustainable economic growth and the decoupling of carbon emissions

While there is a growing body of literature on the potential of the forest bioeconomy to mitigate carbon emissions (Hetemäki, 2014; Giurca, 2018; D'Amato et al., 2018), most of the studies are qualitative analyses conducted at the macro-level (Luhas et al., 2021; Jonsson et al., 2021; Kumeh et al., 2021; Rebolledo-Leiva et al., 2023). Although these studies indicate the good potential for the forest-based bioeconomy to lead to carbon emissions reduction, whether from path dependence in the framework of the sustainable bioeconomy or from the use of state-of-the-art technology (Luhas et al., 2021; Heiskanen et al., 2022), they lack identified actions. Among the few quantitative analyses, there are increasing studies evaluating the role of technological innovations (e.g. as indicated by patent applications) in the forest-based bioeconomy in climate-change mitigation (Lovrić et al., 2020; Ladu et al., 2020; Harrahill et al., 2023). Such literature suggests that the context of applying technological innovation in forest-based bioeconomy and the diffusion pathway of technological innovation are important, because technological innovations in the forest-based bioeconomy can affect emissions differently (positively or negatively), in different countries and at different levels with different approaches taken (Ganda, 2019; Giurca and Befort, 2023). At the same time, the estimation of carbon emissions and their drivers in the same region may produce different results depending on the aggregation level of data used (Wen et al., 2021). However, how innovation diffusion in the forest-based bioeconomy affects carbon emission and how carbon emission fluxes in the ecosystem in one area affect the adjacent and distant regions through spatial interaction and diffusions are still unknown.

The spatial pattern of carbon emissions and the mechanisms of emissions reduction have so far been studied by decomposing the influence of urban agglomerations, technological innovation and industrial upgrading on carbon emissions, e.g., with the Logarithmic Mean Divisia Index (Kalnay and Cai, 2003; Bianco et al., 2024) and Spatial Durbin Model (SDM) (Wen et al., 2021; Chen et al., 2023). Although it is recognized that carbon cycles in the bioeconomy system reflect emissions changes concomitant with land-use change (Wang et al., 2023), the role of inter-regional interactions and their spillover effects remains less scrutinized. Furthermore, the forest-based bioeconomy covers all sectors of the value chain. Although some studies have estimated the effect of substituting non-food biomass for fossil fuels at the sector level using life cycle assessment (LCA) (Phan-huy et al., 2023), the substitution effect may be offset by the carbon emissions generated during the regional production process. This may lead to double accounting when calculating carbon emissions in the eco-economic system.

1.2.3 Innovation and green productivity

Bioclusters can play an important role in the sustainable transition to bioeconomy, especially in Germany. On the one hand, bioclusters are characterized by coupled production systems, leading to a stronger horizontal and vertical implication for industrial integration (Wesseler and von Braun, 2017). The circular production mode, widely embraced in bioclusters, is highly anticipated to allow bridging innovation with climate neutrality (Biber - Freudenberger et al., 2020). This can also facilitate the transition from a linear to a non-linear production model. Furthermore, the close cooperation among biotech companies, research institutes, technology parks, etc., creates sufficient scientific outputs and innovations to support the transition to bioeconomy. Especially for Germany, bioclusters, which are characterized by a high spatial concentration, are emerging as important new technology impulse givers in this respect (Dorocki, 2014). Germany's thriving bioclusters, comprising over 770 biotechnology companies in 2021, have created substantial scientific outputs, offering opportunities to promote green efficiency and productivity at large

(FMEACA, 2022). Although Germany is a leading country in promoting the bioeconomy, it has been found to have low R&D productivity due to a mismatch of production factors and a lack of focus on the efficient allocation of resources. Additionally, the role of innovation in reducing carbon emissions has been overlooked. Thus, there is a need to enhance green productivity in Germany.

Given this, a sustainable development of the bioeconomy requires a better understanding of the implications of establishing bioclusters, as an institutional innovation, on green productivity. The literature suggests that green productivity has certain advantage over R&D productivity (Du et al., 2012; Li et al., 2019; Wang and Jiang, 2020). Unlike the productivity in the traditional linear production model that aims to increase production and economic efficiency only and results in high pollution, green productivity takes the environmental performance into account and allows a whole picture to be considered for achieving harmony between economic development, resources, and the environment (Zhao et al., 2022). To measure green productivity, this calls for some reconsideration about the input-output relationship. So far, approaches like Data Envelopment Analysis (DEA) and Super-efficiency DEA, have been used to estimate green productivity (Guo and Yuan, 2020; Lee and Lee, 2022). Among them, the super slacks-based-measure (super-SBM) model with undesirable outputs proposed by Tone (2002) is widely applied due to its advantages of allowing effectively ranking multiple efficient DMUs. In addition, urban carbon emissions, the primary contributors to global warming, are, in many cases, generated from the process of economic value creation (Amin et al., 2020; Li et al., 2021). Recent studies, therefore, tend to account for carbon emissions as an undesirable output (Gao et al., 2020; Song et al., 2022). So far, the Porter hypothesis has been used to examine the positive impact of institutional innovation on technological innovation (Gimenez and Sanau, 2007; Chhetri et al., 2012; Donbesuur et al., 2020). The close linkage between technological innovation and green productivity has been evaluated empirically as well (Du et al., 2019; Jiakui et al., 2023). However, there is a gap in understanding the mechanisms of institutional innovation on green productivity, especially the performance of institutional innovation in the bioeconomy, which needs to be measured empirically. Thus, empirical evidence on whether and how the establishment of bioclusters affects green productivity is needed.

1.3 Research objectives and questions

The overarching aim of this dissertation is to explore the implication of the bioeconomy on sustainable development. The guiding research question in this dissertation, therefore, is whether and how the transition to bioeconomy can promote sustainable development. Since sufficient technological innovation and political support are two pillars of bioeconomy, the influencing mechanisms of technological and institutional innovation are estimated in this dissertation. Consequently, three specific objectives and associated research questions are identified and addressed in each of the proceeding three chapters, respectively.

Research Objective 1 (Chapter II): The first objective of this dissertation is to estimate the potential mitigation of technological innovation on carbon neutrality, which is one of the most important indicators for sustainability under the transition to bioeconomy.

<u>Research question</u>: *Will the transition to a plant-based bioeconomy reduce carbon emissions?*

To deal with the mitigation effect of agriculture on carbon emissions, this chapter aims to contribute to projecting agricultural emissions by detailing the impact of R&D investments on carbon emissions. Focusing on the agricultural sector in Germany, this dissertation applies a system dynamics (SD) modelling approach to simulate the potential impact of R&D investment on carbon emissions through dynamic interactions among agricultural carbon subsystems. This dissertation evaluates the net effect of R&D investments on carbon emissions, incorporating carbon sinks from land use and plant production, as well as carbon reductions achieved through the re/upcycling of agricultural residues and by-products.

Research Objective 2 <u>(Chapter Ⅲ)</u>: The second objective is to analyse the direct and indirect impacts of the forest-based bioeconomy on carbon emission.

As biomass sources mainly originate from agriculture and forest, the mitigation effects of forest and agriculture sectors on carbon emissions are distinguished.

Research question: *Will the transition of a forest-based bioeconomy reduce carbon emissions"?*

Given that there is currently limited understanding of the impact of the forest-based bioeconomy on carbon emissions in Germany, this dissertation aims to estimate the spatial impact of the forest-based bioeconomy, especially the role of technological innovation in the forest-based bioeconomy on carbon emissions. Using an extended Spatial Durbin Model and 401 NUTS-3 level panel data from 2000 to 2021, this dissertation measures the intra-regional and spillover effects of technological innovation, the size of the bioeconomy, industrial upgrading and their interactions on carbon emissions empirically.

Research Objective 3 (Chapter IV): The third objective of this dissertation is to measure the impact of bioclusters on sustainable performance where carbon emissions are considered as an undesired output.

Research question: *Will the establishment of bioclusters promote green productivity"?*

Given the research gap about the mechanisms of institutional innovation's effects on green productivity, this dissertation, focusing on Germany at the NUTS-3 level, aims to estimate the causal effects of bioclusters on green productivity mediated by technological innovation. The dissertation uses a quasi-natural experiment, including a series of methods, like difference in differences (DiD), Staggered DiD(SDiD), PSM-SDiD, and difference in difference in differences (DDD), and a mediating model to estimate the impact of establishing bioclusters on green total factor productivity (GTFP) in Germany.

1.4 Structure of the dissertation

This dissertation examines the implications of developing the bioeconomy for promoting sustainable development in Germany, analysing it from two perspectives and three influencing mechanisms. One perspective is obtained from an impact evaluation. Using NUTS-3 panel data from 2000 to 2021, this dissertation examines the impacts a bioeconomy in Germany would have on carbon emission reduction and green productivity empirically, providing empirical evidence regarding the efficiency of the bioeconomy strategy for policymakers and contributing to the relevant body of literature. The other perspective is obtained from a scenario simulation process. This dissertation anticipates the potential mitigation effect of technological innovation on agricultural carbon emissions as well as the dynamic interactions among subsystems from 2020 to 2050, with the simulation period chosen to fit in Germany's goal of attaining carbon neutrality by 2050. Three influencing mechanisms are proposed covering structural changes in the production factors, namely changes in land use and labour, and industrial structure; technological innovation and its spatial diffusion; and institutional incentives in the bioeconomy.

The remainder of the dissertation is organized as follows. Chapter II and III discuss the potential mitigation effects of agriculture and forestry under the transition to bioeconomy on carbon emissions, respectively. Chapter IV analyses the influences of institutional innovations in the bioeconomy on the green total factor productivity, while the final chapter presents the conclusion part (Chapter V) with some policy suggestions and methodological implications. The structure of the dissertation is illustrated in Figure 1.2.

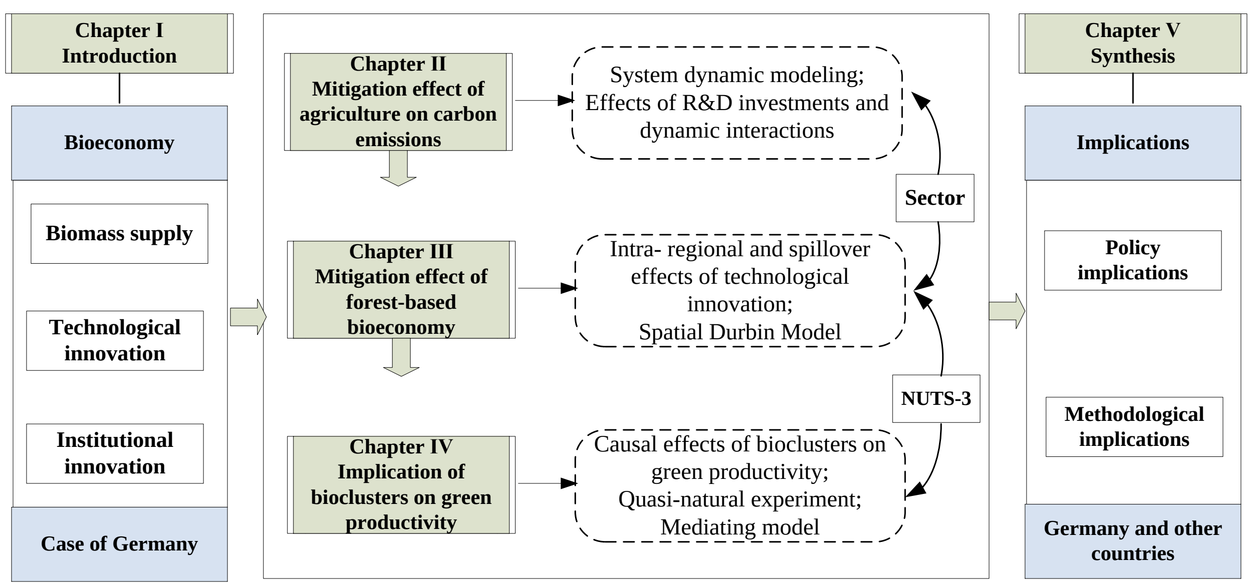


Figure 1.2: Structure of the dissertation

Source: Own operations.

2 Potential mitigation effects of technological innovation in the plant-based bioeconomy on carbon emissions[1]

2.1 Objectives and theoretical framework

2.1.1 Background and organization

Agriculture is the cornerstone of the European Union's bioeconomy due to its role as a primary biomass supplier and as an important sector with great potential for carbon emission reduction. Agriculture can both generate carbon emissions through farming activities and industrial processes and at the same time act as a carbon sink via plant photosynthesis and land use changes (Pataki et al., 2006; Wang et al., 2012; Gutzler et al., 2015). This dual role complicates the measurement of agriculture's actual impact on carbon emissions. The introduction of technological innovation, which is achieved through R&D investment and is an important pillar in the bioeconomy (Schütte, 2018), further adds to the difficulty. This is because such innovation can reduce carbon emissions by improving resource efficiency and enhancing carbon sequestration, but it can also increase emissions due to the rebound effect.

So far, there is little knowledge about whether and how R&D investments can mitigate agricultural carbon emissions with the transition to the bioeconomy. Many studies suggest that technological innovation has the potential to reduce carbon emissions by improving agricultural productivity, reducing the need for cultivated land, enhancing innovation efficiency, and promoting a circular economy (Xiong et al., 2016; Frank et al., 2019; Balsalobre-Lorente et al., 2019; Nwakae et al., 2020). R&D investment, often used as an indicator of technological innovation, has the potential to reduce carbon emissions by advancing biotechnological innovations, improving the production efficiency of biorefineries, and promoting

[1] Author statement: Lanjiao Wen (conceptualization, methodology, software, writing-original draft, and revision); Dr. Zhanli Sun (conceptualization, revision and supervision); Dr. Lioudmila Chatalova (conceptualization and revision); Prof. Dr. Anlu Zhang (conceptualization); Prof. Dr. Alfons Balmann (revision and supervision).

bioenergy (e.g., biogas). However, some agricultural literature argues that the increase in carbon emissions caused by technological innovation may exceed the reductions they offer. This is because the application of certain technologies, such as biotechnology and breeding, requires more biomass and energy to support the transition to a bioeconomy (Henle et al., 2008; Fleiter et al., 2012; Iris and Lam, 2019). The growing demand for biomass can also lead to land use conflicts, biodiversity loss, and an overuse of chemicals and energy (Deininger, 2013; Liobikiene et al., 2020).

With the transition to the bioeconomy, the agricultural carbon emission system becomes more complex, comprising the land use subsystem, agricultural production subsystem, innovation subsystem, coupled subsystem (including resource recycling and upgrading use), and the socioeconomic subsystem. Specifically, in the plant-based bioeconomy, the productivity of technological investments can be affected by many factors, like the input-output relationship, industrial integration, biomass recycling/upcycling use, and innovation efficiency. This not only makes the agricultural carbon system more complex and challenging to quantify, but also highlights the roles of the innovation subsystem and coupled production subsystem, as well as the dynamic interactions among subsystems in carbon emission reduction. Furthermore, the decreasing R&D productivity has been reported in Germany (Schäfer, 2014; Ugur et al., 2016), which makes the role of technological innovation in reducing carbon emissions within the agricultural system even less clear. Therefore, understanding how R&D investments impact carbon emissions through the dynamic interactions among subsystems in the agricultural system is a major question that needs to be answered.

The present study aims to contribute to projecting agricultural emissions by detailing the impact of R&D investments on carbon emissions. Focusing on the agricultural sector in Germany, this study applies a system dynamics modelling approach to simulate the potential impact of R&D investments on carbon emissions through considering the dynamic interactions among the agricultural carbon subsystems. To present the net effect of R&D investments on carbon emissions, this study takes carbon sinks and carbon emission reduction into account, including, e.g., carbon sequestration from land use and plant production, and carbon reduction from re-/upcycling of agricultural residues and by-products.

The rest of this chapter is organized as follows. Section 2.1.2 outlines the relationship among carbon emissions, carbon sinks, and carbon emission reduction in the agricultural system. Section 2.2 introduces the data and methodology used for simulating net carbon emissions and the dynamic interactions in the agricultural system. Section 2.3 describes the design of scenarios for the simulation. The results and policy implications are summarized and discussed in section 2.4, while the last section 2.5 concludes the analysis.

2.1.2 Theoretical framework

Figure 2.1 illustrates an overview of the subsystems considered under the nexus between agricultural sustainability and carbon emissions. Crop production and animal husbandry are the main agricultural activities and carbon sources as well. Their production involves input and output flows and is associated with carbon emissions from both the farm processes and livestock, while carbon sequestration saved by the green landscape and the recycling and reuse of biomass can reduce the emissions to some degree, forming an agricultural carbon cycle. Since the agricultural carbon cycle is associated with the production process, economic environment, land use cover change, technological level, and producing structure (Lu and Guldmann, 2012; Gu et al., 2019), five subsystems in the plant-based bioeconomy are defined and modelled in the present study. The five subsystems, namely the land use subsystem, agricultural production subsystem, innovation subsystem, coupled production subsystem (including resource recycling and upgrading use), and the socioeconomic subsystem (see Figure 2.1), closely interact with each other.

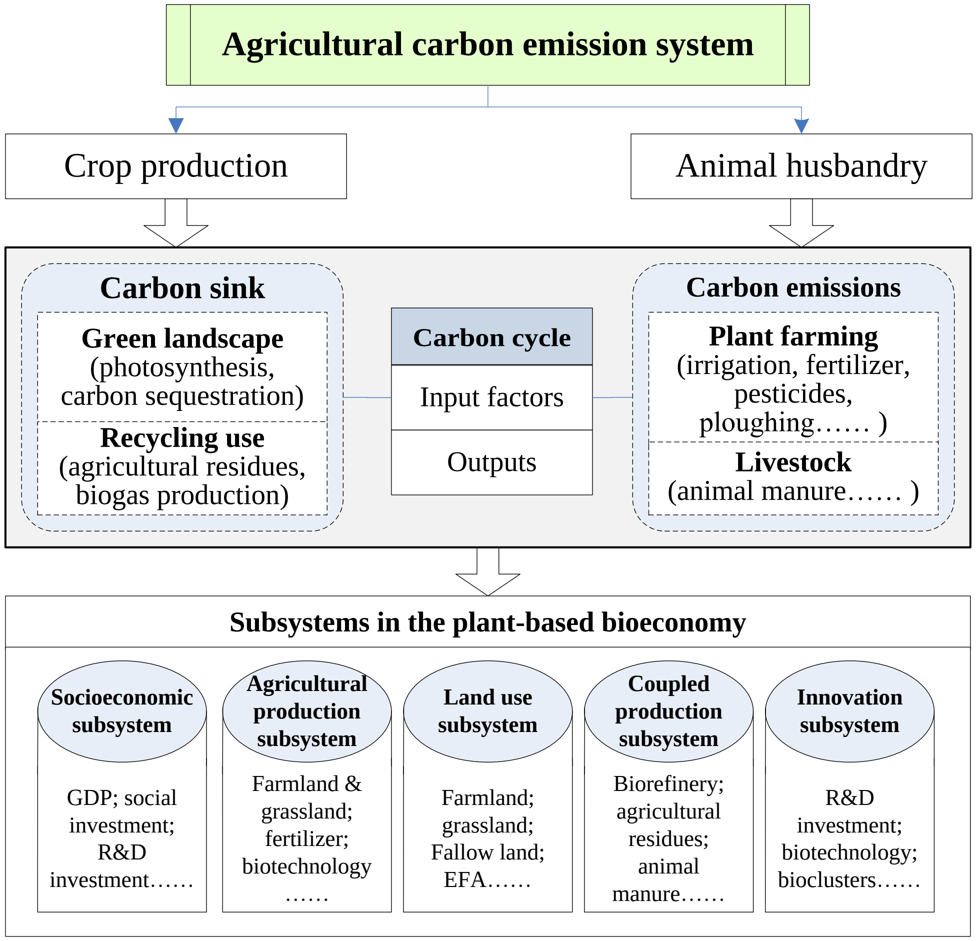


Figure 2.1: Overview of the subsystems

Source: Own operations.

R&D investment can significantly improve technological innovation and industrial integration (e.g., vertical integration) (Wesseler et al., 2015; Wesseler and von Braun, 2017). Thus, the innovation subsystem is crucial in the plant-based bioeconomy. Along with industrial integration, value chain integration through cascading or circular resource utilization can facilitate agricultural production by switching from a traditional linear mode to a non-linear mode, making the interactions between the agricultural production subsystem and coupled production subsystem more relevant to each other. As R&D investment can promote a cascading use efficiency for biomass, e.g. by promoting its use for biogas production, while new patents and biorefineries can contribute to secondary GDP (GDP-2) (Sorda et al., 2013; Grando et al., 2017), they closely link the circular economy with R&D investment in the plant-based bioeconomy (Theuerl et al., 2019; Kardung et al., 2021). This implies that the innovation subsystem closely interacts with the coupled production subsystem and socioeconomic subsystem.

In addition to the innovation subsystem and coupled production subsystem, the agricultural production subsystem, socioeconomic subsystem and land use subsystem are the basic components in the agricultural carbon system. Reverting agricultural land use with natural/perennial vegetation (for instance, fallow land) is regarded as one of the most efficient ways to accumulate organic carbon in soil (Post and Kwon, 2000; Schulp et al., 2008). Thus, sustainable farmland policies, such as the Common Agricultural Policy (CAP) and greening reform of the CAP, have been adopted in Germany to improve the biodiversity of farmland. Especially, the greening reform of the CAP introduced ecological focus areas (EFAs). Even though EFAs have not yet been evidenced to have a positive effect on improving biodiversity as researchers expectated (Pe'Er et al., 2017), they have proven to be effective for carbon sequestration (Ottoy et al., 2018). Therefore, the EFA is considered in the agricultural carbon emission system.

In this study, the land use subsystem mainly includes farmland (cropland and grassland) and green land. Green land is the sum of the fallow land, ecological focus area (EFA), and grassland, which is associated with a net carbon sink. As arable land is associated with the socioeconomic and agricultural production subsystems, the land use subsystem directly interacts with the socioeconomic subsystem and agricultural production subsystem. The agricultural production subsystem covers the planting and livestock, and also their associated carbon emissions. Ploughing and irrigation, which are positively related with the arable land area, together with the capital inputs involved in planting (fertilizer, pesticides, and diesel) are positively related to carbon emissions. Agricultural production subsystem interacts with all the other subsystems directly. This is because agricultural production provides biomass and agricultural residuals for the coupled production subsystem, and R&D investment overall (R&Dvest) and R&D investment specifically in agriculture (AR&D) from the innovation subsystem are beneficial for improving agricultural productivity. Additionally, the basic input factors, such as capital (agricultural investment) and labour, are associated with the socioeconomic subsystem, while the agricultural land is part of the land use subsystem. The innovation subsystem is mainly represented by R&D investment overall (R&Dvest), R&D investment specifically in agriculture (AR&D), R&D staff, and patents. The coupled production subsystem includes bioenergy production and other secondary industries that use biorefineries for production. As it depends on the biomass supply and technological investments, this subsystem directly interacts with the innovation subsystem and agricultural production subsystem. The socioeconomic subsystem is denoted by GDP, secondary GDP (GDP-2), tertiary GDP (GDP-3), labour, population, social investment (Invest) and agricultural investment (Ainvest). It directly interacts with the agricultural production subsystem, land use subsystem and innovation subsystem. This subsystem may not produce agricultural carbon emissions directly, but the activities associated with other subsystems can generate carbon emissions and sequester carbon at the same time.

The effects of the dynamic interactions among R&D investments, land use change and innovation efficiency on agricultural carbon emissions are studied in four scenarios in addition to the base scenario, namely (1) land effect, (2) structure effect, (3) technological effect and (4) their combined effect. All of them are simulated for the period from 2020 to 2050 (see Figure 2.2).

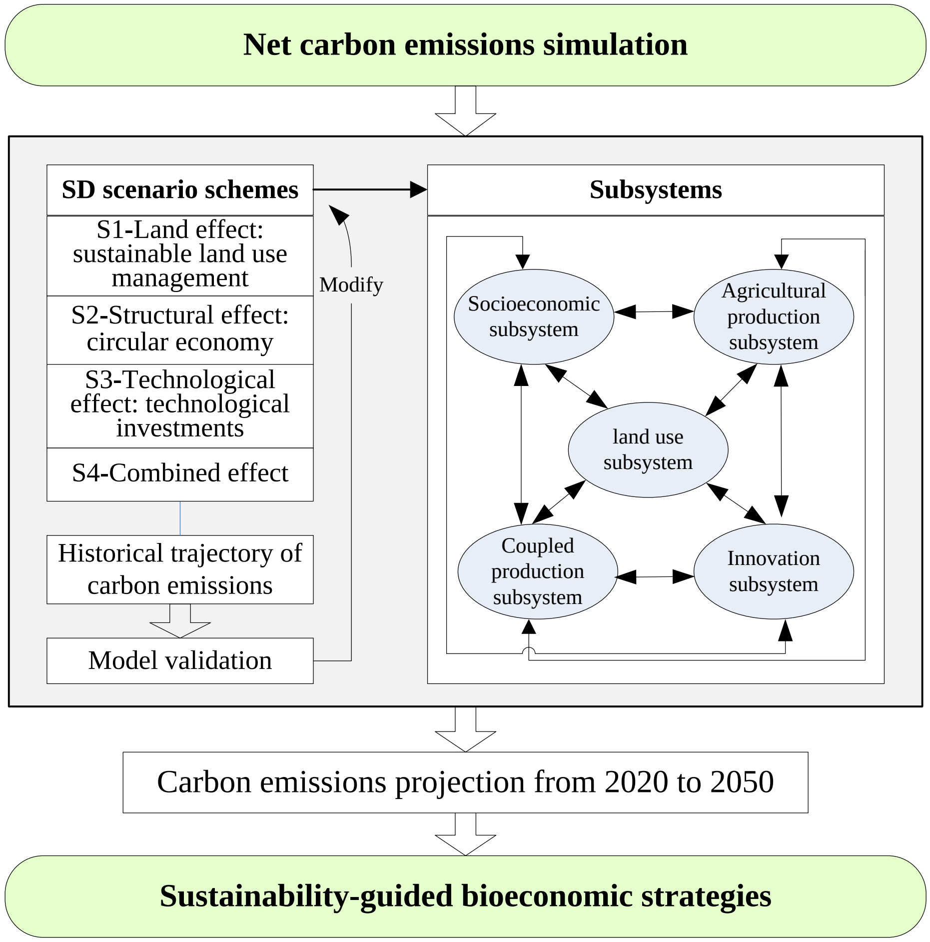


Figure 2.2: Simulation progress for net carbon emissions

Source: Own operations.

2.2 Methodology

With a system dynamics (SD)approach, the net carbon emissions from 2020 to 2050 and the dynamic interactions in the system are simulated. The net carbon emissions over these three decades are projected as Germany aims to attain carbon neutrality by 2045.

2.2.1 Data source and assumptions

The carbon emissions data used in this study were calculated on the basis of land use data and emission parameters for different land use types and different agricultural activities at the federal level in Germany. The historical period was from 2000 to 2019 since the concept of knowledge-based bioeconomy originated in the 2000s (Patermann and Aguilar, 2018). The emission parameters were derived from the Intergovernmental Panel on Climate Change (IPCC) (2019) and related studies. The land use data from 2000 to 2019 were collected from the statistics of the German Federal Ministry of Food and Agriculture (BMEL), Federal Office of Statistics and Thünen-Institut für Ländliche Räume. The other secondary data, such as socioeconomic data, for 2000–2019 were collected from the European Statistical Office (Eurostat), Federal Office of Statistics, and BMEL.

This study assumes that R&D investments have a mitigation effect on agricultural carbon emissions mainly through internal interactions with regard to the land use subsystem and innovation subsystem. In addition, R&D investments are assumed to be positive with social investment and GDP. Besides, agricultural R&D investments are assumed to be positive with R&D investments.

2.2.2 Structure of the SD model

The SD model developed by Jay W. Forrester is a decision-making tool that has been widely used to simulate the complicated behaviour and feedback of real systems (Forrester, 1970). It involves the use of stocks, flows and feedback loops to represent the interdependencies within a system. As an advanced simulation tool, it provides enhanced capabilities for visualization, scenario analysis, and user interactivity, supporting multi-method modelling and combining system dynamics with agent-based modelling. Owing to the complexity discussed previously, the SD model is employed in this study for simulating carbon emissions over the period from 2020 to 2050. The reason for choosing this model is that it offers advantages for integrated and quantitative simulation in the short and medium term (Fong et al., 2009; Fu et al., 2015; Gu et al., 2019).

Figure 2.3 displays the subsystems, variables and their interactions in the SD model for the agricultural carbon emission system. As shown in Figure 2.3, ploughing and irrigation in the agricultural production subsystem, which are positively related to the area of arable land, together with the capital inputs in planting (fertilizer, pesticides and diesel) are positive with regard to carbon emissions from plant farming (CE-1). The carbon emissions from animal products (CE-2) include enteric fermentation from cows, sheep, and pigs. According to the majority of plants that support the bioeconomy in Germany (Eurostat, 2020), wheat, barley, maize, silage maize, sugar beet, potato, and rapeseed are included in the agricultural production subsystem, denoted as plant-1 to plant-7, respectively. The agricultural investment (Ainvest), labour in agriculture (Alabor), and R&D expenditure in agriculture (AR&D) contribute to the total agricultural output (GDP-1). Also, arable land is set to be equal to the product of average arable land per capita (ArabR) and population. The socioeconomic subsystem includes GDP, secondary GDP (GDP-2), tertiary GDP (GDP-3), labour, population, social investment (Invest), and agricultural investment (Ainvest), where Invest is positively related to Ainvest. While in the innovation subsystem, AR&D is positively related to agricultural output (GDP-1), and R&D investment (R&Dvest) can improve the production efficiency of biogas by providing advanced pretreatment technologies (Costa et al., 2013; Hagman et al., 2018). The biorefineries and biogas production (biogas) comprise the coupled production subsystem. Due to the fact that residues, byproducts or waste are no longer disposed but treated as a resource and supplied to biorefineries with the support of technological innovation, biorefineries (Biorefinery) and the number of patents (Patents) contribute to GDP-2. Also, agricultural waste for biogas, animal manure, and R&D investment (R&Dvest) promote the production of biogas. The SD model was implemented using VensimPlus software (Figure 2.3). The cause-effect relationships among the variables in Figure 2.3 reveal the interactions among subsystems. A list of abbreviations of the main variables in the SD model is given in Table A.1.

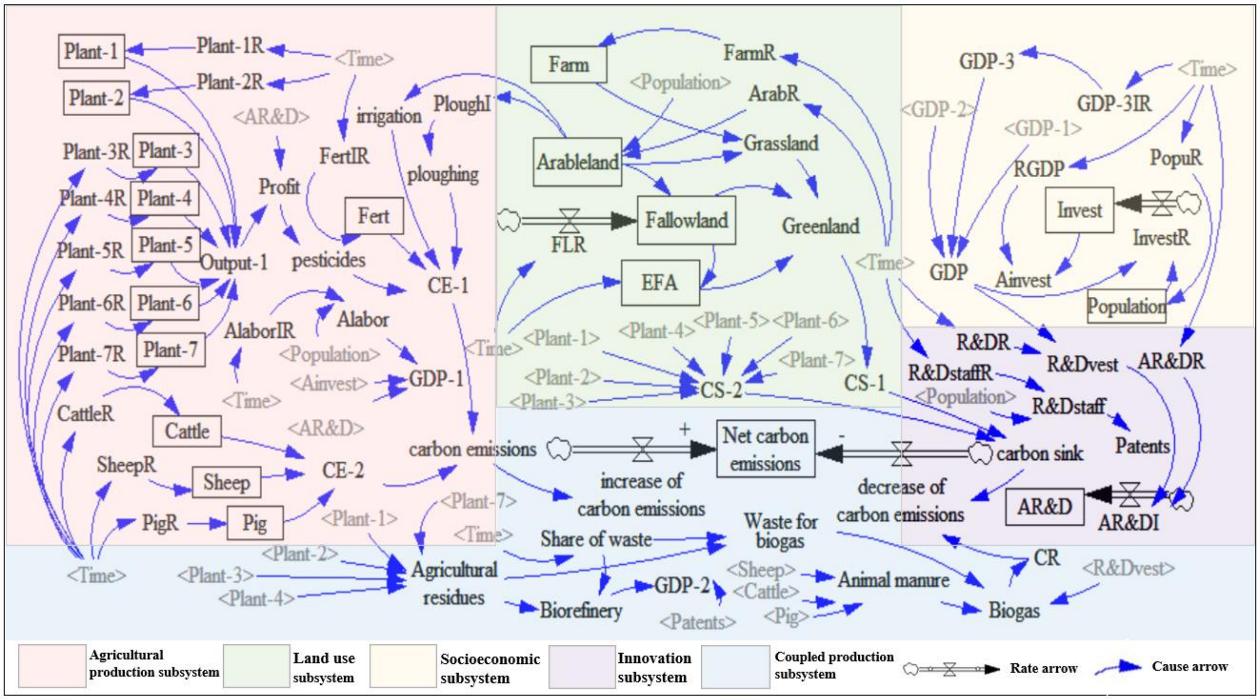


Figure 2.3: SD model of the agricultural carbon emission system

Note: Variables represented with rectangle boxes are level variables (or stock variables, where the level or stock may vary), and variables without boxes are auxiliary variables or constants.

The specific causal relationship between R&D investment and net carbon emissions is shown in Figure 2.4. As R&D investment can reduce carbon emissions by improving biogas production, it has a direct impact on decreasing carbon emissions. It can also affect agricultural productivity through influencing agricultural R&D investment, and thus it has an indirect impact on carbon emissions.

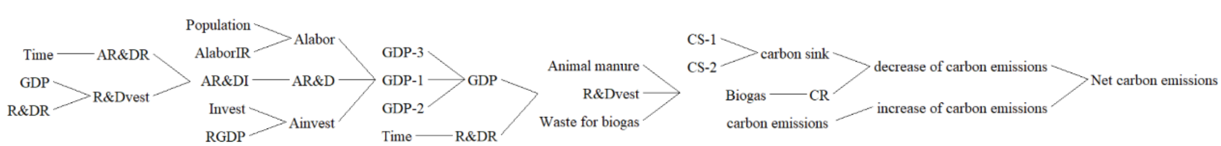


Figure 2.4: Causal tree for the effect of R&D investment on net carbon emissions

2.2.3 Estimation of the net carbon emissions in agriculture

Net carbon emissions (NCE_i) for year *i* are calculated as the sum of the carbon emissions (CE_i), carbon sink (CS_i), and the amount of carbon emissions reduction (CR_i):

$$NCE_i = CE_i - CS_i - CR_i \tag{2-1}$$

where CR_i represents the displacement effect of biogas from a reference system based on fossil-based resources (Bachmaier et al., 2010). An increasing number of studies have pointed out the role of the replacement effect of bioenergy in reducing carbon emissions (Gustavsson et al., 1995; Weiser et al., 2014; Baležentis et al., 2019; IEA, 2020). Referencing Weiser et al. (2014), carbon emission reduction from biogas (CR_i) in this study is calculated by the emissions of the fossil energy carrier (E_{Fi}), the annual production of biogas (E_i) and the emissions of the bioenergy carrier (E_{Bi}). The fossil energy carrier accounts for a mix of natural gas and heating oil for heat provision in Germany and the bioenergy carrier accounts for straw-based energy applications in Germany.

$$CR_i = (E_{Fi} - E_{Bi})/E_{Fi} * 100 * E_i \tag{2-2}$$

Unlike the agricultural GHG emissions estimated by the Federal Environment Agency (Umweltbundesamt, 2019), carbon emissions in this study are estimated by carbon equivalent. Therefore, carbon emissions (CE_i) for each year *i* are defined as:

$$CE_i = \sum \eta_j \cdot A_{ij} + \sum T_k \cdot M_{ik} \tag{2-3}$$

where η_j (j=1,2,3,4) is the carbon emission parameter for the fertilizer, irrigation, ploughing, and pesticide, and A_{ij} is the corresponding area for each type of farming activity *j*. T_k (k=1,2,3) denotes the carbon emission parameter for manure management for the digestate from cattle, sheep, and pigs, and M_{ik} is the corresponding coefficient for the three kinds of animals.

The carbon sink (CS_i) comprises the carbon sequestration in soils and plants. It is calculated as the product of the carbon sink parameters δ_a, carbon absorption rate β_b, plant harvest index H_b(the ratio of plants' economic yield to the biological yield), land size S_{ia} for land use type a and economic yield Y_{ib}, given by the following equation.

$$CS_i = \sum \delta_a \cdot S_{ia} + \sum \beta_b \cdot Y_{ib}/H_b \tag{2-4}$$

where a=1,2,3, representing grassland, fallow land, and the ecological focus area (EFA), and b=1,2,3,4,5,6,7, representing wheat, barley, maize, silage maize, sugar beet, potato, and rapeseed.

All the relevant parameters are shown in Table 2.1. As fallow land has a similar ecoservice function as grassland, its sink parameter is set as 0.191. The EFA is composed of buffer strips, field margins, catch crops, green cover, hedges, agro-forestry, and so on, among which the former four types dominate the whole area. Its carbon sink parameter is also set as the same with grassland.

Table 2.1: Coefficients for carbon emissions calculation

Category	Activities	Items and units	Coefficients	Source
Carbon emissions (CE)	Farming	Fertilizer (kg CE/kg)	0.8956	ORNL
		Pesticide (kg CE/kg)	4.9431	ORNL
		Irrigation (kg CE/ha)	266.48	West, Marland (2002)
		Ploughing (kg CE/km^3)	312.6	IPCC
	Livestock	Cattle (kg CE/head•a)	415.91	IPCC
		Sheep (kg CE/head•a)	35.1819	IPCC
		Pig (kg CE/head•a)	34.091	IPCC
Carbon sinks (CS)	Land use	Grassland (t CE/ha)	0.191	IPCC
		fallow land (t CE/ha)	0.191	Own estimation
		Ecological Focus Area (EFA) (t CE/ha)	0.191	Own estimation
	Crops	Wheat (Plant-1) (%)	β=0.4144,H=0.45	IPCC
		Barley (Plant-2) (%)	β=0.4144,H=0.45	IPCC

	Maize (Plant-3) (%)	β=0.4709,H=0.4	IPCC
	Silage maize (Plant-4) (%)	β=0.4709,H=0.4	IPCC
	Sugar beet (Plant-5) (%)	β=0.4072,H=0.7	IPCC
	Potato (Plant-6) (%)	β=0.4226,H=0.7	IPCC
	Rapeseed (Plant-7) (%)	β=0.45,H=0.25	IPCC
Carbon	E_{Fi} (g CO_2-eq.MJ^{-1})	825	Weiser et al. (2014)
reduction (CR)	E_{Bi} (g CO_2-eq.MJ^{-1})	133.1	Weiser et al. (2014)

Note: ORNL is short for the Oak Ridge National Laboratory in the USA.

2.3 Model validation and scenario designs

2.3.1 Validation of the SD model

Validation is essential for SD modelling as it ensures the validity of the model and assesses how trustful of the model is (Barlas, 1996; Gu et al., 2019). In this study, nine key variables, including net carbon emissions (NCE) and other variables (e.g. CE, CS, CR and FL), are chosen for validation checking (see Table 2.2). The relative errors of the selected variables shown in Table 2.2 indicate that most of the values simulated by the SD model are close to the historical observations from 2015 to 2019, except for EFA and biogas production, implying a valid simulation. As EFA was introduced in 2015, its short-term data structure makes the simulation less robust. Due to the support from the Renewable Energies Act (EEG, introduced in 2004) and guaranteed feed-in tariffs, the number of biogas plants and the average plant capacity increased rapidly in Germany after 2006 (FNR, 2020), leading to a boom in biogas. As this policy support was phased out after 2020, it may be the cause for the high relative error seen for biogas.

Table 2.2: Relative errors in the simulation (%)

Year	Net carbon emissions (NCE)	Carbon emissions (CE)	Carbon sinks (CS)	Carbon emissions reduction (CR)	Fallow land (FL)	Ecological focus areas (EFA)	Output-1	Biogas	R&Dvest
2015	0.280	-0.016	0.023	-0.898	0.003	2.618	-0.334	0.148	-0.898
2016	0.346	0.013	-0.045	-0.826	0.001	-0.564	-0.055	0.293	-0.826
2017	0.418	0.053	-0.041	-0.758	-0.003	-0.519	-0.206	0.415	-0.758
2018	0.239	0.007	-0.055	-0.499	0.004	-0.420	-0.247	0.541	-0.499
2019	0.048	0.021	0.029	-0.048	0.005	-0.201	0.061	1.079	-0.048

2.3.2 Scenario designs

The increase rates observed for the parameters simulated from 2020 to 2050 in the base scenario (Base) are the same as the increase rates found in 2019. The differences in carbon emissions between the base scenario (Base) and the four simulated scenarios reflect their impacts on carbon reduction, specifically through the land effect, structural effect, technological effect, and combined effect. All the related scenarios and parameters are shown in Table 2.3 and the detailed scenario designs are covered in Table A.2.

The land effect arises from the presented by the trade-off between farmland and green land conversion. Farmland involves agricultural R&D investment for biomass production and generates carbon emissions from farming, while its conversion to green land conversion means it acts as a carbon sink. The green land in this study includes grassland, fallow land, and EFA. Since grassland for livestock is a part of farmland and highly depends on the arable land and population, the potential for carbon sequestration by grassland is unclear (Jones and Donnelly, 2004; McSherry and Ritchie, 2013). As fallow land is an important element of the EFA (Pe'Er et al., 2017), sustainable land use management, therefore, is primarily represented by an increase in fallow land. In scenario 1 (Land), the share of fallow land (2.99% in 2019) is set to increase to 5% of arable land in 2020.

In scenario 2, the structural effect is reflected by the development of circular economy. Due to the significant role of biomass in the circular economy and the target to minimize agricultural residues in agriculture (Sherwood, 2020; Sharma et al., 2021), the development of the circular economy is represented by the increasing supply of biomass and increasing share of agricultural residuals sent to the biorefinery. In the first subcase (Structure 2-1), all the plants are assumed to have faster increase rates than that in the base scenario. Alao maize, which usually generates a great number of agricultural residues, is set to have the highest growth rate (3%) from 2020 to 2050 among the plants for biogas production. In the second subcase (Structure 2-2), to highlight the role of biorefineries as raw materials for the industry sector, it is assumed that the share of agricultural residuals for biogas would reduce from 0.4 in 2020 to 0.2 in 2050. Furthermore, in Structure 2-3, both cases are considered.

Direct R&D investment can not only improve production efficiency in the agricultural production subsystem, but also promote the scale of the circular economy by elevating the level of residues pretreatment and the resource use intensity for biorefineries (Amidon et al., 2011; Tayeh et al., 2020). To display the role of R&D investment in the agricultural production subsystem and coupled production subsystem, R&D investment in agriculture (AR&D) and the general R&D investment (R&D) are taken into account in scenario 3. In Tech 3-1, the share of agricultural R&D (AR&DR) is set to increase to 6% in 2020. At the same time, in Tech 3-2, the share of R&D investment in GDP (R&DR) is assumed would increase to 0.06 in 2020. Combining Tech 3-1 and Tech 3-2, AR&DR and R&DR are set to increase in Tech 3-3. The scheme in the Combine 4 scenario includes the Land scenario, Structure 2-3, and Tech 3-3.

Table 2.3: Scenario schemes for different scenarios

Scenario	Schemes
Base scenario	Base: Ratios are set as same as that in 2019
Scenario 1-Land effect	Land: Increasing the ratio of fallow land to 0.05 in 2020
Scenario 2-Structural effect	Structure 2-1: Increasing the supply of agricultural biomass; Structure 2-2: Increasing the share of agricultural wastes for biorefineries (decreasing the share of waste for biogas from 0.4 in 2020 to 0.2 in 2050); Structure 2-3: Increasing both agricultural biomass and the share of agricultural wastes for biorefineries
Scenario 3-Technological effect	Tech 3-1: Increasing the share of agricultural R&D in R&D investment (AR&DR) to 0.05 in 2020; Tech 3-2: Increasing the share of R&D investment in GDP (R&DR) to 0.06 in 2020; Tech 3-3: Increasing both AR&DR and R&DR
Scenario 4- Combined effect	Combine: Increasing the increment ratio of fallow land to 0.05 in 2050, increasing both agricultural biomass and the share of biorefinery, and increasing both AR&DR and R&DR

2.4 Results and analysis

2.4.1 Historical tendency of net carbon emissions

Figure 2.5 shows the historical tendencies of the Net carbon emissions (NCE), carbon emissions (CE), carbon sinks (CS), and carbon emissions reduction (CR) in German agriculture during the period 2000 to 2019 varying by years. Despite the agricultural carbon emissions fluctuating from 10.5 million tons to 9 million tons from 2000 to 2019, an overall downward trend could be observed. This is likely because of the reducing use of fertilizer and ploughing and the decreasing number of cattle and sheep due to technological improvements in the production for farming and husbandry (Jantke et al., 2020). Furthermore, the agricultural carbon sink amount decreased slightly from 1.25 million tons in 2000 to 1.07 million tons in 2013. After 2014, this figure increased gradually; especially after 2015, whereby it increased rapidly to 1.36 tons in 2019. Biogas had a minor replacement effect on carbon emission reduction at the beginning of the period (2000-2005) when the biogas electricity production was relatively low (445 Mio. kWh in 2000 and 1696 Mio. kWh in 2005), but such production grew robustly after 2006, reaching 29,245 Mio. kWh in 2017. This contributed to a rapid growth in carbon emissions reduction, increasing from 0.28 million tons in 2006 to 2.41 million tons in 2019 (see Figure 2.5).

Net carbon emissions (NCE) in German agriculture kept decreasing in the period 2000 to 2019. This tendency was similar to the tendency for carbon emissions from 2000 to 2006, as the carbon sink and carbon emissions reduction remained nearly constant during this period. Since 2006, NCE has declined gradually but in the opposite direction with that of carbon emissions due to the rapid increase in carbon emission reduction. Due to the policy reforms promoting biogas, such as guaranteed feed-in tariffs, biorefineries are encouraged to produce biogas. During the period from 2006 to 2019, the net carbon emissions decreased by almost a third, from 7.79 million tons in 2006 to 5.34 million tons in 2019.

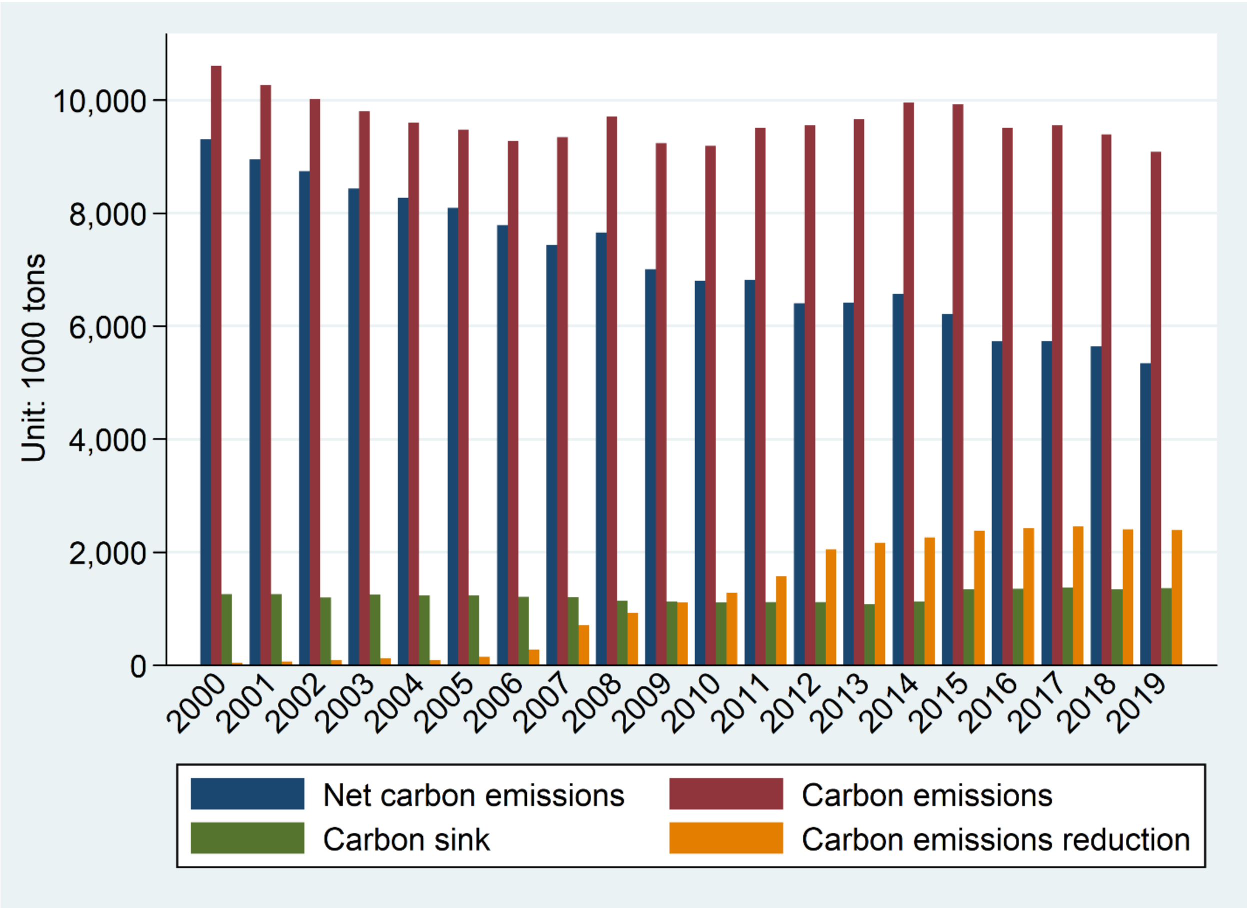


Figure 2.5: Net agricultural carbon emissions, carbon emissions, carbon sink and carbon emissions reduction from 2000 to 2019

2.4.2 Scenario analysis

Using the SD model, the net carbon emissions in the agricultural system are simulated under different scenarios for the period 2020 to 2050 (see Figure 2.6). According to Figure 2.6, net carbon emissions are projected to decrease rapidly during the period from 2020 to 2050. Net carbon emissions under the Structure 2-1 (increase agricultural biomass), Structure 2-3 (increase both agricultural biomass and biorefinery), and Combine (combined effect) scenarios will remain positive during 2020 to 2050. The results from Structure 2-1, Structure 2-3, and Combine imply that increasing biomass production may support the circular economy, but the increased carbon emissions during the production process cannot be offset by the reduced carbon emissions through R&D investment alone. Compared with the Base scenario, the net carbon emissions under the Land (increase the ratio of fallow land), Structure 2-2 (increase the share of biorefineries), Tech 3-2 (increase the share of R&D investment), and Tech 3-3 (increase both agricultural R&D investment and R&D investment) scenarios are smaller. The result of net carbon emissions under Tech 3-2 is the lowest (-2.82 Mt in 2050). This highlights the role of R&D investment in mitigating carbon emissions directly. While the results for Land and Structure 2-2 not only indicate that increasing the amount of fallow land and developing the circular economy can reduce carbon emissions, but also imply that R&D investment can indirectly mitigate carbon emissions through improving the production efficiency of biorefineries and by increasing the amount of green land.

The agricultural carbon emissions calculated in this study correspond to nearly one sixth of carbon dioxide equivalents reported by the Thünen institute (61.8 Mt in 2019, cf. Rösemann et al., 2021). This big difference may result from two aspects: Once, as mentioned previously, the calculation by Rösemann et al. (2021) includes all the GHG emissions from German agriculture, with all kinds of agricultural activities and animals of livestock taken into consideration, whereas fewer production management activities (e.g., fertilizer, ploughing and irrigation) and only three kinds of animals (caw, sheep, and pig) are considered in this study; Second, the carbon emissions calculated by Rösemann et al. is based on carbon dioxide equivalents, while our results are based on carbon equivalents.

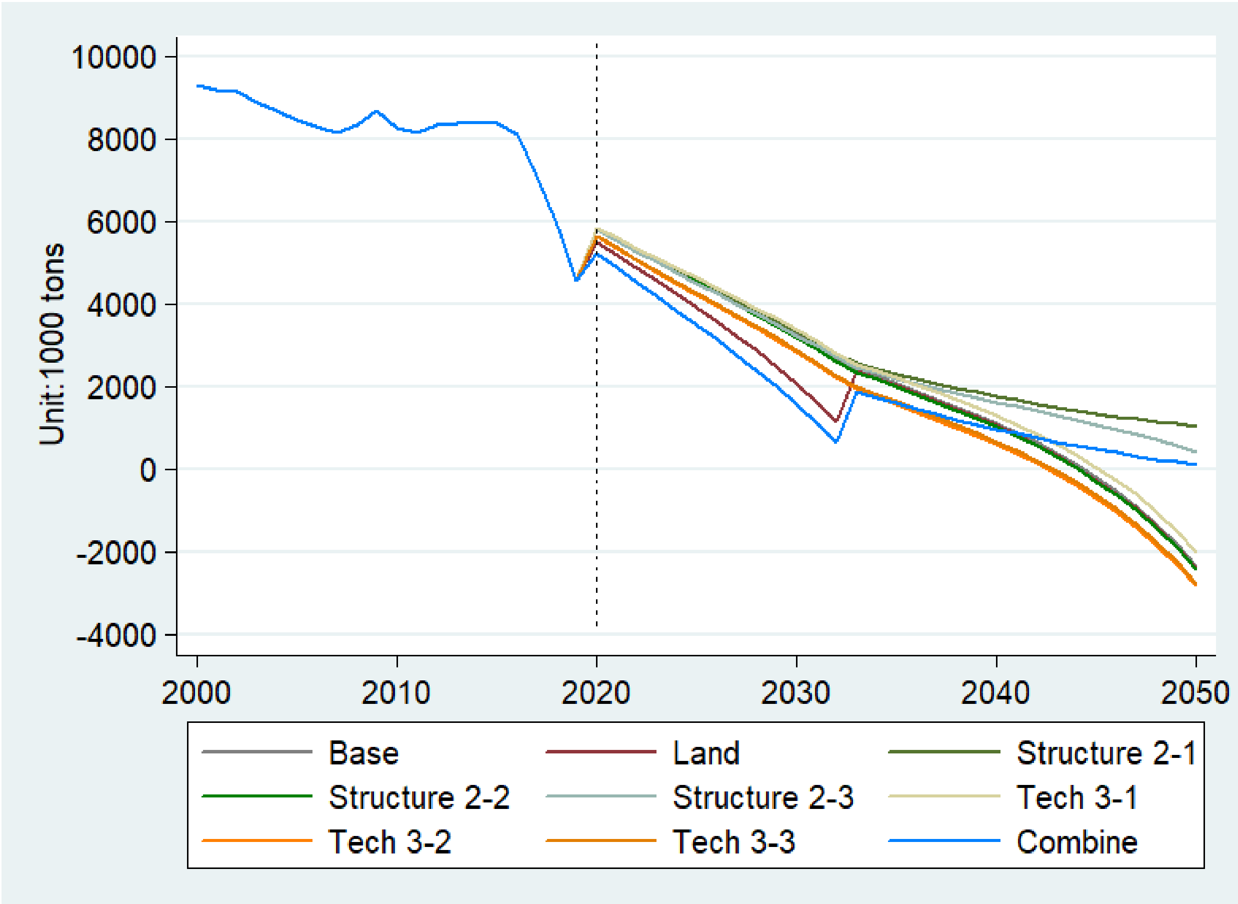


Figure 2.6: Net agricultural carbon emissions under different scenarios from 2000 to 2050

The agricultural carbon emissions and their causal tree during 2000 to 2050 are shown in Figure 2.7. The obtained results show that agricultural carbon emissions will gradually decrease from 2020 to 2050. The similar tendencies for CE-1 (carbon emissions from plant farming) and carbon emissions in the causal tree (in the right of Figure 2.7) indicate that agricultural carbon emissions are mainly caused by farming activities. This adds to the body of the relevant literature by uncovering the mechanism of the technological effects on emissions reduction. Specifically, it shows that R&D and AR&D investments can significantly lower agricultural carbon emissions. The amount of carbon emissions under Structure 2-1 is the lowest (decreasing to 4.33 Mt in 2050), and the figures under Combine (4.44 Mt in 2050) and Structure 2-3 (4.78 Mt in 2050) are less than that under the Base case (5.12 Mt in 2050), illustrating their greater impacts on carbon emissions from the improved circular economy with the increasing biomass supply.

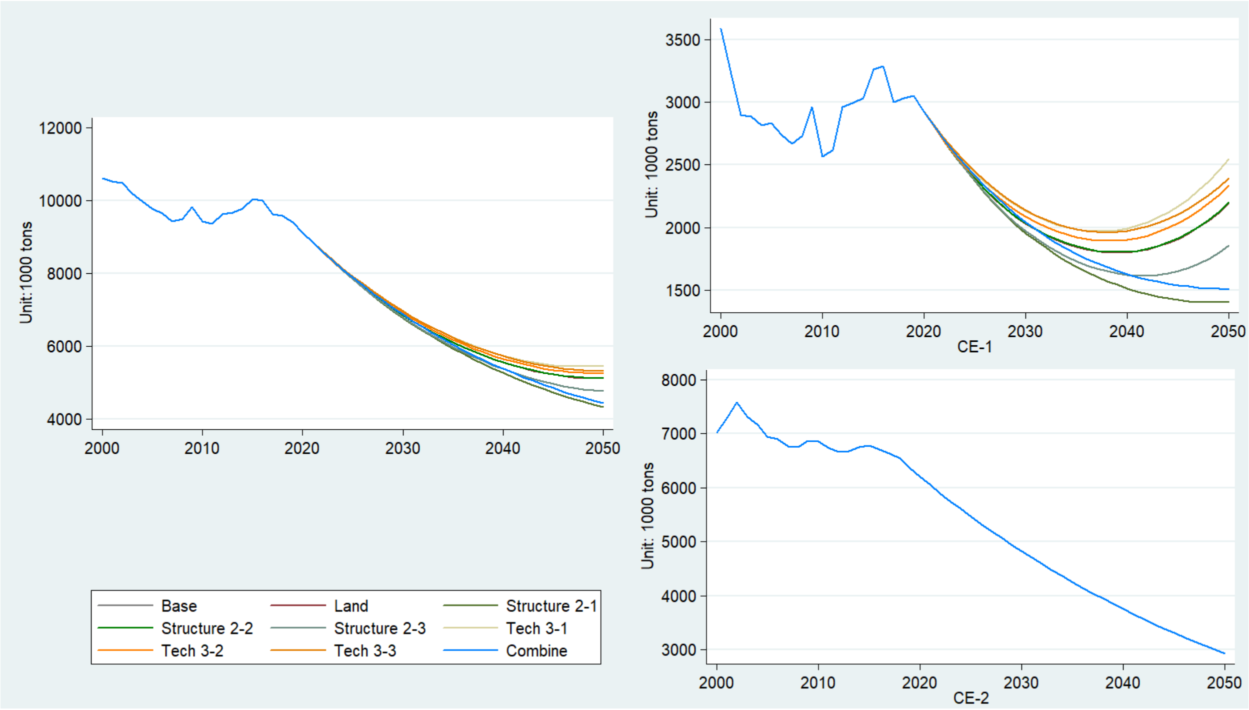


Figure 2.7: Carbon emissions and their causal trees under different simulation scenarios from 2000 to 2050

Carbon sinks, as stimulated in Structure 2-2, scenario 3 (Tech 3-1, 3-2, and 3-3), and in the Base case, are predicted to continuously increase from 2020 to 2050 (see Figure 2.8). While carbon sinks under scenario 1 (Land) and 4 (Combine) first grow rapidly after 2020, they are then forecast to show a sharp decline in 2033, before gradually increasing again from 2034 to 2050. This sharp change is mainly related to the carbon sinks by green land (CS-1), according to the causal tree. Due to the maximum restriction of the EFA, the simulation equation for the EFA changes after 2033 (see the equations in Table A.1). The higher values in the Land scenario (6.83 Mt in 2050) suggest that sustainable land use management and increasing biomass supply will aid the amount of carbon sinks available.

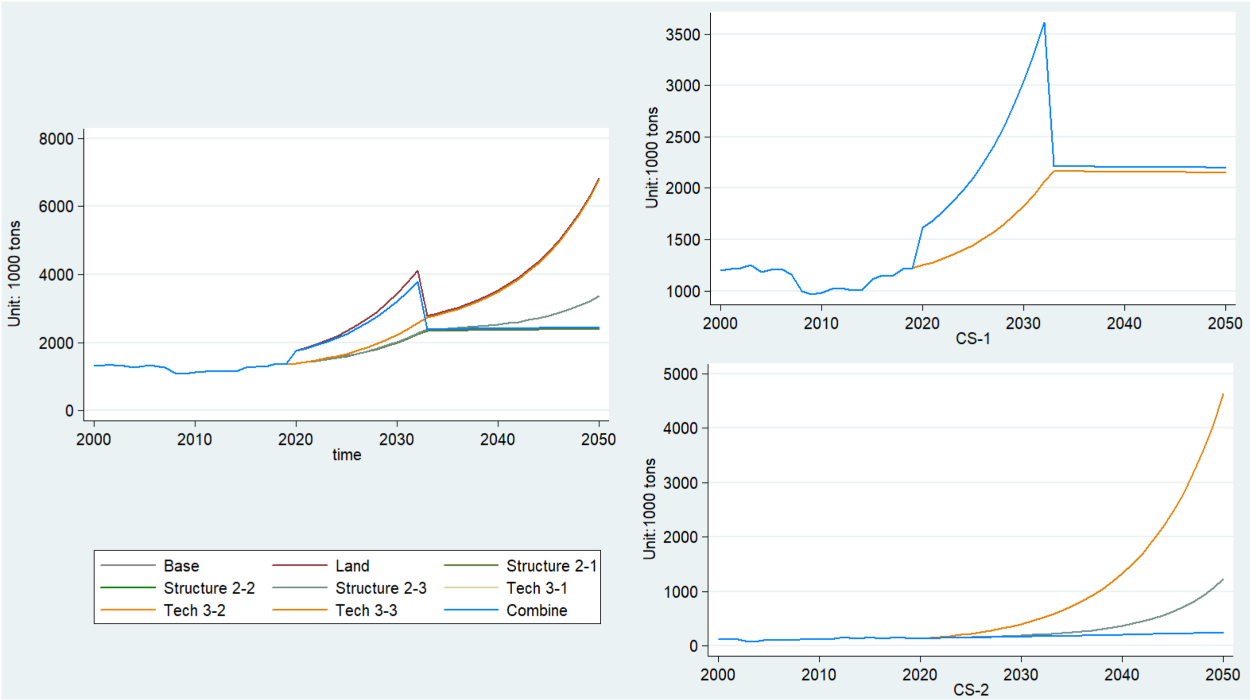


Figure 2.8: Carbon sinks and their causal trees under different simulation scenarios from 2000 to 2050

The observations from the projected carbon emissions reduction from biogas support the findings that biogas production has the potential to improve carbon emission reduction if R&D investment leads to cleaner production (Meyer et al., 2012; Ersoy and Ugurlu, 2020). The projected carbon reduction decreases gradually after 2020. This arises from the replacement effect of bioenergy on the carbon emission reduction. Comparison among the different scenarios indicates that the combined effect has the greatest impact on carbon emissions reduction (1.87 Mt in 2050). The values under Tech 3-2 and Tech 3-3 show stable decrease (1.3 Mt in 2050). This implies that R&D investment can promote the carbon emission reduction at large (see Figure 2.9).

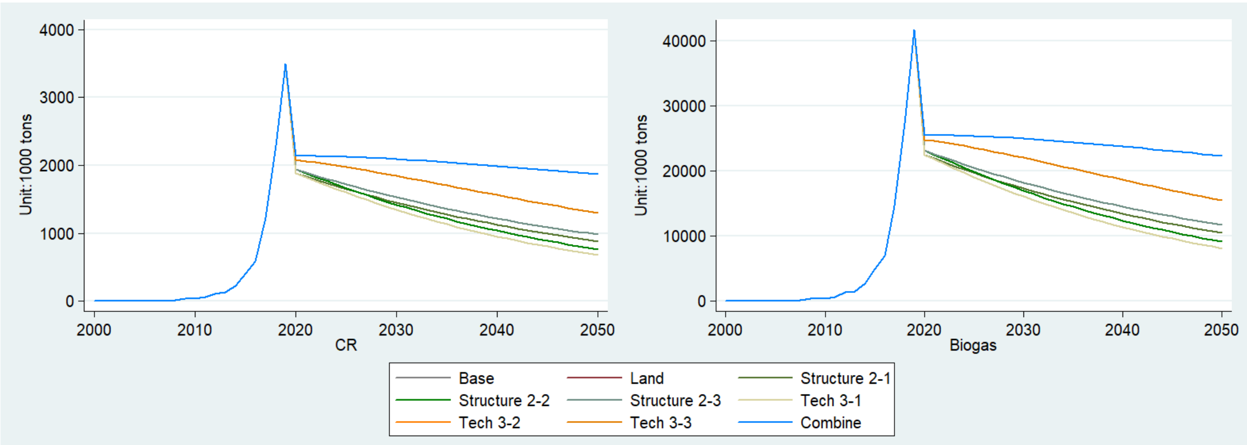


Figure 2.9: Carbon emissions reduction under different simulation scenarios from 2000 to 2050

2.4.3 Sensitivity analysis

The sensitivity of R&D investment's impact on net carbon emissions is shown in Figure 2.10. In order to test the sensitivity, the change rate for the share of R&D in GDP (R&D-to-GDP ratio) is set to increase and decrease by 25%, 15%, 10%, and 5%. The change rates of net carbon emissions represent the percentage difference between net carbon emissions at varying R&D-to-GDP ratios and net carbon emissions under the base scenario. Figure 2.10 shows that most of the net carbon emissions are similar when the change rate of R&D-to-GDP ratio is changed from -25% to 25%. This implies our results are relatively reliable. The negative relationship between the change rates of net carbon emissions and the change rates of the R&D-to-GDP ratio illustrates that net carbon emissions are sensitive to R&D investment. Regarding the tendency of the change rates of net carbon emissions, the tendency showed a decrease from 2000 to 2011 and then an increase afterwards. Among simulated rates, the change rate is the largest when the change rate of R&D-to-GDP ratio increased to 25%, reaching 290% in 2011 and returning to 8.7% in 2019. This may be because of the model restriction to carbon emissions reduction.

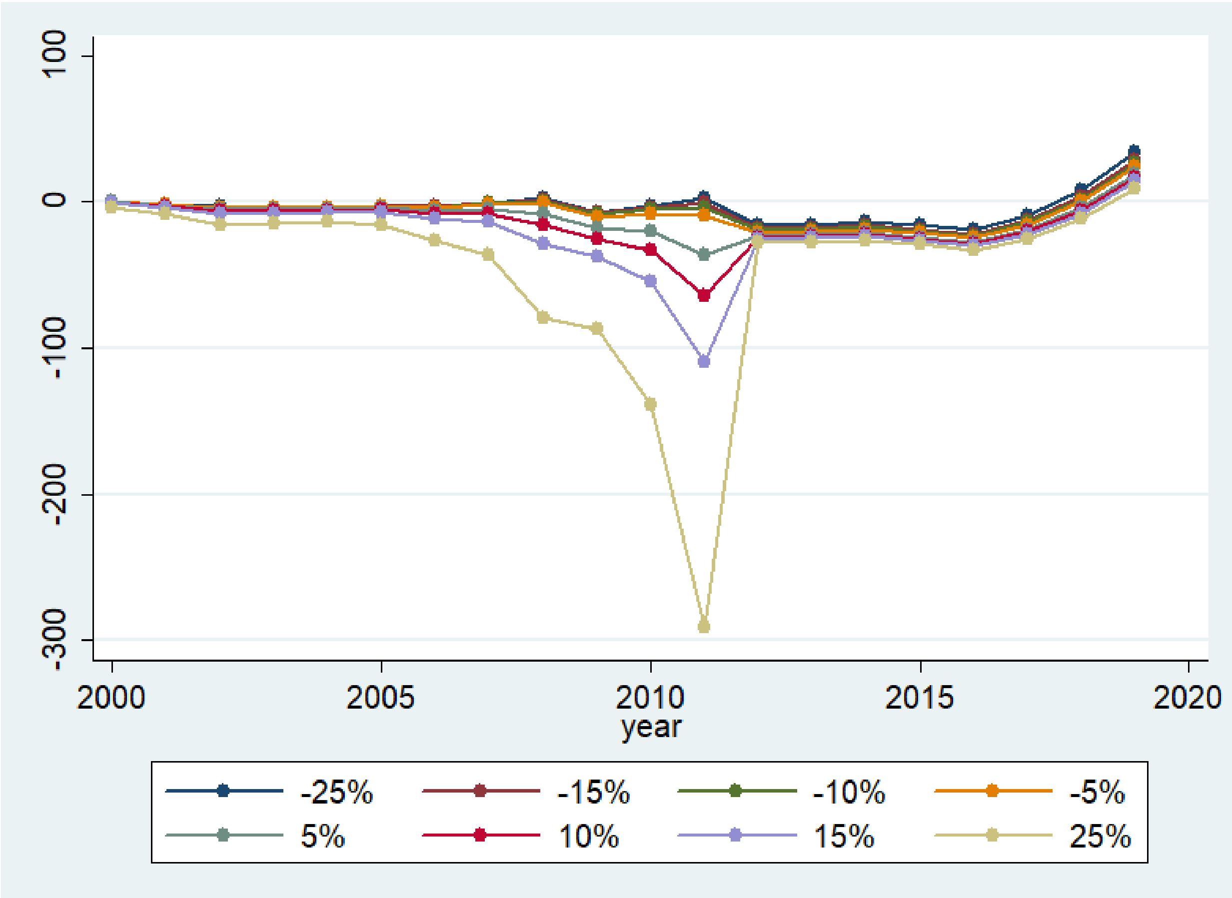


Figure 2.10: Result of the sensitivity analysis

2.5 Discussion and conclusions

2.5.1 Discussion

The above analysis shows that R&D investment can contribute to a reduction in agricultural carbon emissions during 2020 to 2050, helping realize carbon neutrality at the sector level ahead of 2045. The findings regarding the decline in carbon emissions simulated by the SD model under different scenarios add to the body of relevant literature by projecting the impact of R&D investments on carbon emissions and uncovering the dynamic interactions among the various subsystems in the plant-based bioeconomy. Methodologically, the SD model is a cutting-edge approach to understanding and managing the complexities of agricultural practices and their impact on carbon emissions. Unlike general projection models, such as time series regression (e.g. ARIMA) and back-propagation networks, which require strict data stationarity and often function as opaque "black boxes", the SD model has fewer data stationarity requirements and excels at illustrating the interactive influences and feedback mechanisms (Forrester, 1987; Bala et al., 2017). By simulating the diverse interactions within the comprehensive agricultural carbon system, this study delves into the dynamic nature of agricultural carbon systems in the framework of a plant-based bioeconomy. It offers valuable insights for policymakers for forming mitigation strategies in the agricultural sector.

The biggest value difference in the projected agricultural emissions between 2020 and 2050 is simulated under the Tech 3-2 scenario (8.47 Mt), and indicates that increasing R&D investment can significantly lower agricultural carbon emissions directly. The results suggest that this action can more effectively aid in reducing net agricultural carbon emissions than simply increasing agricultural R&D, the amount of fallow land, and the cascade/upcycling use of agricultural residues. This is because R&D investment promotes biogas production and secondary GDP, linking agriculture and industry through innovation and coupled production subsystems (Ehrenfeld and Kropfhäußer, 2017; Popp et al., 2021). The significantly negative effect of R&D investment on carbon emissions during the projected period (2020-5050) reveals that with the support of appropriate technologies (e.g. biological pretreatments and waste-to-energy technologies), the upgrading and cascade use of agricultural residues can be promoted and can stimulate biogas production and then reduce carbon emissions (Zhong et al., 2011; Lovrak et al., 2020). The simulated results extend the findings in other recent studies that suggest a negative effect of technological investment on carbon emissions from agriculture value-added in the bioeconomy (Wang et al., 2020), institutional innovation (Huisingh et al., 2015), and the land-energy-carbon nexus (Zhao et al., 2018).

However, the smaller effect of agricultural R&D investment (-1.99 Mt under Tech 3-1 in 2050) on carbon emissions compared with that of total R&D investment may be at variance with the evidence that advanced agricultural bio-technologies can help reduce carbon emissions (Subramanian and Qaim, 2009; Galliano et al., 2018). This is because agricultural R&D investment can improve the productivity of biomass production. Without agricultural R&D investment, just increasing the biomass alone can lead to a worse result, as shown by the simulation performed under Structure 2-1 (1.05 Mt in 2050). In this scenario, while sufficient biomass would be available to support the circular economy in the agricultural carbon emission system, the higher biomass production generates more carbon emissions if the agricultural productivity remains unchanged. This implies that without improving the production efficiency, the coupled production subsystem may be incompatible with the productivity aspects related to the production factors (Giampietro, 2019). However, enlarging the share of agricultural wastes for biorefineries can not only help develop the circular economy and contribute to secondary GDP, but can also reduce carbon emissions at large (-2.42 Mt under Structure 2-2 in 2050). While it is found that increasing biomass and the share of agricultural wastes for biorefinery at the same time, the effect of the circular economy on carbon emissions would drop off a lot (0.42 Mt under Structure 2-3 in 2050). Since patent productivity, and hence innovation, depends on R&D staff, and as both patents and the utilization of agricultural waste for biorefinery contribute to secondary GDP, the impact of the circular economy on carbon emissions also underscores the role of R&D productivity in reducing carbon emissions. This calls for an improvement in the efficiency of carbon emission reduction (Xiao et al., 2021). The effect of the circular economy on carbon emissions found in this study is in line with reports on the recycling of agricultural waste for biogas in India (Kapoor et al., 2020), as well as waste recycling use in other relevant production activities, such as the agro-food industry (Kumar and Singh, 2020).

Green land helps reduce carbon emissions and interacts with R&D investment indirectly through the socioeconomic, coupled production and agricultural production subsystems, providing carbon sinks to further decrease emissions. If agricultural productivity and the circular economy are improved by R&D investments, it will lead to a growth in GDP. The increase in GDP can, in return, increase the level of R&D investment, which can increase production efficiency so that less farmland will be needed for production and more agricultural land can be converted to fallow land (Ersoy and Ugurlu, 2020). Compared with other scenarios, the higher value gap of carbon sinks between 2020 and 2050 simulated in the Land scenario (5.07 Mt) shows that green land is the main source of carbon sinks. Although increasing the supply of biomass can increase carbon sinks from the plants, it will be offset by the carbon emissions from the production process. This leads to a lowest increase in carbon sink (1.01 Mt during 2020 to 2050 in Structure 2-1). Furthermore, although the EFA has been proven to be ineffective at increasing biodiversity (Pe'Er et al., 2017), it helps to reduce carbon emissions by increasing the carbon sinks, which has been especially noted since 2015 when the EFA was introduced to the CAP.

Yet, compared with other studies, the relatively high error in simulating biogas production may lead to less accurate estimates of carbon emission reduction. The results simulated by Horschig et al. (2016) show that the savings in carbon dioxide equivalents can be extended to 4.483 Mt in 2025 (equal to 1.22 Mt of carbon), which is lower than the amount in 2025 noted from scenario 1 (1.6 Mt), which was the lowest value for carbon emission reduction among the projected results. This is due to the boom in biogas that was experienced in Germany after 2006, stimulated by the European Environment Agency (EEA), and setting of guaranteed feed-in tariffs (Appel et al., 2016; Scarlat et al., 2018). Unlike some studies focusing on biogas production with life cycling assessment (Hijazi et al., 2016; Feiz et al., 2020), this study considers the interactions among subsystems through a system dynamics approach. From this perspective, the simulated results advocate the importance of substitution effect of renewable bioenergy on fossil fuel and its potential to support agricultural emissions reduction at the sector level.

The decreasing tendency for net carbon emissions and increasing tendency for carbon sinks and carbon emission reduction from 2000 to 2019 not only show that carbon sinks and carbon emission reduction have contributed to the decline in carbon emissions but also underline the role of biogas production and green land in reducing carbon emissions. The simulated results further confirm that increasing R&D investment directly, developing the circular economy, and converting farmland to green land are efficient strategies for reducing carbon emissions.

Still, this study has some limitations to note. First, due to the limited availability of data, especially for waste biorefineries for other chemicals, physicals materials, and other industrial sectors, biorefinery production is considered here only for a share of agricultural residuals for biorefinery. Thus, our findings need to be verified by further research, accounting also for the implications of other activities in the coupled production subsystem with sufficient data support. Moreover, the short-term time series of some data, for instance, EFA, can also make the equations less accurate. This can be adjusted with long-term stable data sets in the future. Additionally, most of the carbon emission coefficients were obtained from previous studies and the IPCC. This might lead to some uncertainty to some extent (Gu et al., 2019).

2.5.2 Conclusions

With the transition to a plant-based bioeconomy, R&D investment can reduce carbon emissions directly by improving R&D productivity and indirectly by affecting agricultural productivity, economic growth, and land use conversion in relevant subsystems, respectively. This chapter simulated the mitigation effect of R&D investment on agricultural carbon emissions by establishinhg an agricultural carbon emission system with five subsystems–agricultural production subsystem, land use subsystem, socioeconomic subsystem, innovation subsystem and coupled production subsystem–and estimating the interactions among the subsystems during 2020 to 2050. Four scenarios are considered to represent the land use effect, structural effect, technological effect and integrated effect, respectively. The analysis arrived at five main conclusions.

First, the decline in net carbon emissions highlighted the direct and indirect effect of R&D investment on reducing agricultural carbon emissions. Specifically, increasing R&D investment directly and promoting R&D productivity can contribute to carbon emission reduction. Second, the lowest net carbon emissions simulated by increasing the share of R&D investment in GDP indicates that the direct effect of R&D investment on agricultural carbon emissions is larger than the indirect effect obtained through the land effect (Land), structural effect (Structure) and integrated effect (Combine). Third, R&D productivity can mitigate carbon emissions by increasing carbon sequestration in plants and the soil, and by increasing carbon emission reduction in coupled production subsystem. As R&D productivity is crucial for industrial integration, investment in R&D staff and R&D productivity will matter in the future for carbon neutrality. Fourth, the dynamic interactions in the agricultural carbon emission system suggest that increasing the amount of fallow land, improving the circular economy, and increasing R&D investment are efficient strategies for lowering net carbon emissions. Finally, the historical tendency for net carbon emissions implies that efforts to increase the amount of carbon sinks and enhance carbon emissions reduction may be more efficient than actions solely focused on reducing carbon emissions. This also reveals that it is necessary to calculate the net agricultural carbon emissions by considering more carbon sinks and carbon emission reduction in the plant-based bioeconomy.

The findings point out that appropriate R&D investment has good potential to contribute to net agricultural emissions reduction, shedding light on how an economically sustainable agricultural sector can contribute to lowering carbon emissions with the transition to the bioeconomy. The study thus advocates for a transition to a sustainable plant-based bioeconomy with increased R&D investment to reduce agricultural carbon emissions, while highlighting the interactions among subsystems. It also proves the win-win outcomes of such integration for the economy and the environment, encouraging sustainable modes of agricultural production and more industrial cooperations in the future. The provided insights into the direct and indirect effects of R&D investment on agricultural emissions can alert policy-makers to align the existing sustainability, land management (e.g. the greening of CAP), and innovation strategies to successfully realize carbon naturality at the agricultural sector level (Jantke et al., 2020; Beer and Heise, 2020). The identified interactions among the studied subsystems and the simulated negative net carbon emissions from 2020 to 2050 strongly indicate that German agriculture could achieve carbon neutrality before 2045 (EU, 2020). Additionally, it can contribute to societal carbon neutrality by providing carbon sinks and reducing carbon emissions.

3 Potential mitigation effects of forest-based bioeconomy on carbon emissions[2]

3.1 Objectives and conceptual framework

3.1.1 Background and organization

The bioeconomy "encompasses the production of renewable biological resources and their conversion into food, feed, bio-based products, and bioenergy. This includes agriculture, forestry, fisheries, food, pulp, and paper production, as well as parts of chemical, biotechnological and energy industries" (EC, 2012). The forest-based bioeconomy, including the entire forest value chain, is particularly considered as a key player in the arena of promoting the transition to a bioeconomy for achieving decarbonization.

Although there is more and more literature discussing the mitigation potential of the forest bioeconomy on carbon emissions (Hetemäki, 2014; Giurca, 2018; D'Amato et al., 2018), most of the studies are largely qualitative analyses performed at the macro-level (Luhas et al., 2020; Jonsson et al., 2021; Kumeh et al., 2021; Rebolledo-Leiva et al., 2023). Among the few quantitative analyses, there are increasing studies evaluating the role of technological and institutional innovations (e.g. patent applications and industrial integration) in climate mitigation (Ladu et al., 2020; Lovrić et al., 2020; Harrahill et al., 2023). However, still little is known about how innovation diffusion through industries affects carbon emission and how carbon emission fluxes in the forest bioeconomy in one area affect the adjacent and distant regions through spatial interaction and diffusions. Thus, the real contribution of technological and institutional innovation in the forest bioeconomy as well as their spillover effects on carbon reduction are not clear.

To bridge the research gaps, this chapter, focusing on the forest bioeconomy in Germany, seeks answers to the following three questions: 1) Whether the size of the bioeconomy is decoupled from the carbon

[2] Author statement: Lanjiao Wen (conceptualization, methodology, software, writing-original draft, and revision); Dr. Zhanli Sun (conceptualization, revision and supervision); Dr. Ir. Frans Hermans (data curation); Prof. Dr. Alfons Balmann (revision and supervision).

emissions in the regional eco-economic system from 2000 to 2021 in Germany? 2) How does the diffusion of technological innovation in the forest-based bioeconomy affect carbon emission at the county level? 3) How does the spatial spillover effect of technological innovation in the forest-based bioeconomy determine the emissions reduction potential and direction? By addressing these points, the present study aims to contribute to the currently limited knowledge about the impact of the forest-based bioeconomy on carbon emissions in Germany.

The remainder of this chapter is organized as follows. Section 3.1.2 outlines the relationship between carbon emissions and the forest-based bioeconomy in Germany. Section 3.2 introduces the methods and data sources. The results are summarized in Section 3.3. The last section (3.4) concludes this part of the work.

3.1.2 Conceptual framework: Carbon emissions and the forest-based bioeconomy in Germany

Human activities rely on land-related ecosystem services, necessarily affecting the ecosystem's carrying capacity. Anthropogenic impacts–from unavoidable changes in land cover for creating living and production space to avoidable environmental harms–are associated with carbon emissions (Pataki et al., 2006). Land use change driven by socioeconomic dynamics such as urbanization and industrialization is one of the largest contributors to carbon emissions today. At the same time, it directly affects the ecosystem's capacity to sequester carbon in soils, the forests, and geological formations (Bockstael et al., 1995; Pataki et al., 2006). The carbon cycle is further affected by physical processes in the lithosphere, which are, however, largely outside of human control. Figure 3.1 illustrates carbon emissions production and regulation in a stylized eco-economic system, representing the economic activities that may occur in a regional eco-economic system.

In line with the European Commission, Germany has an ambition to develop a bioeconomy that depends largely on the forest-based sector (Giurca and Späth, 2017). The forest-based bioeconomy in Germany not only produces traditional wood products, such as woodwork, pulp and paper, and wood for bioenergy (Jochem et al., 2015), but also aims to maximize value increment in the whole value chain, which should result in high-value products and offering more job opportunities. Technological innovation is regarded as a key pillar for the forest-based bioeconomy. Both policy makers and scholars acknowledge that slow technological development can hinder the development of the forest-based bioeconomy (BMBF, 2011) and thus confine many relevant technological developments to the laboratory and pilot scale (Hagemann et al., 2016).

According to the theory of endogenous growth, knowledge spillover through learning by doing has a significant positive effect on economic growth (Arrow, 1962). As an endogenous input factor, technological innovation in the forest-based bioeconomy together with other production factors, such as labour, land, and capital, can promote new resource allocation efficiency and economic growth. This will increase the productivity and competitiveness of local industries in the value chain of the bioeconomy. The knowledge spillover effect driven by technological innovation among the value chain will also stimulate industrial integration and labour division through optimizing the factor substitution efficiency, facilitating bioclusters and spatial industrial patterns to develop.

Due to the spatial diffusion of innovations, a higher degree of technological innovation can also improve the competitiveness of adjacent areas (Vaitsos, 1978). Industrial clusters can accelerate industrial upgrading by increasing the competitiveness of the involved industries and their capacities for value-added generation, economic diversification, and employment creation. From this perspective, intra-cluster competitiveness not only contributes to economic growth, but also leads to the reduction of carbon emissions (Gautam, 2014; Cui et al., 2021). While adjacent counties may provide abundant urban land for industrial growth (Guastella et al., 2017; Gao et al., 2020), they have the potential to offer extra job opportunities too, thus attracting labour to move to the areas.

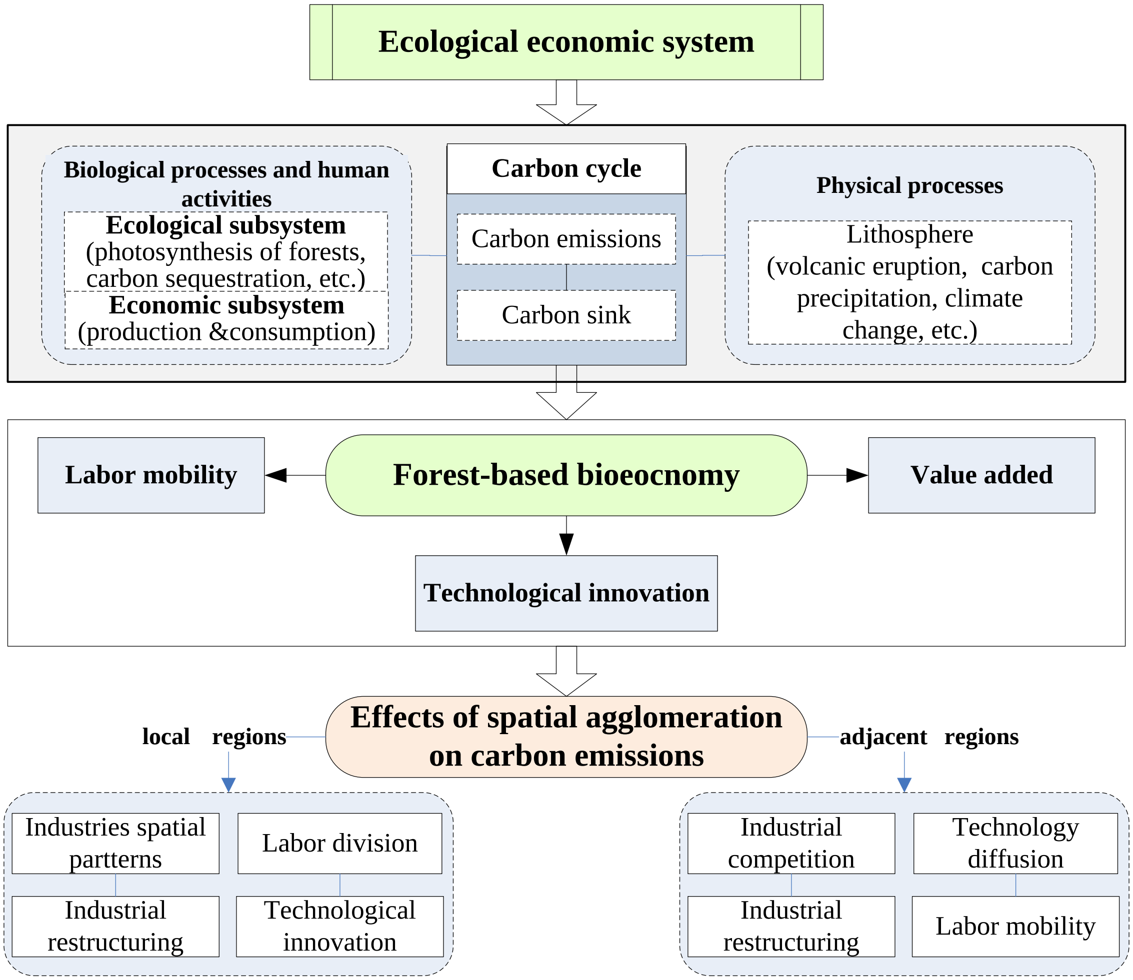


Figure 3.1: Carbon cycle in a regionally integrated land use system

Source: Own representation.

3.2 Methodology

In this research, the analysis entails three steps: First, the net carbon emissions are calculated for the period from 2000 to 2021. Next, the size of the bioeconomy at each county/city is quantified to assess the regional development of bioeconomy. Then, a Spatial Durbin Model is employed to estimate the impacts of the forest-based bioeconomy on net carbon emissions.

3.2.1 Estimations of the net carbon emissions at the county-level

Net carbon emissions are calculated as the sum of carbon emissions and carbon sinks associated with the use of arable land and construction land, which have the highest energy consumption (Zhao et al., 2015; Zhang et al., 2015). In the present study, carbon emissions for construction land are calculated indirectly as the product of the energy consumption per unit of GDP (T_i) and GDP of the secondary and tertiary industries (M_i) in county *i* (Wen et al., 2021). Although crops produced on arable land can, to some extent, absorb carbon emissions, the use of fertilizers, agricultural machinery, and irrigation systems generate high net emissions (Yang et al., 2016). Therefore, carbon emissions (EC_i) for each county/city are defined as:

$$EC_i = \eta_a \cdot C_i + T_i \cdot M_i \tag{3-1}$$

where η_a is the carbon emissions parameter for arable land and C_{ii} is the arable land size.

The carbon sink (ES_i) of county *i* comprises the carbon sequestration in forests, grassland soils, and water areas, calculated as the product of the carbon emissions parameter δ_j and land size S_{ij} for each land use type *j*:

$$ES_i = \sum \delta_j \cdot S_{ij} \tag{3-2}$$

where j=1,2,3 and represent forest, grassland and water, respectively. The net carbon emission (NEC_i) for county *i* is then:

$$NEC_i = EC_i - ES_i \tag{3-3}$$

3.2.2 Measuring the size of the bioeconomy

The size of the bioeconomy varies depending on the definitions and approaches taken. As the majority of studies regarding bioeconomy are qualitative conceptual papers with different definitions, the measurements of the size of the bioeconomy differ accordingly. The diverse definitions and lack of harmonized approaches for comparison are major challenges for quantitative analysis of the contribution of the bioeconomy towards sustainability. Kuosmanen et al. (2020) concluded that there are basically four types of approaches to measure the size of the bioeconomy, namely the output-based approach by nova-JRC, Finnish bioeconomy statistics, the physical supply and use approaches developed by JRC, Statistics Netherlands–CBS, and the Thünen Institute's methodology. Among these, Thünen's approach not only offers the advantage in highlighting the role of resource-based materials flows in the process of production, which is consistent with the definition provided by the German bioeconomy strategy (BMEL, 2014), but also has the advantage of reflecting the direct socioeconomic contribution of the bioeconomy as it focuses on the sectoral level. For this, this study adopts the Thünen Institute's approach to measure the size of the bioeconomy in Germany. Since "value added" has been proven to be preferable to that of gross output to avoid repeated calculations (Kuosmanen et al., 2020), this study measures the size of the bioeconomy by employing the Thünen Institute's approach as reported by Iost et al. (2019) and considering the indicators gross value added and employment.

According to Iost et al. (2019), the agricultural sector, including agriculture, forestry, and fishing, is considered to be 100% bio-based. For the manufacturing sector, the bio-based share used in this study is the average ($\overline{b_m}$) of the different bio-based shares of the sub-manufacturing sectors (at the 4-digit level), including food and feed, textile, leather, wood and wood products, paper and paperboard, printing, chemicals, pharmacy, plastics, furniture, and others. As it is difficult to bring the service sector data in line with the NACE sectors, the average bio-based share ($\overline{b_o}$) of other experimental developments based on natural science and engineering is used as the bio-based share for the service sector (the bio-based shares of relevant NACE sectors at the 4-digit level are shown in Table A.3). Two dimensionalities for the size of bioeconomy in Germany are calculated as below:

$$BV_i = VA_i + VM_i * \overline{b_m} + VO_i * \overline{b_o} \tag{3-4}$$

$$BE_i = EA_i + EM_i * \overline{b_m} + EO_i * \overline{b_o} \tag{3-5}$$

where BV_i and BE_i are the value added of bioeconomy and the number of employees in the bioeconomy for county *i* respectively; *VA*, *VM* and *VO* denote the value added for the agriculture sector, manufacturing sector, and service sector respectively; *EA*, *EM* and *EO* presents the number of employees in the agriculture sector, manufacturing sector, and service sector respectively.

3.2.3 The Spatial Durbin Model

A Spatial Durbin Model (SDM) is developed to estimate the impact of a forest-based bioeconomy on carbon emissions. Prior to modelling, the global spatial autocorrelation index (Moran's I) is calculated to test for spatial autocorrelation and spatial heterogeneity (Odland,1988; Geniaux and Martinetti, 2018; Feng and Chen, 2018):

$$Moran's\ I = \sum_{i=1}^{n}\sum_{k=1}^{n} W_{ik}\,(NCE_i - \overline{NCE})(NCE_k - \overline{NCE})/V^2 \sum_{i=1}^{n}\sum_{k}^{n} W_{ik} \qquad (3\text{-}6)$$

with the mean ($NCE - \overline{NCE}$), variance of net carbon emissions (V) and spatial weight matrix (W_{ik}). The values of Moran's I index are within the range of [-1, 1], indicating either positive or negative spatial correlation among counties (Bai et al., 2012; Anselin, 2013; Gao et al., 2020). If the value is zero, then the counties are not spatially correlated.

Numerous studies suggest that carbon emissions, being affected by the natural environment and human activities, have regional spillover effects (Jun et al., 2017; Wang et al., 2018; Wang et al., 2019). The range of this effect, however, varies depending on the model in use. The advantage of the SDM is that–other than the spatial lag model (SLM) and the spatial error model (SEM)–it can capture the spatial correlation of dependent variables and the spatial spillover effects of independent variables (LeSage and Pace, 2010). Furthermore, the SDM usually has a higher level of goodness-of-fit compared with other spatial panel models (Wen and Liao, 2019). Since the null hypothesis of random effects is rejected (Prob>chi2=0.000 according to Hausman's test), a SDM with fixed effects is applied.

The impact of the forest-based bioeconomy on carbon emissions is twofold. Apart from the size of the bioeconomy, the number of patents in the forest-based bioeconomy and its rate of application (as proxy for technological innovation), as well as their interactions with the size of bioeconomy are selected as the core variables. In accordance with Grossman and Krueger (1995), two dimensionalities of the size of the bioeconomy in Germany, namely the value added of bioeconomy (*BV*) and number of employees (*BE*) in the bioeconomy, are used to estimate the impact of the bioeconomy scale on carbon emissions. The number of patents (*Number*) in the forest-based bioeconomy and their application rate in the current year (*Rate*) are used to present two aspects of technological innovation: the former denotes the intensity of technological innovation and the latter denotes the transformation efficiency of scientific achievements, respectively (Popp et al., 2003; Harrahill et al., 2023). By accounting for the socioeconomic control variables, namely industrial upgrading (*Structure*), which is the ratio of GDP of the tertiary sectors to GDP of the industrial sectors, the labour density (*Labour*), which is the amount of labour per ha, the size of urban construction area (*Urban*) and per capita GDP (*PerGDP*), the basic SDM in the present analysis can be written as SDM 1:

$$lnNCE = \rho WlnNCE + \partial_1 lnBV + \partial_2 lnBE + \partial_3 lnNumber + \partial_4 lnRate + \partial_5 lnLabour + \partial_6 lnPerGDP + \partial_7 lnStructure + \partial_7 lnUrban + \varphi_1 WlnBV + \varphi_2 WlnBE + \varphi_3 WlnNumber + \varphi_4 WlnRate + \varphi_5 WlnLabour + \varphi_6 WlnPerGDP + \varphi_6 WlnStructure + \varphi_6 WlnUrban + \gamma l_n + \varepsilon \quad (3\text{-}7)$$

With the spatial autocorrelation coefficient given by ρ, spatial weight matrix W, spatial lag of the dependent variable $WlnNCE$, spatial lag of the explanatory variables $WlnX$, matrix of the explanatory variables X, an n×1 vector of ones l_n, vectors of respective regression coefficients ∂, φ, γ for X, $WlnX$ and l_n and the error term ε.

Growth-pole theory and empirical observations suggest that the more developed an area is, the stronger its spatial agglomeration effect on neighbouring regions (integration effect), because a higher development level creates centripetal forces on capital, technology and labour (Wen et al., 2016). The effect of technological innovation on net carbon emissions can, therefore, be mediated through the interacting input and output factors (resource allocation). In the extended model (SDM 2), this can be captured by accounting for interactions between the *Number* and mediating variables *BV, BE, Structure,* and *PGDP*:

$$lnNCE = \rho WlnNCE + \partial_1 lnBV + \partial_2 lnBE + \partial_3 lnNumber + \partial_4 lnRate + \partial_5 lnLabour + \partial_6 lnPerGDP + \partial_7 lnStructure + \partial_7 lnUrban + \boldsymbol{\beta_1 lnNumber * lnBV + \beta_2 lnNumber * lnBE + \beta_3 lnNumber * lnStructure + \beta_4 LnNumber * lnPerGDP} + \varphi_1 WlnBV + \varphi_2 WlnBE + \varphi_3 WlnNumber + \varphi_4 WlnRate + \varphi_5 WlnLabour + \varphi_6 WlnPerGDP + \varphi_6 WlnStructure + \varphi_6 WlnUrban + \gamma l_n + \varepsilon \tag{3-8}$$

where β is a regression coefficient vector of the interactions.

Considering the scale effects of GDP and labour on carbon emissions, the expected signs for *BV* and *BE* are positive (+). Technological innovation, denoted as the number of patents (*Number*) in the forest-based bioeconomy and the transformation rate (*Rate*) are assumed to have a negative impact on carbon emissions. Similarly, urban agglomeration (*Urban* and *Labour)* and economic growth (*PGDP*) will rather increase carbon emissions (Nakicenovic, 2000), suggesting the signs for *Urban*, *Labour* and *PGDP* are expected to be positive (+). Upgrading the industrial structure (*Structure*), by contrast, may lead to lower carbon emissions (-). Table 3.1 gives an overview of all the model variables.

Table 3.1: Descriptions of the variables

Name	Units	Obs	Mean	Std.Dev	Min	Max	Sign
NCE	10^6 tons	8822	610291.2	951385.7	62372.67	10600000	
BV	million Euro	8822	1371.585	2056.334	133.294	27605.67	+
BE	10^3 persons	8822	24.739	27.5	3.831	357.031	+
Number	-	8822	17.64	25.68	0	271	-
Rate	%	8822	0.18	0.218	0	1	-
Structure	%	8822	0.520	0.327	0.037	3.994	-

Labour	10^3 persons	8822	24.903	14.777	2.421	73.560	+
PGDP	10^3 Euro	8822	31.280	14.646	11.209	195.809	+
Urban	ha	8822	11978.92	7479.399	1212	62906	+

3.2.4 Data source

The present study combined information from multiple data sources. The net carbon emissions, including direct carbon emissions and indirect carbon emissions as well as carbon sinks, were calculated on the basis of the land use data and emission parameters for different land use types at the county level. The emission parameters were derived from the Intergovernmental Panel on Climate Change (IPCC) (2021) data and related studies. The land use data from 2000 to 2021 were collected from the Thünen Land Atlas and Regional Database Germany. Due to the administrative division adjustment, some counties have been deleted and adjusted according to the counties/districts in 2021. For instance, Osterode am Harz has been adjusted as a municipality in the county of Göttingen since 2016, The annual socioeconomic data for 401 counties from 2000 to 2021 were gathered mainly from the Federal Office of Statistics of Germany, Regional Database Germany, Eurostat Database, and Federal Agency for Agriculture and Food (BMEL). The patent data in the forest-based bioeconomy from 2000 to 2021 were collected from the Organization for Economic Co-operation and Development (OECD) statistics.

3.3 Results and analysis

3.3.1 Spatiotemporal distribution of net carbon emissions

Figure 3.2 summarizes the results for net carbon emissions (NCE) in Germany and for its division in Eastern and Western Germany in the period from 2000 to 2021. The results show a gentle downward trend in net emissions in Germany. A rapid drop in carbon emissions in 2009 followed by a rise again in 2010 may be because of the impact of economic depression caused by the global financial crisis at the time. Later, due to the economic decline resulting from the Covid-19 pandemic, carbon emissions dropped during the pandemic but climbed again significantly in 2021 to erase the earlier drop. Further, the much higher carbon emissions in Western Germany than in Eastern Germany reflects the higher economic growth and industrial development in the former, and hence its higher associated NCE. Western Germany shared the same tendency of carbon emissions with Germany while Eastern Germany had a relatively small and stable fraction of net carbon emissions.

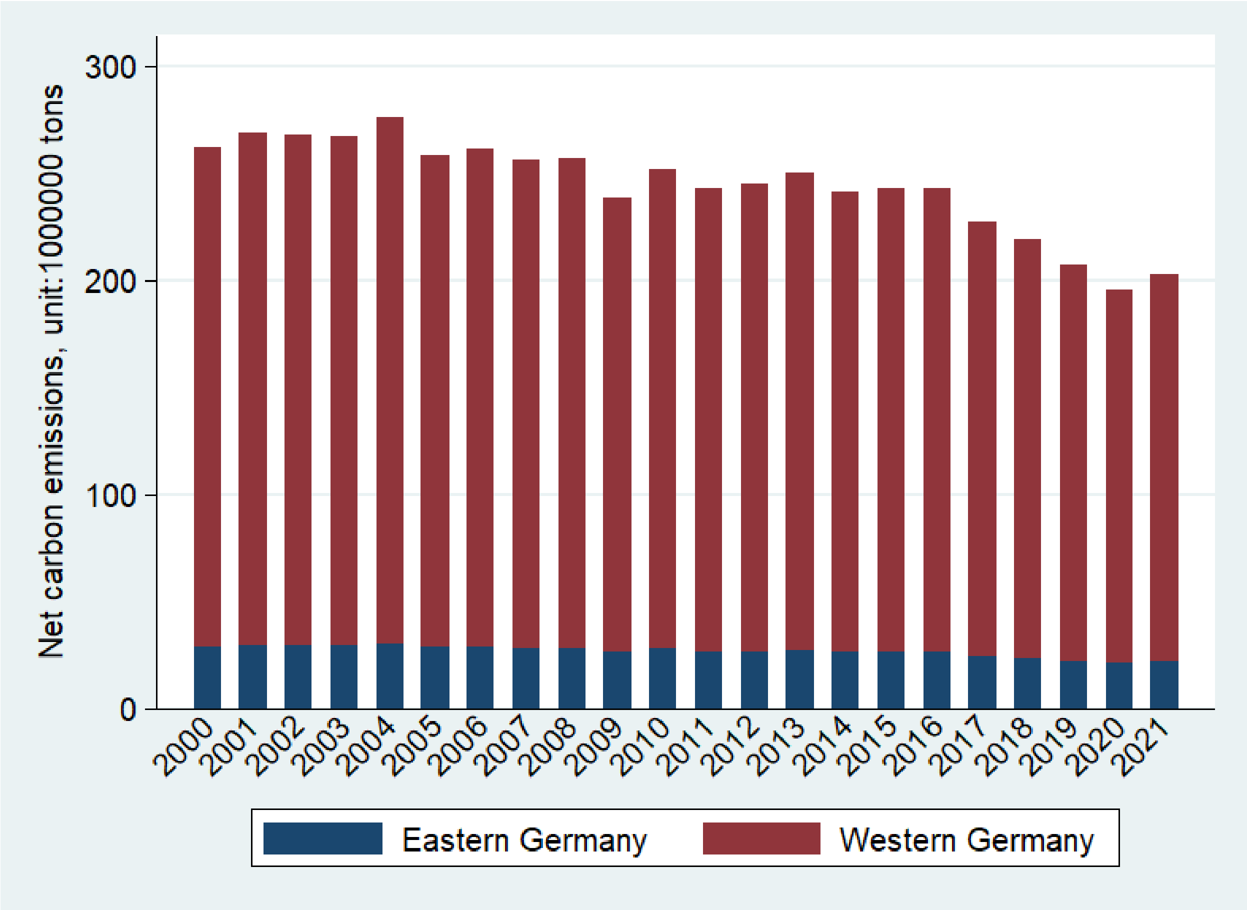


Figure 3.2: Net carbon emissions in Germany during the period 2000-2021

Source: Own representation.

The spatial distribution of net carbon emissions at the NUTS-3 level, as shown in Figure 3.3, changed in intensity over time. In addition to the city-states, like Berlin and Hamburg, the highest NCE (> 2000×10^3 tons) was produced in the western counties, indicating clustering patterns in Western Germany, while the lowest NCE (< 500×10^3 tons) was produced in the eastern counties. Noteworthy, the rapid decline of NCE in categories above 1000×10^3 tons during the period of 2016-2021 implies a faster NCE diffusion compared with that during 2000-2015. Across all the categories, there was a clear increasing tendency over time, especially after 2015.

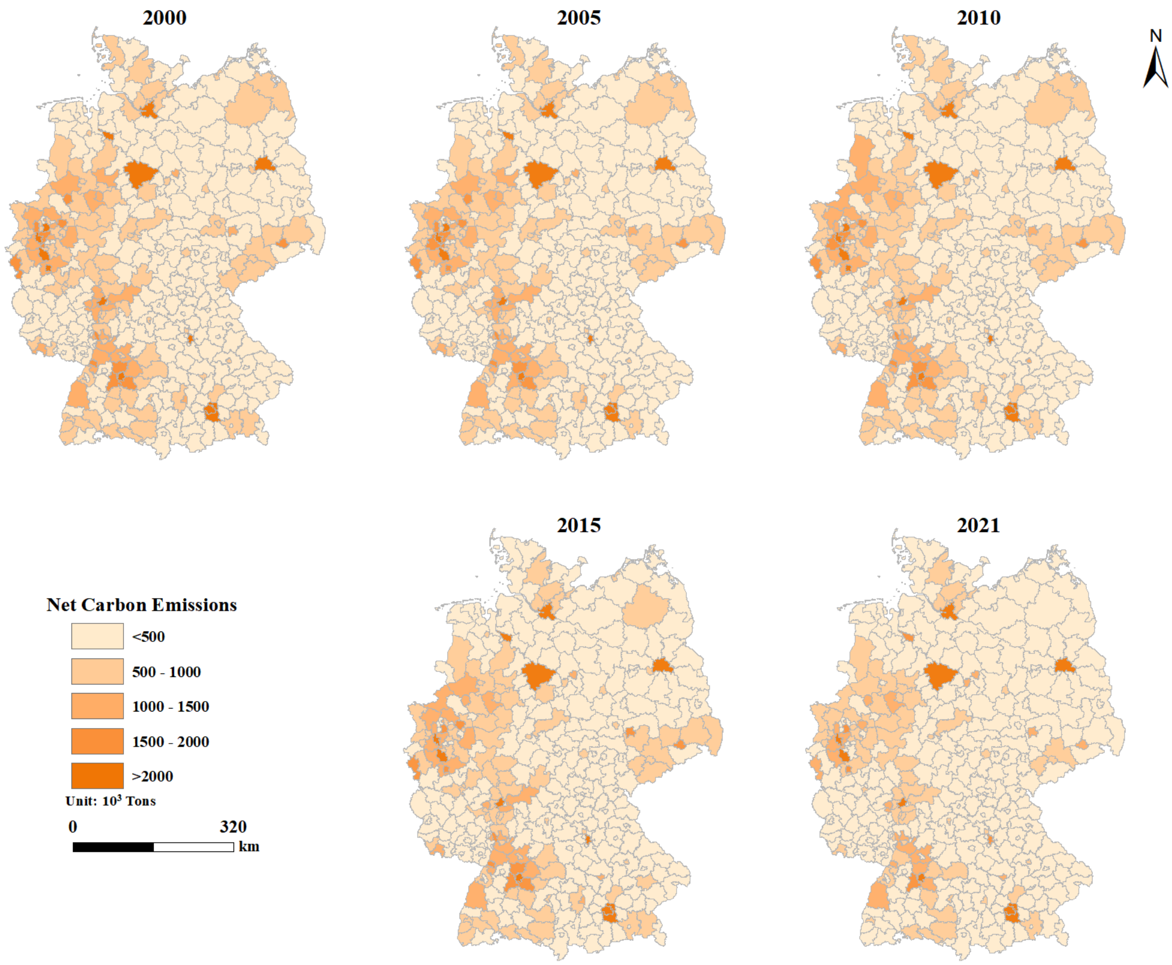


Figure 3.3: Spatial county/district-level distribution of net carbon emissions in 2000, 2005, 2010, 2015 and 2021

Source: Own representation.

3.3.2 Spatiotemporal distribution of the size of the bioeconomy and the number of patents

Figure 3.4 shows that the value added of bioeconomy increased gradually during 2000-2021, rising from EUR 435,340 million in 2000 to EUR 682,777 million in 2021. Suffering from the financial crisis and

COVID-19 pandemic, the value added of the bioeconomy experienced marked falls in 2009 and 2020, correspondingly. Compared with the value added to the bioeconomy, the number of employees in the bioeconomy in this time period fluctuated dramatically. The number decreased from 10 million in 2000 to 9.615 million in 2006 and rose again to 9.884 million in 2008. After that, it declined to 9.73 million in 2010 and slowly climbed to 10.175 million in 2016 but dropped to 10.036 million in the next year. After hitting its peak (10.248 million) in 2019, the figure showed a decreasing trend and was reduced to 9.944 million in 2021, which is lower than that in 2000. The difference between the trend for the value added of bioeconomy and trend in the number of employees in the bioeconomy points to lag effects of the financial crisis and COVID-19 pandemic.

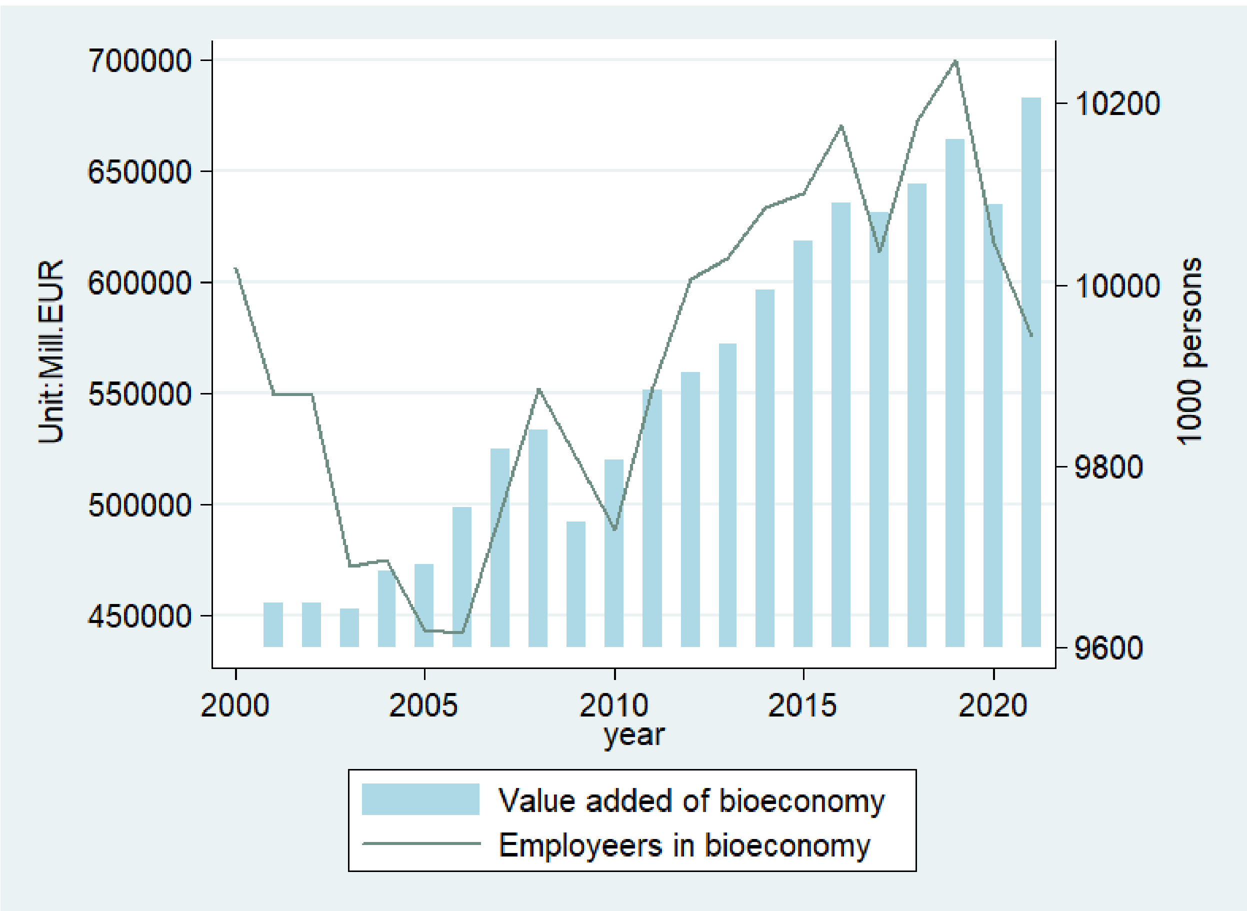


Figure 3.4: Value added of bioeconomy and number of employees in the bioeconomy in the period 2000–2021

Source: Own representation.

The spatial distribution of the value added of bioeconomy (Figure 3.5) revealed a strong economic radiation effect of urban counties on its surrounding areas in 2000—2021, supporting the main tenet of the growth-pole theory (cf. Huang et al., 2015). In 2000, there were only 8 counties with a value added of bioeconomy of more than 4600 (Million euros), with all of them located in Western Germany. In 2010, 4 further counties reached these values. From 2010 to 2021, both the value added of bioeconomy and its spatial spillover effects continued to grow.

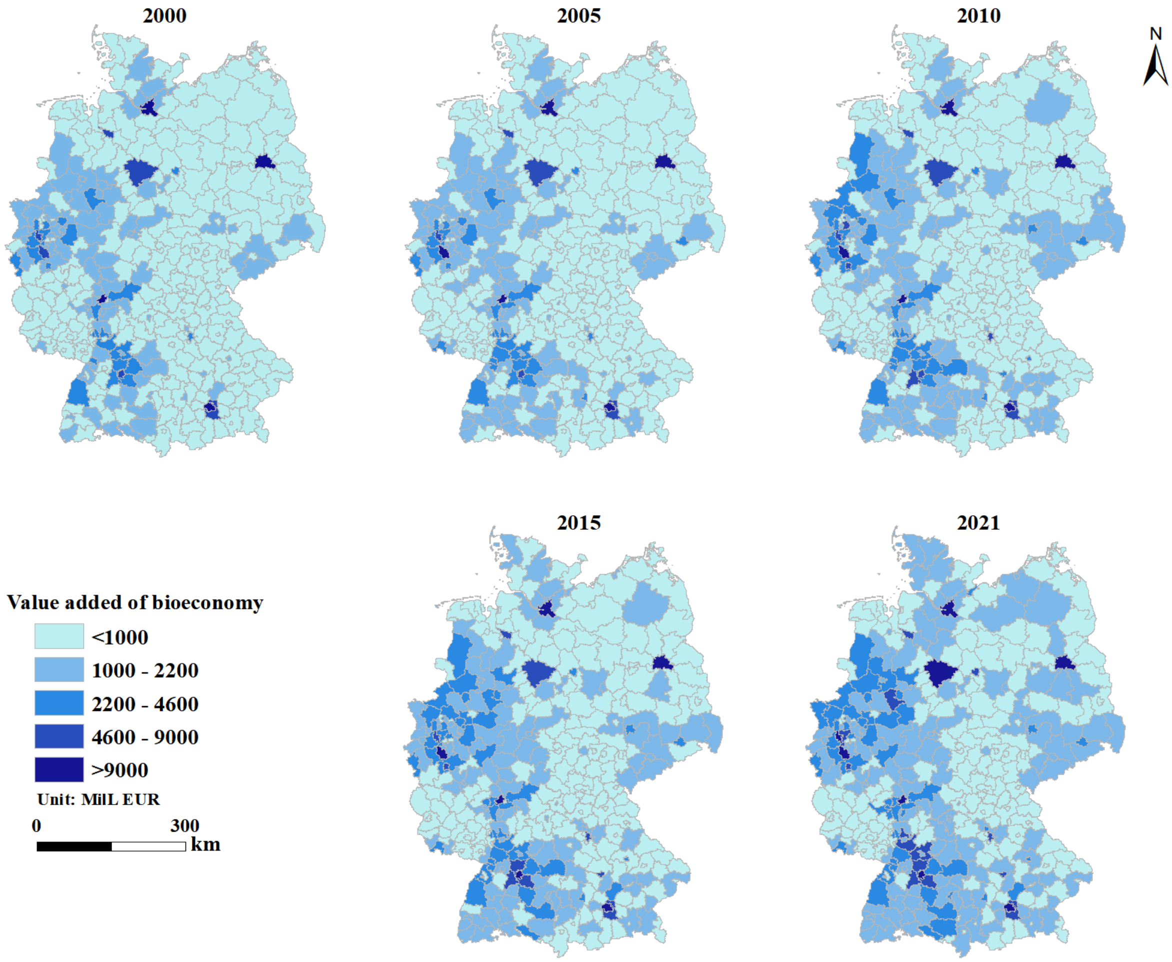


Figure 3.5: Value added of bioeconomy in Germany in 2000, 2005, 2010, 2015, and 2021

Source: Own representation.

The spatial distribution of employees in the bioeconomy (Figure 3.6) illustrates the number of employees were highly concentrated in the western counties, and they had a radiation effect on their surrounding areas in 2000-2021. This may be because the employees can migrate together with the locations of bio-based industries.

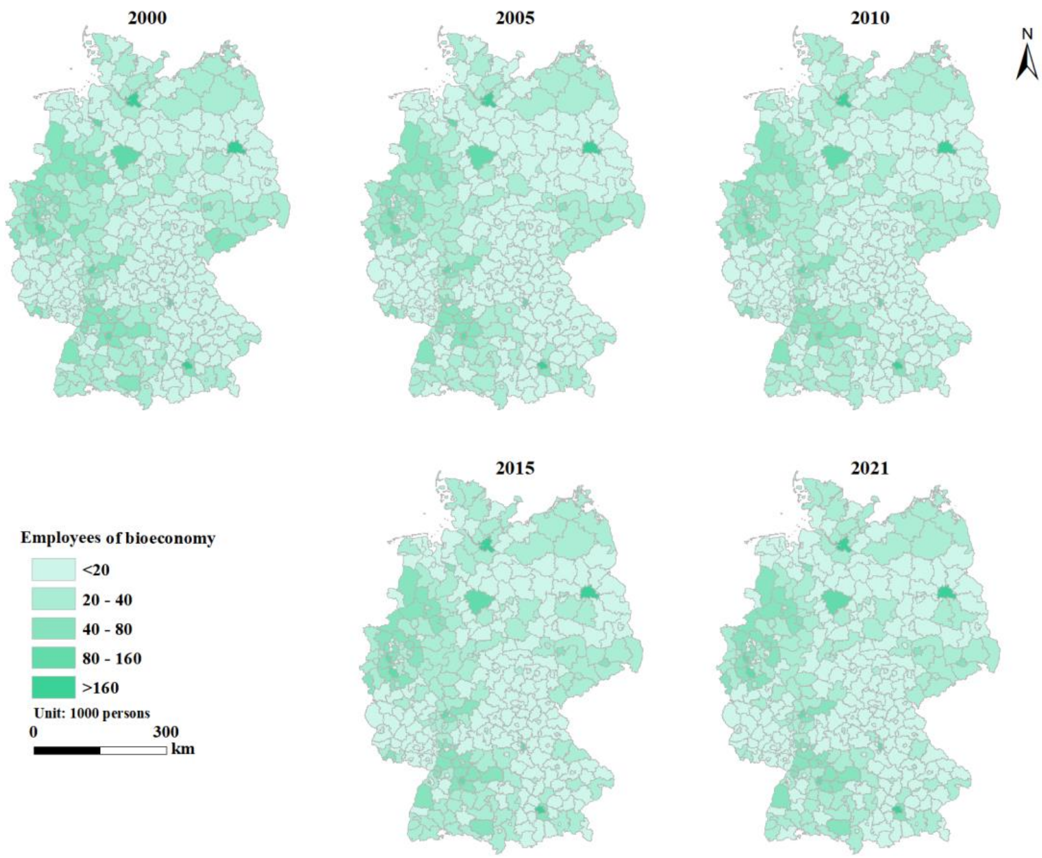


Figure 3.6: Employees of bioeconomy in Germany in 2000, 2005, 2010, 2015 and 2021

Source: Own representation.

The spatial distribution of the numbers of patents related to the forest-based bioeconomy (Figure 3.7) showed a strong clustered pattern for the period 2000–2015. Higher numbers of patents in forest-based bioeconomy (e.g. higher than 30) were found in the western and southern counties, indicating a strong spatial diffusion to surrounding counties. In 2021, the number of patents within all categories decreased sharply, which may have been due to the decline in R&D investment caused by the Covid-19 pandemic.

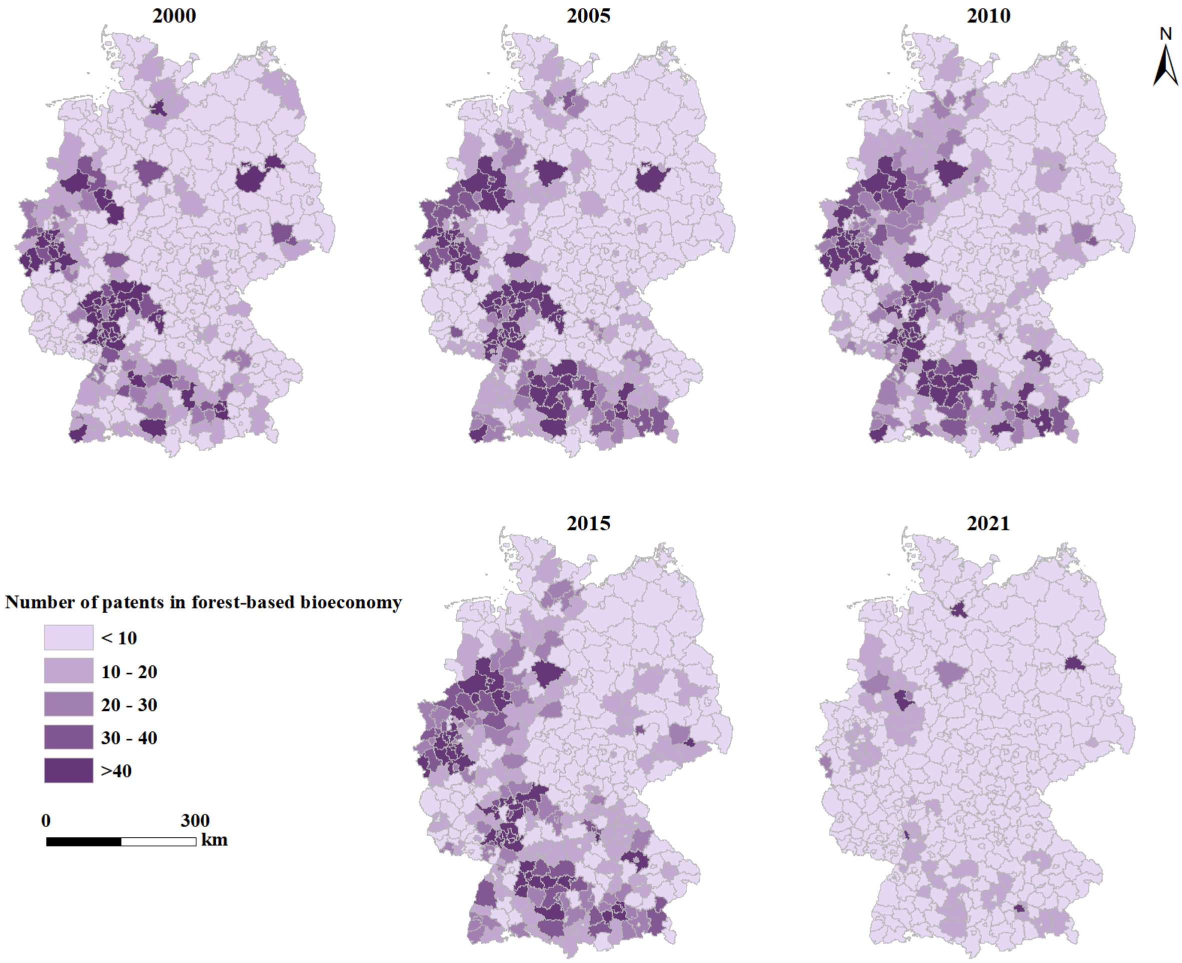


Figure 3.7: Number of patents in forest-based bioeconomy in Germany in 2000, 2005, 2010, 2015, and 2021

Source: Own representation.

3.3.3 Spatial integration effects on carbon emissions in Germany

The results of the Moran's I index test (cf. Equation 3-6) are summarized in Table 3.2 to illustrate the spatial autocorrelations in the observed time period. The low and positive values of all the univariate Moran's I indices indicated a weak positive relationship between the counties/cities. A gradual decrease in the index values since 2007 suggests an emerging spatial diffusion, where counties with similar carbon emissions displayed a greater diffusion tendency. This suggests that spatial effects contribute to the influence of technological innovation in the forest-based bioeconomy on carbon emissions.

Table 3.2: Moran's I values of net carbon emissions from 2000 to 2021

NCE	Moran's I	E(I)	Sd(I)	Z	P-value
2000	0.089	-0.003	0.029	3.143	0.001
2001	0.090	-0.003	0.029	3.183	0.001
2002	0.090	-0.003	0.029	3.183	0.001
2003	0.092	-0.003	0.029	3.250	0.001
2004	0.093	-0.003	0.029	3.268	0.001
2005	0.092	-0.003	0.029	3.255	0.001
2006	0.092	-0.003	0.029	3.239	0.001
2007	0.096	-0.003	0.029	3.364	0.000
2008	0.092	-0.003	0.029	3.252	0.001
2009	0.088	-0.003	0.029	3.106	0.001
2010	0.086	-0.003	0.029	3.053	0.001
2011	0.088	-0.003	0.029	3.107	0.001
2012	0.087	-0.003	0.029	3.070	0.001
2013	0.083	-0.003	0.029	2.961	0.002
2014	0.083	-0.003	0.029	2.957	0.002
2015	0.084	-0.003	0.029	2.978	0.001
2016	0.081	-0.003	0.029	2.877	0.002
2017	0.077	-0.003	0.029	2.774	0.003
2018	0.077	-0.003	0.029	2.762	0.003
2019	0.072	-0.003	0.029	2.587	0.005

2020	0.071	-0.003	0.029	2.569	0.005
2021	0.072	-0.003	0.029	2.614	0.004

Source: Own calculation.

Table 3.3 summarizes the results of the parameter estimations by using two versions of the spatial Durbin model, as described in section 3.2.3. The first model (SDM 1) includes the size of the bioeconomy, technological innovation, and socioeconomic parameters (cf. Equation 3-7), while its extensions control correspondingly for the effects of the interaction terms (SDM 2, cf. Equations 3-8). Varying the variables in two models reveal only insignificant effects, indicating the models' stability and robustness.

Table 3.3: Estimation results from the Spatial Durbin Model and its extensions

	Main effect on *NCE* ($\rho WlnNCE+\partial lnX$)		Spillover effect of *X* on *NCE* ($\varphi WlnX$)	
	SDM 1	SDM 2 Interaction effect	SDM 1	SDM 2 Interaction effect
lnBV	0.198^{***}	0.131^{***}	0.055^{***}	0.004
	(0.006)	(0.007)	(0.013)	(0.013)
lnBE	0.055^{***}	0.116^{***}	0.084^{***}	0.100^{***}
	(0.046)	(0.007)	(0.014)	(0.015)
lnNumber	0.002^{***}	-0.053^{***}	-0.002^{*}	-0.021^{**}
	(0.005)	(0.005)	(0.001)	(0.010)
lnRate	0.001^{***}	0.001^{*}	0.001	0.001
	(0.000)	(0.000)	(0.001)	(0.001)
lnPGDP	0.680^{***}	0.024^{***}	-0.518^{***}	0.007
	(0.008)	(0.002)	(0.142)	(0.004)
lnStructure	-0.025^{***}	-0.026^{***}	-0.013^{*}	-0.0113^{**}
	(-3.24)	(0.002)	(0.007)	(0.004)
lnLabour	0.007^{***}	-0.009^{***}	0.001	0.004
	(0.000)	(0.002)	(0.002)	(0.003)
lnUrban	-0.102^{***}	-0.001	0.115^{***}	0.003^{**}

	(0.007)	(0.001)	(0.012)	(0.001)
LnNumber lnBV*		0.716^{***}		-0.465^{***}
		(0.008)		(0.016)
LnNumber lnBE*		-0.0157^{***}		-0.032^{***}
		(0.003)		(0.006)
LnNumber lnPGDP*		0.00591^{***}		0.001
		(0.001)		(0.002)
LnNumber lnStructure*		-0.076^{***}		0.063^{***}
		(0.007)		(0.011)
ρ	0.420^{***}	0.429^{***}		
	(0.016)	(0.0135)		
R^2	0.622	0.609		
lgt_theta	-4.304^{***}	-4.302^{***}		
	(0.392)	(0.392)		
sigma2_e	0.001^{***}	0.001^{***}		
	($1.07e^{-5}$)	($9.86e^{-6}$)		
Log-Likelihood	19610.264	19719.822		

Source: Own calculation.

*Note: t-statistics in parentheses; *statistical significance on p<0.10 level, ** p<0.05 level, *** p<0.01 level; 8822 observations.*

The results show that within SDM 1 the estimated carbon emissions (*NCE*) are positively correlated with the value added of the bioeconomy (*BV*), employees in the bioeconomy (*BE*), per capita GDP (*PGDP*), and labour density (*Labour*). This finding is in line with existing literature, arguing that economic factors are the main drivers of higher emissions (Wang et al., 2018; Zhang et al., 2020). An increase in urban construction land (*Urban*), in contrast, reduces NCE (-0.102^{***}), because Germany is highly developed and has an advanced industrial division. German factories with high carbon emissions tend to be the less labour-intensive industries, while urban areas in Germany already have a high level of land development (Li et al., 2020). Industrial upgrading (*Structure*), as expected, drives down emissions significantly (-

0.025***), because it stimulates industrial transition towards greater sustainability (Bai et al., 2023; Mehmood et al., 2024).

Contrary to expectations, an increase in the number of patents in the forest-based bioeconomy (*Number*) and the ratio of patents applied for in the current year (*Rate*), seems to give rise to the higher carbon emissions, respectively (0.002*** and 0.001***, respectively). This can be explained by the fact that technological innovation of forest-based bioeconomy in Germany contributes to economic growth, which ultimately lead to higher NCE levels (Khan et al., 2023).

Further, the coefficients of the spatially lagged independent variables suggest that the value added of bioeconomy (*BV*), employees in bioeconomy (*BE*), labour density (*Labour*) and urban construction land (*Urban*) have significantly positive spillover effects in terms of higher emissions on neighbouring counties. The spillover effects of *Number*, *Structure,* and *PGDP* are significantly negative, indicating that counties with high levels of GDP and technological innovation, and thus more developed industries attract more technological investment and natural resources from neighbouring counties (Gao et al., 2020).

The results for SDM 2 suggest that technological innovation in the forest-based bioeconomy can reduce net carbon emissions, given a stronger value added for the bioeconomy, and more jobs for employees in the bioeconomy, a higher per capita GDP, and industrial upgrading. The significantly negative spillover effect of *Number* highlights the role of spatial diffusion of technological innovation in the forest-based bioeconomy in reducing carbon emissions. As shown in Table 3.3, there is a strong interaction between *Number* and *BV*, *BE, PGDP,* and *Structure* compared to SDM 1. The significantly negative interactions between *Number* and *BE* and *Structure* reveal that, considering the impacts of *BE* and *Structure* on carbon emissions, an increase in technological innovation can start to reduce net carbon emissions. The significant positive interactions between *Number* and *BV* and *PGDP* indicate an opposite effect on emissions. Promoting technological innovation in the forest-based bioeconomy can consequently mitigate carbon emissions when combined with a greater number of employees in the bioeconomy and industrial upgrading. The negative spillover effects of the interactions between *Number* and *BV* and *BE* on carbon emissions imply that an increase of technological innovation in the forest-based bioeconomy given the increase of *BV* and *BE* can reduce the carbon emissions in neighbouring counties, while the positive spillover effect of the interaction between *Number* and *Structure* reflects the opposite case.

Table 3.4 displays the direct effect, indirect effect and the total effect of the parameters in SDM 1 and SDM 2. The total effect of *Number* on carbon emissions is negative whether in SDM 1 or SDM 2. This confirms the mitigation effect of technological innovation in the forest-based bioeconomy on carbon emissions. Further, the consistent direction of the direct effects of interaction between *Number* and *BV*, *BE*, *PGDP*, and *Structure* with their total effects not only implies their higher direct effects than direct effects but also stresses the combined action of technological innovation in the forest-based bioeconomy, labour structural change and industrial upgrading on carbon emissions.

Table 3.4: Direct effect, indirect effect, and total effect of the model parameters

	SDM 1			SDM 2		
	Direct	Indirect	Total	Direct	Indirect	Total
lnBV	0.207^{***}	0.230^{***}	0.436^{***}	0.137^{***}	0.098^{***}	0.235^{***}
	(0.006)	(0.019)	(0.019)	(0.007)	(0.019)	(0.022)
lnBE	0.061^{***}	0.177^{***}	0.238^{***}	0.130^{***}	0.253^{***}	0.382^{***}
	(0.004)	(0.022)	(0.023)	(0.007)	(0.022)	(0.024)
lnNumber	0.002^{***}	-0.002	-0.000	-0.056^{***}	-0.074^{***}	-0.130^{***}
	(0.001)	(0.002)	(0.003)	(0.006)	(0.016)	(0.018)
lnRate	0.001^{***}	0.002	0.003	0.001^{*}	0.002	0.003
	(0.000)	(0.002)	(0.002)	(0.000)	(0.001)	(0.002)
lnPGDP	0.664^{***}	-0.387^{***}	0.278^{***}	0.025^{***}	0.029^{***}	0.054^{***}
	(0.009)	(0.024)	(0.025)	(0.002)	(0.007)	(0.007)
lnStructure	-0.027^{***}	-0.037^{***}	-0.064^{***}	-0.028^{***}	-0.038^{***}	-0.066^{***}

	(0.003)	(0.010)	(0.011)	(0.002)	(0.007)	(0.008)
lnLabour	0.007***	0.006	0.013***	-0.009***	-0.001	-0.010
	(0.001)	(0.004)	(0.004)	(0.002)	(0.005)	(0.006)
lnUrban	-0.098***	0.121***	0.022	-0.001	0.004*	0.003
	(0.007)	(0.017)	(0.017)	(0.001)	(0.002)	(0.003)
LnNumber lnBV*				0.701***	-0.262***	0.439***
				(0.009)	(0.022)	(0.024)
LnNumber lnBE*				-0.019***	-0.064***	-0.083***
				(0.003)	(0.008)	(0.009)
LnNumber lnPGDP*				0.006***	0.005**	0.012***
				(0.001)	(0.003)	(0.003)
LnNumber lnStructure*				-0.074***	0.050***	-0.023
				(0.008)	(0.017)	(0.017)

*Note: t-statistics in parentheses; *statistical significance at p<0.10 level, ** p<0.05 level, *** p<0.01 level; 8822 observations.*

3.4 Discussion and conclusions

3.4.1 Discussion

The analysis shows that technological innovation in the forest-based bioeconomy can contribute to decoupling economic development from emissions production. The obtained results are in line with recent studies, which found that technological innovation negatively affects carbon emissions (Erdoğan et al., 2020; Zhao et al., 2021). The results contribute to the body of the relevant literature by showing that the forest-based bioeconomy, combined with technological innovation in the forest-based bioeconomy and the number of employees in the bioeconomy, can improve the net carbon emissions performance within a region and through spatial spillover effects empirically. As shown by the values of coefficients, the number of patents in the forest-based bioeconomy (-0.053***), its interactions (*LnNumber*lnBE* and *LnNumber*lnStructure*), industrial upgrading (-0.108***), and labour intensity (-0.009***) can significantly lower net carbon emissions. Likewise, the value added of bioeconomy (0.131^{***}), number of employees in the bioeconomy (0.116^{***}), application rate of patents in the forest-based bioeconomy (0.001^{*}), and *PGDP* (0.024^{***}) can all aid in reducing emissions. This is consistent with the latest findings suggesting that the growth of the bioeconomy results in a higher demand for biomass, while carbon tax will accelerate market opportunities for bio-based alternatives (Philippidis et al., 2024). Technological innovation in the forest-based bioeconomy also strengthens industrial upgrading (-0.026^{***}), and enhances industry competition and labour division, contributing in this way to a more sustainable transition of industry and society (Bai et al., 2023; Mehmood et al., 2024).

The key effect of the forest-based bioeconomy on carbon emissions is shown to be twofold, determined by the substitution/complementarity of the resources exchanged and technological diffusion among the counties. Resource substitution can drive industrial upgrading and the optimization of resource allocation in counties with high levels of technological innovation and large numbers of employees in the bioeconomy. The resulting negative effect on carbon emissions spills over to their neighbouring counties. Resource complementarity, for its part, weakens administrative barriers and strengthens regional cooperation, which explains the inconsistent spatial diffusion of carbon emissions (Figure 3.4) and value added of bioeconomy (Figure 3.6). This requires an efficient regulation of technological innovation and resource allocation in the bioeconomy to prevent their negative externalities (Zilberman et al., 2013).

Other than the studies by Jonssen et al. (2021), in which the climate-change mitigation effect of the forest-based bioeconomy is investigated by considering the increased carbon storage in harvested wood products (HWP) at the EU level, the present analysis suggests that the contribution of the forest-based bioeconomy to carbon mitigation can not only be reflected by the carbon sinks in HWP but also through technological innovation as well as its spillover effects. The combinations of technological innovation and the number of employees in the bioeconomy and industrial upgrading further highlight their overlapping effects on carbon emissions. These observations allow concluding that an alignment of technological innovation with industrial upgrading and a structural change in employment is needed to boost the forest-based bioeconomy to reduce carbon emissions (Halonen et al., 2022; Hetemäki et al., 2022).

3.4.2 Conclusions

The forest-based bioeconomy, accompanied by the demanding forest biomass, technological innovation and value-added production, affects both the carbon footprint of economic activities and the carbon sink capacity of the ecological environment. Boosting the forest-based bioeconomy to benefit from its potential to promote carbon emissions reduction is a priority in the series of bioeconomy strategies in Germany. The study estimated the spatial impact of a forest-based bioeconomy, especially technological innovation in the forest-based bioeconomy, on carbon emissions. The analysis used the Spatial Durbin Model and county-level panel data for 401 counties/cities and arrived at four main conclusions, as described below.

First, for the observed period 2000 to 2021, the carbon emissions of 401 counties/cities in Germany have been found to be spatially autocorrelated and exhibit clustering patterns in Western Germany, largely reflecting the regional economic development. Second, technological innovation in the forest-based bioeconomy reveals a significant negative spillover effect on carbon emissions, indicating a role of technological diffusion in reducing carbon emissions from the local county/city to the periphery. Yet, the inconsistent diffusion trajectory of carbon emissions and the number of patents in the forest-based bioeconomy implies a high emissions reduction potential of a forest-based bioeconomy. Third, technological innovation in the forest-based bioeconomy can reduce carbon emissions through industrial upgrading and increasing job opportunities in the bioeconomy. Fourth, it can also lower carbon emissions through the negative spillover effect of industrial upgrading and increasing the size of the bioeconomy.

4 Impacts of institutional innovation in the bioeconomy on green productivity[3]

4.1 Background and objectives

4.1.1 Institutional background of bioclusters in Germany

German biocluster is an innovative strategy, serving as an institutional incentive for stimulating biotech industries and economic transformation. Bioclusters in Germany can date back to the 1970s when policymakers worldwide started to focus on biotechnology as a key innovation strategy (Fornahl et al., 2011; Dorocki, 2014). Despite Germany creating a national law on genetic modifications in 1978 to support biotechnology, it eventually fell well behind the global leaders in the following decades. It has been argued that Germany was the least biotechnology development-friendly country in the Western world in the early 1990s (Dohse and Staehler, 2008). However, in 1995, the German Federal Ministry of Education and Research (BMBF) announced the BioRegio competition to speed up the late-starting biotech industry. At that moment, there were only 70 biotech companies in Germany (BMBF, 2004). In this programme, winning regions could get preferential access to federal funding to realize their biotech investment plans (Dohse, 2000). After this initial programme, several others followed, like BioFuture, BioProfile and BioChance (Fornahl et al., 2011). The launch of a series of strategies regarding developing bioclusters has helped Germany reclaim its leading role in the bioeconomy. The German Biotechnology Report 2011 pointed out that the German biotech industry was back on a growth path in 2010, with 400 biotech companies and 809 million euros R&D expenditure (Ernst & Young, 2011).

To better organize the Bioregions, the Council of BioRegions in Germany (AK-BioRegio) (also known as the alliance of the German Biotechclusters) was officially founded at the beginning of 2004 in Leipzig. The

[3] Author statement: Lanjiao Wen (conceptualization, methodology, software, writing-original draft, and revision); Dr. Zhanli Sun (conceptualization, revision and supervision); Dr. Ir. Frans Hermans (conceptualization, data curation and revision); Prof. Dr. Alfons Balmann (revision and supervision).

tasks of AK-BioRegio includes five parts, namely meta-networking, biotech partnering, developing a trend radar (analysis of trends in biotechnology), innovation promotion, the provision of know-how for political decision-makers, and best practice exchange. Before 2004, biocluster managers in the BioRegio competition were competitors for public funding. But after 2004, with the establishment of AK-BioRegio, they established a network for sharing experiences and mutual learning. This further strengthened innovation diffusion and cooperation among companies, institutes, universities, and other stakeholders in the value chain of the bioeconomy. At the same time, the funding source was broadened to include private R&D investment. Now 24 members from Bioregions have come together to optimize and coordinate their regional activities in the interests of German biotechnology.

4.1.2 Objectives and organization

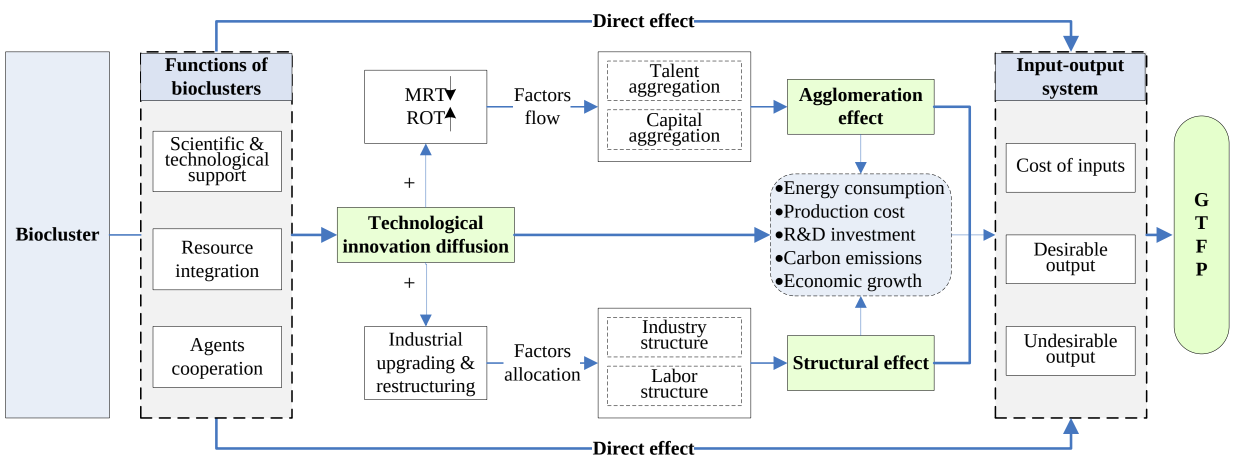
The bioclusters, as an institutional innovation, create suitable ecosystems for the growth of the bioeconomy by linking biotech companies, research institutes and universities, technology parks, and relevant stakeholders in a geographic region together. As such, bioclusters can foster collaboration, innovation, knowledge exchange, and supply chain integration. Thus, bioclusters can greatly contribute to the development of the bioeconomy and facilitate the sustainable transition to the bioeconomy. To date, both national and supernational strategies have tended to focus on the sustainability of the bioeconomy, such as the EU Green Deal ("From Farm to Fork", "Circular Economy Action Plan", etc.). However, there is still little empirical evidence on whether and how the establishment of bioclusters affects green productivity.

To fill in this research gap, this chapter, focusing on Germany at the NUTS-3 level, aims to estimate the causal effects of bioclusters on green productivity mediated by technological innovation. We attempt to answer the following research questions: 1) Does the establishment of bioclusters increase green productivity? If so, by how much? 2) How does the presence of bioclusters affect green productivity increases through technological innovation in the bioeconomy, and how can this effect be assessed through patent data?

The remainder of the paper is organized as follows. Section 4.2 outlines the background of bioclusters in Germany and provides the theoretical analysis and hypotheses. Section 4.3 introduces the study area, data, and methodology. The results are summarized and discussed in section 4.4. Finally, the discussion and policy implications are provided in section 4.5.

4.2 Theoretical analysis and hypotheses

This section discusses the direct effects and indirect effects of bioclusters on green total factor productivity, where the indirect effects include technological, agglomeration, and structural effects. As the purpose of implementing bioclusters is to cultivate new dynamics for economic growth and to promote green development through innovation, bioclusters may have a direct impact on green productivity. Simultaneously, the establishment of bioclusters can contribute to promoting technological innovation, clustering innovation factors, and the transformation of industry structures. Therefore, technological, agglomeration, and structural effects arise that can indirectly influence green productivity (see Figure 4.1).



Note: GTFP=Green total factor productivity; MRT=Marginal rate of transformation; ROT=Return on investment

Figure 4.1: Direct and indirect effects of bioclusters on GTFP

Source: Own representation.

4.2.1 Direct effects

Based on the well-known definition of a cluster from Michael Porter, bioclusters can be defined as a geographically proximate group of interconnected companies and associated organizations in the bioeconomy, linked by commonalities and complementarities (Porter, 1990; Hermans, 2021). With the German government stepping up investment in scientific research with an aim to catch up other EU countries, bioclusters achieved financial incentives to promote innovation, green growth and sustainable development (Hovardas, 2016). Specifically, it is believed that talent introduction, patent applications, and industrial integration supported by the funding in bioclusters would stimulate technological support, resource integration, and agents' cooperation (e.g. industry–university–research cooperation), and then enhance the output and reduce the production costs and waste. The indicators related to the evaluation system for green total factor productivity (GTFP), such as production cost of land and labour, comprehensive energy consumption per unit of GDP, and carbon dioxide emissions, are typically directly improved in counties/cities with bioclusters. At the same time, bioclusters organized by specific organizations, such as AK-BioRegio, have a broad platform to advocate for a green and low-carbon life for residents and encourage low-carbon production for enterprises. Therefore, hypothesis 1 (H1) is put forward as below.

H1: Bioclusters can improve regional green total factor productivity (GTFP) directly.

4.2.2 Technological effects

According to Baumol's entrepreneurial talent allocation model (Baumol, 1996), a better innovation environment and higher innovation dividends via a sufficient supply of innovation factors and optimization of innovation sites can attract entrepreneurs to choose innovative production activities to obtain higher rewards. From this perspective, counties/cities with bioclusters have a great chance to gain extra R&D investment for technological innovation. Schumpeter's endogenous growth theory suggests that technological innovation is the primary driving force for economic growth (Schumpeter, 1935). Biotechnology created by bioclusters is at the core of the scientific and innovative foundations of the bioeconomy (Aguilar et al., 2019), promoting innovative production and productivity. Innovative production activities can produce high-output and low-pollution technological effects (Hovardas, 2016; Lee and Malerba, 2017; Le et al., 2021). This is consistent with the goal of green productivity. As bioclusters are usually clustered in incubators and entrepreneurship parks dedicated to the bioeconomy, they can also provide new market opportunities for innovators and enterprises, bringing about technological innovation through innovative production activities in the bioeconomy (Amoako, 2011; Pradhan et al., 2018). The technological effects of innovative production activities in the bioeconomy will ultimately act on regional development and influence regional green productivity. Accordingly, hypothesis 2 (H2) is proposed as follows.

H2: Bioclusters can generate technological effects on GTFP.

4.2.3 Agglomeration effects

Bioclusters concentrated geographically can attract an inflow of production factors, forming talents and capital aggregation. Enterprises in bioclusters can achieve increasing returns on investment (ROI) and lower marginal rate of transformation (MRT) due to the outward production possibilities frontier and the lower opportunity cost of production caused by technological innovation. This can accelerate the flow of production factors (such as labour and capital) from counties/cities without bioclusters to those with bioclusters during the process of urban development and industrialization (Fujita et al., 2001). Agglomeration effects refer to the geographical concentration of these factors, which increases the compatibility or decreases the costs of economic activities (Hoover, 1937). Duranton and Puga (2004) have summarized that agglomeration effects involve sharing, cooperation, and learning. When production and economic activities are grouped, bioclusters can save space and cost, optimize their resource allocation, shorten transportation distances, and reduce pollutant emissions, ultimately leading to green industry (Li et al., 2019; Tian et al., 2019).

The agglomeration of technology, talented labour and capital resulting from bioclusters, in return, promotes greater cooperation among agents. The industry–university–research cooperation in bioclusters can accelerate the transformation of innovation and improve production efficiency (Zhang et al., 2021). Meanwhile, cooperation among actors (e.g., enterprises), where enterprises gather to form industrial chains and industrial parks, can promote the reuse of intermediate products, improve the efficiency of raw resources, and reduce pollution in the process of production (Wang et al., 2023). Through networks established by bioclusters, like AK-BioRegio, the managers of bioclusters can learn from each other to overcome their common challenges and share the benefit of knowledge and technological innovation spillover. Through learning from more advanced ones, backward enterprises will adjust their production and management methods to improve their productivity (Henderson et al., 1995). Also, advanced enterprises can learn from each other to improve their technological productivity at the same time. As the externalities of agglomeration are influenced by the agglomeration degree of talent, capital, technology, and industry, the higher the agglomeration degree, the larger the agglomeration externalities will be (Zhang et al., 2022). Therefore, hypothesis 3 (H3) is put forward as below.

H3: Bioclusters can generate agglomeration effects on GTFP through factor flows caused by technological innovation.

4.2.4 Structural effects

The technological innovation generated by bioclusters can lead to industrial upgrading and restructuring by optimizing the allocation of production factors. On the one hand, technological innovation can improve the marginal rate of substitution of labour and capital by technology, leading to structural changes in the production factors as well as the industries themselves. On the other hand, higher profits from innovation produced by bioclusters due to their high returns on investment can generate higher market competition pressure on traditional industries. Given the attraction of innovative profits, the pressure from market competition, and the incentive of government policies (e.g., funding support), traditional industries will also seek to introduce new biotechnologies for their industrial upgrading so that the traditional clusters can be transformed into high-efficiency industries themselves (Pan et al., 2020; Zhang and Wang, 2022). In that case, industrial upgrading increases the green efficiency of the traditional industrial land. However, the large-scale construction of high-tech industries in bioclusters may also have a rebound effect, leading to massive energy consumption in the region (Sohag et al., 2015) and reducing the GTFP in return. Therefore, hypothesis 4 (H4) is put forward as below.

H4: Bioclusters can bring about structural effects on GTFP through factor allocations caused by technological innovation.

4.3 Methodology

For the purpose of the present investigation, the regional green total factor productivity (GTFP) is calculated for the period from 2000 to 2021. Next, a natural experiment—staggered difference in differences (DiD) is used to estimate the impact of bioclusters on GTFP. Considering the bioclusters established different year, a staggered difference in differences (SDiD) is employed to measure the impact of bioclusters on GTFP for Bioregions and green clusters, respectively. In this study, counties/cities with Bioregions or green clusters are considered the treatment group, while counties/cities without Bioregions or green clusters, excluding those neighbouring the counties/cities with bioclusters, are the control group. Then, a mediating model is employed to estimate the indirect effect of bioclusters on GTFP.

4.3.1 Study area and data source

The study area includes 401 counties/cities in Germany. We take counties/cities with bioclusters as the treatment group and the other counties/cities, excluding those neighbouring the counties/cities with bioclusters, as the control group. 24 bioclusters from Bioregions after the establishment of AK-BioRegio are considered in this study (Figure 4.2 (a)). Ranging from the local level (*level-1*) to the regional level (*level-2*) and the state level (*level-3*), these Bioregions are scattered across the whole Germany. Among them, bioclusters at the state level dominate the Bioregions, with 12 bioclusters at the state level, seven bioclusters at the regional level, and five bioclusters at the local level. Baden-Württemberg has six bioclusters from Bioregions, all of which are at the regional and local level. Berlin, Munich and Jena are the most popular sites for Bioregions, as all of them have two bioclusters.

Figure 4.2 (b) displays the spatial distribution of green clusters. Green clusters are bioclusters focusing on green development, and data on them here are collected from the European Cluster Collaboration Platform. According to Hermans (2021), the green clusters in this study are grouped into three types, namely agricultural agglomeration (*Type-1*), green chemistry clusters (*Type-2*), and bioeconomy districts (*Type-3*), based on their sectors and technological fields. For instance, green clusters that focus on agriculture, forestry, and fishing are identified by agricultural agglomeration (*Type-1*) due to their strong linkage with the regional primary sector. The detailed biocluster classification is provided in Table A.3. So far, there are 29 green clusters in total. Green clusters are concentrated in southern and eastern Germany. Most of them are bioeconomy districts (*type-3*) and have a small scale of members (less than 100), as shown in Figure 4.2 (b). The largest bioclusters, with over 200 200 members, are mainly located in Berlin, Potsdam, and Bayreuth. The biocluster-Cluster Transport, Mobility, and Logistics Berlin-Brandenburg in Berlin is the largest, with 530 members in total, including 80 large firms, 380 Small and medium-sized enterprises (SMEs), and 70 organizations.

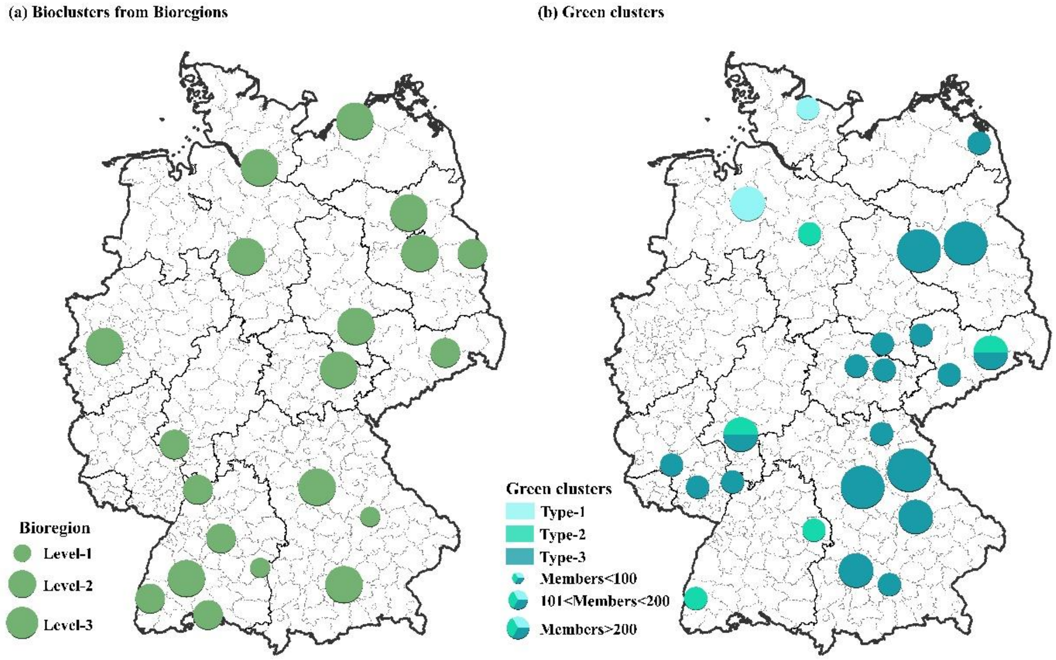


Figure 4.2: Distribution of bioclusters in Germany

Source: Own representation.

Focusing on the implication of bioclusters on green productivity in Germany, we collected economic statistics data at the NUTS-3—city/county (Kreis in German, hereafter counties or cities) level from 2000 to 2021. The data used in this study include the input–output data (urban land, labour, capital, energy consumption, GDP, and carbon emissions), the number of patents in the bioeconomy as well as its characteristics, and socioeconomic data, which were obtained from multiple data sources. The carbon emissions data used in this study were calculated on the basis of land use data and emission parameters for different land use types at the county level. The emission parameters were derived from the Intergovernmental Panel on Climate Change (IPCC) (2021) and related studies. The land use data from 2000 to 2021 were collected from the Thünen Land Atlas and Regional Database Germany. The annual socioeconomic data for 401 counties from 2000 to 2021 were gathered mainly from the Federal Office of Statistics of Germany, Regional Database Germany, Eurostat Database, and Federal Agency for Agriculture and Food (BMEL). The patent data in the forest-based bioeconomy from 2000 to 2021 were collected from Organization for Economic Co-operation and Development (OECD) Statistics. The records of bioclusters were from the German Trade and Invest survey (2022), which is supported by the Ministry of Education and Research and Federal Ministry for Economic Affairs and Climate Action, and the European Cluster Collaboration Platform.

4.3.2 Measuring regional green productivity with Super-efficiency SBM

A super-efficiency Slacks-based measure (super-efficiency SBM) model with undesirable outcomes was employed to estimate the GTFP. Based on Tone(2002), the model is specified as below.

$$GTFP = min \frac{\frac{1}{n}\sum_{i=1}^{n} \bar{x_i}/x_{io}}{\frac{1}{c_1+c_2}(\sum_{r=1}^{c_1} \bar{y}_r^d/y_{ro}^d + \sum_{l=1}^{c_2} \bar{y}_l^{nd}/y_{lo}^{nd})}$$

$$s.t. \sum_{i=1,\neq 0}^{n} \gamma x_i \leq \bar{x}; \sum_{i=1,\neq 0}^{n} \gamma y_i^d \geq \bar{y}_r^d; \sum_{i=1,\neq 0}^{n} \gamma y_i^d \leq \bar{y}_l^{nd};$$

$$\bar{x} \geq x_o;\ \bar{y}^d \leq y_o^d;\ \bar{y}^{nd} \leq y_o^{nd};\ \bar{y}^d \geq 0, \gamma \geq 0 \qquad (4\text{-}1)$$

where $GTFP$ is the urban land green use efficiency, and *o* is the production decision unit (401 decision units in total). Each decision unit has *n* inputs, c_1 desired outputs, and c_2 non-desired outputs. x_{io} presents the input *i* of decision unit *o*; $\bar{x}$ denotes the redundancy of input; y_{ro}^d and y_{lo}^{nd} are the desired and undesired outputs of the decision unit *o*, respectively. $\bar{y}^d$and $\bar{y}^{nd}$are the redundancy of the desired and non-desired outputs, respectively, and γ is the weight vector.

The inputs and outputs are shown in Table 4.1. The sizes of the urban areas, employment population and energy consumption are used to present the fixed capital input, labour input and energy input, respectively. Gross domestic product (GDP) is the desired output and carbon emissions are the undesired output. In this study, the carbon emissions are net carbon emissions and are calculated as the sum of carbon emissions and carbon sink associated with land use at the county level (Wen et al., 2021).

Table 4.1: Input-output indicators for GTFP

Inputs	Descriptions
Capital	Size of the urban areas, as the sum of the settlement area and transport areas, in each county.
Labour	Total employment population in each county.
Energy consumption	Energy use of companies in the manufacturing sector at the NUTS-3 level.
Desired outputs	
GDP	Gross domestic product at the NUTS-3 level.
Undesired output	
Carbon emissions	The net carbon emission (NEC_i) for county *i* is shown as below: $NEC_i = \eta_a \cdot A_i + T_i \cdot M_i - \sum \eta_j \cdot S_{ij}$, where η_a is the carbon emissions parameter for arable land; A_{ii} is the arable land size; *j*=1,2,3 and represent respectively forest, grassland and water; S_{ij} is the land size for each land use type *j*; η_j is the product of carbon emissions parameter collected from the IPCC (2021); T_i is the product of the energy consumption per unit of GDP; and M_i is the GDP of the secondary and tertiary industries in county *i*.

4.3.3 Measuring the impact of Bioregions on green productivity with a staggered DiD

The difference in differences (DiD) method is a widely-used quasi-experimental technique for estimating the effect of a specific intervention or treatment by comparing the changes in outcomes before and after the intervention (Goodman-Bacon, 2021). Considering the bioclusters established in different years, a staggered difference in differences (SDiD) is employed to compare the net effect on GTFP before and after the development of bioclusters. This approach addresses the limitation of traditional DiD that requires it to satisfy a stable unit treatment value assumption (SUTVA) while ignoring spillovers. To measure the treatment effect, counties/cites with bioclusters (Bioregions and green clusters in this study) are considered as the treatment group and counties/cites without bioclusters, excluding those surrounding the counties/cities with bioclusters, are regarded as the control group with consideration of the spatial spillover effect. It assumes that the treatment and control groups display a parallel trend—the two groups would have followed similar trends over time (Slaughter, 2001).

According to Hermans (2018), bioclusters are clusters that specialize in various fields of the bioeconomy with the explicit goal of promoting sustainable development. To better promote close cooperation among biotech companies, research institutes, and technology parks, Germany, one of the best environments for biotechnology R&D worldwide, has established the Council of BioRegions (AK-BioRegio) since 2004. The Bioregions of Germany are regional initiatives set up for the advancement of modern biotechnology in Germany. Up to 2022, there were 24 active members of Bioregions, ranging from those at the local level to state level. In the basic model shown in the following regression, counties/cites with bioclusters from Bioregions are the treatment group:

$$GTFP = \partial_0 + \partial_1 Bioregion_{it} + \partial_c control_{it} + \mu_i + \tau_i + \delta_{it} \qquad \text{(Model 4-1)}$$

with dummy variable *Bioregion* to show whether county/city *i* has a biocluster from Bioregions or not; control variable *control*; constant term ∂_0; estimated parameters (∂_1 and ∂_c); individual effect μ_i, time effect τ_i, and random perturbation term δ_{it}. *Bioregion* is denoted as *Bioregion*=$d_t \times d_u$, where d_u determines whether they are qualified as innovative cities (yes=1, no=0), and *dt* determines whether they have already been designated as innovative cities (yes=1, no=0). Specifically, policy assigns a value of 1 to a city in year t and onward if it attains recognition as an innovative pilot city; otherwise, it receives a value of 0.

In model 4-2, the value added of bioeconomy (*BV*), and employees in bioeconomy (*BE*) are introduced to model 4-1 to further examine the heterogeneous effects of Bioregions on GTFP, as shown below with the estimated parameters (∂_2 and ∂_3).

$$GTFP = \partial_0 + \partial_1 Bioregion_{it} + \partial_2 BV_{it} + \partial_3 BE_{it} + \partial_c control_{it} + \mu_i + \tau_i + \delta_{it} \text{ (Model 4-2)}$$

The patent application rate in the current year (*Ratio*) and regional share (*reg_share*) are used to present the characteristics of technological innovation (see Model 4-3). The patent application rate in the current year (*Ratio*) is the proportion of the number of patents applied for in the current year, which is relevant for assessing the transformation efficiency of scientific research and achievements (Harrahill et al., 2023). The regional share (*reg_share*) means the share of addresses of inventors in cases where an address is allocated to more than one region, therefore indicating regional cooperation (Maraut et al., 2008; Maraut and Martínez, 2014).

$$GTFP = \partial_0 + \partial_1 Bioregion_{it} + \partial_2 BV_{it} + \partial_3 BE_{it} + \partial_4 Reg\_share_{it} + \partial_5 Ratio_{it} + \partial_c control_{it} + \mu_i + \tau_i + \delta_{it} \quad \text{(Model 4-3)}$$

4.3.4 Measuring the impact of green clusters on green productivity with a staggered DiD

As bioclusters are heterogeneous entities, varying widely in structure, evolution, and goals (Zechendorf, 2011), the impact of differential types of bioclusters on regional green productivity is considered in this study. To be specific, the green clusters that work in green sectors and/or technologies are selected from the European Cluster Collaboration Platform. According to Hermans (2018; 2021), green clusters operate with the goal of sustainable development, so they can be included as bioclusters and classified into four types, namely agricultural agglomeration, green chemistry clusters, bioeconomy districts and life science clusters. There are 29 green clusters chosen from the data European Cluster Collaboration Platform.

The basic model of the SDiD is shown as below, where counties/cites with green clusters are the treatment group.

$$GTFP = \beta_0 + \beta_1 Gcluster + \beta_c control_{it} + \mu_i + \tau_i + \delta_{it} \quad \text{(Model 4-4)}$$

with dummy variable *Gcluster* to show whether county/city *i* has a green cluster or not. *Gcluster* is denoted as $Gcluster = d_t \times d_u$, where d_u determines whether they are qualified as innovative cities (yes=1, no=0), and *dt* determines whether they have already been designated as innovative cities (yes=1, no=0). Specifically, policy assigns a value of 1 to a city in year t and onward if it attains recognition as an innovative pilot city; otherwise, it receives a value of 0.

In the extended model 4-5, the value added of bioeconomy (*BV*) and the number of employees in the bioeconomy (*BE*) are introduced.

$$GTFP = \beta_0 + \beta_1 Gcluster + \beta_2 BV_{it} + \beta_3 BE_{it} + \beta_c control_{it} + \mu_i + \tau_i + \delta_{it} \qquad \text{(Model 4-5)}$$

When considering the technological innovation by adding the patent application rate in the current year (*Ratio*) and regional share (*reg_share*) in model 4-6, get the following form.

$$GTFP = \beta_0 + \beta_1 Gcluster + \beta_2 BV_{it} + \beta_3 BE_{it} + \beta_4 Ratio_{it} + \beta_5 Reg\_share_{it} + \beta_c control_{it} + \mu_i + \tau_i + \delta_{it} \qquad \text{(Model 4-6)}$$

4.3.5 Meditating model

Based on Böckerman and Ilmakunnas (2009), a mediating model is developed to estimate the indirect effect of bioclusters on GTFP. With the introduction of the mediating variable M_{it} (Equation 4-4) into model 4-3, the extended SDiD model 4-7 is shown as below.

$$M_{it} = \alpha_0 + \alpha_1 Bioregion + \alpha_c control_{it} + \mu_i + \tau_i + \delta_{it} \qquad (4\text{-}4)$$

$$GTFP = \kappa_0 + \kappa_1 Bioregion_{it} + \kappa_2 BV_{it} + \kappa_3 BE_{it} + \kappa_4 Reg\_share_{it} + \kappa_5 Ratio_{it} + \kappa_m \partial_c M_{it} + \kappa_c control_{it} + \mu_i + \tau_i + \delta_{it} \qquad \text{(Model 4-7)}$$

Where α and κ are the respective regression coefficients. Similarly, adding $M_{it}^{'}$ (Equation 4-5) into model 4-6 gives the extended SDiD, as shown in model 5-8, with vectors for the respective regression coefficients ξ.

$$M_{it}^{'} = \zeta_0 + \zeta_1 Gcluster + \zeta_c control_{it} + \mu_i + \tau_i + \delta_{it} \qquad (4\text{-}5)$$

$$GTFP = \xi_0 + \xi_1 Gcluster + \xi_2 BV_{it} + \xi_3 BE_{it} + \xi_4 Ratio_{it} + \xi_5 Reg\_share_{it} + \xi_m M_{it}^{'} + \xi_c control_{it} + \mu_i + \tau_i + \delta_{it} \qquad \text{(Model 4-8)}$$

The indirect effect of bioclusters on GTFP encompasses three distinct effects: technological, agglomeration, and structural, denoted respectively by technological innovation (*Patent*), market capacity (*MC*), and industrial structure (*ST*). Usually, the number of patents (*Patent*) is denoted as the intensity of technological innovation, while the application rate of each patent can denote the transformation efficiency of scientific research and achievement (Popp et al., 2003; Harrahill et al., 2023). The number of patents (*Patent*) is used to signify the technological effect, as patent applications can serve as indicators of both the quantity and quality of innovations within a county/city during a specific timeframe (Liu et al., 2023). The ratio of the tertiary industry to the secondary industry *(ST)* serves as an indicator of industrial upgrading, whereby a higher ratio signifies a more advanced industrial structure within the county/city. Market capacity (*MC*) is utilized to represent the agglomeration effect, given that enterprises often gravitate towards regions with robust market potential, fostering the clustering of resources within such counties/cities (Wu and Shao, 2016). *MC* is calculated using Equation 4-6.

$$MC_{it} = \frac{STGDP_{it}}{d_{it}} + \sum_{i \neq k} \frac{STGDP_{kt}}{d_{ik}}; d_{it} = \frac{2}{3}\left(\frac{area_i}{\pi}\right)^{\frac{1}{2}} \tag{4-6}$$

where MC_{it} denotes the market potential of county/city *i*. $STGDP_{it}$ and $STGDP_{kt}$ denote the output value of secondary and tertiary industries in county/city *i* and *k* respectively in year *t*. d_{it} denotes the internal distance of county/city *i* in year *t*, and $area_i$ denotes the urban area of city county/city *i*. d_{ik} is the distance between county/city *i* and *k*, calculated using latitude and longitude data.

4.3.6 Variables

Considering the positive contribution to economic output, the expected signs for *BV* and *BE* are positive (+). As the higher level of bioclusters, the more competitive the clusters are, the sign for the local level of biolcusters (*Level-1*) is expected to be negative, while for the regional and state level the signs are positive. Technological innovation in the bioeconomy is assumed to have a positive impact on regional green productivity, where the signs for the number of patents (*Patent*) and patents' transformation rate (*Ratio*) are positive, while that for regional share (*Reg_share*) is negative. In terms of the type of green clusters, all types are assumed to have a positive impact on green productivity. Among them, green chemical clusters (*Type-2*) may have the highest contribution. Similarly, upgrading the industrial structure (*Structure*), and number of De-domain (*Domain***)** rather increase the regional productivity (Dierckx and Stroeken, 1999), suggesting the signs for *Structure* and *Domain* are expected to be positive (+). The development of the Internet has a significant effect on promoting improvements to GTFP in this region and the surrounding areas, but also suggests that the long-term effect is greater than the short-term effect (Yu, 2022). Table 4.2 gives an overview of all the model variables.

Table 4.2: Descriptive statistics of variables

Name	Units	Mean	Std.Dev	Min	Max	Sign
GTFP	-	0.205	0.125	0.062	1.354	
BV	10 million Euro	1371.585	2056.334	133.294	27605.67	+
BE	10^3 persons	24.739	27.5	3.831	357.031	+
Bioregion		0.041	0.198	0	1	+
Level-1		0.004	0.065	0	1	+
Level-2		0.019	0.138	0	1	+
Level-3		0.031	0.174	0	1	+
Gcluster		0.037	0.190	0	1	+
Type-1		0.002	0.040	0	1	+
Type-2		0.007	0.084	0	1	+
Type-3		0.033	0.177	0	1	+
Patent		19.659	29.506	0	389	+

Ratio	%	0.181	0.217	0	1	+
Reg_share	%	0.664	0.310	0	1	-
Structure	%	0.520	0.327	0.037	3.994	+
Domain		27566.59	45225.02	0	630403	+

4.4 Results and analysis

4.4.1 Spatiotemporal distribution of net carbon emissions

Figure 4.3 summarizes the results for the average annual GTFP in Germany in the period 2000 to 2021. The results show an upward trend in GTFP over the study period, indicating an increasing growth in regional green productivity. However, the average value for the GTFP stays below 0.5 during the study period, showing a relatively low green productivity in Germany. Specifically, the average GTFP from 2000 to 2015 grew slowly, albeit with a slight drop in 2009 due to the delayed impact of the global financial crisis. After 2015, the average GTFP increased more rapidly, increasing from 0.21 in 2015 to 0.441 in 2021. In particular, during the period from 2018 to 2021, the GTFP grew at an even higher rate, despite the economic decline after the Covid-19 pandemic. The obtained results are not surprising, given the series of strategies from the government targeted primarily at boosting the bioeconomy to deal with the increasing climate crisis (BMBF, 2020). In addition, the COVID-19 pandemic also contributed to the reduction of carbon emissions, leading to the sharp increase of GTFP.

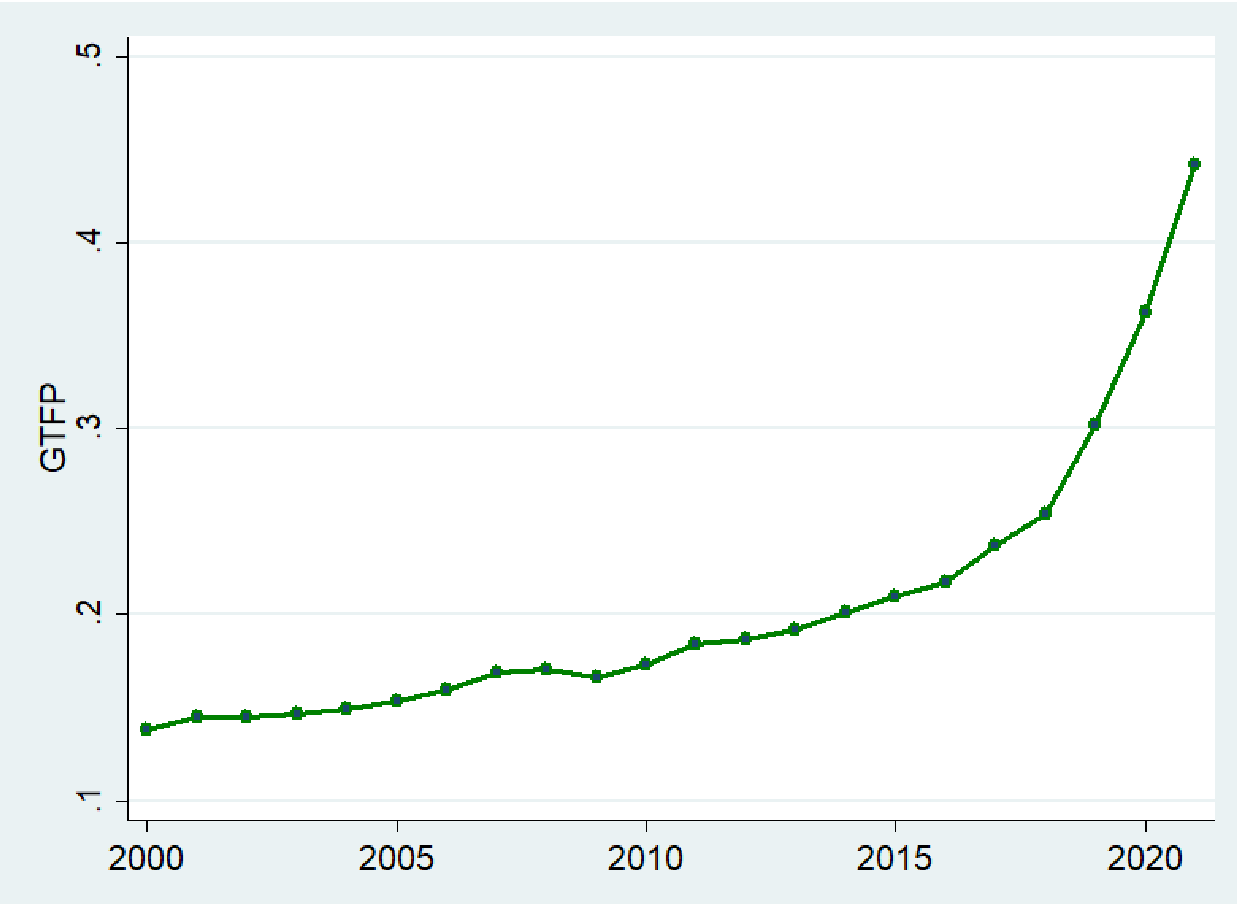


Figure 4.3: Average annual GTFP in Germany during the period 2000–2021

The spatial distribution of GTFP at the county level, as shown in Figure 4, changed in intensity over time. Western and southern counties tend to have higher GTFPs. Counties in eastern Germany (e.g. Wittenberg and Salzlandkreis) have lower but increasing GTFPs observed. Noteworthy, here, most counties surrounding developed municipalities, like Frankfurt and Munich, have large development potential and a relatively high absorbing capacity for investments from more developed economic centres). As a result, the number of counties with the lowest GTFP (<0.2) declined steadily over the observed time period. In all other categories (> 0.2), there was a clear increase trend over time. By overlapping the spatial distribution of GTFP with bioclusters, we found that most counties with bioclusters (e.g., Potsdam) tend to have higher GTFPs. And they showed spillover effects on surrounding counties from 2000 to 2021. For instance, the number of cities/counties around Düsseldorf with a GTFP greater than 0.2 gradually increased from 2000 to 2021. From 2015 to 2021, both the GTFP and its spatial spillover effects continued to grow sharply.

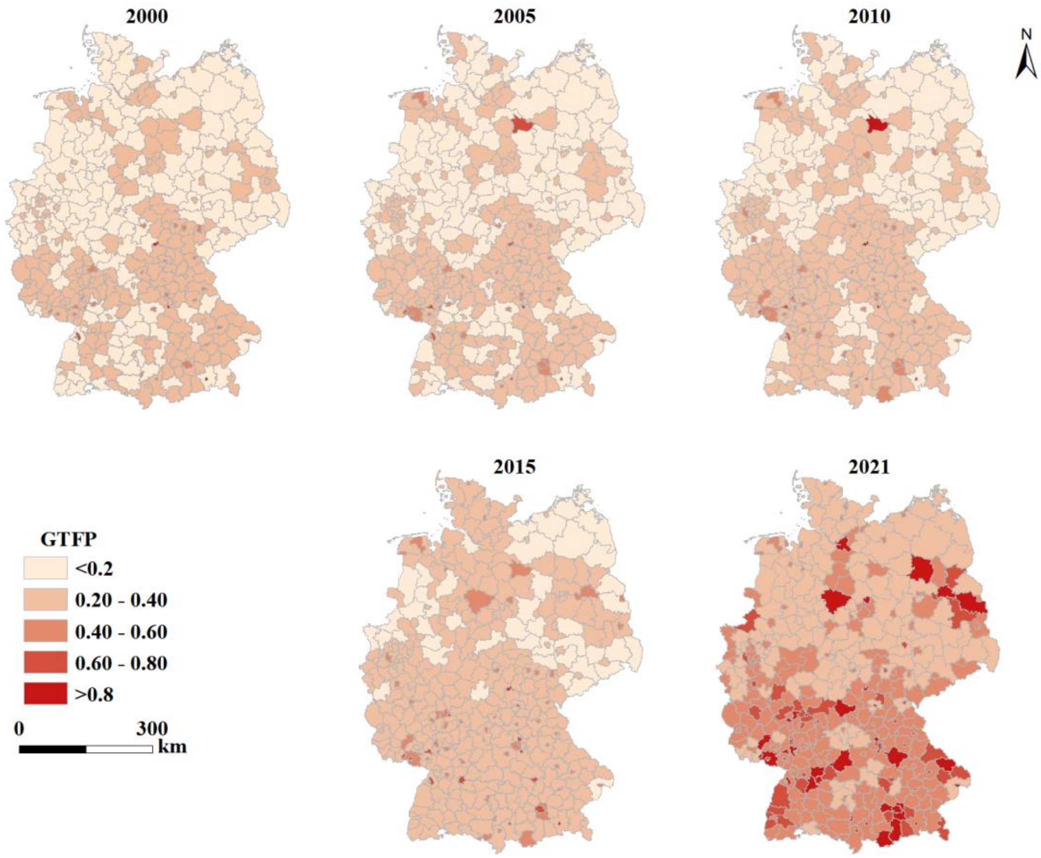


Figure 4.4: Spatial county-level distribution of GTFP in 2000, 2005, 2010, 2015, and 2021

4.4.2 SDiD regression results

Table 4.2 summarizes the results of the parameter estimations using three versions of the SDiD model, developed and described in section 4.3.2. The first model (Model 4-1) only includes the treatment group (*Bioregion*) and the control variable (*Domain*), while its extensions control correspondingly for the effects of the size of the bioeconomy (Model 4-2) and of technological innovation (Model 4-3). Varying the variables, reveals relatively insignificant effects, indicating the models' stability and robustness.

The significantly positive coefficients of *Bioregion* indicate that establishing bioclusters can improve GTFP at large. The negative coefficients of *level*, consistent with our expectation, show that the higher the level of bioclusters, the lower the *GTFP* is. This implies that a lower level of bioclusters may involve closer cooperation between firms and research institutions as bioclusters highly depend on industry-university-research integration (Youtie and Shapira, 2008; Jeong et al., 2023). When introducing the size of bioeconomy, the much higher R^2 reveals the better fitness and robustness of the model. The significantly positive effect of value added in bioeconomy on *GTFP* highlights developing the bioeconomy can promote regional green productivity. However, the number of employees in the bioeconomy, contrary to our expectation, has a negative effect on *GTFP*. This may result from technological innovation and labour division. When adding technological innovation, the number of patents in the bioeconomy surprisingly has a negative and significant effect, at the 1% significance level, on the county's *GTFP*. This implies that applying more patents can promote both the desirable output and the undesirable output. The significant and positive effect of *Ratio* on *GTFP* illustrates the faster transformation capability of patents in the bioeconomy, which can lead to higher regional green productivity. The significant and negative effect of *Reg_share* on *GTFP* presents the role of cooperation across counties in promoting *GTFP*. Compared to the findings of Graf and Broekel (2020), which indicate that the Bioregion initiative increases the network size and innovation activities only during the funding period but not afterward, the present study demonstrates a sustained impact, further emphasizing the role of patent's transformation efficiency in enhancing regional green productivity. The much significantly positive coefficients of *Ratio* and *Reg_share* suggest that technological innovation plays an important role in enhancing the local regional green productivity, thereby validating H1.

Table 4.3: Estimation results of SDiD model for Bioregions

Variables	*GTFP*		
	(Model 4-1)	(Model 4-2)	(Model 4-3)
Bioregion	0.080^{**}	0.029^{***}	0.020^{***}
	(10.910)	(4.200)	(3.090)
BV		0.0001^{***}	0.0001^{***}
		(35.310)	(34.630)
BE		-0.005^{***}	-0.005^{***}
		(-12.540)	(-12.170)
Ratio			0.075^{***}
			(17.930)
Reg_share			-0.0346^{***}
			(-8.940)
Domain	$9.44e^{-7***}$	$0\ 3.41e^{-7***}$	$3.09e^{-7***}$
	(18.830)	(7.060)	(6.590)
Fe	Yes	Yes	Yes
N	6226	6226	6226
R^2	0.043	0.146	0.146

Note: ***p<0.01, **p<0.05, *p<0.1. *Bioregion* denotes the key explanatory variable. *Fe* indicates time fixed and individual fixed. *N* indicates the total sample size. R^2 denotes the coefficient of determination.

Table 4.4 reports the results of the parameter estimation obtained using three versions of the SDID model. The positive and significant effect of green clusters on GTFP not only indicates the green clusters can promote regional green productivity but also further indicates that the establishment of bioclusters can improve GTFP as all green clusters are bioclusters in nature. The other estimated coefficients are similar to those in models 4-1, 4-2, and 4-3, implying the results are robust. These results further confirm that technological innovation can help to increase regional green productivity. Eventhough the coefficients are small, they still make sense as the units of outputs are relatively large.

Table 4.4: Estimation results of SDiD model for green clusters

Variables	*GTFP*		
	(Model 4-4)	(Model 4-5)	(Model 4-6)
Gcluster	0.052^{***}	0.020^{**}	0.018^{**}
	(5.73)	(2.51)	(2.32)
BV		0.0001^{***}	0.0001^{***}
		(42.21)	(41.69)
BE		-0.010^{***}	-0.010^{***}
		(-24.98)	(-25.03)
Ratio			0.078^{***}
			(19.65)
Reg_share			-0.032^{***}
			(-8.94)

Domain	$1.41e^{-6***}$	$3.99e^{-7***}$	$3.29e^{-7***}$
	(26.10)	(7.52)	(6.40)
Fe	Yes	Yes	Yes
N	6512	6512	6512
R^2	0.030	0.258	0.260

Note: ***p<0.01, **p<0.05, *p<0.1. *Bioregion* denotes the key explanatory variable. *Fe* indicates time fixed and individual fixed. *N* indicates the total sample size. R^2 denotes the coefficient of determination.

4.4.3 Parallel trend test

The results of the parallel trend test in Figure 4.5 reveal that the coefficients of the time dummy variables for the three years before the establishment of the Bioregion are not significant. Therefore, there is no significant difference in GTFP between the treatment and control groups. In the second year of establishing the Bioregion, the difference appears but it is not yet stable. Six years after establising the Bioregion, the coefficients began to show a significant positive and increasing trend, indicating that the bioclusters have a positive and stable effect on GTFP with a time lag. A placebo test is provided in Figure A.2 (a).

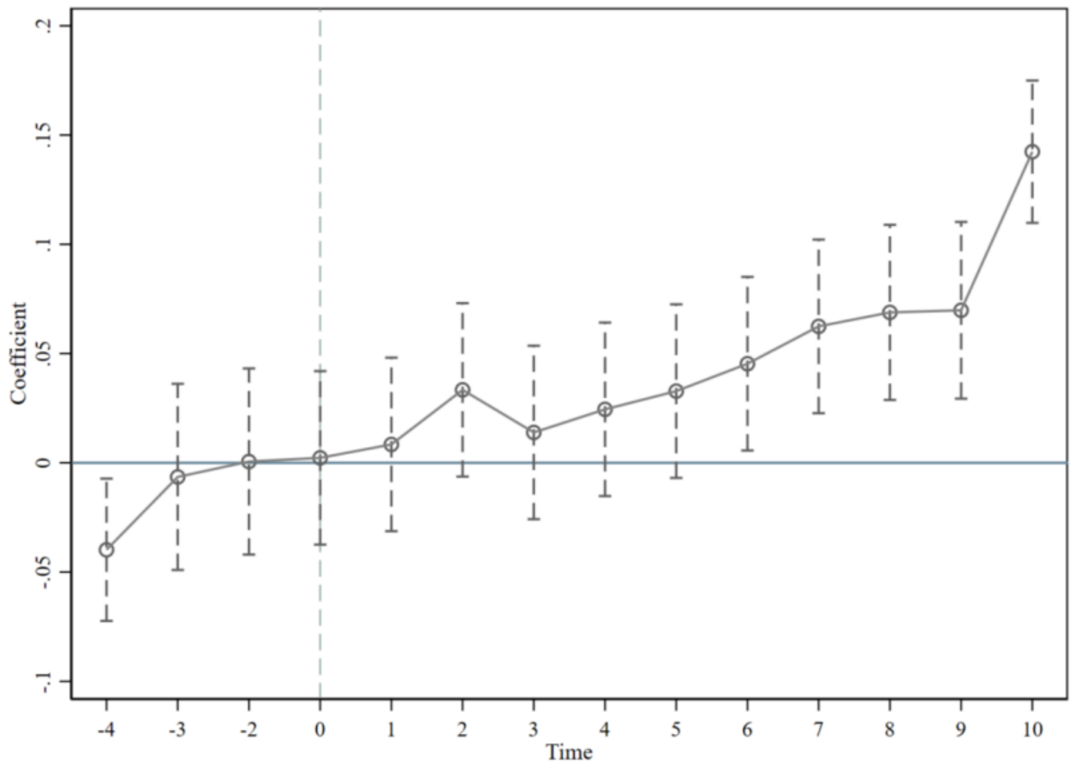


Figure 4.5: Parallel trend test for the Bioregion

Similar to the results in Figure 4.5, the results of the parallel trend test for the green clusters in Figure 4.6 show that the coefficients of the time dummy variables for the three year before policy implementation are not significant. Eight years after establishing green clusters, bioclusters start to have a significant and positive effect on GTFP. A placebo test is provided in Figure A.2 (b).

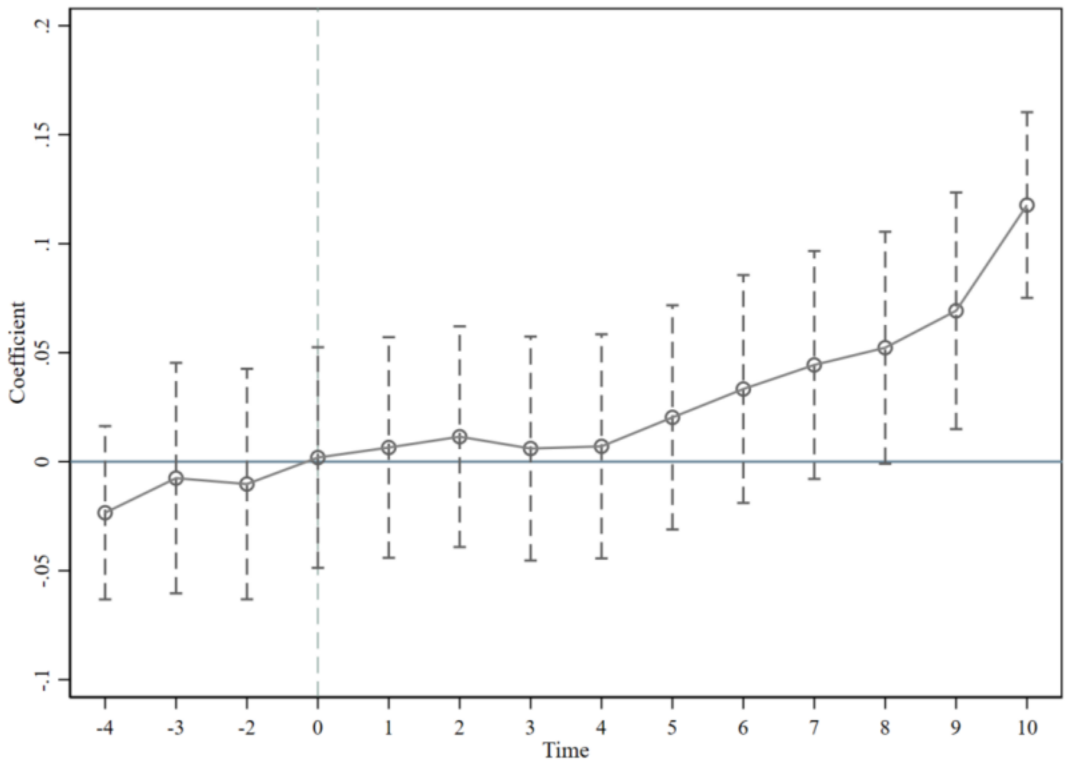


Figure 4.6: Parallel trend test for green clusters

Source: Own representation.

4.4.4 Robust analysis using PSM-SDiD

Although SDiD isolates the average treatment effect of bioclusters, the selection of bioclusters may not be random. Consequently, a multi-temporal propensity score matching (PSM)-SDiD test is conducted to match a comparable control group for the treatment group with the period-by-period matching approach from Böckerman and Ilmakunnas (2009). In this study, counties/cities are matched year by year to generate the panel data required for the regression analysis. The size of the bioeconomy, economic level, and technological innovation are used as matching variables (see Table 4.5). The effect of bioclusters on GTFP is re-estimated using SDiD after the balance of the matched data has been tested. Both estimated coefficients of the *Bioregion* and *Gcluster* remain positive and significant after performing the PSM, further confirming that establishing bioclusters can improve the GTFP. Other coefficients show similar values, indicating a robust result.

Table 4.5: PSM-SDiD regression results

Variables	*GTFP*	
Bioregion	0.020^{***}	
	(3.090)	
Gcluster		0.025^{***}
		(3.240)
BV	0.0001^{***}	0.0002^{***}
	(34.630)	(45.390)
BE	-0.005^{***}	-0.009^{***}
	(-12.170)	(-23.970)
Rate	0.075^{***}	0.071^{***}
	(17.930)	(18.150)
Reg_share	-0.035^{***}	-0.032^{***}
	(-8.940)	(-9.18)
Domain	$3.09e^{-7***}$	$6.70e^{-7***}$
	(6.590)	(12.190)
Fe	Yes	Yes

N	6226	6494
R^2	0.146	0.278

Note: ***p<0.01, **p<0.05, *p<0.1. *Bioregion* denotes the key explanatory variable. *Fe* indicates time fixed and individual fixed. *N* indicates the total sample size. R^2 denotes the coefficient of determination.

4.4.5 Mediating effects of bioclusters on GTFP

The three mediators for technological, agglomeration, and structural effects in Table 4.6 (0.008, 0.121, and -0.004, respectively) show that the agglomeration effect is much greater than the other two. It means bioclusters primarily promote GTFP by enhancing technological innovation and market capacity. Column (1) in Table 4.5 displays a positive and significant impact of bioclusters on local GTFP in the results for the SDiD base regression, providing a basis for the tests of the mediating effects (from column 2 to column 7). All the mediating effects passed the bootstrap tests. In column (3), the significant coefficients of *Bioregion* and *Patent* indicate there is a strong mediation effect (0.01), suggesting that bioclusters can promote technological innovation in the local city. Despite the coefficient of *Patent* being negative, the results from the bootstrap test confirm its validity ([0.201,0.275]). This contributes to the promotion of green production technology and pollution control technology, minimizing emissions, and consequently improving the GTFP. Thus, this finding supports H2. The mediating effect of industrial upgrading is negative because of the negative coefficient of *ST* in column (7).

Table 4.6: Mediating regression results for Bioregions

Variables	Mediating model for Bioregions						
	GTFP	*Patent*	*GTFP*	*MC*	*GTFP*	*ST*	*GTFP*
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Bioregion	0.020***	-0.236	0.022***	175.498***	-0.009*	-0.053***	0.014**

	(3.090)	(-0.220)	(3.090)	(8.07)	(-1.650)	(-5.680)	(2.170)
Patent			-0.001*** (-11.73)				
MC					0.0002*** (51.230)		
ST							-0.117*** (-12.910)
BV							
BE							
Mediating effect			0.008		0.121		-0.004
Control	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fe	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	6226	6226	6226	6226	6226	6226	6226
R^2	0.146	0.090	0.159	0.084	0.175	0.099	0.156

Note: ***p<0.01, **p<0.05, *p<0.1. *Bioregion* denotes the key explanatory variable. *Fe* indicates time fixed and individual fixed. *N* indicates the total sample size. R^2 denotes the coefficient of determination.

The three mediators for technological, agglomeration, and structural effects in Table 4.7 (-0.002, 0.03, and 0.005, respectively) show a similar result, whereby the agglomeration effect is much greater than the other two. It means bioclusters primarily promote GTFP by enhancing market capacity. Unlike the results in

Table 4.6, the coefficient of *Gcluster* in column (6) is negative. This implies that the establishment of green clusters can restrict industrial upgrading. This may be due to the external economies generated by green clusters, which boost the output value of secondary industries and increase their share in the overall economy. The coefficient of *Gcluster* in column (2) is significantly positive, indicating that green bioclusters can promote the intensity of technological innovation. However, the mediating effect of technological innovation on GTFP is negative, meaning that the force of green clusters that promote technological innovation is greater than its mediating effect through technological innovation on GTFP. These results align with the findings of Graf and Broekel (2020), who highlight the impact of Bioregion initiatives in promoting technological innovation only during the funding period. This may be because a simple financial injection into projects to support technological innovation is not able to cause the emergence of clusters for decoupling economic growth from pollution (Kamath et al., 2022).

Table 4.7: Mediating regression results for green clusters

Variables	Mediating models for green clusters						
	GTFP	*Patent*	*GTFP*	*MC*	*GTFP*	*ST*	*GTFP*
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Gcluster	0.018^{***}	3.685^{***}	0.021^{***}	133.318^{**}	-0.003	-0.044^{***}	0.013^{*}
	(2.320)	(2.630)	(2.780)	(4.98)	(-0.45)	(-3.87)	(1.70)
Patent			-0.001^{***}				
			(-13.07)				
MC					0.0002^{***}		
					(50.62)		
ST							-0.111^{***}
							(-13.03)
Mediating effect			-0.002		0.030		0.005

Control	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fe	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	6512	6512	6512	6512	6512	6512	6512
R^2	0.260	0.069	0.203	0.085	0.137	0.011	0.219

Note: ***p<0.01, **p<0.05, *p<0.1. *Bioregion* denotes the key explanatory variable. *Fe* indicates time fixed and individual fixed. *N* indicates the total sample size. R^2 denotes the coefficient of determination.

4.4.6 Heterogeneity analysis with difference-in-difference-in-differences (DDD)

In this study, the level of Bioregions and types of green clusters, are introduced to further explore the heterogeneous implications of bioclusters on regional green productivity. The DDD model is employed in the present study to identify causal effects by comparing differences in changes in outcome variables before and after the intervention between treatment and control groups. Through structuring a third dimension of the treatment group (*Bioregion*Level* and *Gcluster*Type*, respectively in this study), DDD is used to identify the heterogeneous treatment effects of intervention policies across groups. For Bioregions, three levels of Bioregions, namely local level (*Level-1*), regional level (*Level-2*), and state level (*Level-3*) are introduced. The results shown in Table 4.8 illustrate that even though all levels of Bioregions can contribute to the increase of GTFP, the regional Bioregions have a significantly positive impact on GTFP. The higher the level of the bioclusters, the lower the parameter is. This implies a lower level of bioclusters may involve a closer cooperation between firms and research institutions as bioclusters highly depend on industry–university–research integration (Youtie and Shapira, 2008; Jeong et al., 2023).

Table 4.8: Regression results of DDD model for Bioregions

Variables	*GTFP*		
*Bioregion*Level-1*	0.046		
	(1.54)		

*Bioregion*Level-2*		0.032^{**}	
		(2.91)	
*Bioregion*Level-3*			0.010
			(1.25)
BV	0.0001^{***}	0.0001^{***}	0.0001^{***}
	(35.63)	(35.38)	(35.03)
BE	-0.004^{***}	-0.004^{***}	-0.005^{***}
	(-12.09)	(-12.06)	(-12.12)
Ratio	0.076^{***}	0.076^{***}	0.076^{***}
	(18.13)	(18.04)	(18.06)
Reg_share	-0.0348^{***}	-0.035^{***}	-0.035^{***}
	(-8.99)	(-8.95)	(-8.99)
Domain	$3.23e^{-7***}$	$3.13e^{-7***}$	$3.20e^{-7***}$
	(6.91)	(6.69)	(6.83)
Fe	Yes	Yes	Yes
N	6226	6226	6226
R^2	0.142	0.144	0.141

Note: ***p<0.01, **p<0.05, *p<0.1. *Bioregion* denotes the key explanatory variable. *Fe* indicates time fixed and individual fixed. *N* indicates the total sample size. R^2 denotes the coefficient of determination.

For green clusters, three types of green clusters, namely agricultural agglomeration (*Type-1*), green chemistry clusters (*Type-2*), and bioeconomy districts (*Type-3*) are introduced to estimate the heterogeneity. The results shown in Table 4.9 illustrate that all kinds of bioclusters can promote GTFP. Among them, the higher coefficient of green chemistry clusters (*Type-2*) indicates a greater contribution. The coefficients of the other variables are quite similar, showing the results are relatively robust.

Table 4.9: Regression results of DDD model for green clusters

Variables	*GTFP*		
*Gcluster*Type-1*	0.019^{***}		
	(1.31)		
*Gcluster*Type-2*		0.077^{***}	
		(3.78)	
*Ccluster*Type-3*			0.018^{***}
			(2.66)
BV	0.0001^{***}	0.0001^{***}	0.0001^{***}
	(41.91)	(42.11)	(41.95)
BE	-0.009^{***}	-0.009^{***}	-0.009^{***}
	(-24.93)	(-25.19)	(-25.08)
Rate	0.078^{***}	0.078^{***}	0.078^{***}
	(19.65)	(19.60)	(19.69)
Reg_share	-0.032^{***}	-0.032^{***}	-0.032^{***}
	(-8.94)	(-8.88)	(-8.95)
Domain	$3.48e^{-7}$	$3.45e^{-7}$	$3.27e^{-7}$
	(6.83)	(6.78)	(6.36)
Fe	Yes	Yes	Yes

N	6512	6512	6512
R^2	0.226	0.263	0.262

Note: ***p<0.01, **p<0.05, *p<0.1. *Bioregion* denotes the key explanatory variable. *Fe* indicates time fixed and individual fixed. *N* indicates the total sample size. R^2 denotes the coefficient of determination.

4.5 Discussion and conclusions

4.5.1 Discussion

The analysis shows that the development of bioclusters, as an institutional innovation, can contribute to improving regional green productivity. The obtained results are in line with recent studies, which found that technological innovation caused by regulation policies can be a new engine to stimulate economic growth and protect the environment at the same time (Alvarez-Herranz et al., 2017; Balsalobre-Lorente et al., 2020). The results contribute to the body of the relevant literature by showing that the policy of developing bioclusters may improve the green total factor productivity directly and indirectly through mediating effects from technological innovation, factor agglomeration, and industrial upgrading. As shown by the values of coefficients in Table 4-5, both *Bioregion* (0.02^{***}) and *Gcluster* (0.025^{***}) as well as the value added of bioeconomy (0.0001^{***} and 0.0002^{***}, respectively) and patent application rate in the bioeconomy (0.075^{***} and 0.071^{***}, respectively) can significantly promote the increase of GTFP. The mediating effect of factor agglomeration is found to be the biggest, as shown in Tables 4-6 (0.121) and 4-7 (0.03).

Differing from Du and Li (2022), where the mediating effect includes government strategic leadership in addition to technological innovation and industry upgrading, this study instead considers the agglomeration effects. Specifically, the agglomeration effect is found to be the strongest mediating force when bioclusters affect GTFP. This highlights the roles of production factor flows and resource allocation in green urban efficiency, contributing new insights to the literature in this field (Rusiawan et al., 2015; Atesagaoglu et al., 2017; Liu and Xin, 2019). Compared with previous studies where technological innovation is denoted by the number of patents or R&D investment (Du and Li, 2019; Luo et al., 2022), the present analysis suggests that the regional share of patents and the ratio of patent applications that are highly linked with bioclusters can be extended to indicate the level of technological innovation. These observations allow the conclusion that an alignment of bioclusters with technological innovation, regional market capacity, and industrial structure is needed to promote green economic growth and sustainable transition to bioeconomy (Chen et al., 2021; Van Lancker et al., 2016; Wilde and Hermans, 2024).

The heterogeneity analysis shows that the impact of bioclusters on GTFP varies with the types of bioclusters. The obtained results show that all kinds of bioclusters can promote GTFP, but chemical green clusters make the greatest contribution, which is in line with recent studies, which found that green technological innovation can promote GTFP (Liu et al., 2024; Zhang and Wang, 2022). Methodologically, this study addresses the variation in treatment timing when employing DiD (Callaway and Sant'Anna, 2021) by combining SDiD and PSM in the exogeneity test and DDD in the heterogeneous analysis (Du and Li, 2022; Guo and Zhong, 2022). In this way, the mechanism and synergies behind regional green productivity, not detectable from federalor state-level data (Gurney et al., 2019; Li et al., 2020; Wang and Jiang, 2020), can be illuminated. In addition, the observed finding that a lower level of bioclusters has a larger impact on GTFP also implies that lower-level bioclusters are more efficient for improving regional GTFP. Using data at the NUTS-3 level can inform the development of tailored, regionally specific policy instruments for GTFP improvement.

4.5.2 Conclusions

In the context of the increasing demands for environmental and economic alignment in various countries worldwide, boosting the bioeconomy to improve regional productivity through technological innovation and institutional innovation is expected to be an efficient pathway towards future sustainable development. Focusing on the 401 NUTS-3 level (counties/cities) in Germany from 2000 to 2021, the study estimates the impact of bioclusters on green productivity mediated by technological innovation, industrial upgrading, and market capacity. We used a series of DiD models (SDiD, PSM-SDiD, and DDD) and mediating models, and arrived at four main conclusions.

First, for the observed period 2000 to 2021, the regional productivity of the 401 counties/cities were found to be spatially autocorrelated and exhibited clustering patterns, largely reflecting the overlap between bioclusters and regional productivity. Second, developing bioclusters, no matter as Bioregions or green clusters, has a positive effect on GTFP, both in a direct manner and indirect manner through technological innovation and market agglomeration. Third, different types of bioclusters have heterogeneous impacts on GTFP, with chemical green clusters making the greatest contribution. Furthermore, the larger the level of the bioclusters, the less contribution the bioclusters makes to GTFP. Fourth, regional GTFP can be improved through the positive effect of the value added of bioeconomy, while there are negative effects of the number of employees in the bioeconomy, regional share of patents in the bioeconomy, and the level of bioclusters.

The findings point to a high potential of establishing bioclusters to improve the regional green total factor productivity performance. This potential can be realized if policy measures account for the regional heterogeneity in economic strength and resource endowment at a possibly reasonable spatial scale. The study thus advocates for the transition to a bioeconomy, while highlighting the role of different regional drivers of GTFP. Still, due to the limited availability of some county-level data, especially for R&D investment, and sectoral diversity, the findings need to be verified by further research, which should also account for the impact of the more recent programmes for bioclusters.

5 Synthesis

5.1 Main findings

Boosting the bioeconomy through technological and institutional innovation is expected to be an efficient way to achieve future sustainable development. Facing the challenges of an increasing demand for biomass and low R&D productivity in Germany, the transition to bioeconomy requires a better understanding of its real implication on sustainable development. This dissertation, focuses on the bioeconomy of Germany and assesses the mitigation effects of technological innovation on carbon emissions and the impact of bioclusters, which are defined as a regional institutional innovation, on green total factor productivity. In this dissertation, multiple approaches and methods are used in analysing the influencing mechanisms of technological and institutional innovation in the bioeconomy, including super-efficiency SBM, system dynamics, spatial Durbin model, Staggered DiD(SDiD), PSM-SDiD and difference in difference in differences (DDD) and mediating model. The main findings of the dissertation can be summarized as follows.

First, R&D investments can effectively mitigate carbon emissions in the agricultural sector. Focusing on German agriculture, this dissertation measures the potential mitigation effect of R&D investments on agricultural carbon emissions by simulating the net agricultural carbon emissions with a consideration of the dynamic interactions in the agricultural carbon system. Using a system dynamics approach, the dynamic interactions among five subsystems during 2020 to 2050 are considered under four scenarios, where the direct effect of R&D investments on carbon emissions and indirect effect through land use management and the circular economy are investigated. The results show that R&D investments have a mitigation effect on agricultural carbon emissions both directly and indirectly; the direct effect of R&D investment is greater than the indirect effect. Given the role of R&D investment and its impacts in reducing agricultural carbon emissions, increasing the fallow land, improving the circular economy, and increasing R&D investment are rather effective strategies for lowering net carbon emissions. This provides a sustainable pathway for the transition to a plant-based bioeconomy in Germany.

Second, the forest-based bioeconomy and the associated technological innovation have enormous potential for mitigating carbon emissions directly and indirectly. The dissertation uses an extended Spatial Durbin Model and NUTS-3 level panel data to estimate the impact of the forest-based bioeconomy on carbon emissions in Germany. Intra-regional and spillover effects of technological innovation, the size of the bioeconomy, industrial upgrading, and their interactions are measured from 2000 to 2021, covering 401 counties/cities. The results show that the levels of carbon emissions in the 401 counties/cities are spatially autocorrelated and exhibit clustering patterns. Technological innovation in the forest-based bioeconomy reveals a spatially gradual diffusion from the local county/city to the periphery. This can reduce carbon emissions through industrial upgrading and increasing job opportunities in the bioeconomy in local areas and further lower carbon emissions through the negative spillover effect of industrial upgrading and the size of bioeconomy in neighbouring areas. The findings point to a high potential of a forest-based bioeconomy to improve the net emissions performance, suggesting the need for a combination approach to align the technological patents, employment population and industrial transition strategies.

Third, bioclusters, including Bioregions and green clusters, have positive effects on GTFP directly and indirectly. The dissertation uses a quasi-natural experiment, including a slew of methods, such as staggered DiD(SDiD), PSM-SDiD, and difference in difference in differences (DDD) and a mediating model to estimate the impact of establishing bioclusters on green total factor productivity (GTFP) in Germany at the NUTS-3 level. Results of regional GTFP of 401 counties/cities in Germany during 2000 to 2021 measured by the super slacks-based measure (super-efficiency SBM) are found to be spatially autocorrelated and exhibited clustering patterns, largely reflecting the overlap between bioclusters and regional productivity. The results show that developing bioclusters, both as Bioregions and green clusters, can have a positive effect on GTFP directly and indirectly through technological innovation and market agglomeration. This dissertation also discovers that different types of bioclusters have heterogeneous impacts on GTFP, with the greatest contribution being from chemical green clusters. The findings further point to win-win outcomes of developing bioclusters for both the economy and environment, encouraging support for more sustainable modes of regional development in the future, and suggesting the need for a coordinated approach to align the existing sustainability, industrial structure and bioeconomy strategies.

These findings not only add to the body of relevant literature on the bioeconomy by revealing the influencing mechanism empirically but also contribute by providing insights into the scientific and policy actions that guide the transition of bioeconomy in Germany and other countries, as detailed below.

5.2 Implications

5.2.1 Policy implications

This dissertation explores the implication of developing a bioeconomy on sustainable development by revealing the influencing mechanisms of technological and institutional innovation in the bioeconomy. The findings not only confirm that developing a bioeconomy through technological and institutional innovation is an efficient way to promote sustainable development, but also provide empirical evidences and scientific references and insights for policy makers. The dissertation illustrates that the process of the transition to bioeconomy is accompanied by consideration of the production factor flows and reallocations, as well as industrial upgrading and restructuring, and that just strengthening technological innovation (e.g. increasing R&D investment) may not be enough. In this regard, promoting the synergy of technological and institutional innovation will matter. Pilots' construction and equipped policies and facilities are encouraged to improve the synergy of technological and institutional innovation. Furthermore, the strategies promoting the transition to a sustainable bioeconomy require a comprehensive and systematic consideration, calling for multi-party cooperation (e.g. industry–university–research) and the collaboration of many departments. Even though the bioeconomy can serve as a bridge linking carbon neutrality and competitiveness, the trade-off between climate resilience and competitiveness needs to be considered in developing a bioeconomy. Some specific policy implications are shown below.

First, improving R&D investment and prioritizing the interaction between R&D investment and land use management and coupled production are required for reducing agricultural carbon emissions. The high potential of R&D investment to support net agricultural emission reduction found in this dissertation advocates the need for a transition to a sustainable plant-based bioeconomy with more R&D investment involved in agricultural carbon emissions system. The provided insights into the direct and indirect effects of R&D investment on agricultural emissions can alert policymakers to align the existing sustainability, land management (e.g. the greening of the CAP) and innovation strategies to successfully set up a route for the transition to a bioeconomy (Jantke et al., 2020; Beer and Heise, 2020).

Second, boosting the forest-based bioeconomy by increasing the number of patents in the forest-based bioeconomy, increasing the number of employees in the forest-based bioeconomy, and promoting industrial upgrading is an efficient strategy to reduce carbon emissions. The observations about the combinations of technological innovation, employees in the bioeconomy, and industrial upgrading not only highlight their overlapping effects on carbon emissions, but also call for an alignment of technological innovation with industrial upgrading and a structural change in employment for boosting the forest-based bioeconomy to reduce carbon emissions (Halonen et al., 2022; Hetemäki et al., 2022). At the same time, stronger industry–academic collaboration, such as establishing an industry–university–research regional linkage program and bioclusters (Pant et al., 2019; Ayrapetyan et al., 2022), is required for the sustainable development of a forest-based bioeconomy.

Third, tailored and regionally specific policy instruments are required to promote bioclusters. The findings about the high potential of establishing bioclusters to improve the regional green total factor productivity further prove the win–win outcomes of developing bioclusters for both the economy and environment, encouraging more sustainable modes of regional development in the future. The insights into the combined regional effects of labour division, urban development, and industrial adjustments on green productivity may alert policymakers to align the strategies on enhancing the market capacity, industrial upgrading, and developing the bioeconomy in order to successfully set up the transition to a green economy (Lee, 2020).

In that case, providing subsidies to attract small and medium-sized enterprises to enter bioclusters and promoting collaboration among research institutions, industries, and government departments are effective policy incentives for developing bioclusters. In particular, project-based R&D subsidies for enterprises within bioclusters can be more effective in fostering technological innovation and promoting regional green development.

5.2.2 Scientific implications

In addition to policy implications, this dissertation also makes a few contributions to the scientific research field in the bioeconomy. First, the simulation method we used, i.e. SD, is a promising tool for estimating net carbon emissions across various intertwining sub-sectors in agricultural systems. Using SD, this study reveals the direct and indirect effects of R&D investment on agricultural carbon emissions by simulating the dynamic interactions in the agricultural carbon system in Germany. Additionally, the effects of R&D investment on agricultural carbon emissions highlight the importance of the substitution effect of renewable bioenergy replacing fossil fuel and carbon sinks in the agricultural system, calling for a reconsideration of carbon emissions calculations.

Second, spatial dimensions and spatial method matter for estimating the impact of a forest-based bioeconomy on carbon emissions. Using an extended Spatial Durbin Model and NUTS-3 level panel data, this dissertation measures the degree and direction of intra-regional and spillover effects of technological innovation, the size of the bioeconomy, industrial upgrading, and their interactions empirically. The results advocate for spatial assessment of the mitigation effect of the forest-based bioeconomy and its spillover effects on carbon emissions on a more disaggregated scale. In this way, the mechanism and synergies behind net carbon emissions (Gurney et al., 2019; Li et al., 2020), usually not detectable from national-, state- or city-level data (cf. Feng and Chen, 2018; Zhang et al., 2020; Wang and Jiang, 2020), can be illuminated.

Last but not least, the use of multiple and innovative natural experimental approaches can be effective in estimating the impact of institutional innovation on regional green productivity. This study addresses variations in the treatment timing when employing DiD (Callaway and Sant’Anna, 2021) by combining

SDiD and PSM in an exogeneity test and DDD in heterogeneous analysis (Du and Li, 2022; Guo and Zhong, 2022). In addition, this dissertation establishes a theoretical framework to reveal the direct and indirect effects of institutional innovation on regional green productivity and empirically estimates these effects using a mediating model. The combination of quasi-natural experimental approaches and a mediating model enables a precise estimation of the impact of institutional innovation in the bioeconomy. The observed findings reveal that smaller levels of bioclusters have a larger impact on GTFP, confirming that a small scale is more efficient for improving regional GTFP.

5.3 Outlook and future work

The transition to a bioeconomy is integral to achieving climate neutrality, sustainability, and economic competitiveness in Europe, with Germany playing a pivotal and leading role. This dissertation has delved into the dynamics of technological and institutional innovations in the bioeconomy and their impacts on carbon emissions, and green productivity. However, several avenues remain open for future research to deepen our understanding and provide insights for policy formulation.

First, the data used in this dissertation are mainly secondary data at the sectoral level and NUTS-3 level. While this allows figuring out the implication of the transition to bioeconomy on sustainable development at the middle and macro levels, it fails to demonstrate agents' behaviours in the value chain of the bioeconomy. Future research should prioritize collecting primary data at the individual level from diverse stakeholders, including farmers, enterprises, and local communities, to illustrate the role of agents' behaviours in shaping the transition to sustainable bioeconomy. With the help of farm-enterprise level data obtained by field investigation, how individual farms and enterprises are adapting to and benefiting from the transition to bioeconomy shall be analysed.

Second, linking the findings to the green reform of the CAP will help in aligning national strategies with broader European goals. It has been found that the bioeconomy can reduce carbon emissions by increasing carbon sinks especially since 2015 when EFA was introduced to the CAP. The trade-off between ecological compensation and non-food biomass supply in the decision making of farmers and their impacts on the structural change of agriculture should be measured in the future. Adding farmers' behaviours under the transition to bioeconomy into the green reform of the CAP will facilitate a more cohesive and effective bioeconomic transition, but also promote a unified approach to sustainable development.

Third, comparative studies between Germany and other countries with different bioeconomic strategies will be useful and yield valuable insights into best practices and potential pitfalls. This dissertation mainly focuses on the case of Germany, the leading country in promoting bioeconomy. However, many transition countries, like China and India, have launched bioeconomy strategies. Specifically, the bioeconomy in China got off to a late start and had a relatively small scale, but developed rapidly (the average annual growth rate has exceeded 20%). Up to 2018, China is the third largest bioethanol producer (2050 thousand tons in 2018) in the world after the United State (44100 thousand tons in 2018) and Brazil (21280 thousand ton in 2018) (FAO, 2018). In particular, there are 11 provinces that have been selected as pilot areas to promote the production and application of bioethanol. Therefore, a comparison between Germany and China may provide heterogeneous experiences for other countries around the world.

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Appendix

Table A. 1: Main variables and parameter indexes in the SD model during 2000-2050

Subsystem	Variable	Abbreviation	Unit	Equations
Socioeconomic subsystem	Gross domestic product	GDP	Mill. Euro	GDP-1+GDP-2+GDP-3
	Primary industry GDP	GDP-1	Mill. Euro	EXP(-1.7991*LN(Alabor)+0.5956* LN(Ainvest)- 0.4973* LN(AR&D)+21.7535) (R^2==0.7795, p-value=0.001)
	Secondary industry GDP	GDP-2	Mill. Euro	EXP(-2.0605*LN(Patents)+0.2977* LN(Biorefinery)+32.389) (R^2==0.5913, p-value=0.005)
	Tertiary industry GDP increment rate coefficient	GDP-3IRC	--	WITH LOOKUP (Time, [(2001,-1)-(2050,1)], (2001,0.0421), (2002,-0.0271), (2003,0.0083), (2004,0.0227), (2005,0.0134), (2006,0.0317), (2007,0.0345), (2008,0.0239), (2009,-0.0086), (2010,0.0164), (2011,0.0425), (2012,0.0174), (2013,0.0324), (2014,0.0399), (2015,0.0345), (2016,0.0295), (2017,0.0396), (2018,0.0349), (2019,0.0369))
	Tertiary industry GDP increment rate	GDP-3IR	%	GDP-3IRC(Time)
	Tertiary industry GDP increment	GDP-3I	Mill. Euro	GDP-3*GDP-3IR
	Social investment	Invest	Mill. Euro	INTEG (Invest*InvestR, 16844.8)
	Increase of social investment rate	InvestR	%	WITH LOOKUP (GDP/Pop, [(0,-1)-(100,1)], (24.0757,0.0015),(24.3586, -0.0919), (24.4825,-0.0563), (25.1630,-0.0746), (25.4455,0.0150), (26.5724,-0.0228), (27.7537,-0.0238), (28.3487,0.1667), (27.2459,0.2805), (28.3487,0.1667), (28.7191,-0.21497), (28.7191, -0.2150), (30.6695, 0.1696), (31.3688,-0.0254), (32.5659,0.0078), (33.4158, -0.0511), (34.2742,0.0393), (35.5249, 0.1020), (36.4885,0.1143))
	Population	Pop	10^3	INTEG (Pop*PopR, 81457)
	Population increment rate	PopR	%	WITH LOOKUP (Time, [(2001,0)-(2050,1)], (2001, 0.0007), (2002,0.007), (2003,-0.0004), (2004,-0.0011), (2005,-0.0015), (2006,-0.002), (2007,-0.0022), (2008,-0.0028), (2009,-0.0035), (2010,-0.0025), (2011,-0.0006), (2012, 0.0021), (2013,0.0023), (2014,0.0042), (2015, 0.0066), (2016,0.0109), (2017, 0.0038), (2018,0.0027), (2019,0.0022))
	Ratio of Agricultural GDP to GDP	RGDP	%	WITH LOOKUP (Time, ([(2001,0)-(2050,1)], (2000,0.011), (2001,0.012), (2002,0.01), (2003,0.0092), (2004,0.0105), (2005,0.008), (2006,0.0082), (2007,0.0087), (2008,0.0093), (2009,0.0078), (2010,0.0089), (2011,0.0101), (2012,0.0094), (2013,0.0105), (2014,0.01), (2015,0.0076), (2016,0.0078), (2017,0.0092), (2018,0.0074), (2019,0.008))

Subsystem	Variable	Abbreviation	Unit	Equations
	Agricultural investment	Ainvest	Mill. Euro	Invest*RGDP
Land use subsystem	Farmland	Farm	ha	INTEG (FarmI, 16844800)
	Farmland increment rate coefficient	FarmIRC	--	WITH LOOKUP (Time, [(2001,-1)-(2050,1)], (2001,-0.0011), (2002,-0.0039), (2003,0.0021), (2004,0.0010), (2005,0.0012), (2006,-0.0050), (2007,0.0002), (2008,-0.0018), (2009,-0.0021), (2010,0.0111), (2011,0.0010), (2012,-0.0032), (2013,0.0020), (2014,0.0014), (2015,0.0002), (2016,-0.0040), (2017,0.0018), (2018,-0.0026), (2019,0.0013))
	Farmland increment rate	FarmIR	%	FarmIRC(Time)
	Farmland increment	FarmI	ha	Farm* FarmIR
	Arable land	Arab	ha	Population*ArabR(Time)
	Average arable land per person	ArabR	ha/person	WITH LOOKUP (Time, [(2000,0)-(2050,1), (2000,0.144905), (2001,0.144915), (2002,0.144535), (2003,0.145028), (2004,0.146075), (2005,0.146346), (2006,0.146183), (2007,0.146644), (2008,0.147745), (2009,0.148418), (2010,0.147564), (2011,0.147595), (2012,0.147191), (2013,0.147371), (2014, 0.146669), (2015,0.145428), (2016,0.142843), (2017,0.142403), (2018,0.141529), (2019,0. 141005))
	Grassland	Grass	ha	Farm-Arab
	Fallow land	FL	ha	Arab*FLR(Time)
	Fallow land ratio	FLR	%	WITH LOOKUP (Time, [(2000,0)-(2050,1)], (2000,0.0697), (2001,0.0719), (2002,0.0708), (2003,0.0794), (2004,0.0659), (2005,0.0667), (2006,0.0625), (2007,0.0546), (2008,0.0259), (2009,0.0206), (2010,0.0213), (2011,0.0193), (2012,0.0183), (2013,0.0168), (2014,0.0159), (2015,0.0262), (2016,0.0264), (2017,0.0270), (2018,0.0307), (2019,0.0299), (2050, 0.05)
	Ecological Focus Area	EFA	ha	IF THEN ELSE (100000<=Fallowland: AND: Fallowland<=1e+06: AND: 2000<= Time: AND:Time<=2033, EXP(1.7386*LN(Fallowland)+0.125*Time-260.74), 6e+06) (R^2=0.8731, p-value=0.000)
	Greenland	Green	ha	Grass+FL+EFA
	Carbon sink form land	CS-1	Tons	0.191*Green
	Carbon sink from plants	CS-2	Tons	Plant-1*0.4144/0.45+ Plant-2*0.4144/0.45+ Plant-3*0.4709/0.4+ Plant-4*0.4709/0.4+ Plant-5*0.4072/0.7+ Plant-6*0.4226/0.7+ Plant-7*0.45/0.25
	Carbon sink	CS	Tons	CS-1+CS-2
Agricultural production system	Wheat	Plant-1	10^3tons	INTEG (Plant-1I, 21622)
	Wheat increment rate	Plant-1R	%	WITH LOOKUP (Time,[(2000,-1)-(2050,1)],(2001,0.0562), (2002,-0.0885), (2003, -0.748), (2004,0.3202), (2005,-0.682), (2006,-0.0534), (2007,-0.7134), (2008,0.2478), (2009,-0.0307), (2010,0.0559), (2011,-0.0421), (2012,-0.0164), (2013,0.1165), (2014,0.1106), (2015,-0.0445), (2016,-0.0786), (2017,0.0007), (2018,-0.1723), (2019,0.1381), (2020,-0.03868), (2050,0.01))

Subsystem	Variable	Abbreviation	Unit	Equations
	Wheat increment	Plant-1I	10^3tons	Plant-1*Plant-1R(Time)
	Barley	Plant-2	10^3tons	INTEG (Plant-2I, 12106)
	Barley increment rate	Plant-2R	%	WITH LOOKUP (Time,[(2000,-1)-(2050,1)],(2001,0.1147), (2002,-0.1902), (2003, -0.0304), (2004,0.2262), (2005,-0.1061), (2006,0.0304), (2007,-0.1323), (2008,0.1524), (2009,0.0268), (2010,-0.1596), (2011,-0.1543), (2012,0.1897), (2013,-0.0045), (2014,0.1178), (2015, 0.0058), (2016,-0.0773), (2017,0.0114), (2018,-0.1169), (2019,0.2094), (2020,-0.0638) , (2050,0.01))
	Barley increment	Plant-2I	10^3tons	Plant-2*Plant-2R(Time)
	Maize	Plant-3	10^3tons	INTEG (Plant-3I, 3324)
	Maize increment rate	Plant-3R	%	WITH LOOKUP (Time,[(2000,-1)-(2050,1)],(2001,0.0545), (2002,-0.0665), (2003, -0.1027), (2004,0.2522), (2005,-0.0279), (2006,-0.2114), (2007,0.1829), (2008,0.3405), (2009,-0.1134), (2010,-0.0696), (2011,0.2308), (2012,0.0639), (2013,-0.2045), (2014,0.1721), (2015,-0.2273), (2016,0.0113), (2017,0.1319), (2018,-0.2647), (2019,0.0960), (2020,0.0578) , (2050,0.03))
	Maize increment	Plant-3I	10^3tons	Plant-3*Plant-3R(Time)
	Silage maize	Plant-4	10^3tons	INTEG (Plant-4I, 52006)
	Silage maize increment rate	Plant-4R	%	WITH LOOKUP (Time,[(2000,-1)-(2050,1)],(2001,-0.0348), (2002,-0.7836), (2003,3.1018), (2004,0.2298), (2005,0.0488), (2006,-0.0760), (2007,0.3029), (2008,0.0253), (2009,0.0367), (2010,-0.0191), (2011,0.3415), (2012,-0.0207), (2013,-0.1745), (2014,0.2678), (2015,-0.1208), (2016,0.0558), (2017,0.0802), (2018,-0.2210), (2019,0.1188), (2020,0.0868) , (2050,0.2))
	Silage maize increment	Plant-4I	10^3tons	Plant-4*Plant-4R(Time)
	Sugar beet	Plant-5	10^3tons	INTEG (Plant-5I,27870)
	Sugar beet increment rate	Plant-5R	%	WITH LOOKUP (Time,[(2000,-1)-(2050,100)],(2001,-0.1127), (2002,0.1251), (2003, -0.1476), (2004,0.1452), (2005,-0.0690), (2006,-0.1834), (2007,0), (2008,0.1141), (2009,0.1268), (2010,-0.0960), (2011,0.2623), (2012,-0.0639), (2013,-0.1755), (2014,0.3031), (2015,-0.2412), (2016,0.1296), (2017,0.3358), (2018,-0. 2310), (2019,0.1350), (2050,0.02))
	Sugar beet	Plant-5I	10^3tons	Plant-5*Plant-5R(Time)

Subsystem	Variable	Abbreviation	Unit	Equations
	increment			
	Potato	Plant-6	10^3tons	INTEG (Plant-6I, 13193)
	Potato increment rate	Plant-6R	%	WITH LOOKUP (Time,[(2000,-1)-(2050,100)],(2001,-0.1281), (2002,-0.0338), (2003, -0.1078), (2004,0.3155), (2005,-0.1089), (2006,-0.1370), (2007,0), (2008,0.1334), (2009,0.0276), (2010,-0.1318), (2011,0.1670), (2012,-0.0989), (2013,-0.0934), (2014,0.2003), (2015,-0.1066), (2016,0.0388), (2017,0.0880), (2018,-0.2388), (2019,0.1884), (2020,0.0894) , (2050,0.01))
	Potato increment	Plant-6I	10^3tons	Plant-6*Plant-6R(Time)
	Rapeseed	Plant-7	10^3tons	INTEG (Plant-7I, 3527)
	Rapeseed increment rate	Plant-7R	%	WITH LOOKUP (Time,[(2000,-1)-(2050,100)],(2001,0.1659), (2002,-0.0732), (2003, -0.0669), (2004,0.4727), (2005,-0.0443), (2006,0.0583), (2007,0), (2008,-0.0300), (2009,0.2240), (2010,-0.0956), (2011,-0.3267), (2012,0.2551), (2013,0.2005), (2014,0.0816), (2015,-0.1977), (2016,-0.0867), (2017,-0.0669), (2018,-0.1399), (2019,-0.2305), (2020,0.2439) , (2050,0.02))
	Rapeseed increment	Plant-7I	10^3tons	Plant-7*Plant-7R(Time)
	Output of plants	Output-1	10^3tons	Plant-1+ Plant-2+ Plant-3+ Plant-4+ Plant-5+Plant-6+ Plant-7
	Irrigation area	Irrigation	ha	0.031*Arab
	Ploughing area	Plough	ha	INTEG (PloughI, 823188)
	Ploughing area increment	PloughI	ha	WITH LOOKUP (Arab,[(0,-1000)-(35702000,1000)],(11813000,27.012), (11790910,-15.631), (11826880, 104.1008), (11898660, -154.277), (11903340,9.3938), (11866100,-52.6862), (11877000,-92.9), (11932500,-338.7), (11945100,-63.9), (11847000,6.8), (11874100,-23.7), (11834000,-14.1), (11876000,-15.6), (11869200,-10.4), (11846400,121.6), (11771900,0.189), (11771900, 7.211), (11730900,42.2), (11731700,-9.7))
	Fertilizer	Fert	tons	INTEG (FertI, 3694499)
	Fertilizer increment rate	FertIR	%	WITH LOOKUP (Time,[(2000,-1)-(2050,1)],(2001,-0.1102), (2002,-7.65E-05), (2003, -0.0293), (2004,0.0031), (2005,-0.0361), (2006,-0.0285), (2007,0.0255), (2008,0.0911), (2009,-0.1489), (2010,0.0217), (2011,0.1429), (2012,0.0088), (2013,0.0157), (2014,0.0794), (2015,0.0092), (2016,-0.1002), (2017,0.004), (2018,0.0069), (2019,-0.0495))
	Fertilizer increment	FertI	tons	Fert* FertIR (Time)
	Pesticide	Pestic	tons	EXP(0.6569*LN(Profit) +3.5412) (R^2=0.8502, p-value=0.000)
	Cattle	Cattle	1000	INTEG (CattleI, 14537.93)

Subsystem	Variable	Abbreviation	Unit	Equations
	Cattle increment rate	CattleIR	%	WITH LOOKUP (Time,[(2000,-1)-(2050,1)],(2001,0.0448), (2002,-0.0421), (2003, -0.0246), (2004,-0.0328), (2005,-0.0122), (2006,-0.022), (2007,-0.0048), (2008,0.0223), (2009,-0.0019), (2010,-0.0185), (2011,-0.014), (2012,-0.0017), (2013,0.0143), (2014,0.0044), (2015,-0.0084), (2016,-0.0134), (2017,-0.0149), (2018,-0.027), (2019,-0.0259))
	Cattle increment	CattleI	1000	Cattle* CattleIR(Time)
	Sheep	Sheep	1000	INTEG (SheepI, 2743.304)
	Sheep increment rate	SheepIR	%	WITH LOOKUP (Time,[(2000,-1)-(2050,1)],(2001,0.0101), (2002,-0.0179), (2003, -0.009), (2004,-0.0061), (2005,-0.0264), (2006,-0.031), (2007,-0.0086), (2008,-0.0398),(2009,-0.0357), (2010,-0.1111), (2011,-0.2064), (2012,-0.0101), (2013,-0.0433),(2014,-0.0196), (2015,-0.0131), (2016,-0.0035), (2017,-0.0002), (2018,-0.0026),(2019,-0.0085))
	Sheep increment	SheepI	1000	Sheep* SheepIR(Time)
	Pig	Pig	1000	INTEG (PigI, 25633.36)
	Pig increment rate	PigIR	%	WITH LOOKUP (Time,[(2000,-1)-(2050,1)],(2001,0.0059), (2002,0.0124), (2003, 0.0089), (2004,-0.0256), (2005,0.0467), (2006,-0.0126), (2007,0.0228), (2008,-0.0162), (2009,0.0098), (2010,-0.0017), (2011,0.0186), (2012,0.0339), (2013,-0.007), (2014,0.0073), (2015,-0.0242), (2016,-0.01), (2017,0.0074), (2018,-0.0411), (2019,-0.0196))
	Pig increment	PigI	1000	Cattle* CattleIR(Time)
	Number of livestock	Output-2	1000	Cattle+Sheep+Pig
	Labor in agriculture	Alabor	1000	INTEG (AlaborI, 25633.36)
	Alabor increment rate	AlaborIR	%	WITH LOOKUP (Time,[(2000,-1)-(2050,1)],(2001,-0.0073), (2002,-0.0074), (2003, -0.0074), (2004,-0.0103), (2005,-0.0104), (2006,-0.0098), (2007,-0.0099), (2008,-0.0405), (2009,-0.0422), (2010,-0.044), (2011,-0.024), (2012,-0.0245), (2013,-0.0252), (2014,-0.0263), (2015,-0.027), (2016,-0.0277))
	Alabor increment	AlaborI	1000	Alabor * AlaborIR(Time)
	Agricultural profit	Profit	Mill. Euro	EXP(0.3561*LN(Output-1)+0.2682*LN(AR&D)+4.8758) (R^2=0.8512, p-value=0.000)
	Carbon emissions from planting	CE-1	Tons	0.8956*Fertilizer+266.48*Irrigation/1000+3.126*Plough/1000+4.9341*Pestic

Subsystem	Variable	Abbreviation	Unit	Equations
	Carbon emissions from livestock	CE-2	Tons	415.93*Cattle+35.1819*Sheep+34.091*Pig
	Carbon emissions	CE	Tons	CE-1+CE-2
Coupled subsystem	Agricultural residues	AR	tons	Plant-1*1.42+ Plant-2*1.42+ Plant-3*1.42+ Plant-4*1.42+ Plant-7*2.05
	Animal manure	AM	tons	0.07*Cattle/2+0.07*Sheep/2+0.06*Pig/2
	Waste for biogas	Waste	tons	AR*Share of waste
	Share of agricultural waste for biogas	Share of waste	%	SMOOTH(0.4, -0.0001*Time)
	Agricultural wastes for biorefinery production	Biorefinery	tons	AR*(1-Share of waste)
	Biogas production	Biogas	Mio. kWh	IF THEN ELSE (0<"R&Dvest":AND:"R&Dvest"<=70000, EXP(6.3519*LN(Animal manure) +11.5097*LN("R&Dvest")-0.6381*LN(Waste for biogas)-155.922), EXP(2.7776*LN(Animal manure)+1.0145*LN("R&Dvest")-0.1158*LN(Waste for biogas)-19.8757)) (R^2=0.9412, 0.8257; p-value=0.000, 0.053)
	Carbon reduction	CR	tons	Biogas*(825-133.1)/825*100
Innovation subsystem	R&D in agriculture	AR&D	Mill. Euro	INTEG (AR&DI* AR&D, 313.5)
	Increase rate of R&D in agriculture	AR&DI	%	WITH LOOKUP (AR&DR*R&Dvest,[(0,-1)-(10000,1)], (1343.5359, 0.02105), (1400.8330,0.0125), (1472.6282, 0.03363), (1406.5830,-0.0863), (1404.7186,0.0131), (1552.5295,0.0761), (1772.6756,0.1577), (2269.2674,0.4012), (2414.7095,0.0813), (2425.7134,-0.0093), (2626.3765,0.0952), (2382.7774,-0.0190), (2540.4166,0.0053), (2620.0314,0.0195), (2766.1400,0.0796), (31535.3337,0.1242), (3238.0567,-0.0082), (3779.1876,0.2548))
	Share of agricultural R&D in total R&D	AR&DR	%	WITH LOOKUP (Time,[(2000,-1)-(2050,1)], (2000, 0.0295), (2001,0.0285), (2002,0.0289), (2003, 0.0299), (2004,0.0281), (2005,0.0278), (2006,0.0291), (2007,0.0275), (2008,0.0296), (2009,0.0378), (2010,0.0384), (2011,0.0357), (2012,0.037),(2013,0.0332), (2014,0.0335), (2015,0.0329), (2016,0.0333), (2017,0.0348), (2018,0.0342), (2019,0.0383), (2030, 0.05), (2050,0.05))
	Research and	R&Dvest	Mill. Euro	R&DR(Time)*GDP

Subsystem	**Variable**	**Abbreviation**	**Unit**	**Equations**
	development investment			
	Share of R&D investment in GDP	R&DR	%	WITH LOOKUP (Time,[(2000,-1)-(2050,1)], (2000, 0.0241), (2001,0.024), (2002,0.0244), (2003, 0.0247), (2004,0.0244), (2005,0.0244), (2006,0.0247), (2007,0.0246), (2008,0.0262), (2009,0.0274), (2010,0.0273), (2011,0.0281), (2012,0.0288),(2013,0.0284), (2014,0.0288), (2015,0.0293), (2016,0.0294), (2017,0.0307), (2018,0.0313), (2019,0.0318), (2050, 0.06))
	R&D staff	R&Dstaff	1000	WITH LOOKUP (Time,[(2000,-1)-(2050,1)], (2000, 0.0241), (2001,0.024), (2002,0.0244), (2003, 0.0247), (2004,0.0244), (2005,0.0244), (2006,0.0247), (2007,0.0246), (2008,0.0262), (2009,0.0274), (2010,0.0273), (2011,0.0281), (2012,0.0288),(2013,0.0284), (2014,0.0288), (2015,0.0293), (2016,0.0294), (2017,0.0307), (2018,0.0313), (2019,0.0318), (2050, 0.06))
	The number of patents	Patents	1000	EXP(-0.2115*LN(R&Dstaff)+13.2032) (R^2=0.6451, p-value=0.000)
Net carbon emissions		NCE	tons	CE-CS-CR

Note: The figures changed for different scenario analysis are in blue.

Table A. 2: Scenario design

Scenario	Schemes	Parameters
Base scenario	-	Same as 2019
Scenario 1-land effect	Increase the increment ratio of follow land to 0.05 in 2050	FLR (2020, 0.05) (2050, 0.05)
Scenario 2-structure effect	2-1 Increase agricultural biomass	Plant-1R (2020, 0.01) (2050,0.01); Plant-2R (2020, 0.01) (2050,0.01); Plant-3R (2020, 0.03) (2050,0.03); Plant-4R (2020, 0.02) (2050,0.2); Plant-5R (2020, 0.02) (2050,0.02); Plant-6R (2020, 0.01) (2050,0.01); Plant-7R (2020, 0.02) (2050,0.02)
Scenario 3-techological effect	3-1 Increase the share of agricultural R&D to 0.05 since 2030	AR&DR (2020, 0.05), (2050,0.05)
	3-2 Increase share of R&D investment in GDP to 0.06 in 2050	R&DR (2020, 0.06), (2050, 0.06)
	3-3 Increase both AR&DR and R&DR	AR&DR (2020, 0.05), (2050,0.05); R&DR (2020, 0.06), (2050, 0.06)
Scenario 4- combined effect	Increase the increment ratio of follow land to 0.05 in 2050 Increase agricultural biomass Increase both AR&DR and R&DR	FLR (2020, 0.05) (2050, 0.05); Plant-1R (2020, 0.01) (2050,0.01); Plant-2R (2020, 0.01) (2050,0.01); Plant-3R (2020, 0.03) (2050,0.03); Plant-4R (2020, 0.02) (2050,0.2); Plant-5R (2020, 0.02) (2050,0.02); Plant-6R (2020, 0.01) (2050,0.01); Plant-7R (2020, 0.02) (2050,0.02); AR&DR (2020, 0.05), (2050,0.05); R&DR (2020, 0.06), (2050, 0.06)

Table A. 3: Biocluster classification at the 3 digit level

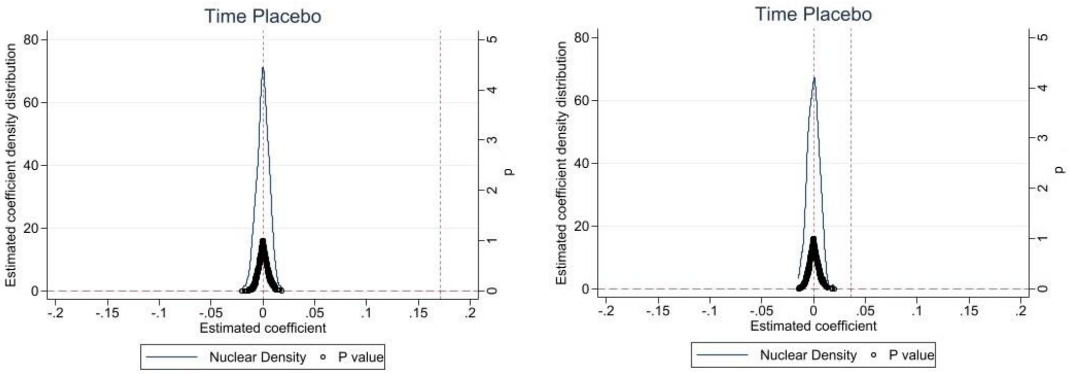
Sector (3 digit)	Fields description	Types of bioclusters
A01	Agriculture; Forestry; Animal Husbandry; Hunting; Trapping; Fishing	AA
A22-23, A24	Baking; Edible Doughs; Butchering; Meat Treatment; Processing Poultry or Fish; tobacco; Cigars; Cigarettes; Smokers' Requisites	BD
A23	Foods or Foodstuffs; their Treatment, not Covered by Other Classes	MP
A41-47	Wearing Apparel; Headwear; Footwear; Haberdashery; Jewellery; Hand or Travelling Articles; Brushware; Furniture; Domestic Articles or Appliances; Coffee Mills; Spice Mills; Suction Cleaners in General	BD
A61	Medical or Veterinary Science; Hygiene	LC
A62-63	Life-Saving; Fire-Fighting; Sports; Games; Amusements	MP
B01, B03-07	Physical or Chemical Processes or Apparatus in General; Separation of Solid Materials Using Liquids or Using Pneumatic	GC

	Tables or Jigs; Magnetic or Electrostatic Separation of Solid Materials From Solid Materials or Fluids; Separation by High-Voltage Electric Fields; Centrifugal Apparatus or Machines for Carrying-Out Physical or Chemical Processes; Spraying or Atomising in General; Applying Liquids or Other Fluent Materials to Surfaces, in General; Generating or Transmitting Mechanical Vibrations in General; Separating Solids From Solids; Sorting	
B02	Crushing, Pulverising, or Disintegrating; Preparatory Treatment of Grain for Milling	MP
B08-09	Cleaning; Disposal of Solid Waste; Reclamation of Contamined Soil Soil	MP
B21-28	Mechanical Metal-Working Without Essentially Removing Material; Punching Metal; Casting; Powder Metallurgy; Machine tools; Metal-Working not otherwise provided for; Grinding; Polishing; Hand tools; Portable Power-Driven tools; Manipulators; Hand Cutting tools; Cutting; Severing; Working or Preserving Wood or Similar Material; Nailing or Stapling Machines in General; Working Cement, Clay, or Stone	MP/BD
B29	Working of Plastics; Working of Substances in A Plastic State, in General	GC
B30	Presses	BD
B31-33	Making Articles of Paper, Cardboard or Material; Worked in A Manner Analogous to Paper; Working Paper, Cardboard or Material Worked in A Manner Analogous to Paper; Layered Products; Additive Manufacturing Technology	GC
B41-44	Printing; Lining Machines; Typewriters; Stamps; Bookbinding; Albums; Files; Special Printed Matter B42Bpermanently Attaching together Sheets, Quires or Signatures; Writing or Drawing Implements; Bureau Accessories B43Kimplements for Writing or Drawing; Decorative Arts	MP/BD
B60-64, B66-68	Vehicles in General; Railways; Land Vehicles for Travelling otherwise Than On Rails B62Bhand-Propelled Vehicles, e.g. Hand Carts, Perambulators; Sledges; Ships or Other Waterborne Vessels; Related Equipment; Aircraft; Aviation; Cosmonautics; Hoisting; Lifting; Hauling; Opening, Closing {or Cleaning} Bottles, Jars or Similar Containers; Liquid Handling; Saddlery; Upholstery	MP/BD
B65	Conveying; Packing; Storing; Handling Thin or Filamentary Material	GC
B81-82	Microstructural Technology; Nanotechnology	LC
C01	inorganic Chemistry	LC
C02-04	Treatment of Water, Waste Water, Sewage, or Sludge; Glass; Mineral or Slag Wool; Cements; Concrete; Artificial Stone; Ceramics; Refractories	MP/BD
C05-11	Fertilisers; Manufacture thereof; Explosives; Matches; organic Chemistry; organic Macromolecular Compounds; their Preparation or Chemical Working-Up; Compositions Based thereon; Petroleum, Gas or Coke industries; Technical Gases; Containing Carbon Monoxide; Fuels; Lubricants; Peat; Animal And Vegetable Oils, Fats, Fatty Substances And Waxes; Fatty Acids therefrom; Detergents; Candles	GC
C12	Biochemistry; Beer; Spirits; Wine; Vinegar; Microbiology; Enzymology; Mutation or Genetic Engineering	LC

C13-14	Sugar industry; Skins; Hides; Pelts; Leather	MP/BD
C21-23, C25	Metallurgy of Iron C21Bmanufacture of Iron or Steel; Metallurgy; Ferrous or Non-Ferrous Alloys; Treatment of Alloys or Non-Ferrous Metals; Coating Metallic Material; Coating Material With Metallic Material; Chemical Surface Treatment; Diffusion Treatment of Metallic Material; Coating by Vacuum Evaporation, by Sputtering, by Ion Implantation or by Chemical Vapour Deposition, in General; inhibiting Corrosion of Metallic Material or incrustation in General; Electrolytic or Electrophoretic Processes; Apparatus therefor	MP/BD
C30	Crystal Growth	MP
C40	Combinatorial Chemistry C40Bcombinatorial Chemistry; Libraries, e.g. Chemical Libraries	GC
D01	Natural or Artificial Threads or Fibres; Spinning	GC
D02-10	Yarns; Mechanical Finishing of Yarns or Ropes; Warping or Beaming; Weaving; Braiding; Lace-Making; Knitting; Trimmings; Non-Woven Fabrics; Sewing; Embroidering; Tufting; Treatment of Textiles or the Like; Laundering; Flexible Materials not otherwise provided for Ropes; Cables Other Than Electric; Indexing Scheme Associated With Sublasses of Section D, Relating to Textiles	BD
D21	Paper-Making; Production of Cellulose	GC
E01-06, E21	Construction of Roads, Railways, or Bridges; Hydraulic Engineering; Foundations; Soil Shifting; Water Supply; Sewerage; Building; Locks; Keys; Window or Door Fittings; Safes; Doors, Windows, Shutters, or Roller Blinds in General; Ladders; Earth Drilling; Mining	MP
F01-05	Machines or Engines in General; Engine Plants in General; Steam Engines; Combustion Engines; Hot-Gas or Combustion; product Engine Plants; Machines or Engines for Liquids; Wind, Spring Weight and Miscellaneous Motors; Producing Mechanical Power; or A Reactive Propulsive Thrust, not otherwise provided for; Positive Displacement Machines for Liquids; Pumps for Liquids or Elastic Fluids; Indexing Schemes Relating to Engines or Pumps in Various Subclasses of Classes F01-F04	MP
F15-16	Fluid-Pressure Actuators; Hydraulics or Pneumatics in General; Engineering Elements And Units; General Measures for Producing And Maintaining Effective Functioning of Machines or installations; thermal insulation in General	MP
F17	Storing of Distributing Gases or Liquids	GC
F21-28	Lighting; Steam Generation; Combustion Apparatus; Combustion Processes; Heating; Ranges; Ventilatin; Refrigeration or Cooling; Combined Heating And Refrigeration Systems; Heat Pump Systems; Manufacture or Storage of Ice; Liquefaction Solidification of Gases; Drying; Furnaces; Kilns; Ovens; Retorts; Heat Exchange in General	MP
F41-42	Weapons; Ammunition; Blasting	MP
G01-12	Measuring; Testing; Optics; Photography; Cinematography; Electrography; Holography; Horology; Controlling; Regulating; Computing; Calculating; Counting; Checking-Devices; Signalling; Education; Cryptography; Display; Advertising; Seals; Musical Instruments; Acoustics; Information Storage; Instrument Details	MP
G16	Information And Communication Technology [Ict]; Specially Adapted for Specific Application Fields	LC

G21	Nuclear Physics; Nuclear Engineering	MP
H01-05	Basic Electric Elements; Generation; Conversion or Distribution of Electric Power; Basic Electronic Circuitry; Electric Communication Technique; Electric Techniques not otherwise provided for	MP
Y02, Y04, Y10	Technologies or Applications for Mitigation or Adaptation Against Climate Change; Information or Communication Technologies Having An Impact On Other Technology Areas; Technical Subjects Covered by former Uspc	MP

Note: AA=agricultural agglomeration (*Type-1*); GC=green chemistry clusters (*Type-2*); MP, BD and MP=bioeconomy districts (*Type-2*); LC=life science clusters.



(a) Placebo test for Bioregion **(b) Placebo test for green clusters**

Figure A. 1: Results for Placebo test

Eidesstattliche Erklärung / Declaration under Oath

Ich erkläre an Eides statt, dass ich die Arbeit selbstständig und ohne fremde Hilfe verfasst, keine anderen als die von mir angegebenen Quellen und Hilfsmittel benutzt und die den benutzten Werken wörtlich oder inhaltlich entnommenen Stellen als solche kenntlich gemacht habe.

I declare under penalty of perjury that this dissertation is my own work entirely and has been written without any help from other people. I used only the sources mentioned and included all the citations correctly both in word or content.

Datum / *Date* Unterschrift des Antragstellers / *Signature of the applicant*

Curriculum Vitae

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Academic career

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2012- 2017	Ph. D. in land resource management, Huazhong Agricultural University, China
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