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Essays on Macroeconomic Effects and Determinants of Green Technical Change

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Chapter 1

Introduction: Sustainability, Technical Change, and Macroeconomic Theory

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Abstract

Organizing the interdependence of the economic system and the natural environment in a sustainable way is a major challenge for humankind. A key mechanism towards an environmentally sustainable economy is green technical change. This introductory chapter provides a holistic view on the issues of sustainable development with respect to the natural environment and the role of technology. Starting from a broad perspective, it first defines the interdependence between the economic system and the natural environment and discusses the potential environmental limits for economic growth. Second, it discusses the political and societal approach to sustainable development, highlighting the core role of technical progress in these attempts. Third, it reviews the role of technical change in economic theory and what insights modern macroeconomic theory provides for environmentally sustainable growth. These approaches provide the theoretical foundation for the following empirical chapters. Finally, it provides an overview of the empirical papers, shows their connection to the concepts discussed previously, highlights their contributions, and discusses their results.

Keywords: Sustainability; Climate Change; Green Growth; Directed Technical Change; Green Innovation

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1.1 Introduction

In the last century, global economic growth has been accompanied by considerable increases in the use of natural resources (e.g., Krausmann et al., 2009), demonstrating the dependence of the economic system on the natural environment. Arguably, especially the dependence on fossil fuels has received increasing attention in the global and national policy agenda because of its direct relation to CO_2 emissions and, hence, climate change.[1] For example, the European Commission recently announced its new European Union (EU) External Energy Strategy (European Commission, 2022) to reduce the dependence on fossil fuels, establish energy security, and tackle climate change. However, the interdependence of the economic system and the natural environment is multidimensional and complex (Ekins, 1992) and so is the interdependence between different crucial Earth system processes (Rockström et al., 2009; Steffen et al., 2015). These processes are directly affected by economic activity and the extraction and dissemination of natural resources that comes along with it (e.g., Ekins et al., 2003; Schramski et al., 2015; Steffen et al., 2015). As a result, current patterns of economic activity appear unsustainable in several other dimensions in addition to climate change (Steffen et al., 2015), making environmental sustainability a comprehensive challenge for humankind. A central element to contribute to this challenge might be technical change. The development, improvement, and implementation of environmentally-friendly technology is often seen as a cornerstone to decouple economic activity from environmental impact (Popp et al., 2010; Hickel and Kallis, 2020), for example, by enabling a net-zero energy system (e.g., Davis et al., 2018; Probst et al., 2021) and/or by reducing the dependence on (specific) scarce natural resources in general (e.g., Hassler et al., 2021).[2] Hence, a profound understanding of technical change along several dimensions is crucial for the evaluation of sustainability of future economic development with direct policy relevance (Popp et al., 2010).

This thesis revolves around the concept of green technological change in four scientific papers (Chapters 2–5) and this introduction (Chapter 1), which frames the four empirical papers. Chapter 2 considers the long-term trend in the use of natural resources relative to economic activity for a large sample of developing and developed countries. Chapter 3 analyzes the dependence of economic growth on overall natural resource use and four

[1] For the scientific evidence on this relation see, e.g., the Intergovernmental Panel on Climate Change (IPCC) and its assessment reports (IPCC, 2007, 2021).

[2] In this introductory chapter, I use the terms "green", "environmentally-friendly", "environmental", and "clean" technical or technological change (or technology) interchangeably.

subcategories of resource use: fossil fuels, minerals, metals, and biomass. It is examined whether this dependence is systematically different between countries with different institutional settings. Chapter 4 aims to determine the impact of green technology development on economic productivity in European regions. Chapter 5 analyzes the impact of shocks to the global oil market on the development of green energy technologies. Chapter 1 embeds the contributions of the single papers into the broader context, establishes the theoretical foundation on which they build, shows their connection to the concepts discussed previously, highlights their contributions, and discusses their results.

Section 1.2 establishes the basic societal framework within the empirical papers operate in a broad perspective. First, it outlines the basic interdependence of the economic system and the natural environment and the challenge for sustainable development. Second, Section 1.2.1 discusses the state of the critical functions of the natural environment in a holistic approach drawing on insights from natural science. Third, Section 1.2.2 considers one particular challenge to environmental sustainability – climate change – in greater detail. Section 1.2.3 considers the concept of "green growth", which is an attempt to achieve sustainable development at the institutional level. It highlights that green technical change is at the core of the green growth approach. Section 1.2.4 discusses deviating views to the green growth concept. It emphasizes that although other approaches might be more pessimistic regarding the feasibility of continued economic growth, they typically require technical change as well.

Given the importance of technical change in the discussion on sustainability, Section 1.3 considers the role of technical change in economic theory more formally. It provides the theoretical groundings to inform the empirical papers of this dissertation. Section 1.3.1 gives a brief overview of the central role of technological change in modern growth theory and introduces important concepts and notions. Furthermore, it adds to the discussion of green growth and opposing views more formally. Section 1.3.2 discusses the theory of directed technological change in endogenous macroeconomic models in greater detail, which gives important insights regarding economic incentives to develop clean technologies and the role of path dependencies in technological progress. Section 1.3.3 connects the discussion of directed technical change with the policy framework of green growth and provides some key lessons from the theory. Finally, Section 1.3.4 briefly discusses some limitations of the sketched theory and provides further considerations, which are important for the empirical chapters.

Section 1.4 provides an overview of the four empirical papers of the dissertation and shows how the papers can be classified and how they link to the theory presented in the previous sections. Sections 1.4.1–1.4.4 provide a more detailed overview of each paper, highlighting the scientific contributions and the implications of the results. Section 1.5 concludes the introductory chapter of this dissertation.

1.2 Economy and the Natural Environment: Groundings, Science, and Policy

The modern debate around environmental sustainability is rooted in developments in the 1960s and 1970s (Drews and van den Bergh, 2016; Purvis et al., 2019). A well-known contribution during that time is the report "The Limits to Growth" (Meadows et al., 1972). This report highlights four essential limits to economic growth: the amount of available land for agriculture; the productivity of agricultural output; the amount of available extractable non-renewable resources; the ability of the environment to assimilate wastes (Perman et al., 2011). In response to these insights and the revolving debate, the World Commission on Environment and Development (WCED) released the so-called "Brundtland report" (WCED, 1987), which was very influential in popularizing the concept of sustainable development in the political agenda (Perman et al., 2011). In the definition of the Brundtland report, "Sustainable development seeks to meet the needs and aspirations of the present without compromising the ability to meet those of the future" (WCED, 1987, p. 43). In general, sustainability can be understood as the ability of something to perpetuate in the future (Ekins, 1993; Kajikawa, 2008).

Typically, the debate on sustainability and sustainable development evolves around a three-pillar concept, including social, economic, and environmental sustainability (Purvis et al., 2019).[3] This introductory chapter focuses on environmental sustainability. However, it is important to emphasize that the three dimensions are not mutually exclusive (Hansmann et al., 2012).

To discuss environmental sustainability in the following sections, it is necessary to introduce the basic interdependence between the economic system and the natural en-

[3]These dimensions are explicitly mentioned in the Sustainable Development Goals (SDGs) of the United Nations (United Nations, 2015) and the World Bank approach to green growth (World Bank, 2012), discussed in Section 1.2.3.

vironment.[4] The economic system is embedded in the natural environment and their interdependence can be categorized along four general functions (e.g., Common, 1995; Ekins et al., 2003; Perman et al., 2011; Ekins, 2014).[5] These functions comprise: 1) the provision of resources, e.g., the provision of minerals and fossil fuels; 2) the absorption of wastes from economic activity, e.g., a sink for pollution in form of greenhouse gas (GHG) emissions; 3) amenity services from the environment to individuals, including recreational facilities and other sources of pleasure, e.g., hiking in the wilderness; 4) the provision of basic life-supporting functions for humans. This category includes, e.g., the provision of appropriate climatic conditions and fresh water supply (Ekins et al., 2003; Perman et al., 2011; Ekins, 2014).[6]

In economics, these functions might be abstractedly thought of as being the flows of goods and services from a stock of natural capital (Ekins et al., 2003; Perman et al., 2011; Ekins, 2014). In this view, wealth is created by using flows from different kinds of capital stocks, which might or might not substitute for each other in their contribution to welfare (Ekins et al., 2003) and which interact in complex ways (Ekins, 1992). For example, Ekins (1992) differentiates four stocks of capital: 1) natural capital; 2) human capital (e.g., health, motivation, knowledge); 3) physically produced capital (e.g., machines, buildings, infrastructure); 4) social/organizational capital (e.g., legal, political, family). The maintenance of these stocks, i.e., their ability to perpetuate their flows to wealth creation in the future, indicates sustainability. Hence, each type of stock might be linked to a specific type of sustainability (Ekins et al., 2003). If overall sustainability is characterized by the maintenance of human welfare and hence by the maintenance of the total stock of capital (the entirety of all disaggregated stocks), a crucial question is how well (or if at all) the stocks or their components can substitute for each other (Ekins et al., 2003).[7] This gives rise to the important distinction between weak and strong sustainability. Weak sustainability rests on the assumption that manufactured capital or other stocks of capital can generally substitute well for natural capital, such that only the overall stock of total capital has to be maintained. Strong sustainability presumes that

[4] In what follows, natural environment and environment are used interchangeably to refer to the system of the Earth and its atmosphere (Perman et al., 2011).

[5] Note that the Earth and its atmosphere are by themselves embedded in the environment of outer space (Perman et al., 2011).

[6] It should be stressed here that not all wastes cause pollution. They only do when exceeding the capacity of the environment to absorb or recycle them (Ekins, 1992).

[7] Of course, targets might also be related to well-being of other species or the entire ecosystem in and of itself, regardless of whether the functions serve human welfare (e.g., Victor and Sers, 2019). The preservation of the ecosystem regardless of human purpose might be termed conservation (Kajikawa, 2008).

the substitution is very limited and each stock itself has to be preserved (van den Bergh, 2001; Ekins et al., 2003).

As discussed by Ekins et al. (2003), a further useful distinction of the basic environmental functions, introduced above, are "functions for" humans and "functions of" natural capital. Latter "functions of" natural capital contain all processes in the internal functioning of the natural system, which retain its overall integrity. The "functions for" generate human welfare of different kind directly and are inherently dependent on the "functions of" natural capital (Ekins et al., 2003). Hence, following latter authors, environmental sustainability might be defined as maintenance of the critical functions, whose contribution to welfare cannot be substituted, or which could be irreversibly lost. Although there is much uncertainty around this given the huge complexity of natural systems, it can be regarded as likely that many "functions of" natural capital are critical (Ekins et al., 2003).

The following sections provide the broader framing to environmental sustainability along three main parts: First, they describe the current state of natural capital along selected lines of the system functions based on insights from natural science. Second, they analyze the political approach of green growth, which is designed to achieve sustainable development.

1.2.1 Planetary Boundaries

As discussed in the previous section, principles of environmental sustainability can be derived along the critical system functions of the natural environment. These principles might include to sustain sink functions, i.e., the capacity of the environment to assimilate wastes without damage or change to the ecosystem; to foster the renewal of renewable resource; to balance the depletion of non-renewable resources with the development of substitutes for it; and to maintain the life-support functions of the natural environment (Ekins et al., 2003). Ekins et al. (2003) identify as the core environmental problem that extensive use of the "functions for" human activity has a negative impact on the natural capital and its "functions of", which are responsible for the stability of the Earth system. Latter notion is closely connected to what sometimes is referred to the "Great Acceleration", describing the huge increase in population and economic activity after the Second World War (Steffen et al., 2007) and its impacts on the environment. This section discusses the above themes on a natural science base. First, it states the laws of thermodynamics, which provide the basis for the subsequent discussion. Second, it exemplifies the potential scarcity of natural resources with respect to energy and metals. Third, it considers the planetary boundaries approach (Rockström et al., 2009; Steffen et al., 2015) as an integrated framework to characterize the state of human impacts on important processes of the Earth system.

The laws of thermodynamics are important to understand the implications of the following discussion. They relate to energy, which is, in its simplest definition, the potential to perform work (Perman et al., 2011; Schramski et al., 2015). More precisely, it is the distance of a property from equilibrium, which can be used to perform work (Schramski et al., 2015). In thermodynamics it is furthermore important to distinguish between "open", "closed", and "isolated systems" (Perman et al., 2011). Open systems exchange matter and energy with the environment (Perman et al., 2011), whereas closed systems exchange only energy, and isolated systems exchange neither energy nor matter (Bianciardi et al., 1993; Glucina and Mayumi, 2010; Perman et al., 2011; Mayumi, 2017). The Earth and its atmosphere are a closed system (Glucina and Mayumi, 2010; Perman et al., 2011). The first law states that energy can be transformed (e.g., between work and heat) but neither created nor destroyed; the total quantity is conserved (Glucina and Mayumi, 2010; Perman et al., 2011; Schramski et al., 2015; Mayumi, 2017). The second law essentially states that as energy changes forms, although its quantity is conserved, its quality eventually degrades into low-quality heat energy (Schneider and Kay, 1994; Schramski et al., 2015).[8]

These laws have direct consequences. An often-used approximated concept that derives from the first law of thermodynamics is the so-called materials balance (or mass balance) principle (van den Bergh, 1999). In essence, it states that matter/materials cannot be created or destroyed (van den Bergh, 1999; Glucina and Mayumi, 2010; Perman et al., 2011; Mayumi, 2017). This implies that economic activity cannot create anything in a material sense, but only transform extracted materials (Perman et al., 2011), and that stocks can be exhausted as matter-energy cannot be created (Glucina and Mayumi, 2010; Mayumi, 2017). It furthermore implies that there is necessarily waste output, which goes back to the environment in some form (Glucina and Mayumi, 2010; Perman et al., 2011; Mayumi, 2017). The waste output can be reduced by recycling, but the extent of recycling depends on the amount of available energy, which might set limits for recycling

[8]The second law can also be stated in terms of entropy, which is a measure of irreversibility (Schneider and Kay, 1994). It essentially implies that the entropy of an isolated system increases with energy conversion (Costanza et al., 1997; Perman et al., 2011).

in practice (Bianciardi et al., 1993; Perman et al., 2011). The second law implies furthermore that energy coming from fossil fuel stocks is only available once (it cannot be recycled), and that there are theoretical limits to energy efficiency (Glucina and Mayumi, 2010; Mayumi, 2017).

Implications of the laws of thermodynamics regarding usable energy are illustrated by the Earth-space battery paradigm developed by Schramski et al. (2015). According to this, the Earth can be seen as a battery of stored chemical energy. It has got charged by sunlight over the course of millions of years, as living biomass has stored solar energy into high-quality chemical energy by photosynthesis. According to Schramski et al. (2015), the recoverable energy storage mainly consists of two kinds of organic chemical compounds, fossil fuels and biomass (in addition to nuclear energy potential). In contrast to the non-renewable fossil fuel stocks, biomass represents renewable energy deposits, which are constantly recharged by photosynthesis of incoming solar radiation. However, while using energy to perform work for economic activity, humankind is depleting the stocks of fossil fuels rapidly, and is also reducing the amount of energy stored in living biomass. Hence, the chemical energy battery is currently being discharged (Schramski et al., 2015).

The calculations by Schramski et al. (2015) highlight the depletion of energy storage in both non-renewable fossil stocks and renewable biomass (i.e., the depletion of biomass energy exceeds its rate of renewal driven by photosynthesis). While fossil energy sources, such as oil, are completely consumed upon use, metal resources can be recovered and reused (Gordon et al., 2006). In essence, metals can be part of three stocks: the ore reserves in the ground, the stocks of metals in use, and the stock transferred to wastes (Gordon et al., 2006). Gordon et al. (2006) calculate that with existing technology, the whole stocks of copper, zinc, and possibly platinum ores in the ground would be required to lift a large part of the world's population at the levels of services consumed in the highly developed countries. Sustaining these (or even lower levels) worldwide is even more complicated, as losses in the recycling of the metals in use need to be compensated for by new extraction (Gordon et al., 2006). With regard to limited natural resources, it appears reasonable to assume that certain renewable resources might substitute for non-renewable ones. For example, renewable energy might substitute for fossil based energy (e.g., Gielen et al., 2019) or alternative materials might substitute for the relatively scarce ones (Gordon et al., 2006).

However, as noted above, a key environmental concern can be linked to the state of the environmental system itself, which is affected by using its functions for economic activity. The planetary boundaries approach (Rockström et al., 2009; Steffen et al., 2015) provides a comprehensive scientific framework that relates to these important functions. It defines a safe operating space for human activity by proposing global boundaries (in terms of specific control variables) for critical processes of the Earth system. Crossing these boundaries has the potential to substantially impact the functioning of the Earth system. In total, nine processes are defined. They are 1) climate change; 2) biosphere integrity, comprising genetic diversity (extinction rates) and functional diversity (biodiversity loss); 3) land-system change; 4) freshwater use; 5) biogeochemical flows; 6) ocean acidification; 7) atmospheric aerosol loading; 8) stratospheric ozone depletion; 9) the introduction of novel entities (i.e., new substances and new life forms that have potential for unwanted geophysical and/or biological effects). The first two processes, climate change and biosphere integrity, are considered to form the core boundaries. This is because both boundaries are highly integrated, system-level processes that are fundamentally important for the Earth system (Steffen et al., 2015).

Steffen et al. (2015) document that the two biogeochemical flows, phosphorus and nitrogen, as well as genetic diversity (biosphere integrity) are beyond the zone of uncertainty, implying a high risk of serious impact. Land-system change and climate change are in the zone of uncertainty, implying increasing risk. Stratospheric ozone depletion, ocean acidification, and freshwater use were within the boundary, implying a safe state. The state of the other boundaries was not quantified by Steffen et al. (2015). However, current calculations by Persson et al. (2022) document that the boundary related to novel entities is crossed, as annual production and releases are increasing quickly enough to surpass the global capacity for assessment and monitoring. Additionally, Wang-Erlandsson et al. (2022) refine the boundary relating to freshwater use by dividing it into green and blue water (freshwater change), whereby the original boundary included only blue water (rivers, lakes, reservoirs, and renewable groundwater stores). In contrast to blue water, the authors document that the green water (terrestrial precipitation, evaporation, and soil moisture) boundary is crossed, implying increasing risk.

As highlighted above, the extraction and use of resources flows has a direct impact on the state of the natural capital, represented by the planetary boundaries. First, the land-use change and deforestation linked to mining activities (e.g., Sonter et al., 2017) and agricultural use directly relate to land-system change and to the loss of habitats, which affects species population and biodiversity (Smil, 2011; Schramski et al., 2015). Biodiversity might also be directly affected by the extraction of fossil fuels (Butt et al., 2013).

Biodiversity is crucial for ecosystem resilience and evolutionary potential (Folke et al., 2004; Perman et al., 2011).[9] The loss in biodiversity is especially threatening as ecological systems at local and global scale can experience tipping points, i.e., they might shift abruptly and irreversibly to another state when critical thresholds are crossed (Barnosky et al., 2012). As the main anthropogenic impact on the nitrogen and phosphorus cycles arise from fertilizer application (Steffen et al., 2015), agriculture and, thus, biomass use are directly linked to the biogeochemical flows, which are already at high risk according to the planetary boundaries calculation.

To summarize, this section highlights the need to consider the environmental sustainability debate in an integrated, holistic framework. The planetary boundaries framework provides a comprehensive account of the state of critical natural capital and emphasizes several crucial processes of the Earth system. It is highlighted that economic activity and the associated extraction and use of natural resources is directly linked to the boundaries and that current calculations suggest that several boundaries are already at risk. One of the identified core boundaries is climate change. Given its high relevance from a scientific point of view and in the public and political debate, the following section is devoted to climate change in greater detail. However, it shall be emphasized that the other planetary boundaries have to be considered as well in a holistic approach to environmental sustainability.

1.2.2 Climate Change

To discuss the current state of climate change, this section first briefly introduces basic notions, drawing extensively and closely on the elaborations by the Intergovernmental Panel on Climate Change (IPCC) in its Fourth Assessment Report (IPCC, 2007). The atmosphere, the land surface, oceans and other bodies of water, and living things (biosphere) are major parts of the complex climate system. Climate is, in a broader sense, the state of the climate system, and can be defined, in a narrower sense, as "average weather" over a long period (about 30 years). Hence, climate can be described in terms of the mean

[9] An ecosystem is a set of animal and plant populations that interact and their non-living environment (Perman et al., 2011). Two crucial concepts in relation to ecosystems are resilience and stability, which can be defined according to Holling (1973): "Resilience determines the persistence of relationships within a system and is a measure of the ability of these systems to absorb changes of state variables, driving variables, and parameters, and still persist. In this definition resilience is the property of the system and persistence or probability of extinction is the result. Stability, on the other hand, is the ability of a system to return to an equilibrium state after a temporary disturbance. The more rapidly it returns, and with the least fluctuation, the more stable it is. In this definition stability is the property of the system and the degree of fluctuation around specific states the result" (Holling, 1973, p. 17).

and variability of temperature, precipitation, and wind over a period of time. Climate change can be broadly defined as significant changes in these properties of climate that persist over a longer period (IPCC, 2007).[10]

As discussed above, the Earth is a thermodynamically closed system (Glucina and Mayumi, 2010; Perman et al., 2011) – solar radiation brings a constant flow of energy to the Earth and its climate system. About one third of the sunlight is directly reflected back, while the non-reflected part is absorbed by the surface and the atmosphere. The reason the Earth's surface is at current moderate temperatures is the presence of GHGs in the atmosphere, which partially prevent the energy to escape. The primary GHGs are water vapor (H_2O), carbon dioxide (CO_2), nitrous oxide (N_2O), methane (CH_4), and ozone (O_3) (IPCC, 2007). The climate system depends crucially on the net balance of energy on Earth's surface. The distribution of energy thereby plays a major role for the circulation of the ocean and the atmosphere, which in turn determine the structure and functioning of ecosystems (Steffen et al., 2015). The radiation balance of the Earth can be influenced by changing the concentration of GHGs in the atmosphere, which in turn can influence climate (IPCC, 2007).

The latest report – the Sixth Assessment Report – of the IPCC gives a recent scientific overview of the consequences of anthropogenic GHG emissions for the climate (IPCC, 2021). A key consequence is global warming.[11] The global surface temperature between 2011 and 2020 is estimated to be 1.09°C higher than 1850–1900, while the best estimate of the human-caused increase from 1850–1900 to 2010–2019 is 1.07°C. The major positive contribution is attributed to GHGs, which likely contributed a warming between 1.0–2.0°C (IPCC, 2021).[12]

Changes in the climate system, including hot extremes such as heatwaves, heavy precipitation, and droughts are expected to become more frequent and intense in relation to increasing global warming (IPCC, 2021). Providing a comprehensive assessment, Schleuss-

[10] Note that this definition includes human-caused climate change as well as climate change due to natural processes (IPCC, 2007).

[11] Global warming usually refers to the increase in global surface temperature compared to the pre-industrial period (1850–1900) (e.g., IPCC, 2021; UNEP, 2021; Meinshausen et al., 2022). Global surface temperature is used to refer to both global mean surface temperature (GMST) and global surface air temperature (GSAT) measurements by IPCC (2021). For the ease of exposition, I follow this simplification.

[12] The IPCC uses a system of evaluating the findings based on the level of confidence of each statement. Thereby, the likelihood of an outcome is indicated with the terms: virtually certain (99–100% probability); extremely likely (95–100%); very likely (90–100%); likely (66–100%); about as likely as not (33–66%); unlikely (0–33%); very unlikely (0–10%); exceptionally unlikely (0–1%). In the text, I use these terms as they appear in the original report. For further details, the reader is referred to IPCC (2021).

ner et al. (2016a) document that differences in extreme events (e.g., heat waves and heavy precipitation) might even be substantial between a 1.5°C and 2°C global warming. For example, Dosio et al. (2018) calculate that global warming of 1.5°C significantly increases heat wave magnitude over Africa, South America, and Southeast Asia. Compared to that, 2°C warming would be associated with a doubling of extreme heat wave frequency around most of the world.[13] Kang and Eltahir (2018) report that under a business-as-usual GHG emissions scenario, the North China Plain is likely to experience strong heatwaves, potentially threatening outdoor working.

An important theme in the discussion of trajectories of the climate system is the acknowledgment of potential irreversibility and non-linear developments. Steffen et al. (2018) discuss the existence of a planetary threshold (in terms of global warming), which, if crossed, would prevent a stabilization of the climate at intermediate temperatures, since the Earth system would follow an irreversible pathway driven by feedback processes. Of importance in this regard are tipping points in several climate system components, which can lead to so-called tipping cascades (Steffen et al., 2018). In a recent contribution, Armstrong McKay et al. (2022) estimate the risk of crossing several tipping points in climate subsystems (tipping elements). They define the concept as "Tipping points occur when change in part of the climate system becomes (i) self-perpetuating beyond (ii) a warming threshold as a result of asymmetry in the relevant feedbacks, leading to (iii) substantial and widespread Earth system impacts" (Armstrong McKay et al., 2022, p. 1). Using this definition, Armstrong McKay et al. (2022) show that there are six Earth-system components for which tipping points become likely even under the goal of the Paris Agreement (UNFCCC, 2015) to keep global warming between 1.5°C and 2°C. These include the collapse of the Greenland and West Antarctic ice sheets and abrupt permafrost thaw. With about 2.6°C global warming, another tipping point becomes likely and another three become possible. As highlighted above, crossing the tipping points might lead to feedback mechanisms, such that crossing other tipping points becomes more likely, leading to a tipping cascade and a planetary threshold in the worst case (Armstrong McKay et al., 2022).

[13] These two values for global warming are important because the Paris Agreement by the parties of the United Nations Framework Convention on Climate Change (UNFCCC) includes the goal of "Holding the increase in the global average temperature to well below 2°C above pre-industrial levels and pursuing efforts to limit the temperature increase to 1.5°C above pre-industrial levels . . ." (UNFCCC, 2015, p. 22).

Notably, the best point estimate of the global surface temperature increase compared to pre-industrial times is roughly 1.5°C for the lowest GHG emission scenario considered by IPCC (2021) in the long term (2081–2100). While the near-term (2021–2040) best point estimate is roughly 1.5°C for all scenarios, it is 2.7°C in the long run already for the intermediate emissions scenario. A similar calculation is provided by the United Nations Environment Programme (UNEP) in its 2021 Emissions Gap Report (UNEP, 2021). Under the unconditional nationally determined contributions (NDCs) made until 30 August 2021 within the Paris Agreement (UNFCCC, 2015), the increase in global surface temperature compared to the pre-industrial base period is estimated to be around 2.7°C by the end of the century.[14] Even under addition of the announced long-term net-zero emissions targets, the point estimate would only be reduced to 2.2°C.[15] In a recent study that uses the NDCs and long-term targets made until after the 2021 United Nations Climate Change Conference on 11 November 2021, Meinshausen et al. (2022) estimate similar, yet slightly more optimistic numbers. Considering all NDCs and long-term targets to be implemented completely (including conditional and unconditional ones) and timely, the median estimate of peak global mean temperature increase relative to the pre-industrial base period is just below 2°C in the projection until 2100 (Meinshausen et al., 2022).

Increases in cumulative CO_2 emissions directly relate to global warming (IPCC, 2021). From 2010 to 2019, the average growth rate of global GHG emissions was 1.3% per year, while the COVID-19 pandemic resulted in a sharp drop of CO_2 emissions in 2020 (UNEP, 2021). To get an impression where GHG emissions originate from, figure 1.1 shows the share of global GHG emissions by relevant sources in 2019. Roughly three quarters of global GHG emissions result from the use of energy. This includes, e.g., electricity consumption in buildings, the use of fuels in vehicles, and industrial energy use. Roughly 15% of global GHG emissions originate from agriculture, forestry, and land use. This includes emissions produced from the animal metabolism and net emissions from land degradation but not emissions attributable to the first category, e.g., transportation in the agricultural sector. About 6% of global GHG emission are produced as a byproduct in industrial processes, e.g., the cement production (see, e.g., Dean et al., 2011). Again,

[14]The NDCs build the core of the Paris Agreement. They should be updated every five years and become progressively more stringent (Schleussner et al., 2016b). There are unconditional NDCs and NDCs that are contingent on specific conditions (UNEP, 2021).

[15]In 2021, the following Group of Twenty (G20) members had net-zero emission targets by around mid-century: Argentina, Brazil, Canada, China, the EU, France, Germany, Italy, Japan, Republic of Korea, UK, USA. These might differ in detail and whether all GHGs or sectors are included (UNEP, 2021).

this excludes emissions from energy inputs which belong to the first category. Finally, waste accounts for about 3% of global emissions, mainly coming from organic processes in wastewater and landfills.[16]

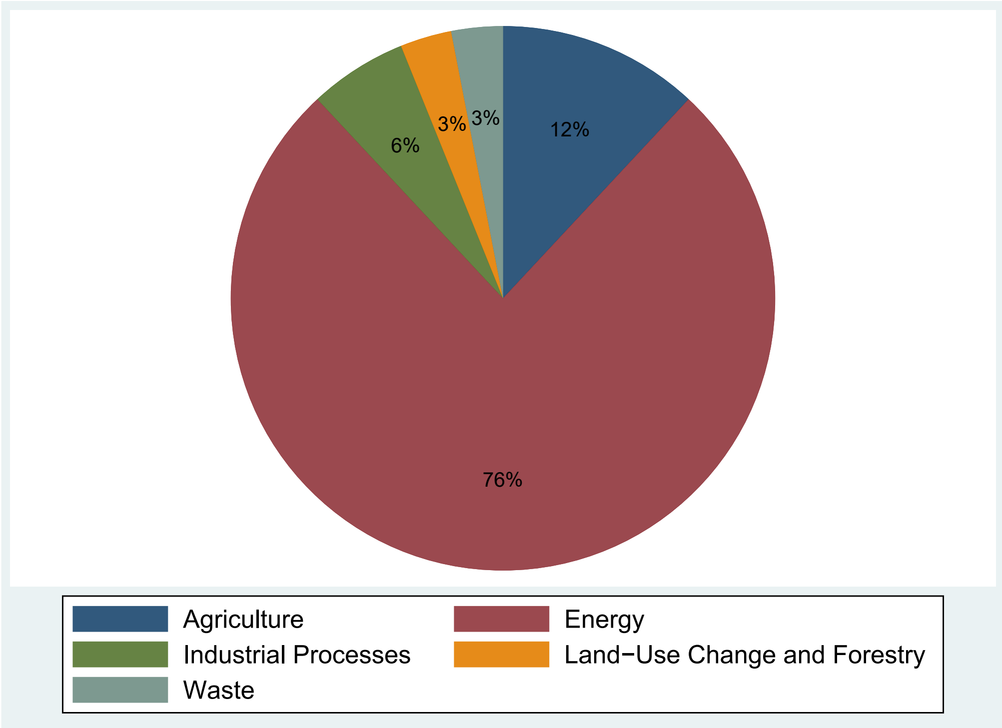

Figure 1.1. Sources of global GHG emissions in 2019. The shares are rounded to integer values. Source: Own calculations based on data retrieved from Climate Watch (2022). The data by Climate Watch (2022) is partly based on data from FAO (2022) and OECD/IEA (2021).

Given that emissions resulting from the use of energy make up roughly three quarters of total global emissions, it appears natural to prioritize a reduction of emissions that are linked to, e.g., industrial energy use and the combustion of fuels in transport. However, since the remaining quarter of emissions originates from different sources, any economy-wide net-zero-emissions endeavor needs to consider all sources. Besides the direct link between fossil fuels and energy-related emissions, other natural resource categories – biomass, metal ores, and minerals – relate to figure 1.1 as well.[17] Biomass mostly relates to agriculture, forestry, and land use. Construction minerals are linked to cement production and, hence, industrial processes. However, metals, minerals, and biomass are also to different degrees connected to energy requirements and corresponding GHG emissions in their respective supply chains (Behrens, 2016). Furthermore, the extraction of each of

[16] The description of the sectors is closely adapted from Ritchie (2020), who in turn bases the description on the report by the IPCC (2014) and Baumert et al. (2005). The interested reader is referred to Ritchie (2020) for more disaggregated statistics on global GHG emission for the year 2016.

[17] Giljum et al. (2016) show that the largest share of the material footprint in the EU in tonnes, i.e., all raw materials that are used by domestic final consumption of EU countries along the whole value chain (Wiedmann et al., 2015), is attributable to industrial and construction minerals, followed by biomass, fossil fuels, and metal ores.

the materials potentially comes along with deforestation and land-use change and, thus, directly contributes to climate change in this regard. For example, Sonter et al. (2017) document that mining activities caused 9% of the Amazon Forest loss between 2005 and 2015, which acts as a sink for CO_2 emissions (Hubau et al., 2020). Given the interplay between natural material use, energy requirements, and emissions, and considering potential limits to energy efficiency and substitution towards non-fossil energy sources, reducing overall material use (e.g., recycling) might be required for a credible emissions reduction strategy (Behrens, 2016).

Taken together, climate stability is an important dimension of the state of the natural capital and thus related to all system functions: anthropogenic climate change is mainly caused by GHG emissions, which are the waste mostly associated with the use of a specific kind of resources – namely, fossil fuels. Moreover, climate change might as well reduce the flow of amenity services (e.g., biodiversity loss, desertification). Finally, climate change might directly threaten the life-supporting services of the natural capital, as it potentially impacts the whole Earth system functioning. Given the need for action highlighted in this and the previous sections, it is of immediate interest how the global policy landscape with respect to endeavors for environmental sustainability is shaped. Hence, the following section discusses the approach "green growth", which is a major theme in the political framework of many countries and organizations globally.

1.2.3 The Policy Framework of Green Growth

According to Hickel and Kallis (2020), the term "green growth" became a central topic at the Rio+20 Conference on Sustainable Development in 2012. By now, green growth is a major theme in the political framework of many countries and organizations around the world. The concept is used by international institutions including the Organisation for Economic Co-operation and Development (OECD), the World Bank, and the United Nations (Jacobs, 2013; Victor and Sers, 2019), and, more recently, by the European Commission in its European Green Deal (European Commission, 2019).

However, despite this increase in popularity, Jacobs (2013) and Bowen and Hepburn (2014) emphasize that the concept of green growth exists since the time period around the Brundtland report (WCED, 1987). Indeed, green growth is a political approach to achieve sustainable development (or at least a subset of sustainable development), not a new paradigm (OECD, 2011; World Bank, 2012).[18] While the term sustainable development can be regarded to circumvent the fundamental question of the compatibility of economic growth and environmental protection by reframing the economic objective to "development", green growth directly stands for this compatibility (Jacobs, 2013).

Hence, the core of any green growth strategy is to achieve economic growth while at the same time protecting the natural environment (Jacobs, 2013; Bowen and Hepburn, 2014). In terms of the concept of natural capital, introduced in Section 1.2, green growth might be stated as economic growth that maintains (critical) natural capital (Bowen and Hepburn, 2014). Yet, exact definitions might differ in their actual degree of environmental protection and are often somewhat imprecise (Jacobs, 2013; Bowen and Hepburn, 2014). Nevertheless, a central concept to green growth strategies in general is so-called decoupling of environmental impacts from economic growth (Parrique et al., 2019; Hickel and Kallis, 2020). Thereby, decoupling can be either relative or absolute. Relative decoupling implies that the ratio of environmental impact to economic activity decreases but economic growth still leads to increasing impacts. Absolute decoupling means that positive economic growth goes hand in hand with constant or decreasing environmental pressures (Wiedmann et al., 2015; Parrique et al., 2019).

To illustrate the ambiguity regarding the "green" part of growth, I follow Bowen and Hepburn (2014) and state the widely used definitions formulated by the World Bank and the OECD. First, according to the World Bank, "Green growth can be thought of as economic growth that is environmentally sustainable. More specifically, it aims to operationalize sustainable development by enabling developing countries to achieve robust growth without locking themselves into unsustainable patterns. The World Bank's environmental strategy defines green growth as growth that is efficient, clean, and resilient – efficient in its use of natural resources, clean in that it minimizes pollution and environmental impacts, and resilient in that it accounts for natural hazards and the role of environmental management and natural capital in preventing physical disasters" (World Bank, 2012, p. 30). Second, the OECD states that "Green growth [. . .] is about fostering economic growth and development while ensuring that natural assets continue to provide the resources and environmental services on which our well-being relies. It is also about

[18] This is especially noticeable in the definition of the World Bank. The basic premise is that economic goals (economic growth) were largely complementary to social goals and the main conflict of objective was between economic growth and the environment, hence the need for green growth. In this view, inclusive green growth is the vehicle to agree the three pillars of sustainable development (World Bank, 2012).

fostering investment and innovation which will underpin sustained growth and give rise to new economic opportunities" (OECD, 2011, p. 18).

The two definitions have subtle differences. The World Bank's definition can be considered to be weaker (Hickel and Kallis, 2020). First, its notion does not define an exact degree of environmental protection (Jacobs, 2013). Second, the definition aims to reduce impacts of future growth, which does not necessarily include the reduction of current levels of impact. Hence, the definition would even be consistent with an increase in impact overall (Hickel and Kallis, 2020). The OECD definition can be considered slightly stronger (Jacobs, 2013; Hickel and Kallis, 2020), as it explicitly aims to maintain the system functions of the environment (Hickel and Kallis, 2020). Importantly, however, they are both more comprehensive than just encompassing climate change (Bowen and Hepburn, 2014).

Additionally, when considering the "growth" part of green growth, an immediate question arises as to what economic growth implies. It might be narrowly defined as growth in gross domestic product (GDP), but it might also more broadly relate to human well-being in general (Bowen and Hepburn, 2014). According to Bowen and Hepburn (2014), the narrow understanding of economic growth as GDP growth is common in policy debates and, therefore, what is often referred to. Hence, I follow the broad consensus in the literature (e.g., Jacobs, 2013; Bowen and Hepburn, 2014; Smulders et al., 2014; Victor and Sers, 2019) and focus on the narrow definition relating to GDP growth.

The core premise of green growth is that economic growth is compatible with the maintenance of (critical) natural capital. With regard to the mechanisms to achieve green growth, a common ground between the notions is that they rely on substitution and technical change to achieve decoupling, and environmental policies to direct this process (Hickel and Kallis, 2020). However, there are different views on how green growth compares to a business-as-usual growth scenario. Jacobs (2013) differentiates two versions of green growth arguments, calling them "standard" and "strong" green growth. The standard green growth argument implies that the adjustments towards green growth will put a drag on economic growth in the short run, but ensure higher growth in the long run, because costs of inaction are ultimately higher. The strong argument states that appropriate green growth policies can enhance economic growth, and thus generate win-win opportunities even in the short run, and Jacobs (2013) provides three different kinds of argument for this position. The two more relevant for this introductory chapter are: First, green policies correct market failures and increase short-run growth by eliminating these inefficiencies; second, green policies might lead to innovation and investment which gives national firms a comparative advantage in the newly emerging industries.[19]

The central elements can also be found in the European Green Deal (European Commission, 2019). Specifically, "It is a new growth strategy that aims to transform the EU into a fair and prosperous society, with a modern, resource-efficient and competitive economy where there are no net emissions of greenhouse gases in 2050 and where economic growth is decoupled from resource use" (European Commission, 2019, p. 2). Obviously, the aim of the framework is to achieve economic growth while at the same time reducing environmental pressures. Furthermore, it is highlighting the prominent role of technology to achieve the goals, stating that "New technologies, sustainable solutions and disruptive innovation are critical to achieve the objectives of the European Green Deal" (European Commission, 2019, p. 18). Finally, the European Green Deal puts emphasize on highlighting potential win-win opportunities, thus having overlaps with the notion that environmental policies can even generate growth.

Taken together, this section highlights that green growth is a major policy concept in the pursuit of sustainable development. The basic premise is that economic growth can be made compatible with the protection of the natural capital. One central mechanism in this concept is technical change that facilitates to decouple economic growth from environmental pressures. While green growth appears to be a dominant view (Parrique et al., 2019), there are opposing views as well. The following section discusses some of these alternative concepts in greater detail to provide a comprehensive account.

1.2.4 Alternative Policy Concepts

There has been an extensive intellectual debate evolving around economic growth and its relationship with environmental quality since the discussions around sustainable development emerged (Drews and van den Bergh, 2016). In a broader sense, the discussion evolving around green growth can be embedded into the so-called "growth debate", which asks whether economic growth is desirable, feasible, and controllable (van den Bergh, 2001). As evident from the subsequent section, green growth assumes that economic growth is desirable and feasible, while the question whether growth is controllable lies outside the scope of the concept. However, different views exist, which, for example, postulate the need for negative growth or not to prioritize economic growth as policy goal, labeled as

[19] An example is the famous Porter hypothesis, which states, in its strong version, that environmental policies can increase competitiveness through induced innovation (Porter and van der Linde, 1995).

"degrowth" (e.g., Kallis et al., 2012; Victor, 2012; Hickel, 2021) and "a-growth" (e.g., van den Bergh, 2011, 2017), respectively.

The concept of degrowth comes in different notions (van den Bergh, 2011; Hickel, 2021). One particular conceptualization of degrowth is directly aiming for negative GDP growth (van den Bergh, 2011).[20] A-growth can be regarded as having a neutral, indifferent position to economic growth. The concept aims to accept economic growth when it is feasible, but also accepts a GDP decline, if this is the inevitable outcome of a policy that tackles crucial environmental or social problems. Hence, a-growth can be seen as having the broadest search space for potential environmental policies. Degrowth, conceptualized as negative GDP growth, restricts the search space for policies to the realm where policies go hand in hand with negative growth, disregarding potential win-win opportunities. Green growth, on the other hand, only considers policies that are compatible with economic growth (van den Bergh, 2011, 2017).

In economics, the different views regarding economic growth broadly correlate to the scientific fields of environmental and resource economics (ERE) and ecological economics (EE). It shall be emphasized that these categorizations should be treated with due caution, as there is naturally a continuum of different, potentially overlapping views within the fields. In general, according to van den Bergh (2001), it can be concluded that ERE is more optimistic regarding the feasibility of economic growth than EE. This results from a more optimistic view on price responses and substitutability between inputs and technological change in response to resource scarcity in the field of ERE (van den Bergh, 2001).[21] It is further argued by van den Bergh (2001) that EE can be considered much more pessimistic, highlighting the complexity of ecosystems and that substitution and technical change are limited by the laws of thermodynamics.[22]

However, it is important to emphasize that the disagreement appears to be in general not whether technical change might contribute, but rather whether this is enough in itself (e.g., Hickel and Kallis, 2020). With regard to the specific sustainability dimension of climate change, Jakob et al. (2020) highlight that technical change is a key ingredient in

[20]Hickel (2021) assures that the notion of degrowth is not about reducing the rate of GDP growth or GDP itself, but to reduce material and energy throughput. The reduction of GDP would just be the likely consequence of this, not the actual target. However, the interpretation of GDP decline appears to be widespread (van den Bergh, 2017).

[21]These channels are explored in greater detail in Section 1.3.

[22]The notions of technical change and substitution are introduced more formally in Section 1.3.1, adding this formal dimension to the debate.

all approaches from green growth to degrowth.[23] This is since net-zero emissions cannot be reached without clean energy technologies regardless of the level of energy use, i.e., regardless of whether economic activity/energy throughput is reduced.

Taken together, there are different positions regarding the possibility of environmentally sustainable economic growth, which are more or less optimistic regarding the factual possibilities of technical change and substitution. Nevertheless, technical change can be considered to be important for most notions in order to achieve environmental sustainability, and specifically net-zero GHG emissions. This importance of technical change is also reflected in economic theory, which provides important insights regarding effects and determinants of technical progress. The following sections unfold how technical change is conceptualized in economic theory.

1.3 Macroeconomic Theory, Technology, and Green Growth

Technical change has long been recognized as the driving engine of economic growth (e.g., Solow, 1956, 1957). Similarly, technical change plays a pivotal role in the sustainability debate and approaches discussed in the previous sections. However, technical change per se is likely not contributing to environmental sustainability, as the type of technology developed and employed is crucial. The rate and direction of technical change are shaped by economic incentives (e.g., Grubb et al., 2021). Modern economic theory is able to provide important insights into this direction of technical change and the implications for economic growth and environmental policy. The following sections consider the role of technical change in economic theory to provide the theoretical foundation that is necessary to inform the empirical chapters of this dissertation.

1.3.1 Technology and Economic Theory

In general, and adopting the illustration by Jaffe et al. (2002), the production technology of an economy can be represented as

$$Y = f(K, L, E; t), \tag{1.1}$$

[23] Jakob et al. (2020) use the term "Neoclassical economics" and not green growth, but the concepts are mostly congruent.

where the production function $f(.)$ maps a list of possibly arbitrarily many inputs on the right-hand side into a measure of achievable aggregate output Y. Inputs may include capital goods K, labor inputs L, and environmental inputs E. Technological change means that the functional relationship between those inputs in production and achievable output levels depends explicitly on time t (Jaffe et al., 2002). In the following section, an explicit functional form is employed to introduce crucial theoretical concepts that are important for the upcoming chapters.

1.3.1.1 Aggregate Production

To illustrate some central notions, consider the constant elasticity of substitution (CES) production function studied by Hassler et al. (2021) as an example of a common functional form:

$$Y_t = \left[(1-\gamma)(A_t K_t^{\alpha} L_t^{1-\alpha})^{\frac{\varepsilon-1}{\varepsilon}} + \gamma(A_{et}E_t)^{\frac{\varepsilon-1}{\varepsilon}}\right]^{\frac{\varepsilon}{\varepsilon-1}}, \tag{1.2}$$

where output Y in period t is produced from a Cobb-Douglas aggregate of labor L_t and capital K_t in addition to fossil energy E_t; γ is a share parameter; ε is the elasticity of substitution between the capital/labor aggregate and fossil energy; A_t and A_{et} represent capital/labor-augmenting and energy-augmenting technical change, respectively.

In general, the elasticity of substitution between different input factors is of vital importance for the implications of the model. The CES production function implies that when $\varepsilon = \infty$, the inputs are perfect substitutes; when $\varepsilon = 0$ the inputs are perfect complements, implying a Leontief production function; and when $\varepsilon = 1$, the production function becomes Cobb-Douglas. Besides these extreme cases, it is useful to introduce the terms gross substitutes and gross complements, which refer to the cases $\varepsilon > 1$ and $\varepsilon < 1$, respectively (Acemoglu, 2002). The factor-augmenting technical change series provide a very general way to characterize technological improvements in the aggregate production process. All else equal, the same level of output can be achieved by less energy when the level of energy-augmenting technical change is higher.[24] It is worth emphasizing that the elasticity of substitution is often assumed to be a static property of the production function, remaining constant over time, whereas technical change is explicitly dynamic and changes over time (Couix, 2019).

[24]It should be stressed that factor-augmenting technical change does not need to be factor-saving (Acemoglu, 2008), e.g., because higher demand for the more productive factor overcompensates the increases in productivity (e.g., Haas and Kempa, 2018). This effect might depend on the elasticity of substitution and is taken up again in Section 1.3.2.

The CES production function (1.2) already highlights the crucial role of technology for the sustainability debate. The observed energy intensity $\frac{E_t}{Y_t}$ might depend directly on the level of energy-augmenting technical progress and is therefore sometimes used (in its inverted form $\frac{Y_t}{E_t}$) as an indicator of technical change (André and Smulders, 2014; Saunders et al., 2021). However, it is important to emphasize that such an aggregate outcome measure of technical change depends on efficiency improvements within sectors or shifts between sectors, i.e., structural change (e.g., Haas and Kempa, 2018) and other potential macroeconomic influences (Saunders et al., 2021).

Similar insights can be obtained from a simple decomposition exercise. Following Grossman (1995), I define Y_t as aggregate output as above, i.e., the scale of economic activity, s_{it} as the share of output coming from sector i and a_{it} as the amount of energy generated per unit of output in sector i. Hence, total energy use in period t is given by $E_t = \sum_i a_{it}s_{it}Y_t$. This decomposition demonstrates that, ceteris paribus, an increase in economic output increases energy use proportionally. However, the scale effect can in principle be offset by changes in the sectoral composition of the economy (s_{it}) or the energy efficiency of the individual sectors (a_{it}), which might be called technique effect (Copeland and Taylor, 2004).[25] Hence, economic growth can be accompanied by changes in technology and structural factors, which might partly or fully offset the scale effect (Stern, 2004, 2017). These factors and the variables that underlie changes in the structural and technical factors – such as environmental awareness and policy – are at the core of the so-called Environmental Kuznets Curve (EKC) hypothesis. In this view, the underlying factors are assumed to change with income growth, such that structural and technical factors might overcompensate the scale effect with continued economic growth (Stern, 2004, 2017). Hence, economic growth is not only seen as compatible with environmental sustainability but even as necessary to push income above a certain threshold (van den Bergh, 2017).[26]

Taken together, technical change is an important feature of how the production process is conceptualized in economic theory. It is discussed that measures of production factor intensity/productivity can be seen as a general way to measure factor-saving technical

[25] The technique effect might be further disaggregated into a technology effect and into an effect resulting from a change in the input mix of the sector (Stern, 2004, 2017).

[26] A further well-known decomposition is the so-called IPAT identity (Ehrlich and Holdren, 1971, 1972). The IPAT identity decomposes any environmental impact (I) into the factors population (P), affluence per capita (A) and impact (waste, resource use) per unit of output, i.e., technology (T) (Perman et al., 2011). Sticking to the example above, energy use might be decomposed into $E_t \equiv P_t \times \frac{Y_t}{P_t} \times \frac{E_t}{Y_t}$, where P_t is population. Again, this highlights the notion of $\frac{E_t}{Y_t}$ as an abstract measure of technology.

change at the aggregate level. The following section focuses on the process of technical change in greater detail.

1.3.1.2 Technical Change

With regard to macroeconomic theory, an important distinction arises in how the technological series are modeled. Technological change might either be considered to be exogenous or endogenous. Employing an exogenous specification of technology implies that the process of technology is an autonomous function of time (Gillingham et al., 2008; Popp et al., 2010). For example, the seminal Solow growth model uses an exogenous technology specification (Solow, 1956). Similarly, the prominent DICE (dynamic integrated climate-economy) model (Nordhaus, 1992, 1994) is originally based on an exogenous technology assumption. However, technical change is driven by economic incentives, such as factor prices (e.g., Hicks, 1932; Popp, 2002; Aghion et al., 2016; Grubb et al., 2021), and a correct understanding of development processes should take these potentially time-changing incentives into account. In this spirit, early contributions highlight the importance of endogenous technological change for macroeconomic growth (e.g., Romer, 1990; Helpman, 1992; Grossman and Helpman, 1994). Modeling technological change endogenously amounts to regarding innovation efforts of firms, which in turn react to economic incentives, as important driver of technological change (Coe and Helpman, 1995; Coe et al., 2009). This implies that these incentives affect the evolution and direction of technological developments (Gillingham et al., 2008; Naqvi and Stockhammer, 2018).

Furthermore, an important theme for the economic analysis of technical change is the presence of externalities that might counteract these incentives. First, a central market failure for technology in general is the presence of knowledge spillovers. These arise from the public goods nature of knowledge (Arrow, 1962). Individuals might benefit from technology or knowledge originally developed by others (Griliches, 1992; Keller, 2004). Because this social benefit is not internalized, R&D investment tends to be below the social optimum (Popp et al., 2010; Stern and Valero, 2021). In the context of environmental technology, a second market failure relates to the presence of environmental externalities (e.g., GHG emissions). If not internalized by markets (e.g., due to efficient carbon prices), environmental externalities counteract the incentives to invest in clean technologies that are designed to reduce these externalities (Popp et al., 2010; Popp, 2011; Stern and Valero, 2021).

The discussion above mainly focuses on an abstract, aggregate notion of technical change. However, the process of technical change can be further distinguished. Based on ideas of Schumpeter (1942) as cited in Jaffe et al. (2002), Löschel (2002), and Popp (2011), three stages can be specified: invention, innovation, and diffusion (adoption). The first term, invention, describes the emergence of an idea of a new product or process. An innovation is achieved when the invention becomes commercially feasible and introduced to the market. Both stages can be subsumed under the term R&D. In the case of green technical change, the outcome of the innovation process is typically termed environmental or green innovation. It can be defined broadly as ". . . any innovation that reduces environmental harm" (Kanerva et al., 2009, p. 7). The third stage, diffusion, describes the continual spread of an innovation that is increasingly adopted by economic agents. Although each stage is important on its own, Allan et al. (2014) emphasize that only through diffusion the (environmental) benefits of the technology spread and are likely to have an impact. An important aspect in this regard is the international diffusion of technology (Keller, 2004), as technology development is rather restricted to developed countries (Keller, 2004; Probst et al., 2021).

The economic and environmental impact of technology depends on all of those stages (Jaffe et al., 2002) and the decisions at each stage are influenced by market incentives (Popp, 2011).[27] Furthermore, the existence of path dependencies is a central feature of all stages of the innovation process. According to Aghion et al. (2019), they occur in the generation of knowledge because of knowledge spillovers, since scientists might select areas that are well supported and feature excellent peers. Additionally, there is path dependence in the deployment and adoption of technology. This is because existing infrastructure can make the willingness-to-pay for certain green technologies much lower. Additionally, the benefits of using new technology might rise with others using it (network effects), such that incentives for deviating technology choice are reduced (Aghion et al., 2019; Stern and Valero, 2021).

To summarize, economic theory highlights several aspects that are crucial to the process of technical change, which include the role of economic incentives, the presence of market imperfections in the research system due to externalities, and related path dependence. These aspects are important parts of the theory of directed technical change (DTC), which is discussed in detail in Section 1.3.2. The following section adds to the

[27] It is worth emphasizing that not all research is profit-oriented and spillovers from research conducted under different motivation and the successful commercialization of the potentially important inventions should be considered as well (Weyant, 2011).

discussion on the possible contribution of technical change to environmental sustainability (see Section 1.2.4) on some of the concepts introduced in the previous sections.

1.3.1.3 The Debate Between EE and ERE

The introduction of the production function framework in the previous sections facilitates the more formal discussion of the controversy between EE and ERE (see Section 1.2.4). As extensively discussed by Couix (2019), at the heart of the debate between proponents of ERE and EE is the notion of unbounded resource productivity, i.e., that the average product of resources in the production function has no upper bound. According to Couix (2019), this idea was incorporated in the models by, e.g., Stiglitz (1974) and Solow (1974), which can be attributed to the school of ERE. Central mechanisms to achieving unbounded resource productivity are a high degree of substitution between resource inputs and capital or labor and technical change. For example, if the energy input and the capital/labor aggregate in equation (1.2) are gross complements, the productivity of energy is bounded in the absence of technical change (Couix, 2019). Proponents (and intellectual founders) of EE (e.g., Georgescu-Roegen, 1975) referred to the laws of thermodynamics (see Section 1.2.1) and argued that these put an upper bound to the processes of technical change and substitution and hence resource productivity (Couix, 2019).

Couix (2019) argues that the debate is exacerbated by methodological issues. This is because technical change and substitution in the aggregate production function framework are mathematical properties, which are not mutually exclusive in real world scenarios (Couix, 2019). Related to this issue of aggregation and abstraction, van den Bergh (1999) discusses that the notion of substitution might not be meaningful within an aggregate context discussed above. Specifically, drawing on the conceptualization by Georgescu-Roegen (1971), the author argues that such an aggregate notion misses on important differences between different types of inputs, namely stocks, funds, and flows, which have different substitution and complementarity relations between them. Additionally, the level of aggregation might be problematic as clean activities are interrelated with many other, dirtier goods through intermediate goods and services (van den Bergh, 2017).

While Couix (2019), after discussing the debate, concludes with the claim that both positions remain unproven because of the methodological difficulties, it is important to bear these challenges in mind in the discussions in the following sections. In the past decade, endogenous growth models with directed technical change (DTC) have been extensively used to deal with optimal policy in an environmental setting in the presence of the incentives and externalities central to the research sector.[28] Accordingly, these models provide an important theoretical grounding to inform the empirical chapters of this dissertation. Given this important function, the following sections consider selected DTC models related to environmental topics in depth, with specific emphasis on the structure of the production and research system, the implications, and the intuition behind them.

1.3.2 Directed Technical Change

A useful categorization for the theoretical literature on DTC in an environmental setting is proposed by Hémous and Olsen (2021): one class of models analyzes technical change between two substitute inputs in which one is clean and the other dirty; the other class models the choice between energy-saving and labor/capital-saving technical change. In this review, I follow this categorization broadly and focus on structural aspects regarding production and the innovation system as well as implications of the models that inform the empirical chapters.[29]

1.3.2.1 Clean and Dirty Inputs

The first class of models analyze the choice between a dirty and a clean input. In their seminal paper, Acemoglu et al. (2012) study the direction of technical change between these inputs, the role of path dependency, how policy incentives can change the direction, and whether economic growth can be sustainable for the environment.

These questions are addressed by Acemoglu et al. (2012) using the following model structure. In an aggregate CES production function, the final good is produced from two goods (dirty and clean), which might be either gross substitutes or gross complements (see Section 1.3.1). Each good is itself produced from a continuum of sector-specific machines and labor. Both sectors differ insofar that the production of the dirty good reduces environmental quality proportionally (environmental externality). The machines for both sectors are supplied by monopolistically competitive firms (Acemoglu et al., 2012), allowing for profits as incentive to innovate (Hémous and Olsen, 2021). Acemoglu et al. (2012) model the innovation process the following way. At the beginning of each period, scientists decide whether to research in dirty or clean technologies – this decision

[28] The seminal DTC model by Acemoglu (2002) is not explicitly tailored towards an environmental setting.
[29] This review is not comprehensive, but focuses on selective studies that are considered to be of importance. An interesting (yet also not comprehensive) review is provided by Hémous and Olsen (2021).

is based on the relative expected profits across the sectors – and successful innovation improves the quality of a machine on which the scientists receives patent protection.

Acemoglu et al. (2012) arrive at the following implications in the market equilibrium. The profits for innovation depend on three components: first, research favors the more productive sector (direct productivity effect). This is because innovation builds on the existing quality of machines within each sector, involving a so-called "building-on-the-shoulders-of-giants" effect (knowledge externality). Second, scientists favor the sector with higher prices (price effect). Third, research is directed to the sector with higher employment, i.e., the larger market for machines (market size effect). The overall effect depends crucially on the elasticity of substitution between the sectors. When the two goods are gross substitutes, the more productive sector has also larger market share and the price effect (which favors the less productive sector) is dominated.[30] Hence, there exists a path dependency in the approach by Acemoglu et al. (2012). The economy innovates only in the initially more advanced dirty technology and the productivity gap between the two sectors increases. This has severe consequences for the environment. Environmental quality decreases until a point of no return, which has the basic intuition of a climate threshold (see Section 1.2.1). In the model by Acemoglu et al. (2012), this threshold can be avoided with appropriate policy if the goods are gross substitutes, but the design of the policy depends on the degree of substitution. In general, optimal policy involves a carbon tax to correct for the environmental externality and a research subsidy to correct for the knowledge externality. However, whether policy support is required only temporarily depends on whether the degree of substitution is sufficiently strong. In contrast, when the sectors are gross complements, the environmental threshold can only be avoided if economic growth stops in the long run.[31] Regarding the potential scarcity of natural resources (see Section 1.2.1), the model also contains an interesting insight. When the dirty good is produced with an exhaustible resource, increasing scarcity leads to higher prices in the dirty sector and incentives to innovate in clean technology, which makes the environmental disaster less likely in the substitutes case (Acemoglu et al., 2012).

[30] The assumption of gross substitutes is considered to be more plausible by Acemoglu et al. (2012).

[31] Whereas innovation occurs only in one sector in the long run in the case of substitutes (Fried, 2018), an interesting feature is that when sectors are gross complements, the less productive sector is favored (because the market size effect favors it now). This implies that the initially less advanced sector catches up, closes the initial gap, and there is technical change in both sectors in the long run (Acemoglu et al., 2012). This feature is discussed more formally by Hémous and Olsen (2021).

1.3.2.2 Energy Intensity

The second class of models studies energy-saving or resource-saving innovation. These models typically do not include an environmental externality but ask how the energy share of output evolves with long-run growth.

Haas and Kempa (2018) aim to decompose the change in energy intensity into a structural and a technological effect to analyze the heterogeneity in energy-intensity developments across countries. The structural effect is the relative share of the sectors in final output, whereas the technological effect is the efficiency of each sector (see Section 1.3.1). Therefore, Haas and Kempa (2018) draw on the model by Acemoglu et al. (2012) and consider an energy-intensive and a non-energy-intensive but labor-intensive intermediate sector (instead of clean and dirty). The research system is structured similarly to Acemoglu et al. (2012): When sectors are gross substitutes, research favors the technologically more advanced sector and a higher exogenous energy price makes research in the labor-intensive sector more profitable. When the sectors are gross complements, research favors the technologically less advanced sector and a higher exogenous energy price makes research in the energy-intensive sector more profitable (Haas and Kempa, 2018). Based on this structure, Haas and Kempa (2018) highlight several scenarios, which again depend on the degree of substitution between the sectors. Of special interest for the empirical chapters are the implications for technical change in the energy-intensive sector and for exogenous energy price shocks. First, innovation in the energy-intensive sector can result in an overall increasing or decreasing energy intensity growth rate. The structural effect is positive, the efficiency effect is negative, and the elasticity of substitution between the sectors determines which effect dominates. In the case of gross complements, the efficiency effect dominates the structural effect and the growth rate of energy intensity decreases. However, the substitutes case produces a variant of the rebound effect (e.g., Witajewski-Baltvilks et al., 2017), because the demand effect overcompensates the efficiency effect. Second, a growing energy price always leads to a declining energy share, because both the structural effect and the efficiency effect tend to be negative. In the gross-substitutes case sufficiently strong energy shocks can change the direction of technical change, similar to the insights for the price policy instruments by Acemoglu et al. (2012). For example, when research is initially directed to the energy sector, sufficiently strong energy price growth can redirect innovation to the labor sector. This is because the output in the energy-intensive sector decreases in response to the cost shock; since the demand effect dominates the price effect, innovation in the energy-intensive sector becomes eventually less profitable than innovation in the labor sector (Haas and Kempa, 2018).

In a recent paper, Hassler et al. (2021) directly relate to the relevance of exogenous energy price shocks and deal with the ability of technical change to substitute for scarce resources. They empirically show that the US energy cost shares and energy prices closely follow each other, implying strong complementarity between energy and the capital/labor composite in the production function in equation (1.2). Assuming this very low elasticity of substitution, Hassler et al. (2021) calculate the implied energy-augmenting technological change series from the production function with US data to show that energy-augmenting technical change appears to have been initiated after the oil shocks in the 1970s. Based on these observations, Hassler et al. (2021) develop an endogenous growth model to study the choice of a representative firm between energy-saving and capital/labor-saving technologies.[32] The model predicts that the energy share will only respond slightly to resource scarcity because of the technology response facing higher fuel prices (Hassler et al., 2021). Hence, it highlights the interplay between the elasticity of substitution and technical change discussed in Section 1.3.1. Although the static elasticity of substitution is very low, energy-augmenting technical change can substitute for energy inputs over time, and hence compensate for resource scarcity.

Fried (2018) develops a more detailed model to quantify the effects of a carbon tax on endogenous innovation and energy use. The richer model structure is designed to captured the economy-wide effects of directed technical change, as it explicitly features an energy and a non-energy sector, in contrast to Acemoglu et al. (2012). Specifically, output in the model by Fried (2018) is produced from a nested CES production function. On the highest level, final output is produced from energy and non-energy intermediate goods, which are hard to substitute.[33] The energy input in turn is a CES function of green and fossil energy. Finally, fossil energy can be produced from domestic fossil energy or oil imports. Hence, energy used in final production is provided from either green energy sources, from domestic fossil energy (i.e., a mixture of coal, oil, and natural gas) and oil imports. It is assumed that the three energy sources (green, fossil, and oil imports) are gross substitutes.[34] Fossil energy, green energy, and non-energy intermediates are produced with labor and sector-specific machines. The sector-specific machine producers

[32] Since the structure of the model adds little to the expositions in this section, it is not considered in greater detail.
[33] This assumption mirrors Hassler et al. (2021).
[34] This premise is similar to the preferred assumption of gross substitutes by Acemoglu et al. (2012).

can hire scientists to improve the quality of their machines (Fried, 2018). Based on this rich structure, Fried (2018) report the following results. Similar to Acemoglu et al. (2012), there is a path dependence in innovation, implying that, ceteris paribus, innovation is directed to the technologically more advanced sectors. However, a noticeable contrast to Acemoglu et al. (2012) is that Fried (2018) also models cross-sector spillovers. These catch-up spillovers are rationalized by the idea that if a sector is less advanced, there is a lot of knowledge already used in other sectors that could be easily implemented to improve technology. Thus, in contrast to the within-sector spillovers, the between-sector spillovers direct innovation, ceteris paribus, to the less advanced sectors.[35] Furthermore, an interesting implication is that while oil price shocks increase innovation incentives in domestic fossil energy and green energy, carbon taxes only increase incentives for green innovation (Fried, 2018). Finally, Fried (2018) reports that the endogenous innovation response renders carbon taxes more effective compared to a scenario without endogenous innovation.

1.3.2.3 The International Dimension

While the models discussed so far focus on technical change in a single country, there are also approaches that take the international dimension of knowledge diffusion into account.

Acemoglu et al. (2014) build on the approach by Acemoglu et al. (2012) to explicitly analyze global policy coordination and international knowledge spillovers. Thus, Acemoglu et al. (2014) model two regions (North and South), which both produce output from dirty or clean inputs. A key difference between the regions is that scientists in the North improve technologies in both sectors, while scientists in the South only imitate technologies already invented in the North (Acemoglu et al., 2014). This is related to the empirical observation that innovation activity concentrates in the highly developed countries (e.g., Keller, 2004; Probst et al., 2021). The two regions are interdependent directly via trade or indirectly through the environmental and knowledge externalities (Acemoglu et al., 2014). Based on this structure, Acemoglu et al. (2014) discuss that incentives to innovate in the North are governed by the same forces as in Acemoglu et al. (2012), namely a price effect, a market size effect, and a productivity effect. The incentives to imitate in the South involve an international knowledge externality, since it is more profitable to imitate the more productive technology from the North. Hence, the

[35] Given appropriate parameter settings, these effects might create a scenario where there is long-run innovation in both sectors.

social value of innovation in the North includes the "building-on-the-shoulders-of-giants" effect – as in Acemoglu et al. (2012) – and an externality because of giving the South the opportunity to imitate better technology (international knowledge spillover). Similar to Acemoglu et al. (2012), when the dirty technologies are initially sufficiently more advanced, the economies end up in an environmental disaster. A key insight by Acemoglu et al. (2014) is that when there is a sufficient amount of trade, avoiding the disaster requires environmental policy in both world regions. For example, unilateral policy in the North can create a "pollution haven" effect, in which the dirty good production moves to the South, resulting in a specialization in the dirty sector.

Hémous (2016) deals with a similar objective, namely to analyze whether unilateral environmental policies can ensure sustainable growth. This is addressed in a trade framework in which one world region (North) is willing to implement a carbon tax, whereas the other world region (South) is not. However, in contrast to Acemoglu et al. (2014), both world regions improve on technology, there is an energy and a non-energy sector, and pollution from the energy sector depends on the direction of technical change towards either dirty or clean input goods within the energy sector. The model by Hémous (2016) is structured the following way. There are two goods that enter final consumption, a polluting and a non-polluting good. The polluting good is produced from a clean and a dirty input that are assumed to be gross substitutes (Hémous, 2016). Hence, the approach considers not only the energy sector, similar to Fried (2018). Innovation efforts are made by profit-maximizing firms in both world regions that can hire scientists and that can direct research efforts to the non-polluting sector or at clean and dirty technologies within the polluting sector. In the baseline setting, Hémous (2016) further deviates from Acemoglu et al. (2014) and abstracts from cross-country knowledge spillovers. Based on this structure, Hémous (2016) documents a similar path dependence as discussed in the previous models. The path dependency leads to comparable results to Acemoglu et al. (2012) and Acemoglu et al. (2014): if the dirty technology is more advanced in the beginning, long-run growth results in an environmental disaster. Similar to Acemoglu et al. (2014), a unilateral carbon tax in the North produces a pollution haven effect. Compared to Acemoglu et al. (2014), the unilateral carbon tax is even more ineffective, potentially contributing to accelerated pollution. In contrast, a combination of clean research subsidies and a trade tax might be more effective. This is because it can provide an opportunity for the North to establish a comparative advantage in the polluting sector and to improve the environmental performance of that sector by innovating in the clean input. Thus, optimal unilateral policy combines a carbon tax, clean research subsidies, and a trade tax on the polluting good (Hémous, 2016).

Taken together, the theory of DTC delivers important insights regarding the incentives that impact the direction of research and how externalities and related path dependencies influence these incentives. The following section summarizes the key lessons from the discussed theory and relates them to the policy agenda of green growth.

1.3.3 Directed Technical Change and Green Growth

The following section discusses what the insights from the models presented in the previous Section 1.3.2 imply for the prospects of green growth. It is important to emphasize that the models capture only a small fraction of what is implied by green growth by design. Thus, "growth" relates to the narrower notion of GDP growth in the following, while "green" only refers to the decoupling of GDP growth from emissions or from the use of energy.

In general, the literature on DTC emphasizes the importance to consider the endogenous incentives for clean technical development when analyzing long-run developments and economic and environmental policies. Depending on the circumstances, these incentives can hinder a clean transition (e.g., Acemoglu et al., 2012, 2014), but they can also contribute to more effective environmental policy (e.g., Acemoglu et al., 2012; Fried, 2018).

Specifically, first, the theory of DTC emphasizes to consider the role of price signals. Hassler et al. (2021) discuss how the choice of energy-saving technical change responds to global fuel prices (e.g., oil price shocks). Because of this price-induced technical change, the scarcity of fossil fuel resources only puts a slight drag on consumption growth in their model. However, Hassler et al. (2021) do not consider environmental pressures directly, which might restrict growth before the limits to extraction become binding. Dealing with pollution explicitly, Acemoglu et al. (2012) discuss that the environmental disaster becomes less likely if a scarce resource is need for the production of the dirty good because of similar price responses in the markets. Similarly, in the approach by Haas and Kempa (2018), energy price shocks always induce a declining energy share. Finally, these insights also extend to price policies. Induced innovation in response to a carbon tax can make the tax more effective compared to a scenario without induced innovation (Fried, 2018), and hence to a more optimistic policy scenario in some circumstances (Acemoglu et al., 2012).

Second, path dependencies are important.[36] As discussed by Acemoglu et al. (2012) and Acemoglu et al. (2014), when the dirty sector is sufficiently more advanced in the initial period, green growth can generally not be achieved without policy intervention.[37] There is, hence, the possibility of a lock-in in dirty technologies, which would make green growth infeasible. Similarly, Haas and Kempa (2018) show that research that is initially directed to the energy-intensive or labor-intensive sector can only be redirected to the other sector for sufficiently high or low growth rates of the exogenous energy price. A direct consequence of path dependence is that policy intervention should be implemented quickly, as an increasing gap between the dirty and the clean sector makes waiting costly (Acemoglu et al., 2012; Aghion et al., 2019). Indeed, path dependence implies that in general, there will be some costs in terms of reduced output growth during the transition. This is because the clean sector is less productive and needs time to catch up (Aghion et al., 2019). Although other effects, such as cross-sectional spillovers, could counteract the path dependence, there might still be transition losses in terms of aggregate growth (Fried, 2018). Hence, the model predictions are rather pessimistic regarding short-run gains and align more with the "standard" argument of green growth discussed in Section 1.2.3.

Third, the elasticity of substitution between the sectors is in general crucial. This is especially striking for the approaches by Acemoglu et al. (2012) and Acemoglu et al. (2014). As Acemoglu et al. (2012) discuss, when the two sectors are sufficiently substitutable, only a temporary intervention is necessary and the environmental goals can be reached without any or much of a drag on economic growth. When the sectors are substitutable but not sufficiently, a permanent policy intervention might be necessary. When the sectors are gross complements, the environmental disaster can only be avoided by stopping economic growth, and hence this situation would imply infeasibility of green growth. Additionally, if sectors, such as an energy-intensive sector and a labor-intensive sector, are sufficiently substitutable, technical progress in the energy sector can even increase overall energy intensity of the economy because of overcompensating demand (Witajewski-Baltvilks et al., 2017; Haas and Kempa, 2018). Hence, the appropriate policy response might substantially depend on whether inputs are easy to substitute (Aghion et al., 2019).

[36] However, depending on the degree of substitution.

[37] While path dependence arises from the history in these models, path dependence might also stem from expectations about the future (van der Meijden and Smulders, 2017).

Fourth, as highlighted by Acemoglu et al. (2012) and Acemoglu et al. (2014), the optimal policy response might include a mixture of different measures, involving both "technology-push" (i.e., green research subsidies) as well as "demand-pull" (i.e., a carbon tax).[38] Indeed, in the context of international trade, even more differentiated policy designs might be necessary, including trade taxes (Hémous, 2016). Additionally, Acemoglu et al. (2014) highlight the pronounced importance of global policy coordination and the need to ensure that clean technologies are effectively transferred to less-developed countries. A similar implication can be drawn from the insights by Hémous (2016), as the carbon taxes and research subsidies in the North should be accompanied by policies that facilitate technology transfer and build absorptive capacity in the South (Stern and Valero, 2021). As summarized by Aghion et al. (2019), more developed countries should act as technology leaders and they should aim to transfer (provide better access to) the technologies for less developed countries. At the same time, they should consider border carbon adjustments against countries that aim to take advantage of the environmental policies by specializing in fossil-fuel-extensive goods.

To conclude, the theory of DTC offers insights relating to incentives for green technical change, the role of path dependencies, the critical role of the elasticity of substitution between factors of production, and optimal policy and policy coordination given these mechanisms. However, the underlying theory is rather stylized and implications rest on specific assumption regarding the structure of the model and parameter values, such as the elasticity of substitution. To ensure a comprehensive view and to embed the insights, the following section briefly discusses some possible limitations of the sketched theory.

1.3.4 Limitations

It is important to emphasize again that all models discussed above and hence their implications for green growth relate to specific flows of goods from the natural capital. The models consider the use of a non-renewable resource and/or its associated waste product in form of emissions. They do not consider the state of the natural capital and its "functions of" and the complex interdependence between different functions and feedbacks (see Section 1.2) directly. Whats more, Pottier et al. (2014) criticize the entire climate module in Acemoglu et al. (2012) as miss-specified. Additionally, there is generally no explicit differentiation of different stages of the research process, as discussed in Section 1.3.1.

[38] See Verdolini and Galeotti (2011) and Kruse and Wetzel (2016) for more details on technology-push and demand-pull policies.

For example, in the model by Acemoglu et al. (2012), profit-oriented scientists improve the quality of machines in the beginning of the period, which are always employed in production within the same period. This contrasts the high complexity of the actual processes from development to diffusion of new technology (e.g., Weyant, 2011) and does not allow to analyze the process of diffusion/adoption of clean technologies (Pottier et al., 2014). This high complexity of the research process is highlighted by the literature on innovation systems, which deals with the interplay of heterogeneous actors that form specific networks of interaction and the underlying institutional framework that shapes these interactions (e.g., Lundvall, 1992; Binz and Truffer, 2017).

Additionally, as with any model that works with an abstract representation of aggregate production, the reviewed DTC models are not immune to the critique formulated in Section 1.3.1 regarding the adequate representation of different substitution mechanisms. The DTC models are not designed to model separately different material-product chains, recycling, waste management, and dematerialization in the whole economy. It might be speculated that this observation in combination with the methodological difficulties of the concept of substitution (Couix, 2019) contributed to a disagreement on appropriate assumptions regarding the elasticity of substitution (e.g., Pottier et al., 2014). Pottier et al. (2014) discuss several further limitations of the approach by Acemoglu et al. (2012). In consequence, applying assumptions that they consider more realistic, Pottier et al. (2014) derive more pessimistic numerical predictions.

To conclude, the discussed theories are important to inform the empirical papers regarding the effects and determinants of green technical change. However, their exact implications can depend on specific assumptions regarding model structure and parameter values. This is complicated by the level of abstraction, the complex nature of technical change, and the variety of potential impact factors. Furthermore, there are many important underlying forces that do not enter the models explicitly, such as institutions, which might help to break through a path dependence (Aghion et al., 2019), and which are core parts of innovation systems (Lundvall, 1992). These considerations highlight the role of empirical research to contribute to the understanding of the effects and determinants of technical change. The empirical papers in this dissertation relate to and draw on the theoretical concepts discussed in the previous sections. They contribute in different ways to the understanding of questions relating to decoupling of economic growth from resource use, the potential of win-win opportunities of green technical change, and the price inducement mechanisms of environmental technologies. The following section provides an overview of the empirical dissertation papers, how they relate to the concepts discussed in this introductory chapter, which research gaps they attempt to fill, and what implications they offer.

1.4 Overview of the Dissertation Papers

The four empirical chapters relate to different notions of technical change. To align the empirical papers to the concepts discussed in the previous sections, it is instructive to cluster them along two main categories, which I call "measure" and "objective".

The first category "measure" contains the specific empirical indicator of technical change. As discussed in Section 1.3.1, technical change can be conceptualized in an aggregate notion or it can be further differentiated. Depending on the specific research question under scrutiny, this allows for a variety of empirical measures of technical change. Summarized in a conceptual sketch provided by Grubb et al. (2021), innovation activities might result in technology outcomes (e.g., technology costs reduction), which then might translate into economy-wide, aggregate outcomes. Each of these steps in the process of technical change has related empirical measures. The four empirical papers of this dissertation either measure innovation activity and hence employ *activity measures* and/or measure macroeconomic outcomes (*outcome measures*).

With regard to *activity measures*, one might traditionally differentiate between input measures, such as R&D investments, and output measures, such as patents (Griliches, 1990). However, as discussed by Griliches (1990), R&D investments and patents are closely related and patents may serve as input as well as output indicator, thus measuring innovation activity in general. *Outcome measures* provide the most comprehensive view, as they consider all stages of the process of technical change, including the successful diffusion of technical innovation (see Section 1.3.1) and whether the diffusion results into actual outcomes (as discussed in Section 1.3.2, their might also be rebound effects such that technical change in the energy sector increases overall energy intensity). Typical *outcome measures* include energy productivity/intensity or labor productivity (Grubb et al., 2021), as indicated by the decomposition exercises in Section 1.3.1. However, this comprehensive view comes at the cost of higher abstraction. Specifically, employing a measure of aggregate resource productivity makes it generally complicated to distinguish between structural change between sectors, substitution between input factors in production or technical change within the sectors (see Section 1.3.1).

The second category contains the objective of the empirical study. Directly following from the first category and the conceptual framework by Grubb et al. (2021), possible lines of research scrutinize the question whether innovation activities actually lead to observable technology/macroeconomic outcomes. In the specific case of green innovation activity, studies can scrutinize whether green innovation activity increases economic output or labor productivity (*economic effects*). Second, empirical studies might analyze whether green technologies save resources/pollution, i.e., whether they actually reduce the environmental impacts of economic activity by using less resources or producing less pollution (*environmental effects*). Combining these two objectives implicitly or explicitly, studies might also ask whether green technical change offers win-win opportunities, i.e., whether both economic productivity (competitiveness) as well as environmental productivity is increased. Third, empirical studies can contribute to the understanding of the drivers of green technical change, i.e., the economic incentives that determine the level and the direction of technical change (*determinants*). Indeed, these three categories are used for the literature review of empirical studies on green innovation by Barbieri et al. (2016). Note that while former two categories employ both an *activity measure* and an *outcome measure*, latter category might use an *outcome measure* or an *activity measure*.

The first empirical paper of this dissertation (Chapter 2) deals with the question of whether countries at different stages of economic development show evidence for developing towards the same long-run levels of resource productivity, i.e., the ratio of GDP to all natural materials that are used. Based on the identified country groups with similar long-run trends, it analyzes whether and which initial, country-specific factors are associated with group membership. Hence, it can be classified to the category of papers that analyze *determinants* of technical change. Moreover, it uses an *outcome measure* of resource-saving technical change (resource productivity). Additionally, as the development of environmental technologies is highly concentrated in high-developed countries (Probst et al., 2021), the chapter indirectly relates to the issue of effective intended knowledge transfer or cross-country knowledge spillovers (see Section 1.3.2).

The second paper (Chapter 3) analyzes the dependence of economic growth on different types of natural materials and asks whether this dependence is heterogeneous across countries and whether the level of country-specific institutional quality moderates the dependence, i.e., whether it is related to the heterogeneity.[39] Hence, while Chapter 2

[39]In this paper, we understand institutions as the basic framework conditions that shape human interactions (North, 1990). In the empirical implementation, we focus on political institutional quality, which

deals with the long-run development of resource productivity, Chapter 3 asks how dependent additional economic growth of countries is on natural resources given a specific level of productivity. Again, the chapter can be classified to the objective of analyzing *determinants* of green technical change and the use of an *outcome measure*.

The third article (Chapter 4) relates to win-win opportunities in the context of green technology development as formulated in, e.g., the European Green Deal (see Section 1.2.3). Specifically, it deals with the question whether European regions can profit from the development of green technologies in terms of labor productivity. According to this research question, it is classified to the objective *economic effects* of green technologies. In this paper, technology development is measured with patent data – an *activity measure* – and labor productivity qualifies as an *outcome measure*. It is worth emphasizing that the paper is not concerned with win-win opportunities directly in the sense that it does not quantify both *economic effects* and *environmental effects*. Instead it focuses on the economic dimension.

The final article (Chapter 5) examines the development of green energy technologies and puts the price inducement mechanism (see Section 1.3.2) under scrutiny. It focuses on the global oil market and disentangles different underlying structural oil market shocks to ask whether the impact on green patent applications varies across these different market disruptions. Hence, the paper can be categorized to the studies analyzing the *determinants* of green technical change by employing an *activity measure*.

Table 1.1. Overview of the dissertation papers

Chapter	Title	Objective	Measure	Sample Length	Level of analysis
2	Convergence in Resource Productivity	Determinants	Outcome measure	1970–2012	Countries
3	Institutions and the Nexus of Economic Growth and Natural Resource Use	Determinants	Outcome measure	1992–2010	Countries
4	Green Technologies and Growth: Evidence from European Regions	Economic effects	Activity & outcome measure	1980–2015	Regions
5	Oil Shocks and Green Energy Technical Change	Determinants	Activity measure	1990–2015	Countries

Table 1.1 provides an overview of the four empirical chapters. First, it summarizes the objective and measure category of the paper. Second, since all papers use panel data, it states the cross-sectional unit of the panel (level of analysis) and the time period for

captures the degree to which a country is democratic, secures a free press and political rights, provides high levels of accountability and bureaucratic quality, while being free of corruption, conflicts, and violence (Kunčič, 2014).

the analysis (sample length).[40] The following sections provide a more detailed account of the individual papers, highlighting the motivation, the contribution, the results, and their implications.

1.4.1 Convergence in Resource Productivity

This paper is motivated by the need to decouple resource use from economic activity in the pursuit of sustainable development, against the background of boundaries for the well-functioning of Earth system processes (see Section 1.2). Indeed, as documented in Section 1.2.3 and as highlighted by UNEP (2011) and UNEP (2016), improvements in resource productivity range high on the political agenda. Thus, the country-specific development paths of resource productivity are central for the outlook of sustainable development (e.g., Stern, 2004; Pothen and Welsch, 2019), with immediate policy relevance. Additionally, in the light of DTC (see Section 1.3.2), it is interesting to observe whether resource productivity has a strong unique component or whether developments are similar to other measures of technical change.[41] In this paper, we explore the long-run development paths of resource productivity across countries at different levels of general economic development and compare these to development paths of labor productivity.

The main contributions of this paper are threefold. First, we analyze the long-run development of resource productivity for a large sample of countries at different stages of economic development over a considerable time period. Second, we explicitly compare the identified patterns for resource productivity with those for labor productivity. Third, we analyze the role of initial, country-specific characteristics as determinants of long-run development paths.

We report three main findings. First, our data does not support that all countries in the sample converge to the same long-run paths. Instead, we find three different groups of countries, which converge to the same growth rates, but not the same levels of resource productivity. To a large extent, the three groups reflect the general economic development of the countries. Second, this observation is generally confirmed by the analysis of initial conditions. We find that higher initial GDP per capita, democracy, higher human capital,

[40] It should be emphasized that the level of analysis also adds an important notion to the categories sketched above. Since all studies of this dissertation apply to a macroeconomic perspective, the categories are tailored towards that purpose. However, studies might of course also deal with the question of whether, for example, innovation activity of a single firm transforms into economic output of that specific firm.

[41] In Section 1.3.1 it is shown how resource or labor productivity can be regarded as a measure of technical change.

temperate climate, higher population density, lower resource abundance, and lower distance to the sea are associated with a higher probability for a country to be on a favorable growth path. Third, despite the fact that the patterns in labor productivity are generally comparable, there are interesting differences. Democracy, human capital, and a temperate climate are more robustly associated with group membership for labor productivity, whereas population density is exclusively associated with group membership for resource productivity.

Our results have important implications. First, given the persistent differences in resource productivity across countries, the international dimension of the sustainability problem is highlighted. Specifically, the results are consistent with the argument that knowledge transfer is currently not sufficient. Second, the analysis of the fundamental factors suggest that country-specific conditions might favor different production and technology patterns, which relate to different patterns of path dependence.

1.4.2 Institutions and the Nexus of Economic Growth and Natural Resource Use

In the previous empirical paper it is highlighted that differences in the long-run development of resource productivity across countries are very persistent and that country-specific factors, such as democracy, relate to different long-run development patterns. This observation motivates to further analyze the development paths and the dependence of economic growth on natural resources for different natural resource classes (see Section 1.2.2 for an overview of the different resource categories).[42] Indeed, our data indicates that there is substantial heterogeneity in the correlation of GDP growth and resource use growth across countries. Hence, in this paper, we deal with the question of which underlying sources are able to explain the observed heterogeneity and argue that country-specific institutional quality might be a promising candidate. This is based on the observation that institutional quality is linked to relative prices and technology, which are potential proximate factors that relate to the relative importance of input factors in production, as highlighted by the theory of DTC (see Section 1.3.2).

Our paper contributes to the literature by examining in detail the heterogeneity of the procyclicality of resource use for different resource classes, linking it to the role of

[42]Since Chapter 2 and Chapter 3 employ different measures of resource use and since the sample periods are very different, it is not straightforward to synthesize their results and attempts to do so are tentative.

institutional quality.[43] This mediating role has been considered in different contexts relating to emissions and other dimensions of environmental quality (e.g., Dées, 2020), but not yet to the procyclicality of resource use.

We report several important empirical findings. First, on average, total resource use growth and resource use growth in the subclasses fossil fuels, biomass, non-metallic minerals and metal ores is coupled to economic growth, but coefficients of the procyclicality are considerably heterogeneous across countries. Second, the procyclicality of total resources, biomass and non-metallic minerals is positively associated with the institutional quality of a country, even if we control for confounding factors such as the level of GDP per capita, the industry share, trade openness or resource rents. The results for metal ores are less robust, but generally point towards a similar association. However, for fossil fuels, we find no evidence for a positive association of institutional quality and the procyclicality of resource use.

These findings have important policy implications. While institutions in general are often regarded as to contribute to environmental protection (e.g., Dasgupta and De Cian, 2018; Dées, 2020), our results indicate that additional economic growth in countries with better institutional quality is associated with a relatively strong increase of resource use growth. Hence, the results are consistent with the claim that additional economic growth in countries with high institutional quality is relatively more dependent on natural resources in general. However, the results for fossil fuels are broadly consistent with the theory that institutional quality is the grounding for environmental policy to be credible and effective, such that well-designed policy might lead to changes in the observed patterns of economic growth in the spirit of the green growth concept (see Section 1.2.3).

1.4.3 Green Technologies and Growth: Evidence from European Regions

This paper is motivated by the win-win potential of green technology development, as highlighted by the green growth approach (see Section 1.2.3). On the one hand side, as discussed in the previous sections, green technical progress is essential to achieve sustainable development as it might contribute to increase environmental productivity (e.g., Popp, 2010). On the other hand side, green technologies might as well enhance economic productivity (e.g., Xepapadeas and de Zeeuw, 1999). If green technology development

[43]Broadly, we refer to procyclicality as the impact of an increase of GDP growth on resource use growth.

can be an engine for regional growth, it might serve regional inclusion in the context of Europe's regional development strategies. In this paper, we focus on the economic dimension and estimate the impact of green technology development on labor productivity of European regions.

The main contribution of this paper is to thoroughly estimate the returns to green technology development at the regional level, while rigorously controlling for unobserved spillovers potentially complex in nature. Additionally, we consider various sources of potential heterogeneous effects across technology types, regions, and over time. As discussed in Section 1.3, spillovers are an integral feature of knowledge generation. In this paper, we choose a flexible approach to account for unknown spillovers instead of modeling specific channels of spillovers based on ex ante assumptions. This allows us to focus on the regional returns to knowledge generation – i.e., whether there is a positive impact of green technology development on labor productivity within a region.

Our main results comprise the following. First, while general technology development is mostly associated with positive regional returns, our data is not supportive of positive regional returns to green technologies in general. Second, despite the absence of regional returns to green technologies in general, we document evidence that the returns are positive for specific subclasses of green technologies and for regions with a sufficiently high level of the regional knowledge base.

These findings have important policy implications. First, our results are generally consistent with empirical evidence on the strong Porter hypothesis (see Section 1.2.3), which is rarely supported (Dechezleprêtre and Sato, 2017). Second, our results imply that comprehensive policies fostering the green transition for all regions alike are potentially in contrast to regional cohesion goals. As our findings suggest, the returns to green technology development appear to depend on the regional knowledge base, such that knowledge intensive regions might especially profit, exacerbating regional inequalities. Accounting for this underlying heterogeneity and the heterogeneity in specific technology types appears to be crucial for inclusive green growth.

1.4.4 Oil Shocks and Green Energy Technical Change

This paper is motivated by the importance of continued technical progress in the pursuit of a net-zero emissions energy system (Davis et al., 2018) and the role that global energy market disruptions play for price induced technical change. Specifically, an argument that is discussed in Section 1.3.2 and that is particularly emphasized by Hassler et al. (2021) is that oil price shocks can trigger green energy technical change. However, oil price shocks can have different underlying sources, which might have different effects on the real economy (e.g., Kilian, 2009; Kim and Vera, 2019). Yet, existing studies on the country level focus on overall real oil price measures (e.g., Guillouzouic-Le Corff, 2018) and do not disentangle the contributions of different underlying shocks. In this paper, I explore the effect of different underlying structural shocks to the global oil market on green innovation activity at the country level.

The main contribution of this paper is to extend the literature on price induced innovation at the country level (e.g., Popp, 2002; Kruse and Wetzel, 2016; Guillouzouic-Le Corff, 2018) by explicitly considering the role of different structural shocks to the oil market. To identify the structural shocks, it relies on recent methodological advances in the literature on structural vector autoregressions for the oil market and utilizes the structural shocks estimated and provided by Baumeister and Hamilton (2019). This facilitate to estimate the impact of oil supply shocks, oil consumption demand shocks, and precautionary demand shocks on green innovation in the three technology classes clean technologies in the energy sector, clean technologies in the buildings sector, and biofuel technologies.

The main results comprise the following. In general, different structural oil market shocks have different associations to green innovation activity, which also depend on the technology area under consideration. First, positive oil supply shocks are in general associated with reduced patenting activity in the following year. This effect is especially pronounced for biofuels, but only negligible for clean technologies in the buildings sector. Second, positive oil demand shocks play only a limited role in general, being only significantly associated with increased patenting activity in the following year for general clean energy technologies. Third, positive speculative demand shocks have a pronounced positive association with patenting activity in biofuels only in the following year.

These results have importing implications. First, since oil supply shocks are robustly associated with green patenting activity, the results are consistent with the hypothesis that technological disruptions, such as the shale gas boom, can hinder green technological progress (e.g., Lazkano and Ayasli, 2022). On the other hand, they are also consistent with the view that supply shortages because of limited oil stocks increase the incentives for green innovation (e.g., Hassler et al., 2021). Secondly, since green innovation responds differently to different structural oil market shocks (at least in the short run), not all oil price movements need to translate into green innovation automatically. Hence, in order to build a resilient green innovation system, the paper highlights that a better understanding of different shocks and their transmission mechanisms is needed.

1.5 Conclusion

This introductory chapter embedded the empirical chapters in the broader societal and scientific context. To outline the basic challenge of environmental sustainability, the interplay between economic activity and the natural environment as well as the state of the natural environment were discussed. Subsequently, political approaches to environmental sustainability were contrasted and the role of green technical change in these approaches was highlighted. Given the central role of technical progress for environmental sustainability, technical change in economic theory was discussed and some implications for sustainable economic growth were derived. It was highlighted that technical change is a complex process and that important areas for empirical research exist, which should be informed by the theoretical contributions. Finally, it was shown how the empirical chapters relate to the discussed theory and concepts and how this dissertation contributes.

Specifically, it contributes to the stream of literature on the effects and determinants of green technical change across different research areas. Chapter 2 and Chapter 3 employ an outcome measure of resource-saving technical change and deal with determinants in the form of country-specific characteristics. The results of Chapter 2 indicate that differences in the long-run development of resource productivity across countries are very persistent and that country-specific factors, such as democracy, relate to different long-run development patterns. Countries that are on a relatively high steady state regarding long-run resource productivity are typically countries that are highly developed in general, highlighting the need for more effective knowledge transfer. Chapter 3 shows that countries with better institutional quality tend to be more dependent on natural resources for additional economic growth. Thus, the prospects for institutional quality alone to further improve resource productivity might be limited. This is complemented with the observation that whether a country is democratic or not is a better predictor for being on a high steady state growth path for labor productivity than for resource productivity, consistent with the assumption that democratic countries tend to invest rather in labor-saving technical change (Chapter 2). Chapter 4 combines an outcome and an activity measure of technical change to shed light on the economic effects of green technical change at the regional level. It highlights the need to consider the heterogeneity across technologies and across regions, as green technologies only have a positive impact on labor productivity for specific types of green technology and for regions with a sufficiently high regional knowledge base. Finally, while Chapters 2 and 3 deal with country-specific determinants of green technical change, Chapter 5 considers determinants in the form of global oil price shocks and how these relate to green innovation activity. It highlights that while energy commodity prices can be an important determinant of green innovation activity, this channel has to be explored in more depth, as the impact varies by the nature of the structural shock to the oil market and the specific green technology field.

Despite these important insights, the empirical chapters share a limitation that should be emphasized. As discussed in Section 1.4, there are different conceptualizations of technical change at several levels of aggregation. The empirical chapters of this dissertation deal with technical change on an aggregate, macroeconomic level. While this comprehensive perspective facilitates to derive important insights on large scale developments for a longer time period, it is difficult to disentangle the complex factors of influence that underlie the observed outcomes. Hence, an interesting avenue for future research is to isolate specific causes and channels of influence in more disaggregated studies or by employing suitable econometric instruments.

Nevertheless, the following main conclusions can be drawn. First, given the central role of green technologies in contributing to environmental sustainability, further improving environmental technology seems to be inevitable. However, the economic effects of green innovation activity are probably heterogeneous across regions and technologies, which has to be taken into account when designing policy instruments towards an environmentally sustainable economy. Second, as many environmental problems are inherently global, the international dimension in the development and diffusion of environmental technology is important. However, differences in how well natural resources are transformed into economic output are quite persistent across country groups, highlighting the role of effective knowledge transfer and the need for technical change that is truly resource saving. Third, global energy markets might play an important role in the transformation towards a sustainable economy. As global markets can be subject to several disruptions of different underlying cause, it is important for national policy to understand the contributions of different shocks and to design policies for a resilient green innovation system.

Chapter 2

Convergence in Resource Productivity

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Abstract

Are countries converging to the same levels of productivity in transforming natural resources into economic output? This question is of high importance as it determines the need for policy intervention in the pursuit of sustainable economic development. In this paper, we explore convergence patterns in resource productivity across more than 100 countries between 1970 and 2012. Additionally, we analyze the role of fundamental factors for convergence patterns and compare these patterns to labor productivity. Instead of overall convergence, our findings show club convergence in resource productivity, with convergence clubs closely mirroring levels of economic development. The clubs converge towards the same growth rates, not the same levels of productivity. We find that initial levels of GDP per capita, human capital, and population density are strongly associated with club membership. There are noticeable differences between the convergence patterns of labor and resource productivity. Democracy, human capital and temperate climate are particularly strong predictors for club membership in the case of labor productivity, whereas population density is exclusively associated with club membership for resource productivity.

Keywords: Resource Productivity; Convergence; Labor Productivity; Sustainable Development

JEL Classification: C33; E24; O13; O47; O5

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2.1 Introduction

In the pursuit of sustainable development, improvements in resource productivity range high on the political agenda in order to confront the daunting environmental crisis (UNEP, 2011, 2016). In light of this, the paths countries take to improve resource productivity have fundamental implications for the further prospects of sustainable development (Stern, 2004; Pothen and Welsch, 2019), which relates to the necessity of policy intervention. Therefore, it is an important empirical question, whether countries are on a path towards similar levels of resource productivity. Correspondingly, whether the patterns of resource productivity are equivalent to general productivity dynamics or have a strong unique component directly relates to the necessity of policy to steer the direction of technical change.[44] In this paper, we explore convergence patterns in resource productivity across countries at all developmental levels, and compare these to convergence dynamics in labor productivity.

We construct a data set of 118 countries for the time period from 1970 to 2012. To measure resource productivity, we utilize the ratio of GDP to direct material input (DMI). For the analysis of the convergence patterns within our sample, we rely on the log t test and the related clubbing algorithm suggested by Phillips and Sul (2007). After determining the convergence clubs, we apply an ordered logit model (Bartkowska and Riedl, 2012; Parker and Liddle, 2017a) to analyze the role of fundamental factors for selection into clubs. Finally, we assess patterns of labor productivity with the same methodology, and compare the findings with those for resource productivity.

We report three main findings. First, our data is not supportive of overall convergence in resource productivity. Rather, our findings suggest that there are three convergence clubs, which converge to the same growth rates but not the same levels of resource productivity. The selection of countries into the three clubs resembles different developmental stages across countries. Second, we find that higher initial GDP per capita, democracy, higher human capital, temperate climate, higher population density, lower resource abundance, and low distance to the sea predict improved club membership. The predictive power of initial GDP per capita and population density is particularly robust. Third, although patterns in labor productivity are generally similar, we observe some noteworthy

[44]We consider resource and labor productivity as displaying technological developments in the sense of labor-saving or resource-saving technological change in the aggregate production function (André and Smulders, 2014). Note that in our aggregate framework this encompasses structural change.

differences. Democracy, human capital, and a temperate climate are relatively stronger associated with club selection for labor productivity, whereas population density is exclusively associated with club selection for resource productivity.

Convergence analysis is commonly used to explore developmental patterns for a wealth of settings and topics. For example, Nghiem et al. (2021) use convergence analysis to compare patterns for income, environmental, and health outcomes in OECD countries. Given our focus on resource productivity, our paper closely relates to the convergence literature on energy productivity and resource use. This literature emphasizes that there is substantial evidence for country-specific steady states (Miketa and Mulder, 2005; Mulder and De Groot, 2007) and club convergence for more homogeneous entities (Parker and Liddle, 2017a,b; Ağazade, 2021), which have similar developmental characteristics (Parker and Liddle, 2017a,b). For example, Parker and Liddle (2017b) find that more highly developed economies perform better than less developed economies. There are only few studies that explicitly analyze convergence patterns of resource use and productivity. Talmon-Gros (2014) assesses convergence patterns in resource productivity – operationalized as the ratio of GDP to domestic material consumption (DMC) – for OECD and BRICS countries from 1980 to 2008. For specific subsets of countries, Talmon-Gros (2014) finds evidence of convergence, while not finding evidence of overall β-convergence. More recent works by Karakaya et al. (2021) and Alataş et al. (2021) analyze convergence of resource use by using the procedure of Phillips and Sul (2007). Karakaya et al. (2021) compare the dynamics of DMC and a measure of material footprint both overall and as per capita values. They analyze convergence patterns for 27 EU countries from 2000 to 2018 and perform a decomposition analysis to identify drivers of resource use within the convergence clubs. They find evidence of club convergence and that clubs display relative convergence, i.e., growth convergence. Only for one subgroup of three countries – namely Italy, Spain, and the United Kingdom – they find evidence of level convergence for DMC per capita. Alataş et al. (2021) analyze the relationship of resource productivity – measured as GDP per DMC – and energy productivity for 28 EU countries from 2000 to 2018. They find five convergence clubs for resource productivity, each displaying relative convergence only.

With the analysis of fundamental factors for club selection, our paper further relates to the broader literature on economic development that aims to find the reasons for inequality in economic, social, or environmental development paths between countries. The factors considered in this literature include initial income levels, human capital, institutions and various geographical determinants (e.g., Savvides, 1995; Glaeser et al., 2004).

We contribute to the literature by analyzing resource productivity for a comprehensive sample of countries over a long period and by explicitly considering the role of fundamental factors for club selection and determination of development paths.

The remainder of this paper is organized as follows. Section 2.2 introduces the data and empirical methodology. Section 2.3 presents and discusses the results. First, we provide an overview on σ- and β-convergence dynamics within our data. Second, we conduct the clubbing algorithm proposed by Phillips and Sul (2007). Third, we analyze the determinants of club convergence for the full sample of 118 countries with an ordered logit model (Bartkowska and Riedl, 2012; Parker and Liddle, 2017a). Fourth, we compare the patterns of resource productivity convergence with labor productivity convergence. Fifth, we discuss and embed our findings in the related literature. Section 2.4 concludes.

2.2 Methods and Data

2.2.1 Econometric Methodology

To empirically test the hypothesis of convergence in resource productivity, we follow the approach developed by Phillips and Sul (2007). This approach has several appealing features for our empirical setup. First, it allows for heterogeneity in convergence behavior across countries and over time, helping to comprise the variety of countries in our sample. As discussed by Phillips and Sul (2009), the traditional notion of β-convergence, which imposes homogeneity on the transition parameters, can be misleading if transitional behavior is indeed heterogeneous. Second, by using a step-wise procedure, it facilitates to find subsets of convergent countries (club convergence) even when overall convergence for the full sample is rejected.

The starting point is to decompose our variable of interest, the natural logarithm of resource productivity ($\log \mathrm{RP}$), into two components

$$\log \mathrm{RP}_{it} = \delta_{it}\mu_t, \tag{2.1}$$

with δ_{it} measuring the share of the common trend μ_t country i experiences in year t and, thus, displaying the transition path of country i. The asymptotic behavior of δ_{it} characterizes the convergence properties. If δ_{it} converges to the same constant δ for all countries, this implies at least growth convergence. If this convergence occurs at a fast enough rate, there might as well be level convergence. To infer these properties, Phillips and Sul (2007) develop a regression test that is based on the cross-country dispersion $H_t = \frac{1}{N}\sum_{i=1}^{N}(h_{it}-1)^2$ of the so-called relative transition parameter, h_{it}, which is given by

$$h_{it} = \frac{\log \mathrm{RP}_{it}}{N^{-1}\sum_{i=1}^{N}\log \mathrm{RP}_{it}} = \frac{\delta_{it}}{N^{-1}\sum_{i=1}^{N}\delta_{it}}. \tag{2.2}$$

Under convergence, the relative transition parameter h_{it} converges to unity and the dispersion H_t converges to zero. Latter property is used to test the null hypothesis of convergence against the alternative hypothesis of divergence or club convergence in the following "log t" regression model:

$$\log \frac{H_1}{H_t} - 2\log(\log t) = a + \gamma \log t + \upsilon_t, \tag{2.3}$$

where υ_t is an error term and $2\log(\log t)$ is a penalty function. As discussed by Phillips and Sul (2007, 2009), a one-sided t-test for $\hat{\gamma}$ can be used to discriminate null and alternative hypothesis. A t-statistic for $\hat{\gamma}$ less than -1.65 leads to a rejection of the convergence hypothesis at the 5% level. The magnitude of the coefficient γ measures the speed of convergence. If $\gamma \geq 2$ and the common growth component μ_t follows a random walk with drift or a trend stationary process,[45] it implies convergence in levels of resource productivity, while $2 > \gamma \geq 0$ implies growth convergence.

A rejection of the null hypothesis for the full sample rejects overall convergence, but the alternative hypothesis comprises the possibility of divergence as well as club convergence. Phillips and Sul (2007, 2009) propose an algorithm to identify the number of convergence clubs and its members as well as the number of divergent units. The algorithm involves the following stylized steps based on log t regressions:[46] (1) Last observation cross-sectional ordering. (2) Core group formation. (3) Sieve individuals for club membership, which involves setting a sieving criterion c^*. (4) Recursion and stopping rule. (5) Club merging.[47]

The procedure sketched above requires to choose some parameters. First, the $\log t$ regression in equation (2.3) involves discarding of a certain fraction of the time series data, such that it is performed for $t = T_0, ..., T$ and the initial observation is $T_0 = [rT]$. We set the fraction of discarded data to $r = 0.3$, which is suggested by Phillips and Sul

[45]In the following we interpret the coefficient assuming that this condition is met.

[46]Due to the established nature of the approach, we only name the stylized steps. See Phillips and Sul (2007, 2009) or Du (2017) for details and developments on the procedure.

[47]Schnurbus et al. (2017) propose simple adjustments to the original algorithm. We report robustness of our main results to their adjustment in step 3.

(2007).[48] Second, the sieving criterion c^* in the third step of the merging algorithm has to be chosen. We follow Phillips and Sul (2007, 2009) and set the sieving criterion to zero, which is suggested for small or moderate time series, which applies to our empirical setting. Finally, as we are interested in the long-run behavior of resource productivity, we follow Phillips and Sul (2007) and remove the business cycle components from the data. In our main results, we use the Hodrick-Prescott (HP) filter (Hodrick and Prescott, 1997) and a smoothing parameter of 6.25, as suggested by Ravn and Uhlig (2002), to extract the long-run component from $\log \mathrm{RP}_{it}$.[49]

2.2.2 Data

This section presents the data used in our analysis. We include all countries in our sample for which we have a full time-series dimension of resource productivity for the period 1970–2012. This leads to a sample of 118 countries for our main analysis.

Our main data for resource use are drawn from the United Nations International Resources Panel (UN-IRP) Global Material Flows Database (UNEP, 2016; UN-IRP, 2018). Indicators of material use are given in tons. For the required time series between 1970 and 2012 there are two candidates as indicators of resource use, namely direct material input (DMI) and domestic material consumption (DMC).[50] DMI captures all material inputs an economy requires for production or consumption. It is constructed as the sum of domestically extracted materials and imported materials. DMC is calculated similar to DMI, with the difference that exported materials are subtracted. For the purpose of this study, we decide to focus on DMI as an indicator of material input, in order to take into account all resources the economy requires in the process of production and consumption. DMC would have the disadvantage that materials embodied in exported goods are no longer

[48] In a recent contribution, Kwak (2022) suggests to adapt the procedure by Phillips and Sul (2007, 2009) and to not discard any time series observation. Thus, regression (2.3) is performed for all available years t. However, the penalty function and the $\log t$ regressor are "shifted" and use $t = [r_2T], [r_2T]+1, ..., T + r_2T$, where r_2 can be chosen as to maximize test properties. The approach might show better size properties and mitigates concerns that the discarded data are important for the convergence results. We show robustness of our full sample results to this alternative method.

[49] We report robustness of our results to various alternative parameter specifications. Given that our time series dimension is rather moderate than small ($T = 43$), it might be reasonable to choose a less conservative c^* and discard less observations (Phillips and Sul, 2009). We use the following combinations of r/c^*: 0.3/0; 0.3/−1; 0.3/−1.65; 0.2/−1.65; 0.2/0. Furthermore, we apply different methods to extract the long-run component and run the $\log t$ regression for the full sample. Specifically, we use unfiltered data, the HP filter with a smoothing parameter of 400, the Butterworth (Butterworth, 1930) and the Christiano-Fitzgerald (Christiano and Fitzgerald, 2003) filter.

[50] Both indicators have counterparts that include upstream flows and, therefore, better control for outsourcing in the process of trade. However, these raw material indicators are only available from 1990 onward, and thus, they cannot be used for the proposed analysis.

counted, although these materials are crucial for the production activities and value generation in the respective country.[51] Further, in this study we focus on total resource use of economies to capture overall resource productivity.[52] We construct resource productivity as the ratio of GDP to resource use, i.e., the GDP generated per ton of resources.

To generate these measures of resource productivity, we utilize GDP from the Penn World Table 10.0 (Feenstra et al., 2015). GDP is given in 2017 US $, and we utilize real output-side GDP in purchasing power parities to ensure comparability across countries and over time. The output-side measure relates specifically to the production possibilities of an economy (Feenstra et al., 2015). Given our focus on technical progress we consider this the preferable GDP measure.[53]

For the analysis of driving forces of club association we include additional variables from various data sources. These variables are extracted for the year 1970 to serve for the analysis of the importance of initial conditions for club selection. We construct initial GDP per capita from the GDP and population data from the Penn World Table 10.0, and we utilize their human capital index. As a proxy of institutions, we apply the measure of democracy proposed by Acemoglu et al. (2019).[54] Further, we use four geographic indicators. Population density and the share of natural resource rents in GDP are taken from the World Bank's World Development Indicators. We take the share of people living in temperate climate zones in the year 1995 as a measure of temperate climate from the Geography Datasets provided by the Center for International Development at Harvard University (Gallup et al., 2010). The mean distance to the nearest coast or river, as a measure of distance to sea, is taken from the same source. Furthermore, for our comparative analysis of labor productivity, we extract the number of engaged persons from the Penn World Table 10.0. We define labor productivity as GDP per engaged person – i.e., US $ per engaged person – analogously to resource productivity. Due to data availability, the sample reduces to 102 countries in this exercise. A detailed overview of the data sources can be found in table A1.

[51] We include a robustness check for our main results with DMC.

[52] Total resource use is aggregated based on four subclasses, which are biomass, fossil fuels, metals, and non-metallic minerals. To improve data quality, we set our indicator to missing if DMI for any subclass was reported as missing.

[53] The traditional real expenditure-side GDP of the Penn World Table captures standard of living. One might also be interested specifically in how well countries are able to transform natural resources into a high standard of living, and consider this as the relevant gains in efficiency. We report robustness of our main findings to this alternative measure of GDP.

[54] We also utilize their regional classification of countries that draws upon the World Bank classification. Both variables are extracted from the supplementary material accompanying Acemoglu et al. (2019).

2.3 Results and Discussion

2.3.1 Descriptive Results

Prior to our main analysis, in this section we provide descriptive evidence on the basic dynamics in our data. For this purpose, we first report the evolution in our sample concerning σ-convergence, before assessing whether there is evidence of unconditional β-convergence.

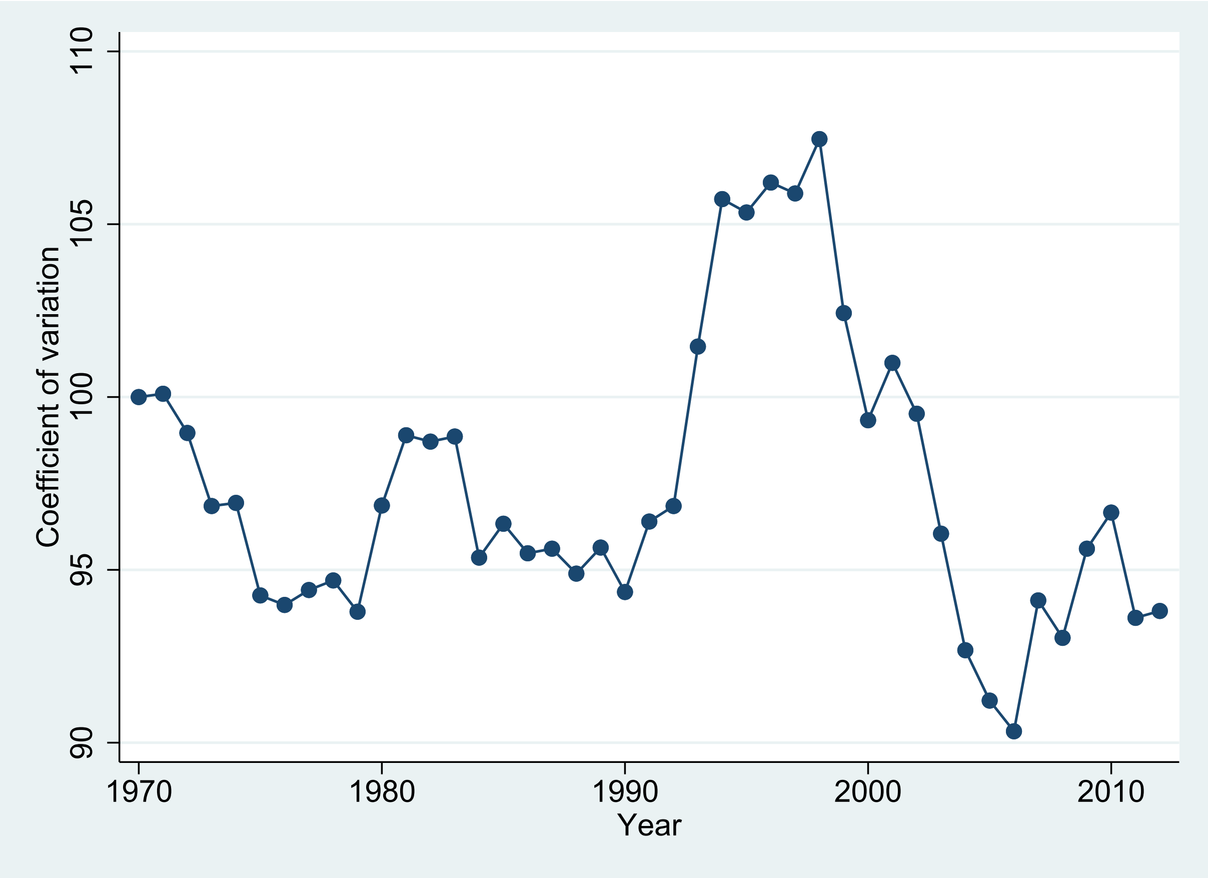

Figure 2.1. Coefficient of variation (CV) of resource productivity. The CV is calculated for the logarithm of resource productivity with unfiltered data as the cross-sectional standard deviation divided by the cross-sectional mean of the respective year. It is normalized to 100 in 1970.

Figure 2.1 shows the coefficient of variation (CV) for our sample of 118 countries over time. σ-convergence provides a basic measure of convergence and refers to a decline in the cross-sectional dispersion of the variable of interest. It is mostly measured as the CV, which indicates whether there is a decline in cross-country inequality (Mohammadi and Ram, 2012). Figure 2.1 shows that the distribution has quite substantial dynamics over time, with a considerable drop in the decade before 1980. A spike in the early 1980s is followed quickly by a decline. The early and mid-1990s are characterized by a substantial increase in inequality, which reaches its maximum in 1998. The beginning of the 21st century is again marked by a substantial decline, with the most equal distribution in 2006. The phase of the financial crisis shows a moderate increase, followed by a moderate decline after 2010. Despite the slight decrease in cross-country inequality from initial to final period, the CV remains of relatively similar magnitude throughout the whole time period, ranging between 90 and over 105. To put this into perspective, Parker and Liddle (2017b) find a relatively stable decrease of the CV for energy productivity from 100 in 1971 to roughly 75 around 2000.[55] Two interesting observations are worth noting here. First, similar to figure 2.1, Parker and Liddle (2017b) report an increase in cross-country inequality in the wake of the financial crisis. Second, the substantial increase in inequality we observe in the 1990s is hardly visible in their data, and they do not observe an overshoot in inequality compared to the initial level, as we do.

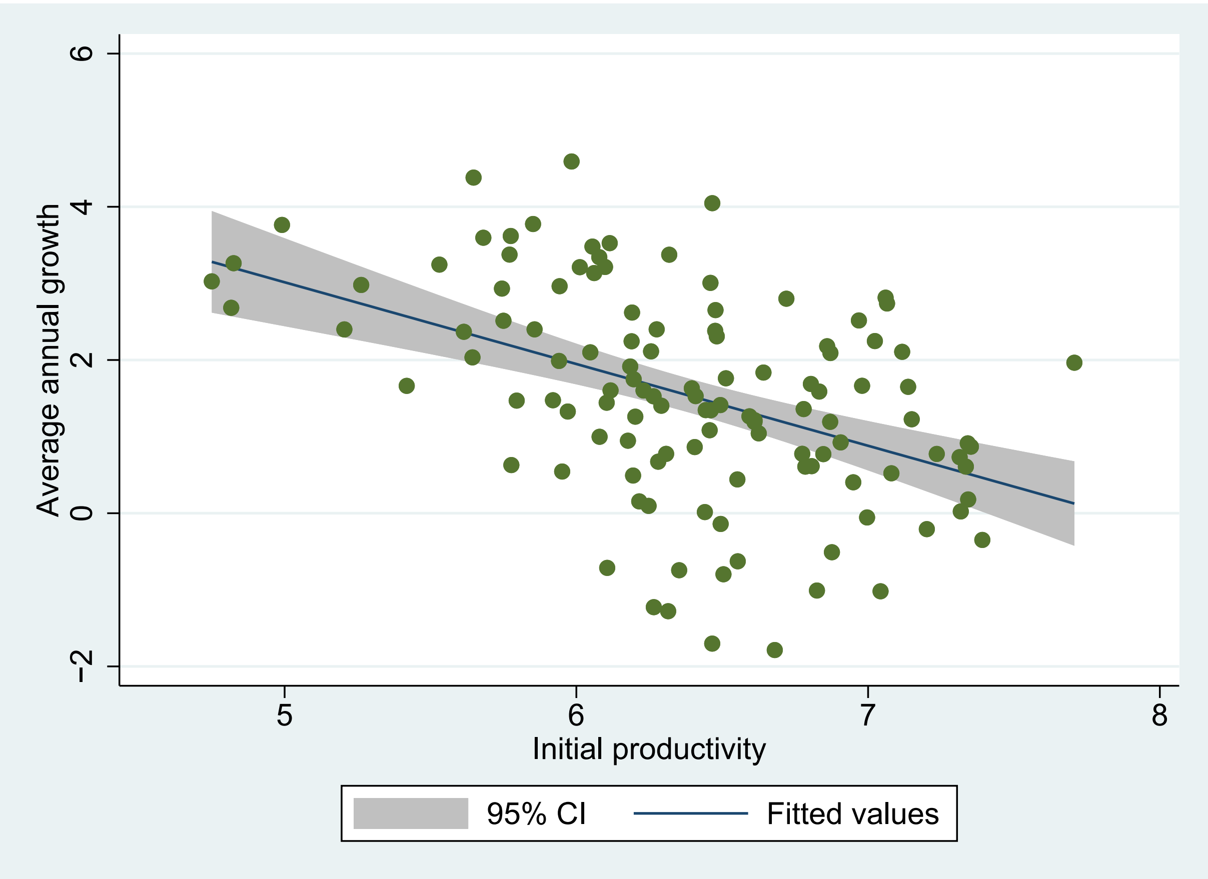

Figure 2.2. β-convergence: Scatter plot of initial resource productivity and its average growth rate. Initial resource productivity in log-levels in 1970 is plotted against the average annual growth rate of resource productivity between 1970 and 2012. The negative slope of the fitted line suggests unconditional β-convergence.

[55]This more pronounced equality in their data should not be overstated as they have a sample of 33 countries. The comparison refers to their economy-wide data figure 1 of their paper.

Table 2.1. Estimation of unconditional β-convergence

	OLS	Robust regression
Initial resource productivity	-1.067***	-1.053***
	(0.150)	(0.197)
Constant	8.351***	8.313***
	(0.957)	(1.261)
R^2	0.2086	-
F-test	0.0000	0.0000
No. of observations	118	118

Note: Asterisks indicate significance at * 10%, ** 5%, *** 1%. Standard errors in parentheses are of Huber/White sandwich type for OLS. Regression of the average annual growth rate of resource productivity on the initial log-level of resource productivity in 1970.

Figure 2.2 and table 2.1 provide some descriptive evidence on the fundamental data dynamics in terms of unconditional β-convergence. Figure 2.2 maps the average annual growth rate of resource productivity on resource productivity in log-levels in the initial period 1970. The negative slope of the fitted line indicates unconditional β-convergence, because countries with higher initial levels experience a lower average annual growth of resource productivity on average. Table 2.1 reports the estimated coefficients from a simple linear regression. The first column uses OLS and the second column controls for potential outliers by using a robust regression.[56] Both results are very similar and support unconditional β-convergence in the traditional regression setting. However, while giving interesting insights into the dynamics of the data, the meaningfulness of β-convergence is severely limited in the presence of transitional heterogeneity. As discussed by Phillips and Sul (2009), estimates of the slope coefficient in traditional Solow regressions that assume homogeneous coefficients are potentially biased due to different sources. Additionally, even a negative coefficient does not necessarily imply convergence and can even occur under conditions of divergence (Phillips and Sul, 2009).

2.3.2 Club Convergence Results

This section presents the results of our main analysis. First, we use the log t regression to determine whether there is overall convergence in resource productivity. Second, we perform the clubbing algorithm briefly described in Section 2.2 to identify convergence clubs.[57]

[56] The robust regression is implemented in Stata using the *rreg* command.

[57] The procedure proposed by Phillips and Sul (2007) is performed in Stata using the routines by Du (2017).

Table 2.2 contains the results for the main analysis. The top row shows that the log t test clearly rejects overall convergence in resource productivity.[58] However, although overall convergence is rejected, the clubbing algorithm detects three convergence clubs.[59]

Table 2.2. Full sample: Convergence in resource productivity

Group	Countries	Log t test
All	All	-0.584 (-31.101)
Club 1	Argentina, Austria, Bahrain, Barbados, Dominican Republic, Egypt, El Salvador, France, Germany, Hungary, Iran, Iraq, Ireland, Israel, Italy, Japan, Jordan, Luxembourg, Netherlands, Panama, Poland, Romania, Singapore, South Korea, Sri Lanka, Spain, Switzerland, United Kingdom, United States of America	0.544 (5.957)
Club 2	Albania, Algeria, Angola, Australia, Bangladesh, Belgium, Belize, Bhutan, Bolivia, Botswana, Brazil, Brunei Darussalam, Bulgaria, Cambodia, Cameroon, Canada, Chad, China, Colombia, Congo, Côte d'Ivoire, Costa Rica, Cyprus, Denmark, Ecuador, Equatorial Guinea, Eswatini, Finland, Gabon, Ghana, Greece, Guatemala, Haiti, Honduras, Iceland, India, Indonesia, Jamaica, Kenya, Laos, Lebanon, Malaysia, Malta, Mauritius, Mexico, Mongolia, Morocco, Mozambique, Myanmar, Namibia, Nicaragua, Nigeria, Nepal, New Zealand, Norway, Oman, Pakistan, Paraguay, Peru, Philippines, Portugal, Qatar, Rwanda, Saudi Arabia, Senegal, Suriname, Sweden, Syria, Tanzania, Thailand, Trinidad and Tobago, Tunisia, Turkey, Venezuela, South Africa, United Arab Emirates, Zambia	0.169 (3.682)
Club 3	Burundi, Benin, Chile, Democratic Republic Congo, Guinea, Mauritania, Malawi, Niger, Togo, Uruguay, Vietnam, Zimbabwe	-0.042 (-0.126)

Note: For the log t test we report the coefficient and the corresponding t-statistic in brackets. As a one-sided test with the null hypothesis of convergence, a t-statistic below -1.65 leads to rejection of the convergence hypothesis.

Regarding the formed convergence clubs in table 2.2 some remarks are in order. First, for all clubs the estimated coefficient $\hat{\gamma}$ is clearly below 2, indicating that there is no evidence for level convergence in any of these groups. Rather, in all three convergence clubs we find relative, i.e., growth convergence. However, Club 3 indicates rather weak convergence given the negative point estimate (Phillips and Sul, 2009). Second, there are

[58] As noted in Section 2.2, overall convergence is similarly rejected when adjusting the log t test in line with the suggestions made by Kwak (2022) or when using unfiltered data or differently extracted trends. Results are available upon request.

[59] The results are very similar for different combinations of sieving criterion and truncation parameter. We also conducted the analysis for the alternative indicator DMC with the same specification choices as for our main results. The results are also very similar to our results for DMI. Spearman's rank correlation coefficient between the club associations for DMI and DMC is 0.55 for the full sample and 0.78 for the reduced sample of 102 countries we use in Section 2.3.4. We further conduct the analysis with the expenditure-side GDP measure. The patterns of emerging convergence clubs are qualitatively virtually identical. All detailed results are available upon request.

interesting patterns with respect to country classification. Club 1 contains many high developed economies, with more than half of the countries being OECD members. Five countries in Club 1 are classified as emerging market economies.[60] In comparison, Club 2 contains relatively less high-developed economies but a larger share of emerging market economies. While less than half of the OECD economies are in Club 2, more than two-thirds of the emerging market economies are part of it. Club 3 only contains one current OECD member and emerging market economy, namely Chile. Hence, the club convergence patterns for resource productivity resemble general developmental distributions and show similarities to the technology clubs found by Castellacci and Archibugi (2008).

There are some noticeable distributions in terms of world regions. In Club 1, roughly half of the countries are Western European and developed countries, while no Sub-Saharan African countries are included. Part of this group are further: two countries from East Asia and the Pacific region, three from Eastern Europe and Central Asia, and one from South Asia. Five countries each are located in Latin America, and the Middle Eastern and North African region. In comparison to that, Club 2 contains less than half of the share of Western European and developed economies as Club 1. Instead, Sub-Saharan African and Latin American countries comprise almost half of the club. The Middle Eastern and North African region has a lower share in Club 2 than it has in Club 1. Club 3 is dominated by Sub-Saharan African countries, which make up three-quarters of the club.

Table 2.3 provides selected descriptive statistics for the three clubs to better understand the club-specific dynamics. In comparison to the other clubs, Club 1 displays the highest average level of resource productivity in the first and final sample period. The relative distance to Club 2 increases from a roughly 20% higher level of resource productivity to a more than twice as high level at the end of the sample. Average productivity growth is almost twice as high for Club 1 than for Club 2. Club 3 falls behind and experiences a decline in resource productivity of -0.55% annually on average. To put these findings into perspective, the dynamics of GDP growth are more balanced. Even Club 3 experienced GDP growth of 2.60% on average, while Club 1 and 2 are almost identical in terms of economic growth, with on average 4.37% and 4.44%, respectively.

[60]We use the classification of emerging markets by Duttagupta and Pazarbasioglu (2021), who identify 20 emerging market economies. 19 of these are included in our sample.

Table 2.3. Descriptive statistics for the convergence clubs

	RP 1970	RP 1991	RP 2012	RP growth	GDP growth
Club 1	802.50	1178.94	2300.47	2.73	4.37
Club 2	676.02	775.26	1127.69	1.41	4.44
Club 3	547.54	565.90	433.56	-0.55	2.60

Note: RP refers to the average level of resource productivity in the three clubs in the years 1970, 1991, and 2012, respectively. It is measured in constant US $ per ton of DMI. RP and GDP growth refer to the average annual growth rate of RP and GDP over the full sample period (in percent).

2.3.3 Determinants of Club Convergence

In this section, we investigate initial, country-specific conditions that might predict the detected club association. A prominent stream of literature on economic development considers path-dependencies, institutions, as well as geography as potential factors that shape developmental paths (e.g., Acemoglu et al., 2001; Glaeser et al., 2004). For example, Glaeser et al. (2004) analyze the effect of initial GDP per capita, human capital, institutions, and geographic factors on subsequent GDP growth. We follow this conceptualization as we look at a measure of technical progress that closely relates to development in general. We assess initial GDP per capita, democracy as a measure of the institutional framework, human capital, and four geographic indicators for their associations with club membership.

In order to identify the link between these fundamental factors and club membership, we employ an ordered logit model (e.g., Bartkowska and Riedl, 2012; Parker and Liddle, 2017a). Club membership qualifies as an ordinal variable, since clubs can be ranked according to the steady states of countries in the respective club (Bartkowska and Riedl, 2012). To explore the effect of variables on the probability to belong to a specific club, we follow related literature and report marginal effects calculated at the means of the variable of interest and all other included explanatory variables. As we are interested in the role of fundamental factors of economic development, we include the initial observation from the full sample ($t = 1970$) as explanatory variable. Although this mitigates endogeneity concerns due to simultaneity, this exercise is not suited to establish causality. Given that we only have one observation of club membership for each country, we are not able to rule out omitted variable bias. Additionally, the causal relation between the fundamental factors is much debated and rather bidirectional. Nevertheless, the exercise facilitates to identify factors that predict the selection into specific clubs. Table A2 shows the correlation between the initial conditions that we employ in the ordered logit regressions. There is an expected, pronounced correlation between several initial conditions such as GDP per capita and human capital across countries. However, the initial conditions are not necessarily correlated in general, and even GDP and human capital are far from being perfectly correlated.

In the following, we discuss the variable choices for the ordered logit regression based on the pertinent literature in greater detail. Initial *GDP per capita* captures a variety of factors that could influence improved club membership. It captures potential path-dependencies in development as well as proximate factors, such as investments (Temple, 1998), that are strongly related with efficiency gains and development (Savvides, 1995). The measure of *democracy* is intended to capture political freedom and rights, which are commonly found to be a source of improved development due to various channels, such as avoidance of bad policy outcomes as well as fostered inclusion and innovation (Savvides, 1995; Moral-Benito, 2012; Acemoglu et al., 2019). *Human capital* is intended to capture levels of education, which directly relate to innovative potential (Glaeser et al., 2004; Baser and Gokten, 2019). However, the detailed interdependencies between institutions, human capital, and GDP per capita are rather multifaceted and complex (Bils and Klenow, 2000; Glaeser et al., 2004; Baser and Gokten, 2019). Hence, the attempt to disentangle their distinct effects in our setting should be treated with due caution.

Characteristics of the natural environment are commonly considered to shape developmental paths (e.g., Gallup et al., 1999). We consider four distinct geographic characteristics, which we derive from the respective literature. First, we consider the share of people of a country living in temperate climate zones. *Temperate climate* has been linked to human behavior, distinct technological possibilities, and different disease burdens (Gallup et al., 1999; Acemoglu, 2008). Second, we utilize the share of natural resource rents in GDP. We treat this initial share as a measure of *resource abundance*, following Sachs and Warner (1995). Higher resource abundance provides distinct economic incentives, and is commonly linked to challenges for development, which is highlighted, for example, in the debate on the resource curse hypothesis (Sachs and Warner, 2001; Stijns, 2005; Torvik, 2009). Third, we capture the *population density* of a country. Population density has been linked to various channels of development, such as higher education (Boucekkine et al., 2007) or increased knowledge spillovers (Fritsch and Schroeter, 2011).[61] Lastly, we

[61] Similar to the share of natural resource rents in GDP, population density is only partly corresponding to a geographical factor. However, as Weisz et al. (2006) argue, it can also be interpreted in the

consider the mean *distance to sea*. Access to sea is considered beneficial for economic development, especially by providing distinct trade possibilities and market access (Bosker and Garretsen, 2012; Bosker et al., 2013).

The observation that Club 3 mainly consists of Sub-Saharan African countries points to the potential relevance of spatial dependencies for club selection. Spatial dependencies that are not captured by our variables, yet correlated to them, might lead to spurious findings. In fact, within the literature on development in Sub-Saharan Africa, neighborhood spillovers as source of spatial dependencies are considered (Hoeffler, 2002). To mitigate concerns that our findings are merely driven by spatial dependencies, we report for all our results a specification that includes a dummy controlling for Sub-Saharan African countries as a robustness check. However, we emphasize caution in treating a loss of significance in these specifications as a rejection of a factors importance for two reasons. First, the Sub-Saharan African dummy removes a substantial amount of variation in club membership. Second, the role of various factors for development with respect to causality or correlation remains contested. It remains beyond the scope of our study to make claims about the nature of these relationships.

Table 2.4 shows the marginal effects at the mean on the probability of belonging to each of the clubs for all our variables. For each variable, a specification together with GDP is reported, as GDP might be interpreted as a "catch-all-term" in the empirical setting. The first column displays the change in probability of belonging to Club 1 for all variables added individually. The estimated coefficients suggest the expected associations. Countries with higher initial GDP per capita, democracy, higher human capital, a more temperate climate, lower resource abundance, higher population density, and better access to the sea tend to belong to higher clubs. For example, a country with initial human capital one standard deviation above the mean has a roughly 16.8 percentage points higher probability to be selected into Club 1 than a country with the average human capital. In the case of democracy, the coefficient corresponds to the discrete change from the base level, i.e., the coefficient in column 1 implies that a democratic country has a 17.8 percentage points higher probability to be in Club 1 than a non-democracy.

context of its reverse indicator, namely land availability. Furthermore, the cross-sectional distribution of population density remains relatively stable over the time period of our sample.

Table 2.4. Marginal effects on probabilities (ordered logit): Full sample resource productivity

	Club 1		Club 2		Club 3	
Panel 1: GDP						
GDP pc	-	0.101***	-	-0.055**	-	-0.047**
		(0.035)		(0.027)		(0.018)
Observations		118		118		118
Panel 2: Democracy						
Democracy	0.178**	-0.008	-0.101*	0.004	-0.077**	0.004
	(0.084)	(0.083)	(0.059)	(0.044)	(0.036)	(0.039)
GDP pc		0.147***		-0.079**		-0.068***
		(0.043)		(0.036)		(0.023)
Observations	108	108	108	108	108	108
Panel 3: Human capital						
Human capital	0.168***	0.153***	-0.101**	-0.093**	-0.067***	-0.061***
	(0.043)	(0.050)	(0.040)	(0.042)	(0.021)	(0.021)
GDP pc		0.022		-0.013		-0.009
		(0.033)		(0.020)		(0.014)
Observations	111	111	111	111	111	111
Panel 4: Temperate climate						
Temperate climate	0.031***	0.026***	-0.017**	-0.014**	-0.014***	-0.011***
	(0.008)	(0.008)	(0.008)	(0.007)	(0.004)	(0.004)
GDP pc		0.043*		-0.024		-0.019
		(0.025)		(0.015)		(0.013)
Observations	112	112	112	112	112	112
Panel 5: Resource abundance						
Resource abundance	-0.081**	-0.093***	0.043*	0.052*	0.038**	0.041**
	(0.034)	(0.034)	(0.025)	(0.027)	(0.017)	(0.017)
GDP pc		0.115***		-0.064**		-0.051**
		(0.035)		(0.029)		(0.020)
Observations	97	97	97	97	97	97
Panel 6: Population density						
Population density	0.089***	0.087***	-0.052**	-0.052**	-0.038***	-0.035***
	(0.022)	(0.021)	(0.023)	(0.022)	(0.010)	(0.010)
GDP pc		0.094***		-0.056**		-0.038**
		(0.027)		(0.022)		(0.017)
Observations	117	117	117	117	117	117
Panel 7: Distance to sea						
Distance to sea	-0.104***	-0.084***	0.057**	0.047*	0.047***	0.037**
	(0.029)	(0.031)	(0.026)	(0.024)	(0.016)	(0.015)
GDP pc		0.052		-0.029		-0.023
		(0.033)		(0.021)		(0.015)
Observations	112	112	112	112	112	112

Note: Asterisks indicate significance at * 10%, ** 5%, *** 1%. The standard errors in parentheses are of Huber/White sandwich type. Marginal effects are calculated at the means. All variables are measured as initial conditions. GDP per capita, population density, and distance to sea are in natural logarithms. Democracy is a dummy variable. Human capital has been standardized to mean zero and standard deviation of one. People living in temperate zones and the measure of resource abundance, i.e., the share of natural resources in GDP, are measured in percentage shares. For ease of display and interpretation, the coefficients for resource abundance and temperate climate are multiplied by 10. That is, the coefficient represents a 10 percentage point increase, e.g., from 50% of people living in temperate climate to 60%.

The second column adds GDP per capita to each one of the other initial conditions. Except for democracy, all variables remain significant. In the specifications with human capital and distance to sea, initial GDP per capita is insignificant. Table A3 shows the same specifications including a dummy that controls for Sub-Saharan African countries, which is always significantly negative associated with Club 1, implying that Sub-Saharan African countries systematically select into lower clubs.[62] In those specifications, distance to sea and resource abundance hardly maintain explanatory power. As discussed before, geographical factors, such as being landlocked, are perhaps responsible for the negative effect of the Sub-Saharan Africa dummy, and thus, their insignificance should not be overstated. Human capital, temperate climate, and population density remain significant at 5% and 1% levels, even in specifications together with GDP per capita and the Sub-Saharan Africa dummy, though the magnitude is reduced.

2.3.4 Comparison to Labor Productivity

In the following section, we compare the convergence patterns of resource productivity (RP) to convergence patterns for labor productivity (LP), in the spirit of Mulder and De Groot (2007). For clarity and convenience, we use these abbreviations and label respective clubs explicitly as LP-Club and RP-Club.[63] The results for the log t test and the clubbing algorithm for LP are displayed in table 2.5. To be able to compare dynamics, table 2.6 reports the results of the clubbing procedure for RP for the reduced sample of the same 102 countries.

A first descriptive assessment of these dynamics provides an indication that there are substantial overlaps in the club association for LP and RP, which are, however, far from perfect. The rank correlation coefficient for the final club associations is 0.55, indicating a moderately high level of correlation. For this reduced sample, the largest clubs are LP-Club 1 with 76 and RP-Club 1 with 73 countries. General findings strongly coincide with our main results. Sub-Saharan African countries dominate the lowest club. OECD countries are now almost exclusively located in the highest club. All 32 OECD countries in our sample are in LP-Club 1, while three rank in RP-Club 2. Also, emerging market economies are now almost exclusively found in the highest club. There is only one emerging market economy in LP-Club 2, while three are in RP-Club 2.

[62] The coefficient for the Sub-Saharan Africa dummy is not reported for reasons of brevity. Detailed results are available upon request.

[63] We use these abbreviations exclusively for this section and all tables related to this section that are displayed in the appendix.

Table 2.5. 102 country sample: Convergence in labor productivity

Group	Countries	Log t test
All	All	-0.629 (-17.210)
LP-Club 1	Albania, Algeria, Argentina, Australia, Austria, Bahrain, Barbados, Belgium, Botswana, Bulgaria, Brazil, Canada, Chile, China, Colombia, Costa Rica, Cyprus, Denmark, Dominican Republic, Egypt, Finland, France, Gabon, Germany, Greece, Guatemala, Hungary, India, Indonesia, Iran, Iraq, Iceland, Ireland, Israel, Italy, Japan, Jordan, Lebanon, Luxembourg, Malaysia, Malta, Mauritius, Mexico, Myanmar, Namibia, Netherlands, New Zealand, Nigeria, Norway, Oman, Panama, Paraguay, Peru, Poland, Portugal, Qatar, Romania, Saudi Arabia, Singapore, South Africa, South Korea, Spain, Sri Lanka, Sweden, Switzerland, Syria, Thailand, Trinidad and Tobago, Tunisia, Turkey, United Arab Emirates, United Kingdom, United States of America, Uruguay, Venezuela, Vietnam	-0.073 (-1.632)
LP-Club 2	Angola, Bangladesh, Bolivia, Cambodia, Cameroon, Chad, Congo, Côte d'Ivoire, Ecuador, Ghana, Honduras, Jamaica, Morocco, Mozambique, Pakistan, Philippines, Senegal, Tanzania, Zambia	-0.025 (-0.350)
LP-Club 3	Democratic Republic Congo, Haiti, Kenya, Malawi, Niger, Rwanda, Zimbabwe	-0.250 (-1.184)

Note: For the log t test we report the coefficient and the corresponding t-statistic in brackets. As a one-sided test with the null hypothesis of convergence, a t-statistic below -1.65 leads to rejection of the convergence hypothesis.

Three countries, namely Uruguay, Haiti, and Vietnam, have an opposite club association between RP and LP. Vietnam and Uruguay are in LP-Club 1, but in the lowest RP-Club 3. Haiti is the opposite by being part of RP-Club 1 and LP-Club 3. For Haiti, the average growth rate of RP amounts to 2.11%, whereas both Uruguay and Vietnam experience negative average growth rates of RP. In the case of LP, however, Uruguay and Vietnam had 1.43% and 3.09% growth per year, respectively, whereas Haiti falls behind with 0.92%.

Table 2.7 reports the distribution of all countries into LP and RP clubs, displaying partly deviating dynamics. By tendency, countries performing well in one are also performing well in the other. This is displayed by the fact that 86% of the countries in LP-Club 1 also belong to RP-Club 1, while only 37% from LP-Club 2 and 14% from LP-Club 3 are in RP-Club 1. Beyond the directly opposite cases discussed above, 18 additional countries are in a higher respective lower club for one than the other indicator.

Table 2.6. 102 country sample: Convergence in resource productivity

Group	Countries	Log t test
All	All	-0.630 (-28.182)
RP-Club 1	Albania, Algeria, Argentina, Austria, Bahrain, Barbados, Belgium, Botswana, Brazil, Bulgaria, Cambodia, Canada, Colombia, Costa Rica, Côte d'Ivoire, Denmark, Dominican Republic, Egypt, France, Gabon, Germany, Greece, Haiti, Hungary, Iceland, India, Iran, Iraq, Ireland, Israel, Italy, Jamaica, Japan, Jordan, Lebanon, Luxembourg, Malaysia, Malta, Mauritius, Mexico, Myanmar, Namibia, Nigeria, Netherlands, New Zealand, Norway, Oman, Pakistan, Panama, Paraguay, Philippines, Poland, Portugal, Qatar, Romania, Saudi Arabia, Singapore, South Africa, South Korea, Spain, Sri Lanka, Sweden, Switzerland, Syria, Tanzania, Thailand, Tunisia, Turkey, United Arab Emirates, United Kingdom, United States of America, Venezuela, Zambia	-0.028 (-0.492)
RP-Club 2	Angola, Australia, Bangladesh, Bolivia, Cameroon, Chad, Chile, China, Congo, Cyprus, Ecuador, Finland, Ghana, Guatemala, Honduras, Indonesia, Kenya, Morocco, Mozambique, Peru, Rwanda, Senegal, Trinidad and Tobago	0.128 (2.613)
RP-Club 3	Democratic Republic Congo, Malawi, Niger, Uruguay, Vietnam, Zimbabwe	-0.448 (-1.541)

Note: For the log t test we report the coefficient and the corresponding t-statistic in brackets. As a one-sided test with the null hypothesis of convergence, a t-statistic below -1.65 leads to rejection of the convergence hypothesis.

Table 2.8 displays descriptive statistics for the obtained clubs. For the three clubs constructed for each LP and RP, the countries in Club 1 always perform best also with respect to the other productivity measure, followed by Club 2 countries, and Club 3 countries performing worst. In both cases, the worst performing club consists of countries that display negative average growth in the productivity measure for which the clubs were formed. However, while in general LP tends to grow stronger, with 1.9% on average in the full sample compared to 1.57% growth of RP, this does not hold for all formed clubs. For example, while the countries in LP-Club 1 clearly grow stronger in terms of LP than RP, the growth performance is close to identical in LP-Club 2 and countries in LP-Club 3 perform better in RP. These patterns might hint that despite substantial joint dynamics, there is some heterogeneity as to whether countries have a balanced improvement in both LP and RP, or whether technology trends differ. Given that we have generally similar growth within the whole sample, it seems interesting to take a look at countries where LP- and RP-growth rates differ substantially. There are 16 countries for which the growth difference is more than 2 percentage points, namely the United Arab Emirates, Bahrain,

Table 2.7. Distribution of countries into LP and RP clubs

	RP-Club 1	RP-Club 2	RP-Club 3
LP-Club 1	65 (85.53)	9 (11.84)	2 (2.63)
LP-Club 2	7 (36.84)	12 (63.16)	0 (0)
LP-Club 3	1 (14.29)	2 (28.57)	4 (57.14)

Note: Number of countries that correspond to the combined club association. In brackets is the % of countries from the respective LP-Club that fall into the specified RP-Club.

Table 2.8. Descriptive statistics for the convergence clubs

	RP 1970	RP 2012	LP 1970	LP 2012	RP growth	LP growth
LP-Club 1	777	1,640	39,122	69,215	1.81	2.28
LP-Club 2	598	879	8,309	13,055	1.10	1.12
LP-Club 3	518	625	4,659	4,374	0.14	-0.13
RP-Club 1	768	1,687	38,228	65,924	1.98	2.14
RP-Club 2	633	869	14,161	28,786	0.86	1.61
RP-Club 3	572	429	7,909	10,744	-0.76	0.02

Note: RP 1970 respective 2012 refers to the level of resource productivity in the first and final period of the sample. It is measured in constant US $ per ton of DMI. RP growth refers to the average growth of this ratio over the sample period, in percent. LP 1970 respective 2012 refers to the level of labor productivity in the first and final period of the sample. It is measured in constant $ per engaged worker. LP growth refers to the average growth of this ratio over the sample period, in percent.

Barbados, Botswana, China, South Korea, Luxembourg, Norway, Panama, Qatar, Syria, Thailand, Turkey, Uruguay, Venezuela, and Vietnam.

Nine of those countries have a higher growth rate for LP, while the United Arab Emirates, Bahrain, Barbados, Luxembourg, Panama, Qatar, and Venezuela gained more in terms of RP. In terms of absolute differences, the United Arab Emirates, Bahrain, China, and Vietnam display the highest heterogeneity with differences larger than three percentage points. The largest differences occur for China and the United Arab Emirates, which both exceed four percentage points into opposite directions. The United Arab Emirates experienced a moderate increase in RP with 0.73% growth on average, while labor productivity declined by 3.82%. In contrast, China gained 0.15% in resource productivity but grew in terms of labor productivity with 4.57% annually.[64]

[64]Noticeably, China has the fifth highest gains in LP behind Romania, Egypt, South Korea, and Botswana, which ranks highest with 6.25%. The highest absolute gains for RP are found for Ireland, Romania, and Panama with 4.05%, 4.38% and 4.59%, respectively.

Finally, tables 2.9 and 2.10 report the results for the ordered logit model for both LP and RP in the reduced sample for 102 countries.[65] The specifications including a Sub-Saharan Africa dummy are displayed in tables A5 and A6. Tables 2.9 and 2.10 show that most variables are similarly associated with club membership for LP and RP. Distance to sea displays no importance for LP and RP, once GDP per capita or the Sub-Saharan Africa dummy are controlled for.[66] Despite these similarities, there are some noticeable differences. First, democracy maintains explanatory power even in more demanding specifications for LP, while it is hardly associated with club membership for RP. Second, the effect of human capital is much more pronounced for LP, where human capital dominates initial GDP per capita, whereas it loses significance in conjunction with GDP per capita for RP. Third, temperate climate is a strong predictor for LP club membership, remaining significant and of relevant magnitude even together with GDP per capita and the Sub-Saharan Africa dummy, as displayed in table A5. For RP, temperate climate loses significance both with initial GDP per capita as well as only together with the Sub-Saharan Africa dummy. Lastly, population density retains a positive association with club membership for RP, though it turns insignificant when the Sub-Saharan Africa dummy is included in this sample. For LP, however, we find no association of population density with improved club membership, not even in the specification with population density only.

To summarize, while the general findings in terms of club association and club size are very similar between RP and LP, there are some interesting idiosyncrasies. These relate to the relative importance of human capital and democracy, as well as for temperate climate and population density.

[65] The correlation of the initial conditions for the reduced sample is reported in table A4.

[66] Similarly, resource abundance is only once slightly significant for LP in conjunction with GDP. Hence, resource abundance can also be considered less relevant.

Table 2.9. Marginal effects on probabilities (ordered logit): 102 country sample labor productivity

	LP-Club 1		LP-Club 2		LP-Club 3	
Panel 1: GDP						
GDP pc	-	0.227***	-	-0.182***	-	-0.045***
		(0.051)		(0.049)		(0.017)
Observations		102		102		102
Panel 2: Democracy						
Democracy	0.319***	0.136*	-0.216***	-0.105*	-0.104**	-0.030
	(0.073)	(0.074)	(0.056)	(0.059)	(0.041)	(0.019)
GDP pc		0.179***		-0.139***		-0.040**
		(0.064)		(0.054)		(0.019)
Observations	95	95	95	95	95	95
Panel 3: Human capital						
Human capital	0.232***	0.144***	-0.185***	-0.119***	-0.048**	-0.025**
	(0.048)	(0.038)	(0.044)	(0.034)	(0.019)	(0.011)
GDP pc		0.099**		-0.082*		-0.017*
		(0.049)		(0.042)		(0.010)
Observations	99	99	99	99	99	99
Panel 4: Temperate climate						
Temperate climate	0.050***	0.031***	-0.041***	-0.027***	-0.009**	-0.004**
	(0.011)	(0.008)	(0.009)	(0.008)	(0.004)	(0.002)
GDP pc		0.106		-0.091		-0.015
		(0.065)		(0.057)		(0.011)
Observations	96	96	96	96	96	96
Panel 5: Resource abundance						
Resource abundance	-0.028	-0.044*	0.017	0.035*	0.011	0.008
	(0.040)	(0.024)	(0.025)	(0.019)	(0.016)	(0.006)
GDP pc		0.262***		-0.211***		-0.051**
		(0.060)		(0.059)		(0.021)
Observations	85	85	85	85	85	85
Panel 6: Population density						
Population density	0.040	0.035	-0.027	-0.028	-0.013	-0.007
	(0.025)	(0.024)	(0.018)	(0.020)	(0.009)	(0.005)
GDP pc		0.226***		-0.183***		-0.043**
		(0.052)		(0.050)		(0.017)
Observations	101	101	101	101	101	101
Panel 7: Distance to sea						
Distance to sea	-0.123***	-0.049	0.092**	0.041	0.032**	0.008
	(0.046)	(0.042)	(0.038)	(0.036)	(0.015)	(0.007)
GDP pc		0.208***		-0.174***		-0.034**
		(0.058)		(0.054)		(0.015)
Observations	96	96	96	96	96	96

Note: Asterisks indicate significance at * 10%, ** 5%, *** 1%. The standard errors in parentheses are of Huber/White sandwich type. Marginal effects are calculated at the means. All variables are measured as initial conditions. GDP per capita, population density, and distance to sea are in natural logarithms. Democracy is a dummy variable. Human capital has been standardized to mean zero and standard deviation of one. People living in temperate zones and the measure of resource abundance, i.e., the share of natural resources in GDP, are measured in percentage shares. For ease of display and interpretation, the coefficients for resource abundance and temperate climate are multiplied by 10. That is, the coefficient represents a 10 percentage point increase, e.g., from 50% of people living in temperate climate to 60%.

Table 2.10. Marginal effects on probabilities (ordered logit): 102 country sample resource productivity

	RP-Club 1		RP-Club 2		RP-Club 3	
Panel 1: GDP						
GDP pc	-	0.174***	-	-0.137***	-	-0.037**
		(0.047)		(0.042)		(0.016)
Observations		102		102		102
Panel 2: Democracy						
Democracy	0.154*	-0.022	-0.110*	0.016	-0.044	0.006
	(0.088)	(0.118)	(0.064)	(0.088)	(0.029)	(0.030)
GDP pc		0.168***		-0.126**		-0.042**
		(0.063)		(0.051)		(0.021)
Observations	95	95	95	95	95	95
Panel 3: Human capital						
Human capital	0.147***	0.051	-0.111***	-0.040	-0.036**	-0.011
	(0.051)	(0.062)	(0.042)	(0.048)	(0.017)	(0.014)
GDP pc		0.133**		-0.103**		-0.030*
		(0.056)		(0.046)		(0.016)
Observations	99	99	99	99	99	99
Panel 4: Temperate climate						
Temperate climate	0.028**	0.010	-0.022**	-0.008	-0.006*	-0.002
	(0.011)	(0.013)	(0.010)	(0.011)	(0.003)	(0.002)
GDP pc		0.146***		-0.119**		-0.027*
		(0.054)		(0.046)		(0.015)
Observations	96	96	96	96	96	96
Panel 5: Resource abundance						
Resource abundance	0.039	0.035	-0.029	-0.028	-0.010	-0.007
	(0.039)	(0.049)	(0.030)	(0.039)	(0.011)	(0.010)
GDP pc		0.182***		-0.144***		-0.038**
		(0.053)		(0.048)		(0.017)
Observations	85	85	85	85	85	85
Panel 6: Population density						
Population density	0.055**	0.059**	-0.040*	-0.047*	-0.014*	-0.012
	(0.027)	(0.030)	(0.021)	(0.025)	(0.008)	(0.007)
GDP pc		0.174***		-0.139***		-0.035**
		(0.050)		(0.044)		(0.015)
Observations	101	101	101	101	101	101
Panel 7: Distance to sea						
Distance to sea	-0.092**	-0.044	0.072**	0.036	0.020	0.008
	(0.045)	(0.047)	(0.036)	(0.038)	(0.012)	(0.009)
GDP pc		0.152***		-0.124***		-0.028**
		(0.052)		(0.046)		(0.014)
Observations	96	96	96	96	96	96

Note: Asterisks indicate significance at * 10%, ** 5%, *** 1%. The standard errors in parentheses are of Huber/White sandwich type. Marginal effects are calculated at the means. All variables are measured as initial conditions. GDP per capita, population density, and distance to sea are in natural logarithms. Democracy is a dummy variable. Human capital has been standardized to mean zero and standard deviation of one. People living in temperate zones and the measure of resource abundance, i.e., the share of natural resources in GDP, are measured in percentage shares. For ease of display and interpretation, the coefficients for resource abundance and temperate climate are multiplied by 10. That is, the coefficient represents a 10 percentage point increase, e.g., from 50% of people living in temperate climate to 60%.

2.3.5 Discussion

Overall, we report three main findings. First, we find evidence for club convergence in resource productivity. Second, we find initial GDP per capita and population density to be strong predictors for the convergence club membership in regard to resource productivity. Third, we find that despite similarities, resource productivity convergence displays some distinct patterns compared to labor productivity convergence. In the following, we discuss these three findings in more depth against the background of the literature.

Our main results show that there is no convergence across all countries with respect to resource productivity. Instead, we detect three convergence clubs. The best performing club consists to a substantial degree of highly developed economies, with over half of them being OECD members. Five of the 19 emerging market economies in our sample, namely Argentina, Egypt, Hungary, Iran, and Poland, are part of this club as well.[67] The middle club is by far the largest with 77 countries, containing more than half of the sample countries. Club 2 contains a substantially larger share of emerging market economies, while the share of OECD economies is much lower. Club 3 contains only one OECD member,[68] and instead contains mostly Sub-Saharan African countries. In this sense, the club associations display to quite some degree developmental levels, though many noticeable exceptions are present. These main findings are consistent with comparable studies on energy and resource productivity. In their study on resource productivity in EU countries, Alataş et al. (2021) detect club convergence and that more developed EU-15 countries are in higher clubs than less developed EU countries. Overall, the association of countries into the different clubs seems to fit well to the distinctions proposed by endogenous growth theory (Howitt and Mayer-Foulkes, 2005) and empirically found for innovation patterns (Castellacci and Archibugi, 2008). Here, a split into clubs based on technology patterns relating to innovation, imitation, and stagnation seems to resemble the distribution of countries into clubs. Innovation patterns directly relate to the level of efficiency with which input factors – like resources – can be transformed into economic value. All clubs have estimated coefficients clearly below 2, indicating that there is no evidence for level convergence in any of these groups. Hence, when it comes to decoupling economic development from natural resource use one cannot focus only on the best performing countries, since less developed countries are not necessarily on a developmental

[67]Notably, Hungary and Poland are also OECD economies.

[68]Only Chile, which joined in 2010, and is also classified as emerging market economy (Duttagupta and Pazarbasioglu, 2021).

path of catching-up. In sum, our evidence suggests that differences between countries are not likely to disappear, and inequality across different groups of countries are even set to become more pronounced.

The analysis of the determinants of convergence club membership yields some interesting findings. First, we find initial GDP per capita to be a good predictor for club membership, yet with varying interrelations to other fundamental factors such as human capital. Second, we find that among the geographic variables, population density is the most powerful predictive factor for club membership. As to our first finding, higher initial GDP per capita is generally strongly associated with improved club membership. However, the interplay with the other fundamental factors is not unambiguous. Among the three socio-economic variables, democracy always appears to be least predictive as it loses explanatory power when included alongside GDP. This interplay, however, is less clear with respect to initial GDP per capita and human capital. In the full sample, human capital carries more explanatory power, whereas initial GDP per capita dominates in the 102 country sample. This ambiguity points towards the difficulties of disentangling the distinct effects in a cross-sectional setting. The nature of the bidirectional relationship of GDP per capita and human capital remains contested (e.g., Bils and Klenow, 2000; Glaeser et al., 2004). However, as both initial GDP per capita and human capital are good measures of developmental stages in a cross-sectional setting, these findings display clearly that more developed countries converge to higher steady states than less developed countries. In this vein, the general positive association of initial GDP per capita is in line with related literature on development and environmental performance. While Savvides (1995) links higher wealth to increased means for investment, Tawiah et al. (2021) recently report that green growth and economic growth are coupled in industrialized countries, while there is no coupling for developing economies. Concerning our second finding, it should be noted that all geographic variables are generally associated in the expected way with club membership. Countries with temperate climate, low dependence on natural resources, a high population density, and access to navigable waterways tend to select into higher clubs. Across samples and specifications, higher population density is most robustly associated with higher club membership. This finding corresponds to insights in related papers on the determinants of resource productivity. Weisz et al. (2006) and Gan et al. (2013) emphasize the high importance of population density for resource productivity and show evidence for various channels that cause this association. First, a high population density might enable material-saving high density settlements and transportation patterns. Second, low land availability restricts domestic resource availability and, thus, reduces incentives to develop material-intensive sectors.

Finally, there are substantial overlaps with respect to club membership for resource and labor productivity. However, there are also some noticeable differences between the patterns shown by the overall club dynamics in table 2.8 and our discussion on individual countries. While some countries, such as the United Arab Emirates and Bahrain, experienced substantial increases in resource productivity despite low increases or even decreases in labor productivity, other countries substantially increased labor productivity but had lower improvements in resource productivity. This includes countries such as South Korea, Norway, or China, which increased labor productivity by more than 2 percentage points more compared to resource productivity over the observed time period.

Mulder and De Groot (2007) provide a rationale with respect to the driving forces of the respective productivities. They find labor and energy productivity to be driven by wages and energy prices, respectively, with wages showing larger cross-country discrepancies than energy prices. A similar argument has been developed by the theoretical literature on directed technical change, which highlights the role of energy prices for energy efficiency improvements. For example, Haas and Kempa (2018) discuss how energy prices drive the energy intensity of aggregate production through technical improvements within sectors and structural change between sectors. We consider this explanation to be highly relevant for our context, because the discrepancy is likely pronounced in the case of resource prices. To a substantial degree, resource prices are driven by global prices instead of domestic characteristics (Agnolucci et al., 2017), whereas wages have a stronger domestic component. Noticeably, as reported by our ordered logit analysis, democracy and higher levels of human capital appear to be more strongly associated with club membership for labor productivity than for resource productivity. This finding might be linked to the determinants of resource prices respective wages in countries. Democracy is found to cause higher wages (Rodrik, 1999), likely via increased labour standards (Palley, 2005). Similarly, higher education, i.e., human capital, is related to higher wages (Berman et al., 1998). Thus, for domestically determined wages both variables likely relate to upward pressures, fostering improvements in labor productivity. As noted above, resource prices are rather determined on a global market, which might explain the weaker association of these factors for club selection in the case of resource productivity.

Furthermore, we report notable differences with respect to geographic factors. Temperate climate is distinctly associated with club membership for labor productivity, whereas population density is distinctly associated with club membership for resource productivity. As discussed before, the effects of climate on productivity might have various channels. For example, findings on reduced agricultural productivity (Ortiz-Bobea et al., 2021) might be linked to considerations on distinct technological possibilities. Here, we focus on the possible relation between human capital and climate conditions. The effects of a warmer climate on human behavior and knowledge accumulation are central to the considerations on geographic factors (Acemoglu, 2008). Interestingly, temperate climate and human capital display the highest pairwise cross-country correlation among the fundamental factors in the analysis.[69] Taking this correlation and the distinct effects of human capital for labor productivity into account, a plausible link is the effect of temperate climate via human capital accumulation. However, we are obviously not able to distinguish whether the association is indeed moderated by human capital accumulation and/or other factors. In fact, Kahn et al. (2021) find general negative effects of increases in temperature on labor productivity within countries, irrespective of country-specific characteristics.

2.4 Conclusion

Are countries converging to the same levels of productivity in transforming natural resources into economic output? This question is of high importance as it determines the need for policy intervention in the pursuit of sustainable economic development. In this paper, we have analyzed the convergence patterns of resource productivity of 118 countries between 1970 and 2012. Consistent with findings from the literature on resource and energy productivity, our data is not supportive of overall convergence in resource productivity. Instead, we find club convergence and the three convergence clubs resemble the stages of economic development of the included countries. Additionally, there is no evidence for level convergence within clubs but only growth convergence. Our second key finding is that the initial values of human capital, GDP per capita, democracy, temperate climate, resource abundance, population density, and access to the sea predict club membership. Especially GDP per capita and population density are robust predictors of club membership, i.e., wealthy countries and those with lower land availability select into better performing clubs. To put these results into perspective, we have compared the convergence patterns of resource productivity to those of labor productivity. The

[69] The correlation coefficient is slightly above 0.7 in both samples.

convergence patterns of resource productivity show generally similar dynamics to labor productivity. However, for some countries substantial differences occur. This suggests that productivity developments with respect to different production inputs do not take place evenly for all countries. Compared to resource productivity, the selection into good performing clubs for labor productivity shows some differences. First, the predictive associations of democracy and human capital are more pronounced for labor productivity. This might point towards the relevance of domestically determined wages that drive labor productivity, which are in contrast to resource prices that are strongly determined at a global level. In terms of geographic factors, we find population density to be distinctly relevant for resource productivity, whereas a temperate climate is distinctly important for labor productivity.

The conducted analysis has some limitations that are worth noting. The first limitation concerns the available indicators for resource productivity. Both our employed indicator DMI and its alternative DMC count imported and exported materials with the actual weight of traded materials. In this way, any upstream material requirements of traded materials, which are not accordingly increasing the weight of imports or exports, are no longer fully detectable in the utilized data. Particularly for highly developed economies this might hide resource use to a relevant degree (Wiedmann et al., 2015). Hence, an analysis with indicators capturing upstream material use could be an important complement to the proposed analysis. However, since these data are currently available only from 1990 onward, long-run analyses are currently hardly possible. The second limitation concerns the level of disaggregation both with respect to the data and the level of analysis. In this paper, we have analyzed total resource use, which is a necessary and established choice to capture all resource requirements of an economy. However, countries might still exert fairly different dynamics with respect to the use of different resource categories. For example, a country might not reduce resource use overall but substitutes fossil resources successively for alternative resources for energy generation. Hence, our indicator does not allow any conclusion about substitution between different natural resources. Similarly, our analysis is at an aggregate level, which prohibits any differentiation with respect to patterns within different sectors.

Some relevant notes on policy based on the results of our analysis are in order. We do not find evidence of overall convergence, but that less developed countries cannot necessarily be expected to catch up. This hints towards an increasing gap between developed and developing economies. Hence, gains in resource productivity that are realized in highly developed economies should not be overrated as lacking increases in less developed countries might prohibit a global reduction of resource use in further developmental processes. Additionally, the less developed countries are consequently more vulnerable when it comes to potential damages from increasing resource scarcity and prices, emphasizing the need for developmental policies.

Our analysis highlights several avenues for further research. First, to deepen our understanding of convergence patterns with respect to resource productivity, further research could consider different types of natural resources in more detail. This can provide important insights concerning different developmental patterns across countries and whether resource types show heterogeneous or homogeneous dynamics. Second, further analyses could take the sectoral level into account. The resource dependence of different sectors can be very different, and understanding in more detail which sectors have fairly homogeneous global dynamics and which ones are developing locally different could provide important implications for policies relating to technology and knowledge transfer. Third, the lacking support of our data for overall convergence points towards the necessity of improving effective knowledge transfer. Fourth, in this paper we have analyzed the relevance of initial conditions for club association. However, an interesting line for further research might be to look into convergence clubs and assess the structural characteristics that determined the idiosyncratic transition paths of countries.

Appendix A

Table A1. Data description and sources

Variables	Description	Source
Data for productivity measures		
DMI	Direct material input of all resources (tons)	UN-IRP Global Material Flows Database (2018)
Employment	Number of people engaged (persons)	Penn World Table 10.0
GDP	Output-side real GDP at chained PPPs (2017 US $)	Penn World Table 10.0
Ordered logit variables		
GDP pc	GDP divided by population (2017 US $)	Penn World Table 10.0
Democracy	Measure of democracy (binary)	Acemoglu et al. (2019)
Human capital	Human capital (index)	Penn World Table 10.0
Temperate climate	People living in temperate climate zones in 1995 (% of population)	Center for International Development at Harvard University (kgptemp)
Resource abundance	Total natural resources rents (% of GDP)	World Bank (NY.GDP.TOTL.RT.ZS)
Population density	People per land area (per sq. km)	World Bank (EN.POP.DNST)
Distance to sea	Mean distance to nearest coastline or sea-navigable river (km)	Center for International Development at Harvard University (distcr)

Table A2. Cross-country correlation of the initial conditions

	GDP pc	Human capital	Democracy	Resource abundance	Temperate climate	Population density	Distance to sea	Sub-Saharan Africa
GDP pc	1							
Human capital	0.611	1						
Democracy	0.617	0.632	1					
Resource abundance	0.076	-0.280	-0.295	1				
Temperate climate	0.475	0.716	0.456	-0.323	1			
Population density	0.004	0.185	0.222	-0.377	0.285	1		
Distance to sea	-0.396	-0.411	-0.339	0.079	-0.300	-0.522	1	
Sub-Saharan Africa	-0.367	-0.454	-0.279	0.172	-0.393	-0.297	0.495	1

Note: Pairwise cross-country correlation between the initial conditions.

Table A3. Marginal effects on probabilities (ordered logit): Full sample resource productivity with Sub-Saharan Africa dummy

	Club 1		Club 2		Club 3	
Panel 1: GDP						
GDP pc	-	0.049	-	-0.034	-	-0.015
		(0.030)		(0.022)		(0.011)
Sub-Saharan Africa	-	Yes	-	Yes	-	Yes
Panel 2: Democracy						
Democracy	0.079	-0.024	-0.055	0.016	-0.024	0.008
	(0.075)	(0.078)	(0.058)	(0.051)	(0.021)	(0.028)
GDP pc		0.089**		-0.060*		-0.029
		(0.043)		(0.032)		(0.019)
Sub-Saharan Africa	Yes	Yes	Yes	Yes	Yes	Yes
Panel 3: Human capital						
Human capital	0.103***	0.098**	-0.074**	-0.070*	-0.029*	-0.028*
	(0.037)	(0.042)	(0.032)	(0.036)	(0.015)	(0.015)
GDP pc		0.008		-0.006		-0.002
		(0.032)		(0.023)		(0.009)
Sub-Saharan Africa	Yes	Yes	Yes	Yes	Yes	Yes
Panel 4: Temperate climate						
Temperate climate	0.018**	0.017**	-0.012**	-0.011*	-0.006**	-0.005**
	(0.007)	(0.007)	(0.006)	(0.006)	(0.003)	(0.003)
GDP pc		0.016		-0.011		-0.005
		(0.025)		(0.017)		(0.009)
Sub-Saharan Africa	Yes	Yes	Yes	Yes	Yes	Yes
Panel 5: Resource abundance						
Resource abundance	-0.052	-0.059*	0.037	0.042	0.015	0.017
	(0.032)	(0.033)	(0.025)	(0.027)	(0.011)	(0.012)
GDP pc		0.048		-0.034		-0.013
		(0.031)		(0.024)		(0.010)
Sub-Saharan Africa	Yes	Yes	Yes	Yes	Yes	Yes
Panel 6: Population density						
Population density	0.058***	0.061***	-0.040**	-0.043**	-0.018**	-0.018**
	(0.019)	(0.018)	(0.017)	(0.017)	(0.008)	(0.008)
GDP pc		0.054**		-0.038**		-0.016
		(0.025)		(0.019)		(0.011)
Sub-Saharan Africa	Yes	Yes	Yes	Yes	Yes	Yes
Panel 7: Distance to sea						
Distance to sea	-0.049*	-0.040	0.033	0.027	0.016	0.013
	(0.026)	(0.027)	(0.020)	(0.020)	(0.010)	(0.010)
GDP pc		0.029		-0.019		-0.009
		(0.029)		(0.020)		(0.011)
Sub-Saharan Africa	Yes	Yes	Yes	Yes	Yes	Yes

Note: Asterisks indicate significance at * 10%, ** 5%, *** 1%. The standard errors in parentheses are of Huber/White sandwich type. The Sub-Saharan Africa dummy is included, but not reported. Further, we do not report observations here, since these remain identical to the corresponding table without the dummy. Marginal effects are calculated at the means of the explanatory and all other variables. All variables are measured as initial conditions. GDP per capita, population density, and distance to sea are in natural logarithms. Democracy is a dummy variable. Human capital has been standardized to mean zero and standard deviation of one. People living in temperate zones and the measure of resource abundance, i.e., the share of natural resources in GDP, are measured in percentage shares. For ease of display and interpretation, the coefficients for resource abundance and temperate climate are multiplied by 10. That is, the coefficient represents a 10 percentage point increase, e.g., from 50% of people living in temperate climate to 60%.

Table A4. Cross-country correlation of the initial conditions: reduced sample

	GDP pc	Human capital	Democracy	Resource abundance	Temperate climate	Population density	Distance to sea	Sub-Saharan Africa
GDP pc	1							
Human capital	0.615	1						
Democracy	0.597	0.606	1					
Resource abundance	0.115	-0.270	-0.280	1				
Temperate climate	0.486	0.723	0.419	-0.341	1			
Population density	-0.014	0.202	0.201	-0.361	0.285	1		
Distance to sea	-0.373	-0.391	-0.327	0.060	-0.320	-0.563	1	
Sub-Saharan Africa	-0.378	-0.444	-0.247	0.113	-0.422	-0.348	0.522	1

Note: Pairwise cross-country correlation between the initial conditions.

Table A5. Marginal effects on probabilities (ordered logit): 102 country sample labor productivity with Sub-Saharan Africa dummy

	LP-Club 1		LP-Club 2		LP-Club 3	
Panel 1: GDP						
GDP pc	-	0.179***	-	-0.158***	-	-0.020**
		(0.050)		(0.048)		(0.010)
Sub-Saharan Africa		Yes		Yes		Yes
Panel 2: Democracy						
Democracy	0.261***	0.138*	-0.218***	-0.121	-0.043*	-0.017
	(0.078)	(0.083)	(0.070)	(0.074)	(0.022)	(0.013)
GDP pc		0.123*		-0.108*		-0.015
		(0.064)		(0.057)		(0.010)
Sub-Saharan Africa	Yes	Yes	Yes	Yes	Yes	Yes
Panel 3: Human capital						
Human capital	0.184***	0.082*	-0.156***	-0.072*	-0.028**	-0.010
	(0.045)	(0.043)	(0.042)	(0.038)	(0.013)	(0.007)
GDP pc		0.121**		-0.106**		-0.015*
		(0.055)		(0.050)		(0.009)
Sub-Saharan Africa	Yes	Yes	Yes	Yes	Yes	Yes
Panel 4: Temperate climate						
Temperate climate	0.041***	0.024**	-0.036***	-0.022**	-0.005*	-0.002
	(0.010)	(0.011)	(0.009)	(0.010)	(0.003)	(0.001)
GDP pc		0.104		-0.094		-0.009
		(0.066)		(0.061)		(0.007)
Sub-Saharan Africa	Yes	Yes	Yes	Yes	Yes	Yes
Panel 5: Resource abundance						
Resource abundance	0.011	-0.011	-0.009	0.010	-0.002	0.001
	(0.028)	(0.027)	(0.022)	(0.024)	(0.006)	(0.003)
GDP pc		0.225***		-0.199***		-0.027*
		(0.061)		(0.060)		(0.014)
Sub-Saharan Africa	Yes	Yes	Yes	Yes	Yes	Yes
Panel 6: Population density						
Population density	-0.029	-0.014	0.024	0.012	0.005	0.002
	(0.035)	(0.029)	(0.029)	(0.026)	(0.007)	(0.004)
GDP pc		0.179***		-0.158***		-0.021**
		(0.053)		(0.050)		(0.010)
Sub-Saharan Africa	Yes	Yes	Yes	Yes	Yes	Yes
Panel 7: Distance to sea						
Distance to sea	-0.014	0.038	0.012	-0.035	0.002	-0.004
	(0.052)	(0.050)	(0.044)	(0.045)	(0.008)	(0.005)
GDP pc		0.194***		-0.176***		-0.018*
		(0.055)		(0.053)		(0.010)
Sub-Saharan Africa	Yes	Yes	Yes	Yes	Yes	Yes

Note: Asterisks indicate significance at * 10%, ** 5%, *** 1%. The standard errors in parentheses are of Huber/White sandwich type. The Sub-Saharan Africa dummy is included, but not reported. Further, we do not report observations here, since these remain identical to the corresponding table without the dummy. Marginal effects are calculated at the means of the explanatory and all other variables. All variables are measured as initial conditions. GDP per capita, population density, and distance to sea are in natural logarithms. Democracy is a dummy variable. Human capital has been standardized to mean zero and standard deviation of one. People living in temperate zones and the measure of resource abundance, i.e., the share of natural resources in GDP, are measured in percentage shares. For ease of display and interpretation, the coefficients for resource abundance and temperate climate are multiplied by 10. That is, the coefficient represents a 10 percentage point increase, e.g., from 50% of people living in temperate climate to 60%.

Table A6. Marginal effects on probabilities (ordered logit): 102 country sample resource productivity with Sub-Saharan Africa dummy

	RP-Club 1		RP-Club 2		RP-Club 3	
Panel 1: GDP						
GDP pc	-	0.136***	-	-0.110**	-	-0.026**
		(0.051)		(0.044)		(0.013)
Sub-Saharan Africa		Yes		Yes		Yes
Panel 2: Democracy						
Democracy	0.093	-0.025	-0.071	0.019	-0.022	0.006
	(0.094)	(0.128)	(0.073)	(0.099)	(0.023)	(0.029)
GDP pc		0.126*		-0.098*		-0.028
		(0.070)		(0.056)		(0.018)
Sub-Saharan Africa	Yes	Yes	Yes	Yes	Yes	Yes
Panel 3: Human capital						
Human capital	0.090*	-0.003	-0.070	0.003	-0.020	0.001
	(0.053)	(0.063)	(0.043)	(0.050)	(0.013)	(0.013)
GDP pc		0.134**		-0.107**		-0.027*
		(0.062)		(0.051)		(0.016)
Sub-Saharan Africa	Yes	Yes	Yes	Yes	Yes	Yes
Panel 4: Temperate climate						
Temperate climate	0.016	0.002	-0.013	-0.001	-0.003	-0.000
	(0.013)	(0.015)	(0.011)	(0.012)	(0.002)	(0.002)
GDP pc		0.131**		-0.109**		-0.022
		(0.059)		(0.050)		(0.013)
Sub-Saharan Africa	Yes	Yes	Yes	Yes	Yes	Yes
Panel 5: Resource abundance						
Resource abundance	0.094	0.093	-0.077	-0.078	-0.018	-0.015
	(0.061)	(0.068)	(0.050)	(0.058)	(0.013)	(0.012)
GDP pc		0.130**		-0.108**		-0.021**
		(0.057)		(0.052)		(0.011)
Sub-Saharan Africa	Yes	Yes	Yes	Yes	Yes	Yes
Panel 6: Population density						
Population density	0.024	0.038	-0.019	-0.031	-0.005	-0.007
	(0.030)	(0.032)	(0.023)	(0.027)	(0.007)	(0.006)
GDP pc		0.144***		-0.117**		-0.027**
		(0.053)		(0.047)		(0.013)
Sub-Saharan Africa	Yes	Yes	Yes	Yes	Yes	Yes
Panel 7: Distance to sea						
Distance to sea	-0.031	-0.001	0.025	0.000	0.006	0.000
	(0.048)	(0.053)	(0.039)	(0.044)	(0.010)	(0.009)
GDP pc		0.134**		-0.112**		-0.022*
		(0.056)		(0.049)		(0.013)
Sub-Saharan Africa	Yes	Yes	Yes	Yes	Yes	Yes

Note: Asterisks indicate significance at * 10%, ** 5%, *** 1%. The standard errors in parentheses are of Huber/White sandwich type. The Sub-Saharan Africa dummy is included, but not reported. Further, we do not report observations here, since these remain identical to the corresponding table without the dummy. Marginal effects are calculated at the means of the explanatory and all other variables. All variables are measured as initial conditions. GDP per capita, population density, and distance to sea are in natural logarithms. Democracy is a dummy variable. Human capital has been standardized to mean zero and standard deviation of one. People living in temperate zones and the measure of resource abundance, i.e., the share of natural resources in GDP, are measured in percentage shares. For ease of display and interpretation, the coefficients for resource abundance and temperate climate are multiplied by 10. That is, the coefficient represents a 10 percentage point increase, e.g., from 50% of people living in temperate climate to 60%.

Chapter 3

Institutions and the Nexus of Economic Growth and Natural Resource Use

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Abstract

For a panel of 159 countries over the period 1992–2010, we estimate how the long-run effect of a permanent increase in the growth rate of GDP on the growth rate of resource use depends on political institutional quality. We study this relationship for total resource use and for the following subclasses: fossil fuels, biomass, non-metallic minerals, and metal ores. Our results show that on average total resource use growth is strongly coupled to economic growth, however, there is pronounced heterogeneity of the procyclicality across countries. This procyclicality of total resource use growth is positively associated with the political institutional quality of a country. For the subclasses biomass and non-metallic minerals we also document this association, while we find no positive association for fossil fuel resources. We discuss our findings considering the different transmission channels through which institutions affect relative factor prices and technology.

Keywords: Resource Use; Economic Growth; Institutions; Dynamic Panel Data

JEL Classification: O43; O44; Q32

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3.1 Introduction

Economic activity is inherently connected to the use of natural resources. In the last century, economic growth and welfare increase in developed and developing countries went hand in hand with increases in resource use (e.g., Krausmann et al., 2009; Agnolucci et al., 2017). However, finite resource stocks, limits to the carrying capacity of the Earth system (e.g., Arrow et al., 1995; Rockström et al., 2009; Hoekstra and Wiedmann, 2014; Schramski et al., 2015), and respective negative externalities connected to the extraction, processing, and discarding of natural resources have severe consequences for humankind and the natural environment. These externalities and consequences become more relevant over time, since the use of natural resources is strongly coupled with economic growth on the aggregate level (e.g., Krausmann et al., 2009; Shao et al., 2017). On a disaggregate level, however, substantial heterogeneity exists across countries. During the period 1992–2010, the within-country correlation between the growth rate of resource use per capita and GDP growth per capita is 0.970 in Russia, 0.887 in the United States, 0.678 in China, and close to zero (0.082) in Nigeria.[70] These examples already indicate the potential differences across countries in the procyclicality of resource use, i.e., the long-run impact of a permanent increase in GDP growth on the growth of resources use (Dées, 2020).[71]

In the following, we argue that the differences across countries in the relationship between economic growth and growth in resource use are linked to political institutions. According to North (1990), institutions are the "rules of the game", i.e., the framework conditions shaping interactions and economic activities. The country examples above already exemplify countries with different political institutional frameworks, and we provide

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[70]See Section 3.2 for data sources.

[71]Note that throughout this paper, we use the term procyclicality instead of the more general term cyclicality. We do this because resource use is expected to be procyclical and the focus of this paper is the role of institutional quality in influencing the degree of procyclicality. In this notion, a negative procyclicality would imply countercyclicality. Additionally, we use the term "long run" in an econometric sense (controlling for lagged adjustments). In fact, the results are generally driven by the coefficient of the contemporaneous impact of GDP growth on resource use, such that short-run and long-run effects generally correspond closely.

detailed empirical evidence on the influence of political institutions on the procyclicality of resource use growth.

Our paper relates to three main strands of the empirical and theoretical literature. First, our paper links to the contributions that estimate the direct connection of economic activity or income and the use of resources. Shao et al. (2017) estimate the effect of economic recessions on resource use and find that material use in general but also for parts of its subclasses is reduced in such periods. Agnolucci et al. (2017) find that there is a causal impact of economic activity on resource use and that this causal impact differs between Western European and Eastern European countries. These country differences give tentative evidence for heterogeneity in the procyclicality of resource use. However, a detailed and encompassing account of the heterogeneity is missing, although the presence of heterogeneity is highlighted in the closely related stream of literature estimating the effects of economic growth on carbon dioxide (CO_2) emissions (e.g., Narayan and Narayan, 2010; Jaunky, 2011; Burke et al., 2015). For example, Burke et al. (2015) document that higher-developed countries (in terms of GDP) tend to have a stronger procyclicality, although the estimate is not significant across all specifications.

Second, our work closely relates to the empirical literature that explicitly estimates the role of institutional quality for different dimensions of environmental quality, especially CO_2 emissions. Farzin and Bond (2006) estimate the role of institutional quality in the emissions-growth nexus for different types of emissions, by controlling for an interaction between GDP and the level of democracy. They find a mitigating effect of democracy on emissions. Dées (2020) estimates an income threshold effect in the relationship between emissions growth and economic growth. The results suggest that both the threshold effect and the procyclicality of emissions depend on the level of institutional quality. However, similar analyses on the broader use of resources in general are absent. Especially the role of institutional quality for the heterogeneity in the procyclicality of resource use is not considered yet.

Third, the general literature on endogenous growth theory provides a starting point for why the institutional framework serves as a fundamental factor in the relationship between resource use growth and economic growth. Endogenous growth theory suggests two proximate factors – namely, input prices and the rate and direction of technological change – that determine how much natural resources or energy are used in production (e.g., André and Smulders, 2014; Witajewski-Baltvilks et al., 2017). For example, Witajewski-Baltvilks et al. (2017) use an endogenous growth model to show that the growth of energy use depends on economic growth, energy prices, and technology. Such factor price changes have two relevant effects in endogenous growth models. They cause shifts in relative factor demand, and, additionally, direct technological change towards saving the relatively more expensive input (e.g., Hicks, 1932; Newell et al., 1999; Acemoglu, 2002; Popp, 2002).

We pick up on this relationship and argue that political institutions serve as a fundamental factor influencing relative prices of production factors and technical change. For example, Acemoglu et al. (2012) and Acemoglu et al. (2016) show that changing the price signal and subsidizing research can redirect economic activity. The adoption and stringency of such regulation has been shown to depend on the political institutional framework (Dasgupta and De Cian, 2018). Furthermore, political institutions are a cornerstone of a well-functioning innovation system (Lundvall, 1992; Nelson, 2002), thereby fostering technical progress. Based on these considerations, we argue that institutions are a fundamental factor mediating the nexus between economic growth and the growth of resource use.

We test the role of institutions in an empirical approach for a balanced panel of 159 countries for the period 1992–2010. We use data on resource use and GDP from the United Nations International Resource Panel Global Material Flows Database (GMFD) (UNEP, 2016; UN-IRP, 2018). The data contain information about the total resource use of a country in a given year and about four subclasses: fossil fuels, biomass, non-metallic minerals, and metal ores. To operationalize the formal institutional environment of a country, we use the Institutional Quality Dataset (IQD) compiled by Kunčič (2014), which is commonly used in similar applications (e.g., Aller et al., 2015; Damijan et al., 2015). We focus on the political institutional quality indicator, which captures particularly those institutional dimensions – namely, democracy, good governance and corruption – that are most relevant for environmental policies and protection (Dasgupta and De Cian, 2016). We apply fixed-effects estimation in a dynamic panel to account for dynamic adjustment processes between economic growth and resource use growth. We provide further robustness tests for omitted variables, weak exogeneity, and asymmetric effects in periods of positive and negative economic growth.

We report three important empirical findings. First, on average, total resource use growth and resource use growth in the subclasses – fossil fuels, biomass, non-metallic minerals, and metal ores – is coupled to economic growth, but coefficients of the procyclicality are considerably heterogeneous across countries. Second, the procyclicality of total resources, biomass, and non-metallic minerals is positively associated with the political institutional quality of a country, even if we control for confounding factors such as the level of GDP per capita, the industry share, trade openness, or resource rents. The results for metal ores are less robust, but generally point towards a similar association. However, for fossil fuels, we find no evidence for a positive association of institutional quality and the procyclicality of resource use. Third, while this association is based on the variation of institutional quality between countries, the evidence of a positive association in the within-country dimension is less pronounced, though still present, especially for total resources. Overall, in both dimensions, the procyclicality of total resource use is more than 1 percentage point higher for a country with a perfect institutional framework compared to a country with the worst institutional quality.

The remainder of the paper is organized as follows. Section 3.2 presents the data and descriptive statistics and Section 3.3 the empirical approach. Section 3.4 reports the results, extensions, and robustness tests. Section 3.5 contains a discussion of the results and potential transmission channels of the effects. Section 3.6 concludes.

3.2 Data and Descriptive Statistics

We construct a balanced panel of 159 countries for the period 1992–2010 (see appendix table B1). We use data for resource use and GDP from the United Nations International Resource Panel Global Material Flows Database (GMFD) (UNEP, 2016; UN-IRP, 2018). We rely on measures of resource input, i.e., all resources that enter an economy within a year, either by being extracted domestically or being imported from abroad (Fischer-Kowalski et al., 2011). We use the raw material input (RMI) indicator, which accounts for upstream resource use in imports.[72] Further, the data are available for both total resource use and resource use disaggregated into four main resource classes. These four resource classes encompass: fossil fuels, biomass, non-metallic minerals, and metal ores.[73] Since there are substantial differences between resource classes concerning both their environmental impacts and socioeconomic relevance (Weisz et al., 2006), we analyze all four different resource classes alongside total resource use. The GMFD provides GDP

[72]Two measures of resource input are possible: direct material input (DMI) and raw material input (RMI). While they conceptually measure the same, they differ how they consider imports. Whereas DMI calculates imported resources and goods by their actual weight when crossing the border, RMI calculates imports by their raw resource equivalents that include the upstream requirements of imported commodities (UNEP, 2016). The difference between DMI and RMI is particularly relevant because the influence of imports can substantially change the picture when accounting for upstream flows of imports (Schaffartzik et al., 2016), which is why we focus on RMI.

[73]In the following, we will refer to these as fossils, biomass, minerals, and metals for brevity.

data in constant 2005 US $. Data on total population to construct per capita series are obtained from the World Bank World Development Indicators database.

To measure institutional quality, we rely on the well-established Institutional Quality Dataset (IQD) provided by Kunčič (2014). The IQD contains country-specific and internationally comparable measures of the formal institutional environment. It provides composite indicators for the three main dimensions – namely, legal, economic, and political institutions.[74] We utilize a composite measure that captures several overlapping dimensions of the overall effective institutional landscape. The use of such composite measures to capture institutions holistically is well-acknowledged (Barasa et al., 2017). We focus on political institutional quality due to our focus on the economy-environment relationship. Dasgupta and De Cian (2016) find democracy, good governance, and corruption to be the most relevant institutional components when it comes to environmental policies and protection. The composite indicator on political institutional quality we employ includes precisely those dimensions. In its entirety, the indicator measures the degree to which a country is democratic, secures a free press and political rights, provides high levels of accountability and bureaucratic quality, while being free of corruption, conflicts, and violence. In addition to these contextual arguments, its broad availability with respect to both countries and years makes this indicator our preferred choice.

For robustness tests we utilize further variables. We control for the role of the industrial sector, trade openness, and resource rents in the GDP of a country. Data for all these variables are obtained from the World Bank World Development Indicators database. A detailed description of variables and data sources can be found in appendix table B2.

In the full dimension of the sample, the resource input and GDP data per capita series display a strong variation in levels. In particular, differences in resource use among countries and time are most pronounced for the subcategories fossils and metals. The countries with the highest total resource inputs per capita on average over all sample years are Qatar, the United Arab Emirates, and Guyana. The lowest overall resource use per capita can be found in Haiti, Bangladesh, and Burundi. Qatar and the United Arab Emirates are, in addition to Brunei, as well among the three countries with the highest fossil resource inputs per capita, while the highest biomass inputs per capita are observed

[74] Each category is constructed from roughly ten established subindicators. The composite indicators are calculated by standardizing all subindicators to range between 0 and 1. Afterwards, all subindicators available within one of the three institutional dimensions are averaged. Hence, the composite indicator itself ranges between 0 and 1, with 0 referring to the lowest institutional quality possible, whereas 1 would imply that the country scores optimal on each subindicator. See Kunčič (2014) for details of the construction.

in Guyana, New Zealand, and Luxembourg. Their counterparts with lowest per capita inputs in the two subclasses are Somalia, Moldova, and Burundi for fossil resources and Yemen, Iraq, and Haiti for biomass. In the two remaining categories, Australia, Chile, and Guyana have highest average per capita inputs of metals, while the highest numbers per capita for minerals occur in Luxembourg, the United Arab Emirates, and Guyana. The lowest per capita values for metals are observed in Belarus, Moldova, and Somalia, and the lowest per capita values for minerals in Somalia, Chad, and Afghanistan. Table 3.1 contains summary statistics for GDP per capita, institutional quality, total resource use per capita, and resource use in the four resource subcategories per capita for all main variables as they enter the main approach. Hence, GDP and resource use per capita are displayed in growth rates and institutional quality in levels.

Table 3.1. Summary statistics

	Unit	Obs.	Mean	S.D.	Min.	Max.
Political institutional quality	Index	3,009	0.50	0.20	0.02	0.93
GDP growth	%	2,862	2.16	5.83	-61.60	65.02
Total resources growth	%	2,862	1.28	8.77	-110.49	73.66
Fossils growth	%	2,862	0.90	13.53	-158.82	214.14
Biomass growth	%	2,862	0.36	8.77	-68.53	82.23
Minerals growth	%	2,862	2.44	18.31	-173.97	137.58
Metals growth	%	2,862	1.96	20.43	-233.56	224.86

Note: S.D.: standard deviation. The descriptive statistics refer to the sample period 1992–2010 with all available observations for each country. GDP and resource use data used to compute the growth rates are expressed in per capita terms.

The political institutional quality indicator shows a high variability as well, covering nearly the full range from 0 to 1. The maximum value of 0.93 is observed in Finland in 2001 and the minimum value of 0.02 in Afghanistan in the same year. With regard to the average in political institutional quality over all years, the highest realizations are observed for Finland, Denmark, and the Netherlands, while the lowest average values appear for Afghanistan, Iraq, and Myanmar.

Table 3.2 presents moments of the between-country distribution of correlation coefficients between the growth rate of GDP per capita and the growth rate of resource use per capita for the sample period. Some remarks are in order. First, the median correlation is relatively high for all resource classes, giving evidence for a pronounced coupling of resource use to economic growth on average. Second, the correlation with total resource use is highest at all quartiles, which appears to be plausible as the resource subclasses can to some degree be substituted for each other, while total resources can only principally substitute for other production inputs such as labor. Third, there is a considerable country variation in correlations, with some countries showing even negative correlations. In the empirical part, we take this as a starting point and analyze the role of institutions in shaping the procyclicality.

Table 3.2. Correlations between annual per capita GDP growth and per capita resource use growth

	Total Resources	Fossils	Biomass	Minerals	Metals
Correlation, 1st quartile	0.312	0.132	0.112	0.148	0.075
Correlation, median	0.518	0.416	0.314	0.403	0.270
Correlation, 3rd quartile	0.684	0.591	0.501	0.616	0.454
Correlation, maximum	0.970	0.946	0.885	0.904	0.923
Correlation, minimum	-0.527	-0.657	-0.535	-0.434	-0.563
Correlation, standard deviation	0.286	0.310	0.260	0.302	0.305

Note: Country-wise correlation coefficients for the period 1992–2010 for all 159 countries.

With regards to the time-series properties of the data, we apply first generation (Harris and Tzavalis, 1999; Maddala and Wu, 1999) and second generation (Pesaran, 2007) panel unit root tests to the variables of our empirical approach. The results are provided in appendix table B3 and generally suggest that the null hypothesis of the variables being I(1) is rejected.

3.3 Econometric Framework

3.3.1 Main Specification

For the analysis of the role of institutional quality as mediating factor in the relationship between natural resource use and economic growth, we start with the following reduced-form autoregressive distributed lag (ARDL) model of the relationship between economic growth and growth of resource use:

$$\Delta r_{it} = \rho \Delta r_{i,t-1} + \gamma_{i0} \Delta y_{it} + \beta_1 \Delta y_{i,t-1} + a_i + \lambda_t + \epsilon_{it}, \tag{3.1}$$

where t and i index years and countries, respectively, Δr_{it} is the log-difference of resource use per capita, Δy_{it} is the log-difference of GDP per capita, a_i are individual-specific, time-fixed effects, λ_t are time-specific, individual-invariant effects, and ϵ_{it} is an error term. We follow recent studies on the nexus between emissions and economic growth and focus our empirical analysis on the relationship of (approximate) growth rates (Burke et al., 2015; Sheldon, 2017; Dées, 2020). The reduced-form nature of the relationship implies that the coefficients include potential contemporaneous and lagged feedback between Δr_{it} and Δy_{it}. Such a reduced-form approach can be derived from a bivariate vector autoregression (VAR) assuming linear dependence of the residuals (Chudik et al., 2016; Dées, 2020). The ARDL approach has useful features in our empirical application. First, it can be used for long-run analyses when variables are stationary (Pesaran, 1997; Chudik et al., 2016). Second, it can be robust against feedback between regressor and regressand, as long as the lag order is appropriate (Pesaran, 1997; Pesaran and Shin, 1999).

Based on our argumentation regarding the fundamental role of political institutions, we assume that the reduced-form coefficients depend on the formal political institutional quality of an economy. Specifically, we assume that the procyclicality of resource use in a given country depends on the average political institutional quality of that country. We introduce this dependence as $\gamma_{i0} = \beta_0 + \beta_2 \bar{Q}_i$ in our main approach, where Q_{it} is political institutional quality in country i and year t and $\bar{Q}_i = T^{-1} \sum_{t=1}^{T} Q_{it}$. Thus, our main model writes as

$$\Delta r_{it} = \rho \Delta r_{i,t-1} + \beta_0 \Delta y_{it} + \beta_1 \Delta y_{i,t-1} + \beta_2 \Delta y_{it} \bar{Q}_i + a_i + \lambda_t + \epsilon_{it}. \quad (3.2)$$

The country-specific long-run coefficients for the procyclicality, i.e., the impact of a permanent increase in GDP growth on the growth of resource use, are given by $\psi_i = (\beta_0 + \beta_1 + \beta_2 \bar{Q}_i)/(1 - \rho) = \eta_0 + \eta_1 + \eta_2 \bar{Q}_i$ (e.g., Haque et al., 2000). In our main approach, we estimate equation (3.2) with two-way fixed effects (FE). As discussed extensively by Haque et al. (2000), care has to be taken regarding the interpretation of the interaction term in our main approach. Since we use between variation of political institutional quality, a statistically significant positive interaction coefficient simply implies that countries with higher institutional quality tend to have a stronger long-run procyclicality of resource growth. It does not say that an individual country's procyclicality will necessarily increase with institutional quality over time, i.e., in the within dimension.

3.3.2 Robustness Tests and Extensions

For additional robustness tests, we extend our analysis in several ways. First, fixed-effects estimators of dynamic panel data models suffer from the well-known incidental parameter bias (Nickell, 1981) in small-T samples. As discussed by Chudik et al. (2018), this bias exists for weakly exogenous regressors in general even when there are no lags of the dependent variable included. To show that the results are not distorted by this possible bias, we consider two common ways to approach it. The panel GMM approach (Arellano and Bond, 1991) circumvents the incidental parameter bias by eliminating the fixed effect by differencing the model. Then, weakly exogenous regressors are instrumented by own lags to account for correlation between them and the error term brought in by differencing. However, the approach can be prone to a weak-/many-instruments problem, especially if T is not small (Roodman, 2009b; Chudik et al., 2018). An alternative to panel GMM is to correct for the bias by applying jackknife procedures. Chudik et al. (2018) show for a linear panel model with time- and individual-specific fixed effects that the incidental parameter bias is reduced and the resulting half-panel jackknife FE (HPJ-FE) estimator is appropriate for N much larger than T. In a nutshell, the sample is split in two halves, and the jackknife-corrected estimate is a combination of the whole sample FE estimate and both split-sample FE estimates. We conduct both approaches and compare them with our main estimation.

Second, recent studies highlight the possibility of asymmetric effects in the relationship between emissions and growth (Burke et al., 2015; Sheldon, 2017) as well as in the relationship between economic growth and resource use (Shao et al., 2017). Hence, we test whether the cyclicality of resource use growth differs between periods of negative and positive economic growth and whether there is an asymmetry in the interaction. For this purpose, we extend equation (3.2) with indicator variables that take on the value 1 if economic growth is positive and 0 else.

Third, an empirical challenge arises due to possible endogeneity in the presence of omitted variables. Institutional quality is potentially correlated with economic development in general, such that the interpretation of institutional quality as mediating variable becomes less straightforward. To test the robustness of the interaction with political institutional quality empirically, we add interactions with several control variables that each might explain the heterogeneity of coefficients to the main approach. These variables include the level of GDP per capita, the industry share, trade openness, and resource rents of a country. GDP per capita captures income levels and thus economic development in general. First, by including the level of GDP alongside institutional quality, we can test whether there is still a positive association between the procyclicality and institutional quality, once the income level is controlled for. Including both interactions in the model likely underestimates the role of institutional quality, since it is generally acknowledged to be a fundamental factor of economic growth itself (e.g., Acemoglu et al., 2019; Colagrossi et al., 2020). Second, the industry share serves as a control variable to check whether institutional quality remains a predictor of high procyclicality once the economic structure is controlled for. Highly industrialized countries are expected to have a different resource dependence of economic growth than countries with a smaller share of the industry sector (e.g., Schaffartzik et al., 2014). Third, we also control for an interaction with trade openness of a country. Accounting for trade openness is of importance, given our chosen indicator of resource use. In the case of material input indicators, resources that are traded between countries are counted multiple times. Hence, we want to control for the possibility that higher levels of resource use are not simply caused by a stronger embeddedness into global value chains and respective resource throughput (e.g., Bruckner et al., 2012). Finally, a relevant cause of different procyclicality could be the importance of resource extraction for a respective country. For example, if a country is fully dependent on resource extraction as its economic activity, the procyclicality might be strongly determined by this (e.g., Sachs and Warner, 1995). Additionally, one might argue that in countries where resource rents are important, countries naturally face a lower incentive to reduce the importance of resources as the respective rents remain in the country. To secure that our results do not merely capture those dynamics, we include an additional interaction with resource rents.

Finally, we explore the within-country dimension and country-specific dynamics by introducing an interaction of the form $\Delta y_{it} Q_{it}$ instead of $\Delta y_{it} \bar{Q}_i$ and a direct effect of institutional quality in equation (3.2). Hence, the model is given by

$$\begin{aligned} \Delta r_{it} = \rho^* \Delta r_{i,t-1} + \beta_0^* \Delta y_{it} + \beta_1^* \Delta y_{i,t-1} + \beta_2^* \Delta y_{it} Q_{it} \\ + \beta_3^* \Delta y_{it-1} Q_{it-1} + \beta_4^* Q_{it} + \beta_5^* Q_{it-1} + a_i^* + \lambda_t^* + \epsilon_{it}^*. \end{aligned} \tag{3.3}$$

This allows the coefficient of the interaction term to be heterogeneous across countries as well. Fully heterogeneous parameters are implemented with the mean group (MG) estimator (Pesaran and Smith, 1995). It estimates N separate country-specific time series regressions, and mean parameters are computed as the (weighted) average of the individual coefficients. For all mean group approaches, we remove common time effects by subtracting the cross-sectional means from the variables prior to estimation (e.g., Bond et al., 2010; Calderón et al., 2015). While the main regression gives insights into whether the degree of procyclicality systematically depends on political institutional quality across countries, this exercise allows to gauge whether this association can be observed within a specific country over time.

3.4 Results

3.4.1 Main Estimation

The results of our main approach are shown in table 3.3. Column 1 uses the growth rate of total resource use per capita as dependent variable, column 2 uses fossils, column 3 biomass, column 4 minerals, and column 5 metals instead of total resources. In line with our initial reasoning, column 1 shows that the coefficient of the interaction term of political institutional quality and GDP growth is highly significant. To interpret the coefficients, it is worth recalling that the long-run procyclicality of resource use is given by $\psi_i = \eta_0 + \eta_1 + \eta_2 \bar{Q}_i$. In table 3.3, $\eta_0 + \eta_1$ refers to the long-run coefficient *GDP growth*, whereas η_2 refers to the long-run coefficient of the interaction term. Since our measure of institutional quality ranges between 0 and 1, the coefficient of the interaction term, if significant, has a straightforward interpretation. Based on the results from column 1, a (hypothetical) country with average political institutional quality of 0 has an estimated procyclicality of 0.172. The point estimate implies that a 1 percentage point permanent increase in GDP growth is accompanied with a 0.172 percentage point increase in the growth rate of resource use. The coefficient is however not significant. A country with the best possible average institutional framework of 1 has an estimated procyclicality of $0.172 + 1.444 = 1.616$. Estimated coefficients for countries with average institutional quality between 0 and 1 range linearly between those two extreme values. If the coefficient of the interaction term is not significantly different from zero, differences in country-specific coefficients of the procyclicality are not systematically associated with the average institutional quality of these countries. It is worth emphasizing that the interpretation of this interaction term is exclusively *across* countries; it does not necessarily imply that the procyclicality of a country depends on its institutional framework over time.

Columns 3–5 show a similar association for the procyclicality of biomass, minerals, and metals. In each of these subgroups, higher average institutional quality is associated with higher coefficients for the procyclicality of resource use. The standard error of the coefficient of the interaction term for metals is relatively high, however. Additionally, the within R^2 indicates that the main model only explains a small amount of variation for metals. In contrast to these resource subclasses, column 2 shows that the data is not supportive of a positive association between the procyclicality of fossils and political institutional quality. In all models, the speed of adjustment parameter $\phi = \rho - 1$ is estimated to be significantly negative and in absolute value smaller than 2, indicating stability.

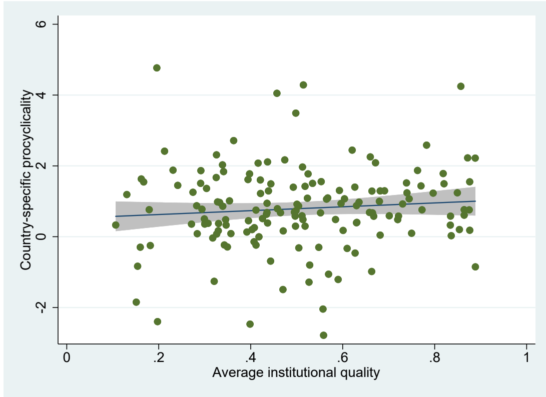
Table 3.3. FE regressions for all material classes based on ARDL(1,1,1)

	Total resources (1)	Fossils (2)	Biomass (3)	Minerals (4)	Metals (5)
Long-run coefficients					
GDP growth	0.172	0.794**	-0.004	0.140	0.234
	(0.141)	(0.312)	(0.051)	(0.251)	(0.190)
Political institutional quality	1.444***	-0.095	1.037***	2.405***	0.993**
× GDP growth	(0.273)	(0.601)	(0.137)	(0.356)	(0.434)
Short-run coefficients					
Speed of adjustment	-1.113***	-1.068***	-1.304***	-1.148***	-1.005***
	(0.065)	(0.082)	(0.045)	(0.070)	(0.042)
Observations	2,703	2,703	2,703	2,703	2,703
Countries	159	159	159	159	159
R^2 within	0.235	0.173	0.191	0.142	0.054

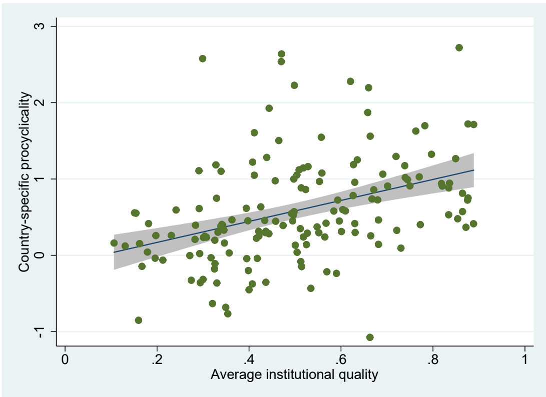
Note: Asterisks indicate significance at * 10%; ** 5%; *** 1%. Standard errors in parentheses are of heteroskedasticity-robust sandwich type. A full set of time dummies is added to each model. Long-run coefficients are computed from the short-run coefficients and their standard errors are based on the delta method.

To illustrate the results from a slightly different angle, we perform an exercise in which the reduced-form model in equation (3.1) is estimated directly for each country. This allows for completely heterogeneous parameters across countries. Common time effects are removed by subtracting the cross-sectional means from the variables prior to estimation (e.g., Bond et al., 2010; Calderón et al., 2015). Figure 3.1 plots the individual-country coefficients against average institutional quality together with a linear trend line and 95% confidence intervals. The trend lines reflect the positive association estimated from the main approach for total resources, biomass, minerals, and metals and the inconclusive results for the interaction coefficient for fossils. Despite the positive association in general, it can be seen that the variation of individual coefficients around the trend line is pronounced at all levels of average institutional quality.

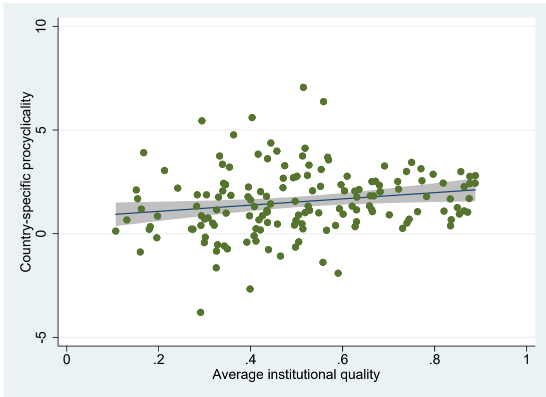
(a) Total resources



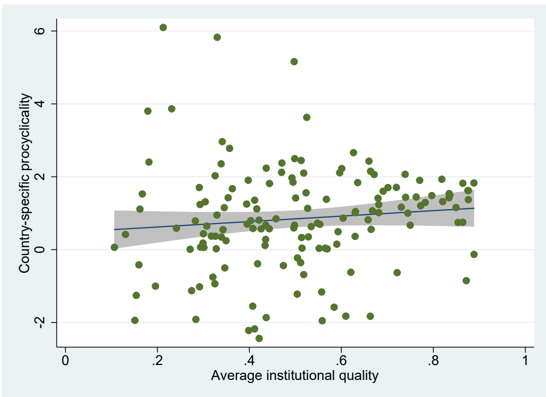
(b) Fossils



(c) Biomass



(d) Minerals



(e) Metals

Figure 3.1. Heterogeneity of individual coefficients of the procyclicality. Individual long-run parameters of the procyclicality estimated from the reduced form model in equation (3.1) and plotted against the average institutional quality of each country for the five resource classes total resources, fossils, biomass, minerals, and metals. The solid line depicts a linear trend and grey shaded areas 95% confidence intervals. Extreme outliers are excluded from the figure. They are identified by performing a robust regression of the individual coefficients on a constant and excluding the coefficients that get assigned a zero weight. The robust regression is performed with the Stata command *rreg*.

Additionally, we use the individual-country coefficients to perform outlier-robust cross-country regressions of the individual coefficients of the procyclicality on average political institutional quality to obtain magnitudes of the interaction effect that are comparable to the main results in table 3.3. Table 3.4 shows that the coefficients of average political institutional quality are significantly positive for total resources, biomass, minerals, and metals and they are of similar magnitude as the interaction coefficients from the main model. Additionally, the insignificant slope coefficient for fossils underlines the ambiguous results for this resource subgroup. In the regressions of total resources and the subgroups fossils, biomass, and minerals, two to three countries are extreme outliers that get assigned an exact zero weight in estimation. For metals, 12 countries are excluded, highlighting the pronounced idiosyncrasies in this subgroup. Finally, the null hypothesis of joint insignificance of the coefficients can be rejected for all models except the regression for the subgroup fossils in column 2.

Table 3.4. Outlier-robust regression of the individual coefficients on institutional quality

	Total resources (1)	Fossils (2)	Biomass (3)	Minerals (4)	Metals (5)
Political institutional quality	1.281***	0.480	1.390***	1.583***	1.508***
	(0.274)	(0.407)	(0.229)	(0.592)	(0.514)
Constant	0.262*	0.543**	-0.180	0.658**	0.019
	(0.148)	(0.220)	(0.124)	(0.320)	(0.278)
Observations	159	159	159	159	159
No. of zero weights	2	3	3	3	12
F-test (p-value)	0.000	0.240	0.000	0.008	0.004

Note: Asterisks indicate significance at * 10%; ** 5%; *** 1%. Standard errors in parentheses. Outlier-robust OLS estimates are obtained by regressing the individual-country coefficients of the procyclicality on the country-specific level of average institutional quality with the *rreg* command in Stata.

Overall, we find a strong positive association between the level of institutional quality of a country and its sensitivity of resource use growth to economic growth for a country's total resource use as well as for the subclasses biomass, minerals, and metals. On the other hand, the data are not supportive of a positive association between political institutional quality and the procyclicality of fossils.

3.4.2 Robustness Tests and Extensions

3.4.2.1 Alternative Specifications

In this section, we present the robustness exercises and extensions discussed in Section 3.3. First, appendix table B4 shows the results of the panel GMM and HPJ-FE estimation to deal with potential incidental parameter bias in the presence of weakly exogenous variables. It shows that the results from both estimation procedures are very similar to the results of the main estimation both qualitatively and quantitatively. The negative coefficient of the interaction between GDP growth and institutional quality for the subgroup fossils is even somewhat more pronounced in GMM estimation, yet only marginally significant.

Second, appendix table B5 extends the main model to allow for potential asymmetric coefficients for negative and positive economic growth. The main results from the main model are not altered in the asymmetric model. Specifically, the coefficients of the interaction term are positively significant for total resources, biomass and minerals, and there is no robust association between institutional quality and the procyclicality of fossils.

To summarize, we take these results as reassuring that the results from the main approach are not distorted from the presence of weakly exogenous regressors and are mostly robust against the use of different estimators. Furthermore, the main results are broadly robust to the possibility of asymmetric effects for negative and positive growth rates.

3.4.2.2 Additional Controls

As discussed in Section 3.3, it is possible that the positive association between political institutional quality and the coefficients of the procyclicality for total resources, biomass, minerals, and metals merely reflects correlation between institutional quality and different structural characteristics of countries, which influence the degree of procyclicality. To this purpose, in this section we add additional controls to the main model that are likely to be related to the degree of resource dependence of economic growth. These controls include the level of GDP per capita, the industry share, trade openness, and resource rents. Table 3.5 uses total resources as dependent variable and presents the results from the main model in which one additional interaction term is added at a time.[75] Due to different data availability for the additional covariates, the sample size is reduced by few countries in the different specifications. The interaction term is always constructed with respect to the average of the respective variable over time in the same manner as done with institutional quality in the main estimation. As the only variation in the within dimension in the interaction terms originates from GDP growth, we only include one additional interaction at a time to the model, since collinearity can reduce precision considerably. Column 1 adds an interaction term with the average natural logarithm of the level of GDP per capita for each country, column 2 adds an interaction with the average industry share, column 3 adds an interaction with the average trade openness, and finally, columns 4 adds an interaction with average resource rents.

Table 3.5. Additional control variables added as interaction

	Total resources (1)	Total resources (2)	Total resources (3)	Total resources (4)
Long-run coefficients				
GDP growth	-0.394*	-0.121	0.269	0.054
	(0.213)	(0.114)	(0.172)	(0.115)
Political institutional quality	0.865***	1.589***	1.398***	1.598***
× GDP growth	(0.308)	(0.215)	(0.318)	(0.215)
GDP level	0.111***			
× GDP growth	(0.037)			
Industry share		0.008***		
× GDP growth		(0.002)		
Trade openness			-0.001	
× GDP growth			(0.001)	
Resource rents				0.004
× GDP growth				(0.003)
Short-run coefficients				
Speed of adjustment	-1.117***	-1.117***	-1.119***	-1.116***
	(0.066)	(0.069)	(0.071)	(0.068)
Observations	2,703	2,618	2,584	2,669
Countries	159	154	152	157
R^2 within	0.242	0.252	0.249	0.243

Note: Asterisks indicate significance at * 10%; ** 5%; *** 1%. Standard errors in parentheses are of heteroskedasticity-robust sandwich type. A full set of time dummies is added to each model. Long-run coefficients are computed from the short-run coefficients and their standard errors are based on the delta method.

[75] For the sake of brevity, we do not report the results for the resource subclasses here. In general, the statements regarding the interaction term with political institutional quality remain robust when adding additional covariates. These results are available upon request.

The results in table 3.5 show that political institutional quality remains strongly associated with the degree of procyclicality when the additional covariates are added. In columns 2–4 the magnitude of the coefficient of the interaction term is comparable to the main model. Column 1 shows that the degree of procyclicality is also strongly associated with per capita income. Although the magnitude roughly halves, the positive association with political institutional quality remains significant and pronounced. Column 2 furthermore shows that the industry share of a country is also a significant predictor of a high degree of procyclicality. As evident from columns 3–4, the association with trade openness and resource rents is not significant.

To conclude, the positive association between institutional quality and the degree of procyclicality of resource use across countries is robust against the inclusion of additional interaction terms, which capture different country-specific structural aspects, such as the log-level of GDP per capita, the industry share, trade openness, and resource rents. These findings support the insights from the main estimation.

3.4.2.3 The Within-Country Dimension

In the following, we consider a more general model for the interaction term compared to the main estimation, including within-country variation as well as exclusively within-country variation. First, we estimate model (3.3) with a general interaction term that is not restricted to the cross-sectional variation of institutional quality. Second, we focus on the within variation and estimate equation (3.3) for each country separately and obtain mean coefficients by averaging the individual coefficients across countries (MG estimation). This approach allows each country to have fully heterogeneous parameters, including heterogeneous coefficients of the interaction term. It facilitates to gauge whether the degree of procyclicality depends on the level of institutional quality within the country over time as well.

Table 3.6 presents the results for equation (3.3), in which an interaction term of the form $\Delta y_{it} Q_{it}$ alongside a direct effect of political institutional quality is included. The results are very similar to the main estimation, and the size and significance levels of the coefficients of the interaction term are similar for total resources, fossils, biomass, and minerals. Only the interaction coefficient for metals is insignificant, contrary to the main estimation.

Table 3.7 presents the results of outlier-robust MG estimation of equation (3.3). The full ARDL(1,1,1,1) approach is very demanding given the medium time series dimension of the sample. Hence, table 3.7 uses the nested ARDL(1,0,0,0) model by assuming that $\beta^*_{i1} = \beta^*_{i3} = \beta^*_{i5} = 0$. It shows that the results regarding the average coefficients of the interaction term are very similar to the main estimation and the corresponding FE estimation in table 3.6, except for the subgroup metals. However, standard errors are larger and only the coefficients for total resources in column 1 and for biomass in column 3 remain statistically significant. Additionally, it is worth emphasizing that there is heterogeneity in the coefficients of the interaction term. Table 3.7 reports the number of countries for which the individual coefficient of the interaction term is estimated positive. Even for the significant average coefficient for total resources, there are more than 50 countries with negative point estimates of the coefficient of the interaction term. Hence, while the average effects across countries are in support of our findings from the main approach even when only the within variation is considered, single country dynamics might be different.

Table 3.6. Using the full variation in the interaction and including the direct effect

	Total resources (1)	Fossils (2)	Biomass (3)	Minerals (4)	Metals (5)
Long-run coefficients					
GDP growth	0.264*	0.643**	0.048	0.199	0.406**
	(0.136)	(0.288)	(0.061)	(0.292)	(0.167)
Political institutional quality	-0.032	0.090	-0.030	0.028	0.123
	(0.035)	(0.057)	(0.032)	(0.075)	(0.154)
Political institutional quality	1.261***	0.325	0.956***	2.365***	0.526
× GDP growth	(0.256)	(0.632)	(0.159)	(0.476)	(0.404)
Short-run coefficients					
Speed of adjustment	-1.112***	-1.069***	-1.304***	-1.152***	-1.006***
	(0.067)	(0.082)	(0.045)	(0.070)	(0.042)
Observations	2,703	2,703	2,703	2,703	2,703
Countries	159	159	159	159	159
R^2 within	0.236	0.176	0.192	0.140	0.054

Note: Asterisks indicate significance at * 10%; ** 5%; *** 1%. Standard errors in parentheses are of heteroskedasticity-robust sandwich type. A full set of time dummies is added to each model. Long-run coefficients are computed from the short-run coefficients and their standard errors are based on the delta method.

To conclude, there is considerable evidence for a positive association between institutional quality and the procyclicality of resource use in the between dimension – that means, countries with higher institutional quality tend to have a higher procyclicality. This insight holds as well broadly when considering the within dimension with regard to the average effect across countries. However, single country dynamics might differ from this average effect.

Table 3.7. Outlier-robust MG estimation for all resource classes

	Total resources (1)	Fossils (2)	Biomass (3)	Minerals (4)	Metals (5)
Long-run coefficients					
GDP growth	0.339**	0.850***	0.185	1.244***	1.307***
	(0.164)	(0.253)	(0.173)	(0.382)	(0.324)
Political institutional quality	-0.039	-0.011	-0.010	0.127	0.010
	(0.047)	(0.061)	(0.041)	(0.099)	(0.111)
Political institutional quality	1.395***	-0.034	0.908**	0.561	-1.010
$\times$ GDP growth	(0.350)	(0.530)	(0.385)	(0.793)	(0.683)
Short-run coefficients					
Speed of adjustment	-1.115***	-1.150***	-1.206***	-1.134***	-1.097***
	(0.021)	(0.024)	(0.021)	(0.023)	(0.023)
No. of pos. interactions	103	80	92	86	68
Observations	2,703	2,703	2,703	2,703	2,703
Countries	159	159	159	159	159

Note: Asterisks indicate significance at * 10%; ** 5%; *** 1%. Standard errors in parentheses. Significance and standard errors refer to testing the difference of the weighted average long-run coefficient from zero. Weighted averages are computed by outlier-robust regression of the individual coefficients on a constant (Bond et al., 2010) with the *rreg* command in Stata. All variables enter as deviations from their cross-sectional mean in each period. The model estimated is an ARDL(1,0,0,0) representation, which is nested in equation (3.3) ($\beta^*_{i1} = \beta^*_{i3} = \beta^*_{i5} = 0$).

3.5 Discussion

The core results from our empirical analysis are threefold: first, for total resource use, we find on average a high degree of procyclicality, which is strongly heterogeneous across countries. Furthermore, the range of country-level procyclicality varies across the resource classes. While it is lowest for biomass, the procyclicality across countries varies the most for minerals. Second, we find that this heterogeneity is linked to differences in levels of political institutional quality. For total resources and most resource subgroups, the results suggest that high institutional quality is associated with a higher procyclicality of respective resource use growth. Third, the mediating role of institutional quality is not equal across all subgroups of resource use. Particularly for fossil fuel resources, we find no evidence for a positive association between institutional quality and the procyclicality of fossil fuel use. In light of the generally positive association of the procyclicality of most resource classes with institutional quality, this points to the importance of specific ways in which institutions affect resource use. Overall, our findings for resources, thus, contrast findings on the role of institutions with respect to CO_2 emissions, where a decrease of procyclicality is found (Dées, 2020). These findings link to the role of resources as an input factor to economic activity. Institutions might hereby act as a fundamental factor that influences the proximate channels of factor prices and technology. We discuss our findings in light of the fact that institutions can relate to different mechanisms that shape factor prices and technological change.[76]

With respect to our first empirical finding, we show that there is substantial heterogeneity in the procyclicality of resource use across countries. This empirical fact aligns well with previous findings on CO_2 emissions (e.g., Jaunky, 2011; Burke et al., 2015). The heterogeneity in procyclicality may stem from different underlying, country-specific factors. While Burke et al. (2015) focus on the business cycle and country characteristics such as GDP levels or resource availability, Dées (2020) analyzes the role of institutions in moderating the procyclicality, finding that higher levels of institutional quality reduce the average procyclicality of emissions. On the contrary, our results associate countries with high institutional quality to higher degrees of procyclicality for resource use. This finding is robust even when controlling for the position in the business cycle or above-mentioned country characteristics, such as GDP levels, resource rents, industry share, or trade openness. Agnolucci et al. (2017) find a higher degree of procyclicality in Western European countries compared to Eastern European countries, which they attribute to relative low energy prices and relative high labor costs in Western Europe compared to Eastern Europe. This highlights the importance of relative prices for differentials in the procyclicality of resource use across countries.

Concerning our second empirical finding, institutional quality can be regarded as a fundamental factor influencing both levels and types of economic activity, due to its effects on crucial factors such as technology (Acemoglu et al., 2005). These can take place through trade liberalization (Fischer, 2010), regulation (Aghion et al., 2016), and other changes that institutions support. Essentially, factor prices and technology determine the relative importance of natural resources in production and how it develops over time (e.g., Haas and Kempa, 2018; Hassler et al., 2021). A shift in relative prices may directly lead to a different relative composition of production inputs, if substitution between resources

[76] It shall be emphasized here that this interpretation does not exhaust all possible explanations.

and capital/labor is possible. This degree of substitutability might increase in the long run, as changes in relative prices direct technological change towards saving the expensive input (Hassler et al., 2021). In this vein, our results might point towards lower relative prices for resources for countries with high institutional quality, corresponding to a higher procyclicality of resource use.

Our third empirical finding shows that a higher procyclicality of resource use at higher levels of institutional quality is not found across all resource types. For total resource use and the subgroups biomass, non-metallic minerals, and metal ores we find that higher political institutional quality is associated with higher procyclicality. Generally, many natural resource prices have a relevant international price component (Agnolucci et al., 2017). One channel by which institutional quality can drive resource prices down is trade liberalization, though this effect is not unequivocal (Fischer, 2010). Due to improved access to resources, we expect a reducing effect of institutional quality on resource prices. Furthermore, for other input factors, such as labor, we expect opposite effects on prices. Here, higher institutional quality can increase labor costs. This could be due to institutional quality being associated with more stringent labor market policies and interventions, which make labor input less flexible (Bertola and Rogerson, 1997; Betcherman, 2012; Kahn, 2012). Additionally, Rodrik (1999) finds that democratic countries pay higher wages in general, even when controlling for levels of labor productivity. Consequently, there is competitive pressure on firms exposed to high political institutional quality to increase the amount of resources per worker, in order to maintain cost-efficient input combinations. In essence, these associations are consistent with higher relative importance of resources in production at higher levels of political institutional quality.

For fossil fuel resources, our results do not support a positive association between political institutional quality and the degree of procyclicality. Fossil fuels are a natural resource type for which a significant amount of political actions has been dedicated to internalize its externalities, e.g., through fuel taxes (Aghion et al., 2016). Internalizing the negative externalities of fossil fuels increases their relative price, which can lead to substitution. Furthermore, it can induce the direction of technological change towards reducing fossil fuel use (e.g., Popp, 2002; Acemoglu et al., 2012, 2016; Aghion et al., 2016). A positive association between high institutional quality and environmental policy adoption and its stringency finds broad empirical support (Dasgupta and De Cian, 2018). For example, Chen et al. (2021) find that in democratic countries, economic growth is transferred more strongly into renewable energy growth. In light of this argument, the specific policies to internalize externalities related to fossil fuels might outweigh the effects of higher institutional quality we find for other resource types.

Overall, our results show that the growth of resource use is highly procyclical. The magnitude of this procyclicality is in general and for most resource types positively associated with political institutional quality. This mediating role might be linked to a relative reduction in resource prices as well as a relative increase of other input factor prices, especially labor costs. However, for fossil fuels, policy interventions aiming to internalize externalities, and thereby increasing relative prices, might outweigh the effect. This indicates that an "automatic" mechanism by which improved institutional quality reduces resource dependency of additional economic growth does not exist.[77] However, good institutional quality allows to implement and enforce policies to directly address negative externalities.

3.6 Conclusion

Institutions are a fundamental factor for economic activity, influencing both the scale and the structure of the economy (e.g., Acemoglu et al., 2005, 2019; Colagrossi et al., 2020). In this paper, we show that institutions mediate the relationship between economic growth and the environment. We analyze the mediating role of political institutional quality for the nexus between economic and natural resource use growth in a panel of 159 countries for the period 1992 to 2010. We find a pronounced heterogeneity in the procyclicality of resource use, i.e., the effect of economic growth on the growth of natural resource use, across countries. Political institutional quality is robustly associated with a higher procyclicality for total resources. On a disaggregated level, for the subclasses biomass and non-metallic minerals, we find similar robust results. The results for metal ores are less robust, but generally pointing towards a similar association. For fossil fuels, we find no evidence for a positive association of institutional quality and the procyclicality of resources.

These results have implications in conjunction with finite resource stocks and limits to the carrying capacity of the Earth system (e.g., Arrow et al., 1995; Rockström et al., 2009; Hoekstra and Wiedmann, 2014; Schramski et al., 2015). We argue that institutions

[77]It is emphasized here that our results are perfectly consistent with countries having high institutional quality having a high level of resource productivity. However, any additional economic growth in the considered time period was more dependent on resource use growth for countries with higher institutional quality.

as fundamental factor influence the nexus between economic growth and resource use via changes in relative prices and changes in the (aggregate) production technology. While institutional quality is generally found as potential factor contributing to environmental protection (e.g., Dasgupta and De Cian, 2018; Dées, 2020), our results provide no evidence that institutions are a general panacea for environmental problems. While countries with better institutional quality might have a higher level of resource productivity, our results support that additional economic growth was more dependent on resource use growth for countries with better institutional quality. Therefore, the role of institutions alone for addressing environmental problems might be overstated. While many studies focus on (territorial) emissions only, we utilize a comprehensive set of resource use indicators. These indicators facilitate a more holistic analysis of the growth environment nexus and to account for global impact via the inclusion of upstream flows.

This finding has relevance for policymakers who aim towards sustainable economic development. Our results imply that better institutions do not act as an automatic mechanism by which environmental problems are resolved. However, the case of fossil fuels can be seen as a first hint on the importance and potential of price changes. The implementation of carbon taxes and emission trading systems becomes more frequent and changes the price signal (Thisted and Thisted, 2020). Changing prices affect input combinations and innovative activity and, thus, could reduce the utilization of resources. Policy measures that increase relative resource prices might lift the potential for substantial long-run substitution (Hassler et al., 2021). Furthermore, as high institutional quality generally provides an important basis for a well-functioning innovation system (Lundvall, 1992; Nelson, 2002), our results call for a targeted innovation policy towards saving natural resources. A prominent example of these approaches are endeavors towards a circular economy (European Commission, 2015).

Given some limitations of the present study we propose various avenues for further research. First, our considered time period is only moderate, due to current data restrictions and our goal to capture an encompassing sample of countries. Studies utilizing longer time series information, even if restricted to specific country groups, could provide additional depth to the dynamics. Second, we focus on formal institutional quality. However, informal institutions, such as environmental awareness, certainly are of importance for the nexus between economic and natural resource use growth. For example, merits of high formal institutional quality could be mediated by underlying informal institutions. Future studies could disentangle this interplay of underlying societal dynamics. Lastly, we propose that institutions shape the economy-environment relationship by affecting factor prices and technology. Further research can include these channels directly and disentangle their interplay.

Appendix B

Table B1. List of the sample countries

Afghanistan	Canada	Germany	Liberia	Norway	Sweden
Albania	Cape Verde	Ghana	Libya	Oman	Switzerland
Algeria	Central African Republic	Greece	Lithuania	Pakistan	Syria
Angola	Chad	Guatemala	Luxembourg	Panama	Tajikistan
Argentina	Chile	Guinea	Madagascar	Papua New Guinea	Tanzania
Armenia	China	Guyana	Malawi	Paraguay	Thailand
Australia	Colombia	Haiti	Malaysia	Peru	Togo
Austria	Costa Rica	Honduras	Maldives	Philippines	Trinidad and Tobago
Azerbaijan	Cote d'Ivoire	Hungary	Mali	Poland	Tunisia
Bahamas	Croatia	Iceland	Malta	Portugal	Turkey
Bahrain	Cuba	India	Mauritania	Qatar	Turkmenistan
Bangladesh	Cyprus	Indonesia	Mauritius	Rep. Congo	Uganda
Barbados	DR Congo	Iran	Mexico	Romania	Ukraine
Belarus	Denmark	Iraq	Moldova	Russian Federation	United Arab Emirates
Belgium	Djibouti	Ireland	Mongolia	Rwanda	United Kingdom
Belize	Dominican Republic	Israel	Morocco	Samoa	United States of America
Benin	Ecuador	Italy	Mozambique	Saudi Arabia	Uruguay
Bhutan	Egypt	Jamaica	Myanmar	Senegal	Uzbekistan
Bolivia	El Salvador	Japan	Namibia	Sierra Leone	Vanuatu
Botswana	Estonia	Jordan	Nepal	Singapore	Venezuela
Brazil	Eswatini	Kazakhstan	Netherlands	Slovenia	Viet Nam
Brunei Darussalam	Fiji Islands	Kenya	New Zealand	Somalia	Yemen
Bulgaria	Finland	Kyrgyzstan	Nicaragua	South Africa	Zambia
Burkina Faso	France	Laos	Niger	South Korea	Zimbabwe
Burundi	Gabon	Latvia	Nigeria	Spain	
Cambodia	Gambia	Lebanon	North Korea	Sri Lanka	
Cameroon	Georgia	Lesotho	North Macedonia	Suriname	

Table B2. Data description and sources

Variables	Description	Source
Resource variables		
Total RMI	Raw material input of all resources (tons)	Global Material Flows Database (UNEP, 2016; UN-IRP, 2018)
Fossil RMI	Raw material input of fossil resources (tons)	Global Material Flows Database (UNEP, 2016; UN-IRP, 2018)
Biomass RMI	Raw material input of biomass resources (tons)	Global Material Flows Database (UNEP, 2016; UN-IRP, 2018)
Minerals RMI	Raw material input of mineral resources (tons)	Global Material Flows Database (UNEP, 2016; UN-IRP, 2018)
Metals RMI	Raw material input of metal resources (tons)	Global Material Flows Database (UNEP, 2016; UN-IRP, 2018)
Economic growth		
GDP	GDP (constant 2005 US $)	Global Material Flows Database (UNEP, 2016; UN-IRP, 2018)
Institutional quality		
Institutions	Political institutional quality (share)	Institutional Quality Dataset (Kunčič, 2014)
Population		
Population	Total population (number of residents)	World Bank World Development Indicators (SP.POP.TOTL)
Control variables		
Industry share	Value added of industry (% of GDP)	World Bank World Development Indicators (NV.IND.TOTL.ZS)
Trade openness	Imports plus exports of goods and services (% of GDP)	World Bank World Development Indicators (NE.IMP.GNFS.ZS & NE.EXP.GNFS.ZS)
Resource rents	Total natural resources rents (% of GDP)	World Bank World Development Indicators (NY.GDP.TOTL.RT.ZS)

Table B3. Panel unit root tests

	HT constant	HT trend	MW constant	MW trend	CIPS constant	CIPS trend
GDP growth	0.000	0.000	0.000	0.000	0.000	0.000
Total resources growth	0.000	0.000	0.000	0.000	0.000	0.000
Fossils growth	0.000	0.000	0.000	0.000	0.000	0.000
Biomass growth	0.000	0.000	0.000	0.000	0.000	0.000
Minerals growth	0.000	0.000	0.000	0.000	0.000	0.000
Metals growth	0.000	0.000	0.000	0.000	0.000	0.000
Political institutional quality	0.000	0.002	0.000	0.000	0.227	0.824

Note: Reported are p-values. HT refers to the Harris-Tzavalis test (Harris and Tzavalis, 1999), MW to the Maddala-Wu test (Maddala and Wu, 1999), and CIPS to the unit root test proposed by Pesaran (2007). MW and CIPS are augmented with one lag. MW and CIPS are implemented with the *multipurt* routine written by Eberhardt (2011), making use of the *pescadf* command by Lewandowski (2007) and the *xtfisher* routine by Merryman (2005) in Stata. GDP and the resource classes are in per capita terms. Common time effects are removed by subtracting the cross-sectional means from the variables prior to testing (Bond et al., 2010; Calderón et al., 2015).

Table B4. Alternative econometric models

	Total resources HPJ-FE (1)	Total resources GMM (2)	Fossils HPJ-FE (3)	Fossils GMM (4)	Biomass HPJ-FE (5)	Biomass GMM (6)	Minerals HPJ-FE (7)	Minerals GMM (8)	Metals HPJ-FE (9)	Metals GMM (10)
Long-run coefficients										
GDP growth	0.248*	0.172	1.106***	1.254***	0.038	0.011	0.210	0.453	0.029	0.190
	(0.134)	(0.228)	(0.263)	(0.428)	(0.075)	(0.205)	(0.272)	(0.499)	(0.363)	(0.601)
Political institutional quality	1.248***	1.585***	-0.662	-1.585*	0.919***	1.749***	2.235***	2.333***	1.159*	1.577
× GDP growth	(0.261)	(0.503)	(0.453)	(0.954)	(0.169)	(0.450)	(0.413)	(0.882)	(0.594)	(0.971)
Short-run coefficients										
Speed of adjustment	-1.068***	-1.065***	-0.990***	-1.055***	-1.281***	-1.129***	-1.124***	-1.121***	-0.929***	-0.963***
	(0.055)	(0.071)	(0.074)	(0.096)	(0.036)	(0.047)	(0.050)	(0.077)	(0.055)	(0.048)
No. of instruments	-	64	-	64	-	64	-	64	-	64
Sargan test	-	0.010	-	0.000	-	0.064	-	0.317	-	0.204
Hansen test	-	0.696	-	0.140	-	0.823	-	0.860	-	0.445
AR(2) test	-	0.597	-	0.629	-	0.524	-	0.579	-	0.221
Observations	2,544	2,544	2,544	2,544	2,544	2,544	2,544	2,544	2,544	2,544
Countries	159	159	159	159	159	159	159	159	159	159

Note: Asterisks indicate significance at * 10%; ** 5%; *** 1%. Standard errors in parentheses are of heteroskedasticity-robust sandwich type. Long-run coefficients are computed from the short-run coefficients and their standard errors are based on the delta method. For HPJ-FE, standard normal critical values are used to determine significance. A full set of time dummies is added to each model. The half-panel jackknife fixed-effects (HPJ-FE) procedure drops the first year observations in order to have an even time-series dimension. Sargan test, Hansen test and AR(2) test report p-values. In the GMM approaches, we use lags dated $t-2$ and earlier of all variables as instruments. The instruments matrix is collapsed (Roodman, 2009b). GMM estimation is performed in Stata using *xtabond2* (Roodman, 2009a). HPJ-FE estimation is performed in MATLAB based on the codes provided by Chudik et al. (2018).

Table B5. Asymmetric coefficients for positive and negative GDP growth rates

	Total resources (1)	Fossils (2)	Biomass (3)	Mineral (4)	Metals (5)
Long-run coefficients					
Positive GDP growth	0.010	1.153***	-0.066	-0.262	-0.391
	(0.126)	(0.441)	(0.096)	(0.342)	(0.524)
Negative GDP growth	0.239	0.430	0.058	0.517	0.849**
	(0.223)	(0.406)	(0.104)	(0.363)	(0.357)
Political institutional quality	1.436***	-1.188	1.037***	2.796***	1.291
× Positive GDP growth	(0.265)	(0.819)	(0.209)	(0.607)	(0.965)
Political institutional quality	1.480***	1.209	1.049***	2.058***	0.776
× Negative GDP growth	(0.486)	(1.058)	(0.264)	(0.791)	(0.848)
Short-run coefficients					
Speed of adjustment	-1.114***	-1.071***	-1.304***	-1.150***	-1.013***
	(0.065)	(0.079)	(0.045)	(0.070)	(0.043)
Observations	2,703	2,703	2,703	2,703	2,703
Countries	159	159	159	159	159
R^2 within	0.236	0.181	0.192	0.146	0.060

Note: Asterisks indicate significance at * 10%; ** 5%; *** 1%. Standard errors in parentheses are of heteroskedasticity-robust sandwich type. A full set of time dummies is added to each model. Long-run coefficients are computed from the short-run coefficients and their standard errors are based on the delta method.

Chapter 4

Green Technologies and Growth: Evidence from European Regions

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Abstract

Green technologies are at the core of endeavors to combine economic and environmental targets to achieve sustainable growth. In this article, we estimate the impact of green technology development on labor productivity of European regions. We rigorously control for unobserved common factors and explore various sources of heterogeneity in the productivity effects. Our results, based on a sample of 158 European NUTS-2 regions over 39 years, imply that general technology development is associated with positive economic returns, but our data is not supportive of positive economic returns to green technologies in general. However, we find evidence of positive regional returns for different subgroups of green technologies and for regions that have a sufficiently high regional knowledge base.

Keywords: Regional Growth; Green Technologies; Heterogeneity; Cross-Sectional Dependence

JEL Classification: C23; O0; O33

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4.1 Introduction

The recently announced European Union (EU) External Energy Strategy (European Commission, 2022) highlights the key role of green technologies in tackling climate change (e.g., Fried, 2018) and establishing energy security. Green technologies are at the core of endeavors to combine economic and environmental targets to achieve sustainable growth, one of the aims of the European Green Deal (European Commission, 2019). First, green technical progress might substantially contribute to increase environmental productivity (e.g., Popp, 2010). At the same time, green technologies might enhance economic productivity (e.g., Xepapadeas and de Zeeuw, 1999). If green technologies are indeed fostering economic productivity, they can serve to stimulate regional growth and perhaps be a tool for regional inclusion. Indeed, technological progress provides the foundation of Europe's regional development strategies (e.g., McCann and Ortega-Argilés, 2015). Although green technologies play a prominent role in recently designed EU policies that focus on strengthening economic growth while tackling climate change (e.g., European Commission, 2019), a thorough empirical investigation of the impact of green technology development on labor productivity of European regions is still missing. The present paper fills this gap.

Our paper contributes to the literature on technological change and regional growth[78] in various ways. First, the focus on the regional level facilitates to estimate general equilibrium effects on a broad empirical base. Second, we rigorously account for cross-sectional dependence (CSD) in our empirical approach. Third, we explore various sources of heterogeneous productivity effects across regions and technologies.

We focus on the economic returns that occur within the same region the technology is developed (including intraregional knowledge spillovers), which we call the regional

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[78] In the following, we use (regional) economic returns, growth effects, and productivity effects or variations of these terms interchangeably to refer to the ceteris paribus impact of green knowledge capital on labor productivity, keeping the other production inputs constant, in line with our empirical approach.

returns. This contrasts the public returns that include potential positive influences on neighboring regions that occur, e.g., through interregional knowledge spillovers. The analysis of the regional returns to green technological knowledge has important policy dimensions. It gives insights whether policies promoting regional green technology development also promote economic development and competitiveness of regions, and hence whether they contribute to both green and inclusive growth.[79]

Our empirical analysis builds upon a panel of 158 European NUTS-2 regions in twelve countries for the period 1980–2018. By relying on the flexible common correlated effects (CCE) approach (Pesaran, 2006), we are able to effectively control for different forms of CSD and other challenges in the estimation of production functions. Additionally, we employ various alternative estimation techniques to get a comprehensive view. Our main results comprise the following: First, we highlight the importance to account for CSD between European regions in the variables of the production function. Second, while general technology development is associated with positive regional returns, our data is not supportive of positive regional returns to green technologies in general. This insight is robust for all applied estimation procedures and a battery of econometric extensions. Third, despite the absence of regional returns to green technologies in general, we document evidence that the returns are positive for specific subclasses of green technologies and for regions with a sufficiently high level of the regional knowledge base.

Related empirical studies have been conducted on the firm or sector-country level. Firm-level evidence points to lower returns to environmentally-friendly innovation compared to other innovation (Marin and Lotti, 2017) or positive effects only for specific types of green technologies (resource-saving) (Ghisetti and Rennings, 2014; Rexhäuser and Rammer, 2014; van Leeuwen and Mohnen, 2017). Evidence on the sector-country level suggests positive, albeit rather small returns (Stucki and Woerter, 2019) and a possibly U-shaped relationship between green knowledge and productivity (Soltmann et al., 2015; Stucki and Woerter, 2019). We contribute to this literature by providing evidence on general equilibrium effects at the regional level.

Furthermore, our empirical approach directly builds upon the econometric literature on cross-sectional dependence (CSD) in panel estimation. Appropriately accounting for CSD is especially important in the empirical setup at hand, as the above-mentioned knowledge spillovers and unobserved common shocks make it a very likely feature of the

[79] As we are focusing on technological knowledge manifested in the form of patents, we use knowledge and technology interchangeably in this article.

data. In this regard, Ertur and Musolesi (2017) highlight the importance to account for CSD, even if specific, potential channels of knowledge spillovers are explicitly controlled for. Furthermore, Eberhardt et al. (2013) and Mitze et al. (2016) detect only limited returns to general knowledge capital at the industry level when unobserved spillovers and common factors are accounted for.

The remainder of the paper is organized as follows. Section 4.2 sketches a simple theoretical framework to motivate our empirical specification. Section 4.3 outlines the empirical framework, with a focus on estimating the degree of CSD in the variables and accounting for CSD in the estimation. Section 4.4 contains a detailed description and discussion of the data. Section 4.5 provides the empirical results of the tests for CSD, the main estimation, various extensions, and a discussion. Section 4.6 concludes.

4.2 Conceptual Framework

The aim of this section is to develop a simple regional growth model with Arrow-Romer type knowledge spillovers as well as spatial externalities. This model serves as a starting point to motivate our empirical framework. We consider a world of R regional interdependent economies, indexed by r with $r = \{1, ..., R\}$. In each period t, each region r produces a single output Y_{rt} with a constant returns-to-scale production function in labor (L_{rt}), green ($K_{g,rt}$), and non-green ($K_{n,rt}$) knowledge stocks, as well as physical capital ($K_{k,rt}$):

$$Y_{rt} = A_{rt} L_{rt}^{\sigma_l} K_{g,rt}^{\alpha_g} K_{n,rt}^{\alpha_n} K_{k,rt}^{\alpha_k}, \tag{4.1}$$

with $\sigma_l + \alpha_g + \alpha_n + \alpha_k = 1$. A_{rt} represents total factor productivity of region r.

We assume that region-specific total factor productivity A_{rt} is driven by region-specific individual, time-invariant characteristics (ψ_r) that are allowed to be correlated with domestic green ($k_{g,rt}$) and non-green per capita knowledge stocks ($k_{n,rt}$). Additionally, total factor productivity is driven by intraregional knowledge spillovers ($k_{g,rt}^{\phi_{g,r}} k_{n,rt}^{\phi_{n,r}}$). Moreover, we account for the possibility of interregional knowledge spillovers. Therefore, we introduce an error term e_{rt} that is potentially spatially affected by foreign stocks of non-green and green knowledge. These potentially spatially autocorrelated errors lead to weak CSD. Additionally, we cannot exclude the possibility that at least one strong but unobserved factor drives the evolution of region-specific labor productivity and also might affect the variation in green and non-green knowledge stocks as well (strong CSD) (e.g., Ertur and Musolesi, 2017).

In formal terms, we can summarize our assumptions as follows:

$$A_{rt} = \nu_{rt} k_{g,rt}^{\phi_{g,r}} k_{n,rt}^{\phi_{n,r}}, \tag{4.2}$$

with

$$\nu_{rt} := \exp\{\psi_r + e_{rt}\}. \tag{4.3}$$

Following Ertur and Koch (2007), the parameters $\phi_{g,r}$ and $\phi_{n,r}$ represent the strength of region-specific spillovers generated by green and non-green knowledge accumulation, respectively. This assumption is in line with the ideas of Arrow (1962) or Romer (1986) that there are within-region knowledge spillovers from investing in green and non-green knowledge. More specifically, we assume that one unit of green and non-green knowledge investment does not only increase the stock of green and non-green knowledge capital, but also contributes to total factor productivity for all operating firms in region r through intraregional knowledge spillovers.

However, these spillovers are likely not confined within the geographical borders of a specific region r. From an econometric perspective, these potential interregional spillovers are captured by the error term. One way to deal with such interregional spillover processes would be to model them explicitly with a specific spatial weighting scheme. However, as pointed out by Eberhardt et al. (2013), there is no reason to believe that CSD is appropriately represented by one specific weighting scheme, especially since spillover processes are likely generated by a complex interplay of several unobserved processes (Eberhardt et al., 2013). A more elaborated discussion of this aspect is delegated to Section 4.3.1 of this paper.

Inserting (4.2) and (4.3) in the per worker version of (4.1) delivers in log-notation our baseline estimation equation:

$$\ln y_{rt} = \sigma_k \ln k_{k,rt} + (\alpha_g + \phi_{g,r}) \ln k_{g,rt} + (\alpha_b + \phi_{n,r}) \ln k_{n,rt} + \nu_{rt}, \tag{4.4}$$

with

$$\nu_{rt} = \psi_r + e_{rt}, \tag{4.5}$$

where ν_{rt} incorporates a region-specific fixed effect ψ_r as well as an error term, which is discussed in more detail in Section 4.3.1. Moreover, $\sigma_{n,r} \equiv (\alpha_n + \phi_{n,r})$ and $\sigma_{g,r} \equiv$

$(\alpha_g + \phi_{g,r})$ represent the regional rate of return to non-green and green knowledge capital including intraregional spillovers, respectively.[80] Note that in this simple framework, potential heterogeneity of the returns to green technology development is introduced by the region-specific coefficient of intraregional spillovers. We explore potential sources of heterogeneity in greater detail in the empirical sections. Further, note that the structure of equation (4.4) is of Griliches (1979)-form, which is a standard approach in the literature dealing with the impact of knowledge on economic growth (e.g., Eberhardt et al., 2013; Mitze et al., 2016; Stucki and Woerter, 2019).

The crucial point is that estimating model (4.4)–(4.5) without controlling for *inter*regional spillovers and unobserved common factors might lead to inconsistent estimates of the regional rate of return to non-green and green knowledge capital, as the error term e_{rt} will contain these unobserved sources of CSD. Hence, we adopt an approach that accounts for unobserved spillovers of unknown form and other common factors without explicitly modeling them (e.g., Eberhardt et al., 2013). The drawback of this procedure is that we cannot quantify the contribution of different sources of spillovers directly (Mitze et al., 2016), which is beyond the scope of this paper, as we focus on the regional returns to knowledge development. Hence, we focus on consistently identifying the parameters of the aggregate production function with implicit *intra*regional spillovers.

4.3 Empirical Framework

4.3.1 Cross-Sectional Dependence

For illustrative purpose, we draw on the depiction by Ertur and Musolesi (2017), which highlights two potential sources of CSD in the error term of equation (4.5)

$$e_{rt} = \boldsymbol{\varrho}_r' \boldsymbol{f}_t + \epsilon_{rt}, \tag{4.6}$$

$$\epsilon_{rt} = \xi \sum_{s=1}^{R} \omega_{rs} \epsilon_{st} + \varepsilon_{rt}, \tag{4.7}$$

where $\boldsymbol{f}_t = (f_{1t}, f_{2t}, ..., f_{mt})'$ is a $m \times 1$ vector of unobserved factors, $\boldsymbol{\varrho}_r = (\varrho_{r1}, \varrho_{r2}, ..., \varrho_{rm})'$ is a $m \times 1$ vector of factor loadings, ω_{rs} is a spatial distance measure for each pair of

[80] To avoid explosive or endogenous growth, we shall assume decreasing regional returns for both types of knowledge stocks, i.e., $\sigma_{n,r} < 1$ and $\sigma_{g,r} < 1$.

individuals, ξ is a spatial autoregressive parameter, and ε_{rt} is a purely idiosyncratic error.[81] The upper equation (4.6) is related to factor models and typically to so-called strong CSD, whereas the lower equation (4.7) is a spatial autoregressive error process satisfying so-called weak CSD (Chudik et al., 2011; Sarafidis and Wansbeek, 2012; Ertur and Musolesi, 2017).[82] Simply put, weak CSD might be thought of as spatial dependence working through local interactions, whereas common effects that are due to unobserved global factors are a form of strong CSD (e.g., Bailey et al., 2016a).[83] This implies that while former dependence is restricted to units that are somehow connected to each other, latter is not (Mitze et al., 2016). The implications for estimation are related to the degree of CSD. For example, the spatial error process in equation (4.7) does itself not affect consistency and unbiasedness of conventional panel estimators, whereas strong CSD, represented by a factor model, does if factors and/or loadings are correlated to the regressors (Sarafidis and Wansbeek, 2012). As Ertur and Musolesi (2017) argue, there is neither a theoretical nor an empirical reason in the context of international technology spillovers to assume the mere prevalence of weak or strong CSD. We argue that this reasoning applies to regional technology spillovers as well. European regions are likely driven by a complex structure of interactions of European-wide factors with region-specific responses to them and spillover effects that occur because of local interdependence. For example, one might think of a global technology trend from which regions profit depending on their individual characteristics and/or local clusters through which spillovers operate.

Due to this complex structure of potential sources of CSD, we follow Ertur and Musolesi (2017) and Ciccarelli and Elhorst (2018) and employ diagnostics to gauge the magnitude and the nature of CSD in the data. These include the CD test (Pesaran, 2004, 2015a, 2021) and the estimation of the exponent of CSD (Bailey et al., 2016b). Both measures are applied as well to the residuals of the main estimation to validate and compare the estimation approaches. As Pesaran (2015a) shows, the CD test has the implicit null hypothesis of weak CSD. Specifically, the null hypothesis is $\alpha < (2-\delta)/4$, where α

[81] The normalized weighting matrix $\mathcal{W} = [\omega_{rs}]$ satisfies specific boundedness conditions (e.g., Chudik et al., 2011; Sarafidis and Wansbeek, 2012).

[82] This depends on the restrictions imposed on the factor loadings (Sarafidis and Wansbeek, 2012). Factor models can also generate different forms of weak CSD if there is no strong factor (Chudik et al., 2011). In fact, the spatial error process in (4.7) can also be represented by a factor process with an infinite number of weak factors (Chudik et al., 2011; Chudik and Pesaran, 2015a). For detailed overviews on weak and strong CSD, the connection to spatial or factor models, and the connection to weak and strong factors see, e.g., Chudik et al. (2011); Sarafidis and Wansbeek (2012); Chudik and Pesaran (2015a); Ertur and Musolesi (2017).

[83] Local can also relate to forms of proximity other than geographic distance, such as economic proximity (e.g., Mitze et al., 2016; Ertur and Musolesi, 2017).

refers to the exponent of CSD (Bailey et al., 2016b), and $\delta \in (0, 1]$ measures the degree of the relative expansion of the sample dimensions, defined by $T = O(N^{\delta})$. Hence, with our sample dimensions, the implicit null can be regarded as roughly $\alpha < 1/3$. The exponent is a measure of the convergence rate of the variance of the cross-sectional average of a specific variable as the cross-sectional dimension increases (Bailey et al., 2016b). α can be in the range $[0, 1]$ and can only be identified if $\alpha > 1/2$. Any process with $\alpha < 1$ fulfills the definition of weak CSD (the variance converges to zero), whereas $\alpha = 1$ corresponds to strong CSD (the variance does not converge to zero). However, different values of $\alpha \in [0, 1)$ indicate different magnitudes of CSD (Chudik and Pesaran, 2015a). Whereas convergence takes place very fast for values of $\alpha \in [0, 0.5)$, for values of $\alpha \in [0.75, 1)$ the variance converges to zero very slowly, still indicating rather pervasive factors (Ciccarelli and Elhorst, 2018). We estimate α as suggested by Bailey et al. (2016b). In our application, we estimate two different versions of the bias-adjusted estimator given by equation (13) of Bailey et al. (2016b): The first one (denoted by $\hat{\alpha}$) is the standard version assuming no temporal structure in the factors and no weak CSD in the error term. The second one is the version that is robust against both issues (denoted by $\tilde{\alpha}$).

An estimation approach that is able to consistently estimate a model with multifactor error structure and spatial error correlations as in equations (4.6) and (4.7) is the Pesaran (2006) common correlated effects (CCE) approach (Pesaran and Tosetti, 2011), which we introduce in due brevity in the following section.

4.3.2 Estimation Strategy

Our estimation strategy follows Eberhardt et al. (2013) and Eberhardt and Teal (2013) in that we contrast several estimators that make different assumptions regarding the data generating process. We do this to get a comprehensive view and to ensure that the results are not driven by specific a priori assumptions. As our main approach, we choose a flexible framework that accounts for several important aspects related to the estimation of production functions (see Eberhardt and Teal, 2011, for an overview). The CCE approach explicitly models an unobserved common factor structure in the residuals (Pesaran, 2006), and is a very convenient way to capture unobserved spillovers that are potentially complex and non-symmetric (Eberhardt et al., 2013). Drawing on Pesaran

(2006) and Pesaran (2015b) we specify the logarithmic aggregate production function (4.4) as follows:

$$\ln y_{rt} = \boldsymbol{a}_r' \boldsymbol{d}_t + \boldsymbol{\beta}_r' \boldsymbol{x}_{rt} + e_{rt}, \tag{4.8}$$

$$e_{rt} = \boldsymbol{\varrho}_r' \boldsymbol{f}_t + \epsilon_{rt}, \tag{4.9}$$

$$\boldsymbol{x}_{rt} = \boldsymbol{A}_r' \boldsymbol{d}_t + \boldsymbol{\Gamma}_r' \boldsymbol{f}_t + \boldsymbol{v}_{rt}. \tag{4.10}$$

Where $\boldsymbol{x_{rt}} = [\ln k_{g,rt}, \ln k_{n,rt}, \ln k_{k,rt}]'$, $\boldsymbol{d}_t = 1$, $\boldsymbol{a}_r' = \psi_r$, and $\boldsymbol{\beta_r} = [\sigma_{g,r}, \sigma_{n,r}, \sigma_{k,r}]'$ collects the coefficients. Strong CSD is introduced as the errors have a multifactor structure, where $\boldsymbol{f}_t$ is a vector of unobserved common effects, $\boldsymbol{\varrho}_r$ is a vector of factor loadings and ϵ_{rt} are idiosyncratic errors. The explanatory variables are driven by a deterministic component, the factors, and an idiosyncratic component, where $\boldsymbol{A}_r$ and $\boldsymbol{\Gamma}_r$ are factor loading matrices, and $\boldsymbol{v}_{rt}$ is the idiosyncratic component. Finally, all coefficients are not ruled out to be heterogeneous across regions. Note that this setup contains the conventional fixed-effects panel approach as special case (Pesaran, 2006) and that the error structure nests time-specific, individual-invariant effects by defining $\boldsymbol{\varrho_r} = 1$ and $\boldsymbol{f_t} = \lambda_t$ (Sarafidis and Wansbeek, 2012).

Pesaran (2006) shows that such a model can be estimated consistently by including cross-sectional averages of the dependent and independent variables to the regression. Two estimators of the mean coefficients are possible: first, the mean group version (CCEMG) in which the coefficients are assumed to be heterogeneous and are hence estimated separately for each region and then averaged. Second, the pooled version (CCEP), in which the average coefficient is identified directly under the assumption of slope homogeneity.[84] Notably, the idiosyncratic term ϵ_{rt} is allowed to contain additional weak CSD (Pesaran and Tosetti, 2011; Chudik and Pesaran, 2015a), an important feature in our empirical setting, as discussed in the previous section. Related to this, Chudik et al. (2011) show that the CCE estimators are consistent in the presence of a fixed number of strong factors (strong CSD) and a potentially unlimited number of weak factors, which represent different forms of weak CSD. Taken together, the CCE approach accommodates various settings of CSD and allows to capture knowledge spillovers, other forms of productivity spillovers as well as different forms of common shocks (Eberhardt et al., 2013).

[84] If coefficients are indeed homogeneous across countries, pooling might be more efficient (Pesaran, 2006). On the other hand, if the deviations of the individual coefficients from the mean coefficient are correlated to regressors or errors, CCEP will no longer be consistent (Pesaran, 2015b).

Furthermore, the CCE approach is robust against several additional potential properties of our data. The first issue is possible non-stationarity of the variables of the production function. Kapetanios et al. (2011) show that the CCE approach remains valid if the factors contain unit roots and are possibly cointegrated. More recently, the examinations by Westerlund (2018) suggest that the requirements on the factors are very flexible, including factors with an unknown but finite order of integration and structural break dummies. Furthermore, the approach allows, by definition, for endogeneity of the input variables, since both $\boldsymbol{x_{rt}}$ and y_{rt} are driven by the unobserved factors.[85] Hence, the approach offers a way to control for endogeneity brought in by unobservables (Ertur and Musolesi, 2017), as long as the endogeneity can be captured by the unobserved factors.

In our static main estimation, we restrict our attention to pooled estimation techniques. In addition to the CCEP estimator, we employ several alternative estimators, which impose different assumptions on the underlying framework. These approaches also vary in the extent to which they control for common factors. They comprise simple pooled OLS (POLS) with and without time dummies, standard one-way (FE) and two-way fixed effects (2FE), and first-difference (FD) estimation with time dummies. As noted above, time-specific, individual-invariant fixed effects are a special case of the general factor structure, in which the effect on regions is homogeneous. In fact, evidence from Monte Carlo simulations by Eberhardt and Bond (2009) suggests that including time dummies can remarkably decrease the bias induced by unobserved common factors. Hence, FD with time dummies, 2FE, and CCEP are our a-priori preferred approaches.

In addition to the main estimation techniques, we report robustness of the main results to a variety of potential pitfalls in the appendix. First, we relax the assumption of common slope parameters and instead assume fully heterogeneous parameters, while retaining the static structure of the main approach. To this end, we implement the mean group (MG) estimator (Pesaran and Smith, 1995), and the CCEMG estimator introduced above. For the former, we subtract the cross-sectional mean from each variable each year. This procedure removes the impact of common factors entirely if their effect is region-invariant. If the effect of the factors is heterogeneous across regions, their impact might still be reduced (e.g., Pesaran et al., 1999; Bond et al., 2010). Furthermore, the assumptions of our main approach are strict exogeneity of the regressors and that no relevant dynamics are missed in the static approach.[86] This includes the CCE approach, which

[85]Endogeneity with respect to the error term e_{rt}.
[86]Exogeneity with respect to the idiosyncratic errors ϵ_{rt}.

does not allow for lagged feedback from y_{rt} onto $\boldsymbol{x_{rt}}$ and for lagged dependent variables among the regressors (Chudik and Pesaran, 2015b). In case of heterogeneous slopes and weakly exogenous regressors, CCEMG might be biased for small T, and CCEP even becomes inconsistent (Pesaran, 2015b). Omitting relevant dynamics might, furthermore, lead to a situation where the results do not correspond to long-run responses (Eberhardt et al., 2013). Hence, we report the results of two different dynamic extensions of the original static CCE approach. First, we implement the cross-sectionally augmented distributed lag (CS-DL) approach (Chudik et al., 2016), which allows to directly identify long-run responses but does not allow for lagged feedback from the dependent variable onto the regressors. Second, we implement the cross-sectionally augmented autoregressive distributed lag (CS-ARDL) approach, which allows for lagged endogeneous variables and weakly exogenous regressors (Chudik and Pesaran, 2015b).[87]

4.4 Data and Descriptive Statistics

The data set covers a time period of $T = 39$ years between 1980–2018 for $R = 158$ European NUTS-2 regions in twelve countries, resulting in a balanced panel of 6,162 observations.[88] The main data sources are, first, the ARDECO database, from which we obtain gross value added (GVA), gross fixed capital formation (GFCF), and employment.[89] Investment and value-added series are deflated to constant 2015 prices and given in millions of euros, employment is given in thousand persons. We include the flow measure gross fixed capital formation as physical capital input directly in the estimation instead of computing physical capital stocks, for example with the perpetual inventory method (e.g., Caselli, 2005). By including the flow series, we circumvent controversial decisions on starting values.[90] Since we use a per capita specification, all variables are divided by employment.

[87]Details on these approaches are provided in the appendix.

[88]We started from a sample of the EU-15 countries plus Norway, since only for these countries data from 1980 onward are available. The United Kingdom is no longer included in the utilized data revision, due to having left the European Union (EU). Various regions are dropped due to missing data on gross value added. This includes all regions from Ireland, Greece, and Luxembourg. The same applies for Eastern German regions. Finally, we exclude three regions – two from Spain and one from France – because they have a green patent stock of zero for every single observed year. Hence, we concentrate on regions which had at least one green technology patent. Therefore, we end up with 158 regions distributed among the following twelve countries: Austria, Belgium, Germany, Denmark, Spain, Finland, France, Italy, Netherlands, Norway, Portugal, and Sweden.

[89]Version 2021b.

[90]We discuss whether the main approach is robust against the inclusion of a capital stock computed with the perpetual inventory method in Section 4.5. To compute the capital stock, we assume a depreciation rate of 6% and follow Caselli (2005).

Secondly, we use the OECD RegPat database to gather information on patent applications and to construct regional knowledge stocks by accumulating patent counts into patent stocks.[91] Patents are one of the most commonly used measures of innovation (Barbieri et al., 2016), as they represent an advantageous indicator in some regards (Griliches, 1990), not least due to their wide and detailed data provision (Haščič and Migotto, 2015). Only few economically significant inventions have not been patented (Dernis and Khan, 2004). Nevertheless, patent data faces some relevant drawbacks that can hardly be circumvented, such as the accounting of strategic patents or the restriction to technological innovation (Barbieri et al., 2016) as well as very limited information on diffusion (Kemp, 2010). Further concerns, such as differing patent quality (Johnstone et al., 2010) or mistakes when searching environmental patents (Lanjouw and Mody, 1996), can be substantially mitigated by the choices made in the search of patents.

We rely on multinational patent applications filed at the European Patent Office (EPO) to create robust measures with respect to patent value and comparability, as only innovations of sufficient expected commercial profitability justify the relatively high application costs (Johnstone et al., 2010). We follow Costantini et al. (2017) by using patent applications with their earliest filing year in order to timely capture the innovative effort. Further, we decide to assign patents based on the residence of the inventor, thus capturing inventive activity (e.g., Kruse and Wetzel, 2016; Wurlod and Noailly, 2018). In case of multiple inventors from different regions or countries, the patent is allocated using fractional counts (e.g., Kruse and Wetzel, 2016; Wurlod and Noailly, 2018). The accumulation into knowledge stocks follows the method proposed by Popp et al. (2011), such that

$$K_{j,rt} = \sum_{s=0}^{\infty} e^{-\beta_1(s)}(1 - e^{-\beta_2(s+1)})PAT_{j,r,t-s}, \tag{4.11}$$

where $PAT_{j,r,t-s}$ is the patent count in period $t-s$ for region r for the patent group $j = \{g, n\}$. The rate of knowledge depreciation is set to 0.1 (β_1) and the rate of diffusion to 0.25 (β_2), as proposed by Popp et al. (2011). Thus, the relevance of a patent application peaks after 4 years (Popp et al., 2011), which seems to be a reasonable dynamic for diffusion patterns of new technology. To mitigate the influence of the initial observation on the knowledge stocks, we calculate all stocks with presample patent data from 1977 onward.[92]

[91] Version 2021a.

[92] Alternatively, knowledge stocks could be constructed with the perpetual inventory method (e.g., Kruse and Wetzel, 2016; Wurlod and Noailly, 2018). Results based on this method are discussed as a robust-

To define the patent groups green (g) and non-green (n), we differentiate green technologies based on the technology classes a patent belongs to. To define green patent applications, we utilize the Y02 tagging scheme implemented within the Cooperative Patent Classification (CPC) by the EPO (Angelucci et al., 2018). Consequently, as soon as a patent belongs to a technology class of the Y02 scheme, it is considered as a green patent. Non-green patent counts are constructed by subtracting environmental patents from the overall patent count. Finally, since we are using logarithmic variables in the estimation, we use $\ln k_{j,rt} = \ln(1 + k_{j,rt})$ for $j = \{g, n\}$ when the per worker knowledge stock is zero ($k_{j,rt} = 0$) and include a dummy indicator variable for when green knowledge is zero, non-green knowledge is zero, or both are zero (Aghion et al., 2016).

Table 4.1. Summary statistics

Variable (unit)	RT	Mean	S.D.	Min.	Max.
Labor productivity (Millions value added per 1,000 persons)	6,162	56.56	14.11	10.67	167.87
Investment (Millions physical capital input per 1,000 persons)	6,162	13.71	4.28	1.24	53.65
Green knowledge stock (Accumulated patent count per 1,000 persons)	6,162	0.07	0.11	0	1.06
Non-green knowledge stock (Accumulated patent count per 1,000 persons)	6,162	0.96	1.18	0	7.85

Note: RT: total number of observations; S.D.: standard deviation. The yearly data spans the period 1980–2019 (T = 39) and comprises 158 European NUTS-2 regions. Physical capital input and value added are in constant 2015 prices. The 1,000 persons refer to employed persons.

Table 4.1 displays some summary statistics for the main variables we employ in the empirical analysis. In the appendix (table C1 and table C2), we present the unconditional correlation matrix of our main variables, including the cross-sectional means that approximate the common factors. As expected, the green and non-green knowledge stocks are fairly correlated. This holds true for both the two specific stocks as well as the cross-sectional averages. Furthermore, appendix table C5 reports the results of panel unit root tests of the second generation (Pesaran, 2007) that allow for one unobserved factor. The results are somehow mixed but suggest that the presence of unit roots cannot always be rejected. As noted in Section 4.3, the CCE estimators are robust against non-stationarity

ness check in Section 4.5. The depreciation rate is set to 10% (Verdolini and Galeotti, 2011). We follow Kruse and Wetzel (2016) by dividing the patent count in the first observed year by 0.25; assuming a previous 15% growth rate of the knowledge stock and a 10% depreciation rate. Appendix tables C3 and C4 show that the correlation between the knowledge stocks computed with both approaches is quite high.

in the factors and different scenarios of cointegration. Since our approach does not rely on cointegration but is robust to various scenarios, we do not test for cointegration, as similarly argued by Eberhardt and Teal (2011). However, to validate the estimation approaches in the empirical part, we test whether the residuals are integrated of order one.

4.5 Results

4.5.1 Estimation of Cross-Sectional Dependence

In this section, we discuss the results of the CD test (Pesaran, 2004, 2015a, 2021) and the exponent of cross-sectional dependence (α) (Bailey et al., 2016b) applied to the variables of our model. Table 4.2 contains the CD test statistics, the point estimates of the bias-adjusted version of α and 90% confidence intervals.[93]

Table 4.2. The degree of cross-sectional dependence

	CD statistic	$\hat{\alpha}^*_{0.05}$	$\hat{\alpha}$	$\hat{\alpha}^*_{0.95}$
Log-levels				
Labor productivity	570.89	0.965	1.001	1.038
Investment	400.52	0.956	0.995	1.033
Green knowledge stock	349.83	0.942	0.978	1.015
Non-green knowledge stock	570.02	0.953	0.997	1.041
First log-differences				
Labor productivity	130.41	0.868	0.921	0.974
Investment	175.59	0.895	0.955	1.051
Green knowledge stock	217.64	0.855	0.940	1.025
Non-green knowledge stock	466.82	0.910	0.978	1.046

Note: Estimation of the bias-corrected version of α (Bailey et al., 2016b) and the CD statistic (Pesaran, 2004, 2015a, 2021). $\hat{\alpha}$ refers to the point estimate of the exponent of cross-sectional dependence according to equation (13) of Bailey et al. (2016b). * 90% level confidence bands. We follow Bailey et al. (2016b) and Ertur and Musolesi (2017) in preferring Holm's procedure over Bonferroni's. The CD statistic tends to $\mathcal{N}(0,1)$ under the null of weak CSD as N and $T \rightarrow \infty$ (Pesaran, 2015a).

As Ertur and Musolesi (2017) note, the exponent of cross-sectional dependence is originally developed for stationary variables. Hence, we adopt their proposed robustness

[93] We implement all estimation steps either in Stata or MATLAB. The estimation procedure for the exponent of CSD (α) is implemented in MATLAB. Codes are based on the GAUSS files obtained from the supplementary material of Bailey et al. (2016b). Some formulations from the panel packages of Álvarez et al. (2017) are adopted as well. CD statistics are also implemented in MATLAB. Any errors in the codes are, of course, our own. The Stata routines we use include *multipurt* (Eberhardt, 2011), *xtdcce2* (Ditzen, 2018, 2021), and *xthreg* (Wang, 2015).

test and estimate both the CD statistic and α for first-differenced variables as well. First, it is evident that the implicit null of weak CSD of the CD test is strongly rejected for all variables based on the critical values at the 1% significance level of the standard normal distribution. This holds true for the variables in log-levels as well as in first log-differences. Secondly, the point estimate of α (denoted $\hat{\alpha}$) is above 0.9 and very close to 1 for all considered variables in log-levels. In first differences, the point estimates are somewhat lower, but still well above 0.9.[94] These observations imply that it is likely that strong CSD is present in our data and that we have to take this into account to consistently estimate the parameters of the aggregate production function. Hence, the results indicate that the common factor approach outlined in Section 4.3.2 is well suited in the empirical context at hand.

4.5.2 Main Estimation Results

In this section, we present the main estimation results for the aggregate production function. Table 4.3 contains the estimation results for the static baseline regression estimated with our preferred estimation approaches – two-way fixed effects (2FE), first-difference OLS (FD), and CCEP – alongside simple pooled OLS (POLS) with and without time dummies and one-way fixed effects (FE). All approaches pool the data under the assumption of common slope coefficients.

We also report various diagnostics for the residuals. First, we apply the cross-sectionally augmented Im-Pesaran-Shin (CIPS) test (Pesaran, 2007) to the residuals to gauge whether they are stationary. Second, we report the CD statistic and both estimates of α, introduced in Section 4.3.1, in order to get an impression of the degree of CSD that is left in the errors. However, as noted by Sarafidis and Wansbeek (2012), the CD statistic might lose power if time dummies are included in the estimation or, equivalently, the data is expressed as deviations from a time-specific mean, since the positive and negative correlations in the residuals might cancel each other out. As Millo (2019) notes, the same effect applies in the CCEP case because of the augmentation with cross-sectional averages. This might lead to a situation where the average (pairwise) correlation coefficient is near zero, and so will be the CD statistic. To detect such a situation, we also report, as suggested by

[94]Estimates of the version of α that is robust against weak CSD in the error term and autocorrelation in the factors provide very similar point estimates to the ones shown here. Results are available upon request.

Millo (2019), the average (pairwise) cross-correlation coefficient ($\hat{\rho}$) as well as the average absolute (pairwise) cross-correlation coefficient ($|\hat{\rho}|$).

Table 4.3. Benchmark estimation of regional returns

	POLS (1)	FE (2)	POLS (3)	2FE (4)	FD (5)	CCEP (6)
Investment	0.471***	0.292***	0.476***	0.277***	0.110***	0.085***
	(0.009)	(0.026)	(0.010)	(0.027)	(0.012)	(0.018)
Green stock	0.014***	0.022***	0.000	-0.001	0.004*	-0.001
	(0.003)	(0.006)	(0.003)	(0.007)	(0.002)	(0.005)
Non-green stock	0.039***	0.060***	0.047***	0.037***	0.026***	0.046***
	(0.003)	(0.008)	(0.003)	(0.013)	(0.005)	(0.016)
Year dummies	No	No	Yes	Yes	Yes	No
Order of integration	I(1)/I(0)	I(1)	I(0)	I(1)/I(0)	I(0)	I(0)
CD statistic	74.72	58.01	4.18	0.53	0.53	2.16
$\hat{\rho}$	0.11	0.08	0.01	0.00	0.00	0.00
$\lvert\hat{\rho}\rvert$	0.42	0.45	0.44	0.45	0.17	0.27
$\hat{\alpha}$	0.85	0.82	0.85	0.59	0.48	0.60
$\tilde{\alpha}$	0.85	0.83	0.89	0.65	0.55	0.61
Observations	6,162	6,162	6,162	6,162	6,004	6,162
Regions	158	158	158	158	158	158

Note: Asterisks indicate significance at * 10%; ** 5%; *** 1%. Standard errors in parentheses are of heteroskedasticity-robust sandwich type for POLS, (2)FE and FD. Standard errors for CCEP are based on the non-parametric variance estimator given in Pesaran (2006). Order of integration refers to the Pesaran (2007) test for unit roots. I(0) refers to the case where the null of a unit root is rejected at 10% level for all lag augmentations until two lags. I(0)/I(1) indicates mixed results, i.e. if null is rejected in some, but not all cases. I(1) refers to the case where the null is never rejected at 10% level. $\hat{\alpha}$ is the bias-corrected version of α given by equation (13) of Bailey et al. (2016b). $\tilde{\alpha}$ refers to the version robust against weak CSD in the errors and autocorrelation of the factors. We use four principal components to construct the estimate robust against weak CSD in the error term. $\hat{\rho}$ is the average pairwise correlation coefficient, and $|\hat{\rho}|$ the average pairwise absolute correlation coefficient.

As evident from table 4.3, the estimated elasticity of labor productivity with respect to physical capital input is significantly positive in all employed approaches. The magnitude ranges from 0.085–0.277 in our preferred estimation techniques, being very similar to comparable studies based on the country-industry level (Mitze et al., 2016; Stucki and Woerter, 2019). With respect to the estimated returns to the two differentiated technology classes, the following pattern emerges. The coefficient for non-green technologies is estimated to be significantly positive in all cases. The range of magnitudes is 0.026–0.046 for our preferred estimators. When multiplying such an elasticity of roughly 0.04 with the average changes in the non-green knowledge stock, our estimates imply that non-green knowledge growth accounts for an approximate 0.49% increase in labor productivity in an average year. Given that labor productivity increases with 1.17% on average, growth in non-green technology accounts for a relevant share. On the other hand, the parameter estimates for the green technology stock are rather insignificant in our preferred approaches. Overall, non-green technology has a positive association with labor productivity in European regions, whereas the parameter estimates for green technology are rather insignificant, once CSD is controlled for.

Turning to the residual diagnostics, the CIPS test strongly rejects the null hypothesis of a unit root for our preferred estimators for FD and CCEP only. The CD statistic is below the critical values at the 1% significance level of the standard normal distribution for 2FE, FD, and CCEP only, indicating that α should be well above 1/3 in all other cases. The estimates of the exponent of cross-sectional dependence indicate that POLS and FE without time dummies and POLS with time dummies are not able to take into account the CSD in the data effectively. For both versions of α, the point estimate is relatively high and well above 0.75, indicating that rather pervasive factors are left in the errors. The point estimates for 2FE, FD, and CCEP are all similarly small, well below 0.75, and rather close to 0.5. This tendency is also confirmed by the average absolute (pairwise) cross-correlation coefficients, which are lowest for FD and CCEP. Taken together, the residual diagnostics suggest that in our preferred approaches strong CSD in the form of pervasive common factors is effectively controlled for. Based on the diagnostics, 2FE, FD, and CCEP are confirmed as preferred estimators, which we employ for the extensions in the following sections.[95]

Our main finding is robust to a variety of robustness exercises. As documented in appendix table C7, it is not sensitive to the inclusion of a capital stock, calculated with the perpetual inventory method, instead of the flow measure of investment. Similarly, the findings are not altered when computing knowledge stocks based on the perpetual inventory method. If patents are assigned to a region based on the address of the applicant instead of the address of the inventor, the effects are slightly less pronounced. Additionally, appendix table C8 reports the robustness of the main results to the assumption of heterogeneous slopes, dynamic specifications, and a relaxation of the strict exogeneity assumption.

Due to our specific interest in the economic effects of green technologies, a potential concern is price induced innovation (Popp, 2002). Energy price shocks potentially decrease output directly and simultaneously increase green innovation. Such a negative correlation

[95]These diagnostics have to be interpreted cautiously, as estimation is performed on the residuals (Bailey et al., 2016b). Nevertheless, our conclusion is additionally supported by the fact that the estimate of α tends to be biased upward in particular for smaller values of $\alpha < 0.75$ (Bailey et al., 2016b).

between productivity and green innovation due to an omitted variable (energy prices) could lead to a downward bias in the estimated coefficient. Because of data availability, it is not possible to directly control for energy prices at the NUTS-2 level. Nevertheless, we are confident in our findings for the following reason. Our empirical framework accounts for unobserved common shocks that are allowed to load heterogeneously on different regions and that drive regressors as well as dependent variable. Hence, global energy commodity price shocks that affect regions differently by their exposure, e.g., because of different sector or energy-use patterns, as well as common European-wide policies are controlled for.[96]

To summarize, while our results point to a robust positive effect of non-green technologies of considerable magnitude, the data is not supportive of regional returns to green technologies in general. While these results line up well with firm-level evidence (Marin and Lotti, 2017), industry-level evidence by Stucki and Woerter (2019) points to rather similar effects between green and traditional knowledge. Our results are more pessimistic with regard to the economic returns to green technologies on the regional level in general.

4.5.3 Sources of Heterogeneity

While our main estimates identify the average effect of green and non-green technologies at the regional level, the regional returns to technology development might vary across regions and over time, as well as across different subclasses of green technologies. This heterogeneity might stem from distinct sectoral effects, the technological content of technologies, the specific technology subclass of green technologies, as well as critical mass phenomena with respect to an available knowledge base. In the following, we assess these sources in greater detail.

4.5.3.1 Sectoral Heterogeneity

A potential source of heterogeneous effects could be distinct partial equilibrium effects within sectors, i.e., sectors experience different productivity gains from the regionally available technologies. In fact, studies at the industry level often focus on a subset of sectors (e.g., Eberhardt et al., 2013; Stucki and Woerter, 2019). To assess this, we perform two separate sets of regressions for the industry and the service sector. Table 4.4 displays our baseline specification. The findings provide practically no evidence for distinct

[96]As Norway does not belong to the EU-15 countries, we test the exclusion of Norway with the results remaining unchanged.

technology effects within the sectoral classifications. The positive effects of non-green technologies are similar in magnitude and significance for both sectors. The magnitudes are also comparable to our findings for the general equilibrium effects, though the results are less significant. For green technologies, we consistently find little evidence for positive returns in both sectors, providing no robust evidence for the consideration that the returns within the industry sector are distinct. It should be noted, however, that due to data availability the sectoral granularity is limited, such that heterogeneous effects within specific industrial sectors are beyond the scope of this exercise.

Table 4.4. Returns in the industry and service sector

	Industry			Services		
	2FE (1)	FD (2)	CCEP (3)	2FE (4)	FD (5)	CCEP (6)
Investment	0.125***	0.082***	0.101***	0.295***	0.081***	0.073***
	(0.027)	(0.009)	(0.027)	(0.026)	(0.012)	(0.019)
Green stock	0.002	0.009*	-0.004	0.001	0.003	0.009
	(0.014)	(0.005)	(0.010)	(0.011)	(0.004)	(0.009)
Non-green stock	0.052*	0.031***	0.036*	0.031	0.032***	0.054**
	(0.029)	(0.007)	(0.021)	(0.019)	(0.007)	(0.027)
Year dummies	Yes	Yes	No	Yes	Yes	No
Observations	5,925	5,770	5,881	5,958	5,800	5,881
Regions	155	155	151	158	158	151

Note: Asterisks indicate significance at * 10%; ** 5%; *** 1%. Standard errors in parentheses are of heteroskedasticity-robust sandwich type for 2FE and FD. Standard errors for CCEP are based on the non-parametric variance estimator given in Pesaran (2006). *Labor productivity* and *Investment* are explicitly measured at the respective sectoral level. The knowledge stocks correspond to those in the total sample, but are here normalized with the sectoral employment numbers. *Industry* corresponds to the NACE Rev.2 sectors B to E. *Services* corresponds to G to N, as non-market services (O-U) were excluded for calculation here. Differing numbers of observations are due to some missing data at the detailed sectoral level.

4.5.3.2 Technological Content

Beyond the effects within different sectors, the gains from technology could differ depending on the quality of the technologies generated (Squicciarini et al., 2013). We utilize two measures of patent quality from the RegPat database to generate knowledge stocks that account for heterogeneity in the content of generated technologies. In all previous estimations, all patents enter the knowledge stocks with the same weight. With our focus on patent applications to the EPO we already control to a relevant degree for different values of patents (Johnstone et al., 2010). However, differences in patent value remain that are potentially relevant to our study. Mewes and Broekel (2022) analyze the effect of technological complexity on regional growth and find evidence for a positive effect. Dechezleprêtre et al. (2014) find that green technology generates more knowledge spillovers, which they find to be based on the higher level of radicalness of green compared to dirty technology. This might be coupled to the digital content of technologies, as they find information technologies (IT) that are clean to provide distinctly large knowledge spillovers. This seems to be in line with findings by Stucki and Woerter (2019), who find information and communication technology (ICT) to provide distinctly large economic effects. Given our interest in regional returns, it is important to consider these possibilities in greater detail, since intraregional spillovers are included in our estimates.

To assess whether the quality of patents affects the gains from respective technologies, we use two indicators by which patents are weighted before entering the knowledge stock. It should be noted that both measures are backward looking, meaning that they are constructed based on the technological content of a patent instead of being based on the subsequent impact. We consider this to be advantageous for our purpose. First, all patents are weighted by a patent scope measure (following Lerner, 1994) that proxies the technological breadth of a patent by counting the number of distinct 4-digit International Patent Classification (IPC) subclasses the patent is allocated to (Squicciarini et al., 2013). Second, patents are weighted by a radicalness index (following Shane, 2001) that captures the degree to which a patent cites IPC classes to which it does not belong itself (Squicciarini et al., 2013). These quality measures capture important dimensions of potential heterogeneity in the effects of technology. While many innovations qualify as incremental innovation and reinforce current activities, radical innovations can trigger entirely new technology trends and undermine current activities (Shane, 2001; Shkolnykova and Kudic, 2022). In a similar vein, the scope of a patent is associated with patterns of commercialization and the degree of market coverage via protected property rights (Shane, 2001).

Table 4.5 shows the results in our baseline setting when utilizing knowledge stocks that account for the heterogeneity in the quality of generated technologies. Our main findings as to the significant productivity effects of non-green and insignificant effects of green technologies are supported when accounting for this potential source of technology heterogeneity. Nevertheless, an interesting pattern emerges with respect to the magnitude of the coefficient of the non-green stock. In columns 4–6 it can be observed that the magnitude is close to identical to our main results when the patent scope is taken into account. Contextually, this implies that the technological breadth of the generated technologies is not associated with larger productivity gains. However, although the scope-weighting leads to relevant differences in level values, the within correlation of both knowledge stocks is 0.996, such that there is little deviating information gained for estimation.[97] When turning to the findings for radicalness, however, the effect of non-green technology is less pronounced both in magnitude and significance.[98] Two remarks on the interpretation of this finding are in order. First, radical technologies could be less productive because emerging technologies and markets require time, such that market benefits cannot be reaped immediately. Second, this finding could be related to the potentially competence-destroying nature of new technologies (Shane, 2001; Stucki and Woerter, 2019). Nevertheless, the fact that the coefficient remains clearly positive implies that any undermining of current activities does not exceed the productivity gains induced by the development of new technology.

Table 4.5. Quality-weighted knowledge stocks

	Radicalness			Scope		
	2FE (1)	FD (2)	CCEP (3)	2FE (4)	FD (5)	CCEP (6)
Investment	0.287*** (0.030)	0.109*** (0.012)	0.094*** (0.017)	0.277*** (0.027)	0.110*** (0.012)	0.082*** (0.016)
Green stock	-0.002 (0.007)	0.003 (0.003)	-0.006 (0.004)	-0.000 (0.007)	0.003 (0.002)	-0.001 (0.004)
Non-green stock	0.024** (0.011)	0.020*** (0.006)	0.014** (0.007)	0.034*** (0.012)	0.024*** (0.006)	0.041*** (0.015)
Year dummies	Yes	Yes	No	Yes	Yes	No
Observations	6,162	6,004	6,162	6,162	6,004	6,162
Regions	158	158	158	158	158	158

Note: Asterisks indicate significance at * 10%; ** 5%; *** 1%. Standard errors in parentheses are of heteroskedasticity-robust sandwich type for 2FE and FD. Standard errors for CCEP are based on the non-parametric variance estimator given in Pesaran (2006). Patents were weighted with the scope and radicalness indicators to arrive at patent counts that are accumulated into knowledge stocks. Both indicators are derived from the RegPat 2021a database as introduced by Squicciarini et al. (2013). The patent scope measure follows Lerner (1994) and the radicalness measure follows Shane (2001).

Finally, as emphasized by Dechezleprêtre et al. (2014) and implicitly shown by the findings of Stucki and Woerter (2019), the interconnection of green and digital technologies might be of importance. To capture this interconnection, we conduct our preferred estimations for a green knowledge stock defined as clean patents in ICT.[99] While the 2FE

[97] The mean value of the scope-weighted non-green knowledge stock is almost twice as large as the non-weighted one (1.75 compared to 0.96).

[98] The within correlation of the radical-weighted non-green stock with the regular one is 0.898.

[99] This corresponds to the Y02 class “Y02D”.

estimate displays a significant effect of green ICT,[100] the estimated coefficients for FD and CCEP are virtually zero.[101] Hence, we conclude that there is no strong evidence for positive regional returns to ICT-based green technologies.

In sum, these results emphasize that accounting for the underlying heterogeneity in technological content does not affect our main findings. Two remarks on these findings are in order. First, as we focus on the regional returns, it is not ruled out that interregional spillovers are larger for these technologies. Second, it is beyond the scope of our study to explore the dynamics of the twin green and digital transition in more detail. In this vein, potential effects that unfold only over a larger time horizon are outside of our scope.

4.5.3.3 Technology Type

As highlighted by firm-level studies, there is evidence for distinct returns for specific types of green technologies (resource-saving) (Ghisetti and Rennings, 2014; Rexhäuser and Rammer, 2014; van Leeuwen and Mohnen, 2017). Hence, we assess the importance of the technology field by defining subclasses of green technologies based on contextual considerations. We define four green subclasses based on the Y02 scheme that have different characteristics and implications regarding their economic effects. We distinguish energy generation from renewable energy sources (Renewable energy), climate-change-mitigation technologies in the production or processing of goods (Production or processing), climate-change-mitigation technologies in the buildings sector (Buildings), and climate-change-mitigation technologies aiming at energy efficiency (Energy efficiency).[102]

The economic gains from *Renewable energy* are strongly dependent on the market size of renewable energy generation, which is in turn dependent on the costs of emissions and, thus, potentially small for most of our analyzed time period. *Production or processing* contains a broader set of technologies, yet aiming strongly at the reduction of greenhouse gas emissions as well. *Buildings* strongly consists of applications that relate to energy efficiency. *Energy efficiency* includes only specific classes from various sections in the Y02 scheme, explicitly relating to energy efficiency. Hence, we focus on two subtypes (*Renewable energy* and *Production or processing*) that primarily relate to the reduction

[100] Still being only one-third of the magnitude from non-green, i.e. 0.015 compared to 0.043.

[101] Detailed results available upon request.

[102] *Renewable energy* corresponds to the CPC class "Y02E 10". *Production or processing* is the Y02 section "Y02P", while *Buildings* corresponds to "Y02B". *Energy efficiency* is a selection of CPC classes from various sections in the Y02 scheme, based on the classification by Wendler (2019). Some adjustments were made due to changes in the Y02 classification scheme and to secure a narrow definition of energy-efficiency technologies. The full list of utilized CPC classes is provided in appendix table C6.

of emissions, which are not a cost factor per se (in the absence of emission pricing). Thus, these technologies might have been associated with few proximate economic advantages. The other two subtypes (*Buildings* and *Energy efficiency*) relate to energy efficiency. Energy is a relevant cost factor and energy efficiency should thus be of economic interest, even in the absence of policy measures.

Table 4.6 displays the findings for our baseline specification for all green subtypes. For both green subtypes related to emissions reduction, we find no evidence for regional returns, in line with our findings for green technologies overall. For the two subtypes relating to energy efficiency, there is evidence for positive regional returns. For *Buildings*, the estimated coefficient is (slightly) significant for all approaches. These tendencies are even more pronounced when focusing on energy-efficient green technologies more specifically. Columns 4–6 report a significantly positive regional return to energy-efficient green technologies for all estimators. The magnitude is especially pronounced for the 2FE estimation in column 4.

These findings provide some evidence towards the importance of the green technology profile, in line with the firm-level evidence highlighted above. Related to this, Wendler (2019) finds evidence that energy-efficiency technologies are associated with reduced resource use, whereas technologies corresponding to the *Production or processing* section or alternative energy production are not.[103] Taken together, our results indicate that the regional returns to green technologies depend on the specific type of technology and that technologies that are related to energy efficiency are more likely to be related to positive returns.

[103]Resource use has similar characteristics to (and encompasses) energy as an input factor.

Table 4.6. Disaggregating green technology types

	Buildings			Energy efficiency		
	2FE	FD	CCEP	2FE	FD	CCEP
	(1)	(2)	(3)	(4)	(5)	(6)
Investment	0.268***	0.107***	0.090***	0.290***	0.107***	0.085***
	(0.027)	(0.013)	(0.016)	(0.027)	(0.011)	(0.016)
Green stock	0.013**	0.003*	0.006*	0.022***	0.004**	0.007*
	(0.005)	(0.002)	(0.003)	(0.006)	(0.002)	(0.004)
Non-green stock	0.030**	0.031***	0.054**	0.043***	0.030***	0.048**
	(0.012)	(0.006)	(0.027)	(0.013)	(0.005)	(0.021)
Year dummies	Yes	Yes	No	Yes	Yes	No
Observations	5,967	5,814	5,967	5,889	5,738	5,889
Regions	153	153	153	151	151	151
	Renewable energy			Production or processing		
	2FE	FD	CCEP	2FE	FD	CCEP
	(7)	(8)	(9)	(10)	(11)	(12)
Investment	0.256***	0.103***	0.091**	0.275***	0.111***	0.102***
	(0.022)	(0.011)	(0.035)	(0.027)	(0.012)	(0.024)
Green stock	-0.002	0.000	-0.001	0.001	0.001	0.004
	(0.005)	(0.002)	(0.004)	(0.007)	(0.002)	(0.005)
Non-green stock	0.036***	0.033***	0.063**	0.050***	0.031***	0.054**
	(0.014)	(0.006)	(0.029)	(0.013)	(0.005)	(0.024)
Year dummies	Yes	Yes	No	Yes	Yes	No
Observations	6,045	5,890	6,045	6,123	5,966	6,123
Regions	155	155	155	157	157	157

Note: Asterisks indicate significance at * 10%; ** 5%; *** 1%. Standard errors in parentheses are of heteroskedasticity-robust sandwich type for 2FE and FD. Standard errors for CCEP are based on the non-parametric variance estimator given in Pesaran (2006). The non-green knowledge stocks are computed case-specific based on the patent counts as the difference between total patents and the respective green area. Regions without knowledge in a respective green subclass are dropped from the sample.

4.5.3.4 Critical Mass Phenomena

Finally, we explore critical mass phenomena with respect to the regional knowledge base, and, thus, allow for potential non-linearities in the relationship between knowledge stocks and labor productivity. For example, as highlighted in our theoretical motivation, the strength of intraregional spillovers might be heterogeneous across regions, and the level of accumulated knowledge might be a source of this heterogeneity. Critical mass phenomena have been found in various contexts, such as broadband infrastructure (Czernich et al., 2011). Indeed, in their related study, Stucki and Woerter (2019) document that the impact of green technology increases as the level of green knowledge increases. Also, they report a corresponding complementarity between green and non-green knowledge. To assess whether the knowledge base of a region determines the regional returns to knowledge, we include interaction terms of both knowledge stocks with themselves and an interaction of green and non-green technology to our baseline specifications. A drawback of an interaction term is that it assumes that the regional return is a linear function of the knowledge stock. Hence, we additionally estimate corresponding threshold regressions, allowing for a kinked technology effect and the explicit identification of the level at which the threshold occurs. Further, the threshold regression exercise allows us to inspect the direction of changes in more detail.[104]

Our baseline specifications with interaction terms are displayed in table 4.7. We report all preferred estimators for each interaction. The first three columns report the findings for a complementarity relationship. The results provide some evidence towards a technology complementarity that is significant in the 2FE and CCEP estimation. The baseline effect for both technologies is similar to our main findings. In terms of interpretation, the different scales of the stocks have to be taken into account. The estimated effect of green technologies at the mean of the non-green stock is equal to $-0.054 + (0.005 * 10.36) = -0.0022$.[105] The corresponding effect of non-green technology equals $0.025 + (0.005 * 7.59) = 0.063$. Columns 4–6 report an interaction term for the green technology stock with itself, assessing whether a critical mass of green technology is needed for

[104]For both the interaction and threshold specifications, we utilize knowledge stocks multiplied by 100,000 (i.e., per 100 million employed persons), compared to the baseline specification. This is done to provide a straightforward interpretation of interaction and threshold effects. The multiplication secures that any non-zero values are clearly above 1, so to avoid that non-zero knowledge stocks take on a negative or zero value in logs. This would have caused some limitation for the interpretation of the interactions and thresholds, as a log value of zero would have covered both a case of a relatively high knowledge base as well as the complete absence of it, and negative log-values would imply larger knowledge stocks than some log-zero values.

[105]Based on the CCEP results.

positive regional returns to be realized. Both the 2FE and FD estimation indicate that the productivity effects of green knowledge slightly increase as the green knowledge base increases. However, the effect remains very small and hardly surpasses 0 at the highest values of green knowledge stocks. The last three columns add a square term of non-green knowledge. The coefficient of the interaction term is most pronounced both in terms of magnitude and significance across all estimators. The regional return is estimated to be even slightly negative for low values up to 8.8, which corresponds to almost 19% of observations. However, at the 90% percentile, the return is estimated to be 0.033.[106]

To assess these findings in more detail, we consider static fixed-effects panel threshold regressions (Hansen, 1999). We allow for one threshold and test all combinations of threshold and regime-dependent variables. The results are reported in table 4.8. The findings provide some very important nuances to the results reported above. In all cases, we find a significant threshold that is usually located above the median observation of the sample, while still including a substantial part of the observations surpassing the threshold. Important insights can be obtained from columns 3 and 4, where the coefficients of both knowledge stocks are allowed to be regime dependent. In both cases, the coefficient of the non-green knowledge stock decreases above the threshold, whereas the coefficient of the green knowledge stock increases above the threshold. In columns 5 and 6, the threshold is estimated to occur at the exact same level as in column 4. Nevertheless, when only including one of the knowledge stocks as regime dependent, the results differ. For green technologies, there is no significant effect above the threshold, and for non-green knowledge the coefficient increases after reaching the threshold. These findings are qualitatively identical, irrespective of whether the threshold is computed based on the level of the green or non-green knowledge stock. In our data, the two technology stocks are highly correlated, so that these phenomena should be related cautiously to the total knowledge base, as regions with high stocks of green knowledge tend to have high stocks of non-green knowledge, and vice versa.[107] As stated above, when the coefficients of both stocks are allowed to be regime dependent, they change in opposite direction and the regional returns to green technologies are even estimated to be significantly positive above the threshold. A possible interpretation might be that the increase of the coefficient of the non-green stock in column 2 and 6 is due to an omission of the kinked productivity effect for green knowledge. The opposite seems to apply for the coefficient of the green knowl-

[106]Based on the CCEP results.

[107]The Pearson correlation coefficient is above 0.85, and the Spearman rank correlation coefficient is roughly 0.95 in the overall dimension.

edge stock in columns 1 and 5, where the effect above the threshold is potentially biased downward because of the omission of the kinked regional return to non-green knowledge. This intuition also sheds light on the findings in table 4.7. While the generally positive interactions hint towards the fact that the total knowledge base increases economic returns, the relative quantitative findings of the individual interactions should be treated with due caution.

When assessing the distribution of regions above the threshold, it seems that the increasing returns to green knowledge and decreasing returns to non-green knowledge are a mixed phenomenon of the time and the regional dimension. 117 regions cross the green threshold at least at the end of the sample, whereas this number of regions increases over time successively, starting from one region in 1985. Thus, our results might be interpreted in a way that regions profit only from non-green technologies in the beginning, whereas at a certain level of the regional knowledge base, the returns to green technologies increase, whereas the returns to non-green technologies decrease. This might support the interpretation of the regional knowledge base in the sense of absorptive capacity (Stucki and Woerter, 2019), especially since green technologies tend to be more complex (Dechezleprêtre et al., 2014). However, despite this indicated tendency, according to our results, the returns to non-green knowledge remain substantially higher than the regional returns to green knowledge above the threshold. Additionally, we emphasize that we cannot completely rule out that regulatory changes are behind the developments over time.

Table 4.7. Knowledge stock interactions included

	Complementarity			Green			Non-green		
	2FE (1)	FD (2)	CCEP (3)	2FE (4)	FD (5)	CCEP (6)	2FE (7)	FD (8)	CCEP (9)
Investment	0.276***	0.110***	0.121***	0.266***	0.110***	0.120***	0.281***	0.111***	0.128***
	(0.027)	(0.012)	(0.039)	(0.027)	(0.012)	(0.039)	(0.028)	(0.012)	(0.049)
Green stock	-0.045**	-0.003	-0.054**	-0.060***	-0.010	0.000	-0.015*	0.001	-0.010
	(0.018)	(0.007)	(0.027)	(0.020)	(0.007)	(0.037)	(0.008)	(0.002)	(0.012)
Non-green stock	0.033**	0.024***	0.025	0.050***	0.025***	0.048	-0.020	-0.007	-0.079*
	(0.014)	(0.006)	(0.026)	(0.014)	(0.005)	(0.042)	(0.022)	(0.018)	(0.047)
Non-green × Green	0.004**	0.001	0.005**						
	(0.002)	(0.001)	(0.003)						
Green × Green				0.004***	0.001**	-0.000			
				(0.002)	(0.001)	(0.003)			
Non-green × Non-green							0.005***	0.002**	0.009***
							(0.002)	(0.001)	(0.003)
Year dummies	Yes	Yes	No	Yes	Yes	No	Yes	Yes	No
Observations	6,162	6,004	6,162	6,162	6,004	6,162	6,162	6,004	6,162
Regions	158	158	158	158	158	158	158	158	158

Note: Asterisks indicate significance at * 10%; ** 5%; *** 1%. Standard errors in parentheses are of heteroskedasticity-robust sandwich type for 2FE and FD. Standard errors for CCEP are based on the non-parametric variance estimator given in Pesaran (2006). Interactions are based on the whole variation. To allow for non-linearities in CCEP, the procedure described by De Vos and Westerlund (2019) is used. Specifically, we augment the regression by cross-sectional averages of the linear regressors only, excluding cross-sectional averages of the dependent variable and the squared term.

Table 4.8. Allowing for thresholds in the coefficients of the knowledge stocks

	Threshold variable: Green			Threshold variable: Non-green		
		Regime dependent:			Regime dependent:	
	Green	Non-green	Both	Both	Green	Non-green
	(1)	(2)	(3)	(4)	(5)	(6)
Investment	0.268***	0.269***	0.266***	0.267***	0.271***	0.272***
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
Green stock		-0.004*				-0.003
		(0.002)				(0.002)
Green stock:	-0.004**		-0.006***	-0.004*	-0.003	
below threshold	(0.002)		(0.002)	(0.002)	(0.002)	
Green stock:	-0.000		0.016***	0.018***	0.001	
above threshold	(0.002)		(0.006)	(0.005)	(0.002)	
Non-green stock	0.045***				0.044***	
	(0.003)				(0.003)	
Non-green stock:		0.045***	0.047***	0.045***		0.043***
below threshold		(0.003)	(0.003)	(0.003)		(0.003)
Non-green stock:		0.048***	0.032***	0.032***		0.047***
above threshold		(0.003)	(0.005)	(0.005)		(0.003)
Threshold value	9.068	9.068	8.870	11.609	11.609	11.609
Threshold p-value	0.000	0.000	0.023	0.013	0.003	0.013
Threshold percentile	75%	75%	75%	75%	75%	75%
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes
Observations	6,162	6,162	6,162	6,162	6,162	6,162
Regions	158	158	158	158	158	158

Note: Asterisks indicate significance at * 10%; ** 5%; *** 1%. Standard errors in parentheses. Threshold regressions are implemented with the Stata package *xthreg* (Wang, 2015). We specify one threshold, a trimming parameter of 0.05, and 300 bootstrap replications. The percentiles used for reporting are 1, 5, 10, 25, 50, 75, 90, 95, and 99%. Hence, a reported threshold percentile of 75% implies that between 50 and 75% of observations are below the value, while at least 25% are above.

4.5.4 Discussion

Our main findings show that green technology development does not increase regional productivity in general, whereas non-green technology development does. This finding at the regional level complements evidence of comparatively lower returns of green innovation at the firm level (Marin and Lotti, 2017) and rather small returns at the sector level (Soltmann et al., 2015; Stucki and Woerter, 2019). However, our findings extend analyses at the firm and sector level, as our regional-level analysis accounts for any intraregional spillovers and captures the general equilibrium effects of green technology development. Dechezleprêtre et al. (2014) report that green technology generally provides larger spillovers. As our estimates show, however, green technology development is not associated with regional returns despite the inclusion of intraregional knowledge spillovers. On the other hand, our results do not preclude that there are substantial interregional productivity spillovers of green technologies.

When considering the general absence of productivity effects within the regions in more detail, it is supportive to consider the fact that our regional level analysis allows for two broad channels of productivity effects. First, an individual firm/sector becomes more productive and/or, second, green technology enables a shift to (new) more productive firms/sectors. While the former is mainly concerned with factor-augmenting technical change that increases the efficiency of cost factors, the second channel presents general equilibrium dynamics that could be especially relevant at the regional level. Despite capturing both of these potential shifts in our empirical setup, we observe no general effects from green technology.[108] This could be related to the fact that within a broad definition of green technology, a substantial share of these technologies is targeted at the reduction of emissions, which are of public good nature for most of the sample period under scrutiny.

However, beyond such direct effects on productivity by reducing cost factors, at the regional level, green technology could also be considered important because of its reduction of environmental externalities. In an earlier version of this paper (Kerner et al., 2021), we suggested a model in which green technology can exert an indirect productivity effect via the reduction of local environmental externalities that negatively affect production. Hence, the absence of positive regional returns implies that either there is no impact

[108] It is important to emphasize that our empirical setting does not consider these structural changes in the longer run, which are beyond the scope of this paper but represent an important area of research.

of green technology development on local environmental quality or local environmental quality does not pose any restriction on economic activity (yet). In sum, the absence of regional returns to green technology development in general points towards the absence (or the reciprocal suspension) stemming from factor-augmenting technical change for cost factors, enabling a shift to more productive firms/sectors, and the reduction of local environmental externalities and/or any impairment of production due to local environmental quality.

The particular importance of the cost-factor-augmenting nature of green technology is emphasized by our findings on the heterogeneity of green technology types. For green technology that increases energy efficiency, we find a robust positive effect on productivity. This finding aligns with previous studies at the firm level, which assess the difference between green innovation in general and resource- or energy-efficiency innovations (Ghisetti and Rennings, 2014; Rexhäuser and Rammer, 2014; van Leeuwen and Mohnen, 2017). While firms are found to profit from resource- or energy-efficiency innovation, for other types of green technologies there are even potential negative effects. Our findings are supportive of positive regional returns for specific green technology classes.

As another source of heterogeneity, we find a moderating effect of the regional knowledge base. Higher levels of technology, regardless of the type, positively affect productivity gains from green technology. In this sense, the knowledge base can be interpreted as regional absorptive capacity that increases intraregional spillovers. These "building-on-the-shoulders-of-giants" externalities are prominently highlighted in the theoretical literature on directed technical change (DTC). The seminal model by Acemoglu et al. (2012) assumes that the productivity of clean and dirty technologies profits from past innovation within the respective technology class, creating a pronounced tendency for path dependencies. Fried (2018) also includes spillovers across the sectors, i.e., past innovation efforts in one sector increase the productivity of innovation in other sectors. This inclusion might mitigate the emergence of a strong path dependency. Our results tentatively suggest that the productivity of green technology appears to increase with a high regional knowledge base, whereas the productivity of non-green technology even slightly decreases. While it is beyond the scope of our paper to disentangle the results regarding whether there are spillovers predominantly across or within knowledge types, our findings highlight that a regional knowledge base appears to be especially important for green technologies, which might be linked to the general high complexity of green technologies (Dechezleprêtre et al., 2014).

Based on our findings, several remarks with respect to policy implications of our study are in order. Given our analysis on the effects of green technology on productivity, our findings can be related to the discussion revolving around the strong version of the Porter hypothesis (Porter and van der Linde, 1995). The strong version of the Porter hypothesis (PH) postulates that stricter environmental regulation will positively affect competitiveness, due to the inducement of innovation by the regulation.[109] Our results imply an ambiguous picture with regard to these statements. First, in general, we do not find positive effects to green technology development. However, there is evidence for heterogeneity of the productivity effect with respect to different types of green technology. Additionally, our data is supportive of thresholds in the productivity effect of green technology, implying that the effect is positive in region-years in which a sufficient knowledge base had been accumulated. However, the elasticity with respect to non-green technology is still higher, such that a crowding out of non-green technology in response to regulation in the favor of green technology might still reduce productivity. When there is no crowding out, our results do not completely rule out the potential presence of the strong PH.[110] In general, these implications align with previous literature on the PH that tends to find little effects of regulation on competitiveness, with a tendency towards slight and sectorally heterogeneous negative effects (Dechezleprêtre and Sato, 2017).

The absence of general productivity effects of green technology merits a further consideration as to how the elasticities might change over time. Conceptually, we introduced the regional returns to green technologies to consist of both a direct and an indirect effect, e.g., due to the reduction of local environmental production externalities. The direct productivity effect could turn significantly positive if environmental benefits, such as lower emissions, turn into a properly priced input to production. During the period under investigation, such environmental input factors mostly have not been relevant cost factors. This is rationalized by the findings on the effectiveness of the EU Emissions Trading System (ETS), which has been considered rather ineffective during most of our observation period (Ellerman et al., 2016).

[109] Though being slightly different concepts, productivity is strongly related to competitiveness. For example, van Leeuwen and Mohnen (2017) empirically analyze effects on productivity and consider this an indirect examination of the strong PH.

[110] This interpretation is of course very limited by design of our empirical application. First, we consider all green technologies that are developed, not only the ones directly triggered as response to climate policy, as we do not control for policy directly. Second, we have in general no information regarding crowding-out effects available.

Finally, our findings have implications with respect to the cohesion policy of the EU. Especially, regional cohesion policy of the EU is explicitly coupled with the green transition. Our findings imply that the potential from fostering the green transition in regions as an effort to create a win-win situation of regional cohesion and climate goals is limited. This is due to the currently small gains from green technology development in general. On the other hand, comprehensive policies fostering the green transition for all regions alike are potentially in contrast to regional cohesion goals. As our findings suggest, the returns to green technology development appear to depend on the regional knowledge base, such that knowledge intensive regions might especially profit, exacerbating regional inequalities. Accounting for this underlying heterogeneity, the heterogeneity in specific technology types, and the lacking economic rewards to green technology development in general appear crucial for inclusive green growth.

4.6 Conclusion

In this paper, we estimate the impact of green technology development on labor productivity for 158 European NUTS-2 regions from 1980 to 2018. To inform our empirical approach, we present a simple theoretical motivation, which highlights the role of intraregional and interregional knowledge spillovers and other unobserved common factors. We estimate the aggregate production function by employing a flexible empirical framework controlling for spillovers between regions and unobserved common factors as well as several important econometric challenges that arise in the estimation of macro panels in general and in the estimation of production functions in particular.

First, we estimate the degree of cross-sectional dependence between European regions in the variables of the production function and our results give strong indication of the presence of an unobserved common factor structure with strong CSD. Hence, we put special emphasis on appropriately controlling for this feature of the data. Furthermore, we contrast several estimators to get a comprehensive view. The results suggest that there are no positive productivity effects of green technologies in general. In contrast, our data is robustly indicating significant positive returns to non-green technologies. The results of the main approach are generally robust to a battery of robustness checks. These include dynamic specifications and estimation approaches robust against weak exogeneity of the production inputs, as well as allowing for fully heterogeneous coefficients across regions.

We provide evidence for several potential sources of heterogeneous returns to green technology. We find no evidence for heterogeneity caused by the technological content of developed technologies, such as the radicalness of innovation. However, we do find that the green-technology profile is of importance, as green technology that increases energy efficiency is found to exert positive regional returns. Furthermore, we find an important role of the regional knowledge base. Our findings provide evidence that the regional returns to green technology increase with a growing knowledge base.

Our results highlight several avenues for future research. First, the heterogeneity of different green technology types merits further consideration. Especially the coupling of green and digital technologies demands closer inspection, as this joint transition relates to long-run developments and possible complex interactions between input factors, which are by design beyond the scope of this study. Second, our findings on the regional knowledge base should be assessed in further detail by future studies. For example, disentangling whether shifts in the productivity effects from green knowledge and non-green knowledge are driven by either (fixed) regional characteristics or a common trend can provide important insights for policy makers and contribute to our understanding of technological change.

Appendix C

Part I: Data, Descriptive Statistics and Time-Series Properties

Table C1. Pairwise correlation matrix, total variation

	y_{it}	$k_{k,it}$	$k_{g,it}$	$k_{n,it}$	$\bar{y}_t$	$\bar{k}_{k,t}$	$\bar{k}_{g,t}$	$\bar{k}_{n,t}$
y_{it}	1							
$k_{k,it}$	0.797	1						
$k_{g,it}$	0.375	0.330	1					
$k_{n,it}$	0.692	0.610	0.571	1				
$\bar{y}_t$	0.501	0.430	0.379	0.5227	1			
$\bar{k}_{k,t}$	0.476	0.452	0.331	0.493	0.952	1		
$\bar{k}_{g,t}$	0.465	0.367	0.407	0.487	0.930	0.813	1	
$\bar{k}_{n,t}$	0.496	0.421	0.376	0.528	0.990	0.933	0.922	1

Note: Pairwise unconditional correlation coefficients. Cross-sectional averages are included.

Table C2. Pairwise correlation matrix, within variation

	y_{it}	$k_{k,it}$	$k_{g,it}$	$k_{n,it}$	$\bar{y}_t$	$\bar{k}_{k,t}$	$\bar{k}_{g,t}$	$\bar{k}_{n,t}$
y_{it}	1							
$k_{k,it}$	0.757	1						
$k_{g,it}$	0.400	0.276	1					
$k_{n,it}$	0.745	0.612	0.502	1				
$\bar{y}_t$	0.835	0.631	0.460	0.807	1			
$\bar{k}_{k,t}$	0.795	0.663	0.403	0.761	0.952	1		
$\bar{k}_{g,t}$	0.776	0.539	0.495	0.752	0.930	0.813	1	
$\bar{k}_{n,t}$	0.826	0.618	0.457	0.816	0.990	0.933	0.922	1

Note: Pairwise unconditional correlation coefficients for the within dimension. Cross-sectional averages are included.

Table C3. Correlation between different knowledge stocks, total variation

	$k^a_{g,it}$	$k^a_{n,it}$	$k^b_{g,it}$	$k^b_{n,it}$
$k^a_{g,it}$	1			
$k^a_{n,it}$	0.571	1		
$k^b_{g,it}$	0.991	0.593	1	
$k^b_{n,it}$	0.555	0.994	0.584	1

Note: Pairwise unconditional correlation coefficients. Compared are knowledge stocks based on our main approach ($k^a_{g,it}$) with those computed with the perpetual inventory method with a depreciation rate of 10% ($k^b_{g,it}$).

Table C4. Correlation between different knowledge stocks, within dimension

	$k^a_{g,it}$	$k^a_{n,it}$	$k^b_{g,it}$	$k^b_{n,it}$
$k^a_{g,it}$	1			
$k^a_{n,it}$	0.502	1		
$k^b_{g,it}$	0.990	0.488	1	
$k^b_{n,it}$	0.488	0.994	0.480	1

Note: Pairwise unconditional correlation coefficients for the within dimension. Compared are knowledge stocks based on our main approach ($k^a_{g,it}$) with those computed with the perpetual inventory method with a depreciation rate of 10% ($k^b_{g,it}$).

Table C5. Panel unit root tests

lags	y_{it}	$k_{k,it}$	$k_{g,it}$	$k_{n,it}$
0	-5.092 (0.000)	-3.135 (0.001)	-36.685 (0.000)	-30.546 (0.000)
1	-2.647 (0.004)	0.559 (0.712)	-7.355 (0.000)	-6.108 (0.000)
2	-1.254 (0.105)	2.233 (0.987)	-5.316 (0.000)	-5.640 (0.000)
3	-2.240 (0.013)	2.115 (0.983)	-1.140 (0.127)	-2.137 (0.016)

Note: Panel unit root test of the second generation by Pesaran (2007). Constant added, no trend. Reported are Z-statistics and p-values in parentheses. All individual groups are integrated of order one under the null hypothesis. Implemented in Stata with the *multipurt* routine written by Eberhardt (2011), making use of the *xtfisher* routine by Merryman (2005) and the *pescadf* command by Lewandowski (2007).

Table C6. CPC classes of Energy Efficiency

Y02B 20/	Y02B 30/	Y02B 40/	Y02B 50/	Y02B 60/
Y02B 70/	Y02B 80/	Y02D	Y02E 20/30	Y02E 40/
Y02P 10/25	Y02P 20/10	Y02P 20/124	Y02P 20/125	Y02P 20/129
Y02P 40/121	Y02P 60/14	Y02P 80/1		

Part II: Further Robustness Results

This section reports the robustness of the main estimation results to various different variable choices and estimation techniques. The results for different variable choices are reported in table C7.

The results for alternative estimation techniques, which we introduce briefly in the following, are displayed in table C8. First, we relax the assumption of common slope parameters and assume fully heterogeneous parameters instead, while retaining the static formulation and the strict exogeneity assumption. This includes the basic MG and the CCEMG approach. For both approaches, we pool the dummy indicator variables for when the green knowledge stock is zero, the non-green knowledge stock is zero, or both are zero, as there are many regions that have no within variation in the indicator variable.

Second, we consider dynamic panel models and relax the assumption of strict exogeneity of the regressors. The starting point is the CS-DL approach. In a nutshell, it is a reformulation of a dynamic panel approach with common factors, in which the long-run coefficients can be estimated directly without estimating the coefficient of the lagged dependent variable explicitly. This requires to augment the regression with contemporaneous and lagged differences of the regressors. Purging the cross-sectional dependence requires the addition of cross-sectional averages of regressors and the dependent variable, as well as lags of the cross-sectional averages of the regressors (Chudik et al., 2016).

Formally, we estimate the model

$$y_{rt} = c_{yr} + \boldsymbol{\theta}'_r \boldsymbol{x}_{rt} + \sum_{l=0}^{p-1} \boldsymbol{\delta}'_{\boldsymbol{rl}} \Delta \boldsymbol{x}_{r,t-l} + \sum_{l=0}^{p_{\bar{y}}} \omega_{y,rl} \bar{y}_{t-l} + \sum_{l=0}^{p_{\bar{x}}} \boldsymbol{\omega}'_{x,rl} \bar{\boldsymbol{x}}_{t-l} + e_{rt}, \tag{C1}$$

where $\bar{\boldsymbol{x}}_t$ is the vector of cross-sectional averages of the regressors in year t, $\bar{y}_t$ is the cross-sectional average of the dependent variable in year t, $\boldsymbol{x_{rt}} = [k_{g,rt}, k_{n,rt}, k_{k,rt}]'$ is the vector of regressors as in the main approach, and $\Delta \boldsymbol{x}_{r,t-l}$ are the contemporaneous and lagged values of the first differenced regressors (Chudik et al., 2016). We follow Chudik et al. (2016) and set $p_{\bar{x}} = [T^{1/3}] = 3$, where $[T^{1/3}]$ denotes the integer part of $T^{1/3}$, $p = p_{\bar{x}} = 3$ and $p_{\bar{y}} = 0$. It is a quite flexible approach as it allows for heterogeneous slopes and offers a mean group (CS-DLMG) and a pooled variant (CS-DLP), which we consider both. However, the CS-DL estimation procedure does not allow for lagged feedback from the dependent variable onto the regressors.

To allow for lagged feedback effects, we additionally consider the CS-ARDL estimator. It is based on a dynamic panel model augmented with cross-sectional averages of the dependent variable and the regressors as well as their lags. The coefficient of the lagged dependent variable is explicitly estimated. Formally, it is based on the following regression

$$y_{rt} = c^*_{yr} + \sum_{l=1}^{p_y} \varphi_{rl} y_{r,t-l} + \sum_{l=0}^{p_x} \boldsymbol{\beta}'_{rl} \boldsymbol{x}_{r,t-l} + \sum_{l=0}^{p_{\bar{z}}} \boldsymbol{\vartheta}'_{rl} \bar{\boldsymbol{z}}_{t-l} + e^*_{rt}, \tag{C2}$$

where $\bar{\boldsymbol{z}}_t = (\bar{y}_t, \bar{\boldsymbol{x}}'_t)'$ is the vector of cross-sectional averages of both dependent variable and regressors, and $p_{\bar{z}} = [T^{1/3}] = 3$ (Chudik and Pesaran, 2015b; Chudik et al., 2016). We consider both an ARDL(1,0,0,0) specification ($p_y = 1$ and $p_x = 0$) and an ARDL(1,1,1,1) specification ($p_y = 1$ and $p_x = 1$). The CS-ARDL estimator is developed as a MG estimator only. The individual long-run coefficients are constructed from the individual short-run coefficients according to

$$\hat{\boldsymbol{\theta}}_i = \frac{\sum_{l=0}^{p_x} \hat{\boldsymbol{\beta}}_{il}}{1 - \sum_{l=1}^{p_y} \hat{\varphi}_{rl}}, \tag{C3}$$

and the average long-run effect is calculated from these individual long-run effects. In both approaches, we include the indicator dummy for when contemporaneous green knowledge is zero, contemporaneous non-green knowledge is zero, and both are zero, which are excluded from the set of regressors whose cross-sectional averages are added. In the mean group approaches, we again pool these dummies.

The main advantage of the CS-DL approach compared to the CS-ARDL is its good performance for moderate values of T between 30 and 50 and its robustness to dynamic misspecification. However, as noted above, it does not allow for lagged feedback from the dependent variable onto the regressors (Chudik et al., 2016). Thus, Chudik et al. (2016) argue that they should be seen as complementing each other.

Table C7. Alternative variable calculations

	Capital stock		Perpetual inventory		Applicant	
	FD (1)	CCEP (2)	FD (3)	CCEP (4)	FD (5)	CCEP (6)
Investment	0.424***	0.209***	0.109***	0.089***	0.111***	0.088***
	(0.029)	(0.068)	(0.012)	(0.015)	(0.012)	(0.016)
Green stock	-0.000	-0.004	0.001	-0.004	0.002	-0.005
	(0.003)	(0.005)	(0.002)	(0.004)	(0.003)	(0.005)
Non-green stock	0.009*	0.044***	0.021***	0.035***	0.020***	0.014
	(0.005)	(0.016)	(0.005)	(0.012)	(0.004)	(0.012)
Year dummies	Yes	No	Yes	No	Yes	No
Observations	6,004	6,162	6,004	6,162	6,004	6,162
Regions	158	158	158	158	158	158

Note: Asterisks indicate significance at * 10%; ** 5%; *** 1%. Standard errors in parentheses are of heteroskedasticity-robust sandwich type for FD and based on the non-parametric variance estimators given in Pesaran (2006) for CCEP. For brevity, in all cases only FD and CCEP results are reported. Capital stock displays the results when including a capital stock, calculated with the perpetual inventory method, instead of investment flows. Columns 3 and 4 use knowledge stocks calculated with the perpetual inventory method. Columns 5 and 6 assign patents based on the address of the applicant, instead of the address of the inventor.

Table C8. Alternative econometric techniques

	Static		Dynamic			
	MG (1)	CCE-MG (2)	CS-DLP (3)	CS-DLMG (4)	CS-ARDL (5)	CS-ARDL (6)
Investment	0.169***	0.109***	0.045	0.114***	0.120***	0.063**
	(0.018)	(0.013)	(0.040)	(0.031)	(0.020)	(0.027)
Green stock	-0.018**	0.002	0.003	0.009	0.015	0.026
	(0.007)	(0.008)	(0.009)	(0.026)	(0.020)	(0.026)
Non-green stock	0.035**	0.046***	0.074	0.071	0.153***	0.123***
	(0.016)	(0.015)	(0.046)	(0.046)	(0.031)	(0.039)
Year dummies	No	No	No	No	No	No
Observations	6,162	6,162	5,688	5,688	5,688	5,688
Regions	158	158	158	158	158	158

Note: Asterisks indicate significance at * 10%; ** 5%; *** 1%. In all approaches, the respective non-parametric estimators of the covariance matrix are used. For MG, variables enter cross-sectionally demeaned. CCE-MG implements the mean group version of CCE. CS-DLP and CS-DLMG refer to the pooled and mean group version of the CS-DL estimator (Chudik et al., 2016), respectively. CS-ARDL refers to the dynamic CCE approach (Chudik and Pesaran, 2015b). For all dynamic specifications, long-run coefficients are reported. For CS-ARDL and CS-DL, the suggested lag lengths of the cross-sectional averages (for both) and the augmented first-differenced regressors (for CS-DL only) are used, as described in the text. Column 5 implements an ARDL(1,0,0,0) specification and column 6 an ARDL(1,1,1,1) specification.

Chapter 5

Oil Shocks and Green Energy Technical Change

Authors: Philip Kerner

Abstract

How is green technical change reacting to different structural shocks in the oil market? To approach this question, I use structural oil market shocks identified from an oil market vector autoregression and country-level patent data in different green technology areas for the period 1990–2015. The results imply that different shocks are associated differently with patenting activity in the following year, and that the response differs by technology area. Positive oil supply shocks are associated with reduced patenting activity for clean energy technologies in general, with a particularly strong association observed for biofuel patents. Oil consumption demand shocks are associated most strongly with clean energy technologies in general, whereas speculative demand shocks are particularly strong associated with biofuel patenting activity.

Keywords: Structural Oil Shocks; Green Technologies; Green Innovation

JEL Classification: O31; Q55; Q41; Q31

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5.1 Introduction

How to control climate change and at the same time establish energy security is an increasingly important topic on the national and international policy agenda. For example, this is evident in the recently announced new European Union (EU) External Energy Strategy (European Commission, 2022). There is general scientific agreement that one mechanism by which dependence on fossil energy sources is reduced is green technical change induced by higher energy prices (e.g., Grubb et al., 2021). The basic intuition is that higher prices for energy inputs in production lead to technological development being shaped to save the more expensive factor of production (Popp, 2002). For example, Hassler et al. (2021) argue that energy-saving technical change in the United States (US) took off after the oil price shocks in the 1970s. Developed countries have been strongly dependent on fossil fuels in the past decades (André and Smulders, 2014), and despite relevant shifts in electricity production and structural changes in the economy, oil remains one of the most important global commodities (Lang and Auer, 2020). The last fifteen years have been characterized by a substantial volatility of global crude oil prices. Coming from historical heights, the nominal price of Brent crude oil dropped from 133.87 US $ per barrel in July 2008 to 41.58 US $ per barrel in December 2008. Similar, huge price movements occurred at the end of the year 2014 and during the Corona pandemic.[111] Oil is determined in global markets, and these pronounced changes in the price of oil are driven by different underlying sources (e.g., EIA, 2017; Lang and Auer, 2020), which can have very different effects on the economy (e.g., Kilian, 2008, 2009; Kim and Vera, 2019). To understand the impact of oil price shocks on green technical change thoroughly, it is therefore important to get an understanding of the contribution of these different sources. In this paper, I contribute to this understanding and estimate the impact of different structural shocks to the global oil market on green innovation activity for a panel of Organisation for Economic Co-operation and Development (OECD) countries.

The present paper links to several strands in the literature. First, it is closely connected to the extensive literature estimating the elasticity of green innovation activity to energy prices in general and oil prices more specifically.[112] Some studies focus on broader measures of energy prices and consider different technology classes. Popp (2002) finds a positive effect of energy prices on energy-efficient innovation for several energy demand

[111]These statements are based on monthly data from the World Bank Commodity Prices.
[112]For recent, extensive literature reviews see Popp (2019) and Grubb et al. (2021).

and supply technologies. Kruse and Wetzel (2016) distinguish specific renewable-energy and energy-efficiency technologies and document that energy prices induce innovation in some but not all technology areas. Noailly and Smeets (2015) focus on clean and dirty innovation in electricity production and account for the heterogeneity of firm size and specialization. They find that an increase in fuel prices (oil, coal, and gas) increases both renewable energy innovation and fossil fuel innovation, while increasing the gap between both technology classes. Some studies use more specific energy price data. Focusing on the automobile industry, Crabb and Johnson (2010) document that energy-efficient automobile innovation in the US is impacted by higher oil prices. Similarly, Aghion et al. (2016) show that fuel prices (average of gasoline and diesel) drive clean innovation and reduce dirty innovation in the automobile sector. Palage et al. (2019) and Nunes and Catalão-Lopes (2020) document that oil prices drive innovation in solar technology and alternative energy technologies in general, respectively. Guillouzouic-Le Corff (2018) focuses on the biofuel sector and reports that oil prices were a major driver of the boom in biofuel innovation in the 2000s. I contribute to this literature by disentangling the impact of oil price changes on innovation in different environmental technology areas regarding the underlying structural shocks to the oil market.

Second, it is connected to the literature disentangling the effect of energy prices onto different measures of technical change regarding their underlying structural causes. Hoang et al. (2019) use the decomposition by Kilian (2009) to analyze the role of different structural oil market shocks for renewable and non-renewable energy consumption in the US. Balcilar et al. (2019) draw on this decomposition and estimate the impact of energy market shocks on the transition to renewable energy, measured by the renewable energy share. They report that oil price uncertainty shocks have a positive effect on the transition to renewable energy. Drawing on a similar decomposition, van de Ven and Fouquet (2017) adopt an historical perspective to estimate how structural shocks to the oil market since 1700 have impacted energy prices and other macroeconomic aggregates in the United Kingdom (UK). Arguably closest to the present paper is the recent working paper by Hu et al. (2022). Using a recent structural decomposition of the global oil market (Baumeister and Hamilton, 2019), their preliminary results indicate that different structural shocks have different effects on green innovation of US firms. Specifically, oil supply shocks always decrease green innovation, while oil-specific demand shocks increase innovation incentives for non-oil firms, but decrease innovation incentives for oil firms. I deviate from their analysis in important ways. First, I employ a sample of OECD countries and focus on aggregate innovation, thus considering general equilibrium effects. Second, I consider more fine-grained classifications of green technologies.

To estimate the impact of different shocks to the oil market on green energy technical change, I construct a panel data set for 27 OECD countries in the period 1990–2015. I follow the empirical literature on induced technical change and use patent data to measure green innovation activity. Specifically, I use patents filed at the European Patent Office (EPO). These are classified into the three technology classes according to the "Y02" tagging scheme within the Cooperative Patent Classification (CPC) developed by the EPO (Angelucci et al., 2018): clean technologies in the energy sector, clean technologies in the buildings sector, and biofuel technologies. In this paper, I am interested in the effects of global price shocks rather than in the effect of country-specific, tax-inclusive energy prices, which also depend on domestic taxation and the energy mix (Sato et al., 2019). Hence, I follow common practice and rely on the price of crude oil (e.g., Cheon and Urpelainen, 2012; Palage et al., 2019; Nunes and Catalão-Lopes, 2020). To decompose changes in the crude oil price into different sources, I draw on the literature on structural global oil market vector autoregressions (VARs) initiated by Kilian (2009). This framework has recently been extended in several ways (e.g., Kilian and Murphy, 2014; Baumeister and Hamilton, 2019). To account for these recent advances, I employ the demand- and supply-driven oil shock estimates reported by Baumeister and Hamilton (2019), which are based on a flexible structural Bayesian VAR framework.

I report several important empirical findings. In general, different structural oil market shocks have different associations to green innovation activity, which also depend on the technology area under consideration. First, positive oil supply shocks are in general associated with reduced patenting activity in the following year. This effect is especially pronounced for biofuels, but negligible for clean technologies in the buildings sector. Second, positive oil demand shocks play only a limited role in general, being only significantly associated with increased patenting activity in the following year for general clean energy technologies. Third, positive speculative demand shocks have a pronounced positive association with patenting activity only for biofuels in the following year. However, there is tentative evidence that they are also associated with innovative activity in the other patent categories after more years.

The remainder of this paper is organized as follows. Section 5.2 discusses the conceptual groundings to inform the empirical approach. Section 5.3 outlines the empirical methodology with special emphasis on how to obtain the structural shocks in the global oil market. Section 5.4 presents the data. Section 5.5 discusses the main results and various robustness exercises. Section 5.6 concludes.

5.2 Conceptual Background

Early contributions by Hicks (1932) and Binswanger (1974) highlight that innovation activity is profit-driven and that the direction of innovation efforts likely depends on relative factor prices. In their seminal paper, Acemoglu et al. (2012) incorporate this mechanism in a model of directed technical change (DTC) that incorporates also environmental constraints. Specifically, they model a clean and a dirty energy sector, in each of which factor-augmenting technical change can take place. Research is a profit-oriented activity and the direction of research into one or the other sector depends on a price effect, a market size effect and a productivity effect. Ceteris paribus, research is directed to the intermediate sector with relatively higher prices, with larger market share and higher productivity. Recently, Fried (2018) provides a richer model that is explicitly designed in a general-equilibrium setting by also including a non-energy sector. Aggregate production is modeled by a nested constant elasticity of substitution (CES) production function. On the highest level, final output is produced from energy and non-energy intermediate goods with a near-Leontief degree of substitutability. The energy input in turn is a CES function of green or fossil energy. Finally, fossil energy can be produced from domestic fossil energy or oil imports. Hence, energy used in final production is provided from either green energy sources, from domestic fossil energy (i.e., a mixture of coal, oil, and natural gas) and oil imports. It is assumed that the three energy sources (green, fossil, and oil imports) are gross substitutes. The marginal return to green energy innovation for the machine producer depends on the value of green energy production, which is green energy price times green energy demand. Positive oil price shocks increase demand for fossil and green energy, increasing both innovation incentives, while carbon taxes only increase the demand for green energy. Hence, according to this theoretical grounding, higher global crude oil prices should increase incentives for green energy innovation. Similarly, Hassler et al. (2021) argue that energy-saving technical change in the US was triggered by oil shocks in the 1970s. However, not all countries in the sample of the present paper are importing oil. Nevertheless, oil price shocks can be expected to have an impact on green innovation for those countries as well, as the price of oil directly relates to the price of domestic fossil energy. The intuition that oil price shocks induce both green and fossil energy innovation can also be rationalized from a different angle. As argued by Grubb et al. (2021), oil price increases enrich oil companies, which partly invest these revenues into research activities related to both oil exploration and alternative energy sources, such as biofuels.

However, there is increasing evidence that the impact of oil price shocks differs fundamentally by their underlying source (e.g., Kilian, 2008, 2009; van de Ven and Fouquet, 2017; Kim and Vera, 2019). The global price of crude oil depends on several underlying factors. Drawing on the framework of the U.S. Energy Information Administration (EIA) (EIA, 2017), which constitutes the basis of the discussion by Lang and Auer (2020), four essential drivers can be differentiated. The price is determined by oil demand and supply, but also depends on oil inventories and financial markets. Supply can be affected by strategic choices of the Organization of the Petroleum Exporting Countries (OPEC) countries or by new extraction technologies, such as shale oil production (Lang and Auer, 2020). Demand for oil might increase because of economic growth and high demand in general, but might also be affected by structural changes, such as the development of alternative fuels in transportation. A specific role is played by oil inventories. Inventories are above ground storage of oil, which can be used to smooth out oil demand (Lang and Auer, 2020). Hence, oil demand does not have to be consumed right away, but can be stored in above-ground inventories (Kilian and Murphy, 2014; Kallis and Sager, 2017; Lang and Auer, 2020). Inventory demand is typically linked to the uncertainty of future oil supply shortfalls, and sometimes termed precautionary demand (Kilian and Murphy, 2014). Finally, oil is a commodity that is traded in the financial markets, which can be a factor of price fluctuations (Lang and Auer, 2020).

In a seminal paper, Kilian (2009) models the global market of crude oil similar to the framework introduced above. Specifically, the author differentiates three shocks: oil supply shocks, i.e., unanticipated shocks to global crude oil supply; aggregate demand shocks, i.e., unanticipated shocks to the global demand of all industrial commodities; and oil-specific demand shocks, i.e., unanticipated residual shocks to the real price of oil that are not captured by the other shocks. In this setting, oil-specific demand shocks comprise changes in oil inventories and financial shocks from the framework above, as long as they are not captured by the other shocks. Kilian (2009) documents that aggregate demand shocks lead to a pronounced increase in the price of crude oil, albeit with some delay. Oil-specific demand shocks increase the price of oil immediately, but the effect declines rather quickly. Contrary to both demand shocks, oil supply shocks have only very little effect on the real price of oil. This translates to how shocks contributed to the historical evolution of the real price of oil. Kilian (2009) documents that aggregate demand shocks caused persistent swings and oil-specific demand shocks are attributed to rather quick increases and decreases in the real price of oil. Supply shocks had only small contributions. Specifically, the huge price increase before 2008 is mostly attributed to global demand shocks in this calculation. Finally, Kilian (2009) demonstrates that the different shocks have very distinctive effects on US GDP growth and the US consumer price index (CPI). It is important to emphasize that oil shocks in this framework are unexpected shifts in one of the three variables oil production, aggregate demand, and the real price of oil, whereby expectations are understood in an econometric way, based on past observations of all three variables (Kilian and Murphy, 2014). Kilian and Murphy (2014) extend the model by Kilian (2009) to include oil inventories directly. They argue that shifts in expectations about future supply and demand conditions as well as uncertainty over future supply and demand conditions are directly reflected by inventory demand. Finally, they argue that financial speculation that drives up the price in the oil futures market leads to increased demand for inventories due to arbitrage. Hence, oil inventory shocks are interpreted as speculative shocks, or precautionary shocks. Using this extended framework, Kilian and Murphy (2014) report that speculative demand shocks play a prominent role in the historical development of the real price of oil.

These considerations have arguably direct implications for the effect of oil price changes on green technical change. First, the relative importance of different structural shocks in driving the real oil price directly relates to whether the shocks are linked to incentives to invest in green innovation. Second, even if the structural shocks do not drive the real oil price directly, they might relate to specific expectations about economic conditions that are not reflected by the oil price. Third, similar to the argument by Hu et al. (2022), one important aspect might be whether oil price shocks are related to uncertain economic conditions.[113] In general, the body of theoretical literature put forward different approaches of how uncertainty is related to economic activity. One important channel is the so-called real options channel (Bloom, 2014). The basic premise is that if economic agents face uncertain conditions, they might delay investment decisions to observe how the future unfolds until uncertainties dissipate ("wait-and-see" behavior). This mechanism requires decisions that are costly to reverse or irreversible due to adjustment frictions. In

[113]In this paper, I follow Bloom (2014) and Meinen and Röhe (2017) and refer to uncertainty as a broad concept potentially comprising both risk and uncertainty in the classical notion by Knight (1921).

this environment, investment cycles can arise because waiting for information yields temporarily higher returns than early commitment (Bernanke, 1983; Pindyck, 1991; Bloom, 2009). The same argumentation applies to R&D investments, which are considered to be highly irreversible (Goel and Ram, 2001; Czarnitzki and Toole, 2011). However, a difference might be the degree of adjustment costs. Bloom (2007) analyzes uncertainty and the dynamics of R&D investments. Assuming flow adjustment costs for R&D investments instead of stock adjustment costs for physical investment, the author highlights that higher uncertainty reduces the responsiveness of R&D spending to changes in demand conditions (caution effect). Furthermore, uncertainty has a direct negative effect on investment (delay effect).

The present paper uses patent data as activity measure of technical change, which has important implications. First, the option value of waiting disappears when the goal is to be the first to bring a patent to the market Bloom (2014). Second, the distribution of possible returns might be limited at the lower bound. Past R&D costs are already sunk and bringing the product to the market has higher expected returns when the distribution has a higher variance (Bloom, 2014). Goel and Nelson (2021) argue that while there should be an adverse effect of uncertainty on R&D investment, the effects on innovation are ambiguous, and generally depend on the potential role of new innovation to hedge against the sources of uncertainty.

Taken together, I argue that it is important to consider the underlying source of oil price shocks when estimating the impact of green technical change. However, different shocks might be related to different economic states and provide different implicit information to economic agents. Given the complex interplay of potential underlying channels of influence, I argue that identifying the sign and magnitude of the impact of different oil shocks on green technical change is ultimately an empirical challenge.

5.3 Empirical Methodology

5.3.1 Benchmark Estimation

First, I consider a benchmark model in which the real price of crude oil is related to patents as a measure of technical change to embed the results into the literature. In the second step, I use the preferred specifications and include the structural shocks to the global oil market.

The dependent variable is the count of new patent applications in a given year. Hence, I follow the related literature and adopt a Poisson specification (e.g., Noailly and Smeets, 2015; Aghion et al., 2016; Kruse and Wetzel, 2016; Guillouzouic-Le Corff, 2018; Sterlacchini, 2020) for the determination of green energy innovations in a given country and a specific green technology class. The following specification is broadly based on the model considered by Kruse and Wetzel (2016) and shall include the most important determinants while being parsimonious:

$$\begin{aligned}\mathrm{PAT}_{G,it} =&\exp\big\{\beta_{G,1}\ln \mathrm{OIL}_{t-1} + \beta_{G,2}\ln \mathrm{K}_{G,it-1} \\ &+\beta_{G,3}\ln \mathrm{TPAT}_{it-1} + \boldsymbol{b_G x}_{it-1} + \lambda_G t\big\}\eta_{G,i} + u_{G,it},\end{aligned} \tag{5.1}$$

where $\mathrm{PAT}_{G,it}$ is the number of green patents applied for by country i in year t for one of the three considered technology classifications G; $K_{G,it-1}$ is the stock of green technology knowledge at the beginning of the period t for technology class G; OIL_{t-1} is the global real oil price; TPAT_{it-1} is the amount of total patent applications; $\boldsymbol{x}_{it-1}$ is a vector of further controls; t is a liner time trend to capture common time effects (e.g., Kruse and Wetzel, 2016; Guillouzouic-Le Corff, 2018); $u_{G,it}$ is an error term; and $\eta_{G,i}$ is a country-fixed effect. All explanatory variables enter the model lagged by one period to mitigate contemporaneous feedback problems and to account for the time lag in patenting behavior (Aghion et al., 2016; Kruse and Wetzel, 2016). With respect to oil price increases, a rather short lag of one year appears to be appropriate. As Probst et al. (2021) summarize their reading of the literature, patenting responds rather quickly to price changes. One reason why this is plausible is that some inventions might have already been developed and only get patented as soon as market factors render them profitable (Probst et al., 2021). In the main estimation, the vector of controls contains an additional dummy for the period after 1997 to control for higher propensity of green innovation after the Kyoto Protocol was signed (e.g., Nesta et al., 2014) and total environmental policy stringency (EPS) lagged by one year. As lagged knowledge stocks and total patent counts are zero for some countries in some years, I follow Aghion et al. (2016) and include two dummy variables for when lagged green knowledge is zero and lagged total patents are zero.

For the main estimation, I follow the standard approach in the literature and control for the country-fixed effect $\eta_{G,i}$ as suggested by Hausman et al. (1984). With regard to this specification, two potential problems need to be addressed. First, as I use the fractional count of patent applications as dependent variable, patent counts in some country-years might not be integers. However, as Kruse and Wetzel (2016) argue drawing on the evidence by Silva and Tenreyro (2006), Poisson specifications are still preferable in the near-integer case present. In fact, Wooldridge (2010) emphasizes that the Poisson model works even for a non-negative continuous dependent variable. Second, the method to control the fixed effects requires strict exogeneity of the regressors. While the global real oil price might be strictly exogenous to the country-specific errors, the lagged knowledge stock is a function of lagged dependent variables by construction. To provide robustness against the assumption of strict exogeneity in the main model, I implement the approach to control for the fixed effect developed by Blundell et al. (1995, 1999, 2002), which approximates the unobserved fixed effects by presample means of the dependent variable. This approach allows for weak exogeneity of regressors, but requires the presample mean to be informative for patenting behavior over the whole sample period.[114] Finally, I estimate equation (5.1) with a negative binomial model to account for potential overdispersion of the dependent variable (Hausman et al., 1984), as done by Johnstone et al. (2010) and Palage et al. (2019).

5.3.2 Structural Oil Shocks

Many empirical studies document that the effect of oil price shocks on different measures of economic activity differs by the nature of these shocks (e.g., Kilian, 2008, 2009; van de Ven and Fouquet, 2017; Kim and Vera, 2019, 2022). A prominent way to disentangle different shocks in the global market of crude oil are structural vector autoregressions (SVARs) that build upon the seminal work by Kilian (2009) (e.g., van de Ven and Fouquet, 2017; Ahmadi et al., 2019; Balcilar et al., 2019; Maghyereh and Abdoh, 2020).

In general, SVARs of the global oil market can be represented by a system of equations of the following form (e.g., Baumeister and Hamilton, 2019; Kim and Vera, 2022):

$$\boldsymbol{\mathcal{A}}_0 \boldsymbol{z}_s = \boldsymbol{\alpha} + \sum_{i=1}^{p} \boldsymbol{\mathcal{A}}_1 \boldsymbol{z}_{s-i} + \boldsymbol{\varepsilon}_s, \tag{5.2}$$

where $\boldsymbol{z}_t$ is a vector of structural oil market variables at month s, $\boldsymbol{\mathcal{A}}_0$ is a matrix of coefficients for the contemporaneous relation between the variables, $\boldsymbol{z}_{s-i}$ is a vector of lagged values of $\boldsymbol{z}_s$ with p periods of lagged influence, $\boldsymbol{\mathcal{A}}_1$ contains the coefficients of the lagged variables, and $\boldsymbol{\varepsilon}_s$ is a vector of structural oil market shocks. These shocks to the

[114] See the discussion in the appendix to Aghion et al. (2016). Similar to Aghion et al. (2016), I include a dummy indicator variable for when the presample mean is zero.

oil market are unexpected in an econometric sense, i.e., shocks that are not predicted by lagged values of the endogenous variables. Furthermore, the shocks are structural in the sense that they are mutually uncorrelated (Kilian, 2009; Kilian and Murphy, 2014).

In a seminal paper, Kilian (2009) specifies a three-variable model with $\boldsymbol{z}_s = (q_s, y_s, p_s)'$, where q_s is the growth rate of global oil production, y_s is an index of global real economic activity, and p_s is the real oil price. Furthermore, the author allows for $p = 24$ months of lagged feedback. Hence, there are three structural oil shocks: First, shocks to the physical global supply of crude oil (oil supply shocks). Second, shocks to the demand for crude oil that are driven by the demand for all commodities (aggregate demand shocks). Third, shocks to oil-specific demand (oil-specific demand shocks).

The structural innovations are identified from the reduced-form VAR by imposing timing restrictions, such that $\boldsymbol{\mathcal{A}}_0^{-1}$ has a recursive structure. In consequence, the reduced form errors can be represented as $\boldsymbol{e}_s = \boldsymbol{\mathcal{A}}_0^{-1}\boldsymbol{\varepsilon}_s$:

$$\boldsymbol{e}_s \equiv \begin{pmatrix} e_s^{\Delta \ln \text{PROD}} \\ e_s^{\text{REA}} \\ e_s^{\ln \text{OIL}} \end{pmatrix} = \begin{bmatrix} a_{11} & 0 & 0 \\ a_{21} & a_{22} & 0 \\ a_{31} & a_{32} & a_{33} \end{bmatrix} \begin{pmatrix} \varepsilon_s^{\text{oil supply shock}} \\ \varepsilon_s^{\text{aggregate demand shock}} \\ \varepsilon_s^{\text{oil-specific demand shock}} \end{pmatrix} \tag{5.3}$$

The decomposition implies that all variables in the model potentially react contemporaneously to oil supply shocks, i.e., unexpected shifts in global oil production. Real economic activity and the real oil price potentially react contemporaneously to aggregate demand shocks, i.e., unexpected shifts in real economic activity, whereas oil supply only reacts with one month delay. Finally, unexpected shifts in the real oil price only affect the real oil price contemporaneously and both other variables with one period delay.

The three-variable VAR has been extended by Kilian and Murphy (2014) to contain above-ground oil inventories as a fourth variable in order to capture shocks to the precautionary demand for crude oil. Instead of identifying the structural shocks with timing restrictions, Kilian and Murphy (2014) rely on a combination of sign restrictions and upper bounds for specific parameter values.

Recently, Baumeister and Hamilton (2019) argue that both identification schemes are rather restrictive and are based on strong prior beliefs. Additionally, they highlight the potential problem of measurement error in the measure of global crude oil inventories. They suggest a Bayesian approach which allows to incorporate prior information and to model potential measurement error in a convenient way. Baumeister and Hamilton (2019) consider a variant of model (5.2) with four variables such that $\boldsymbol{z}_s = (q_s, y_s, p_s, \Delta i_s)'$, and $\boldsymbol{\varepsilon}_s = (\varepsilon^*_{1s}, \varepsilon^*_{2s}, \varepsilon^*_{3s} - \chi^{-1} e_s, \chi\varepsilon^*_{4s} + e_s)'$ containing the structural residuals and the introduced measurement error. The variables of the system for the main estimation are measured as: the growth rate of crude oil production (q_s); the growth rate of OECD+6 industrial production (y_s); the growth rate of US refiner's acquisition costs of crude oil (p_s); and the change in estimated OECD inventories as a percent of the previous month's oil production (Δi_s). Baumeister and Hamilton (2019) demonstrate how to recover the structural residuals from this system using Bayesian techniques.[115]

Given the challenges arising due to correct variable choice and specification, I draw in the present paper on the recent advances by Baumeister and Hamilton (2019) to recover the structural residuals. Specifically, I am interested in the structural shocks that are oil market specific, and hence the estimated structural residuals $\hat{u}^*_{1s}$ (oil supply shocks), $\hat{u}^*_{3s}$ (oil-specific demand shocks), and $\hat{u}^*_{4s}$ (precautionary demand shocks).[116] Structural oil shocks based on above method are also used by recent studies (e.g., Adekoya and Oliyide, 2020; Salisu and Adediran, 2020; Huang et al., 2021; Hu et al., 2022; Kim and Vera, 2022). In the empirical application, I follow related literature on lower (annual) frequency (e.g., Chen and Hsu, 2012; Jibril et al., 2020; Hu et al., 2022; Kim and Vera, 2022) and average the monthly structural residuals to yearly frequency in order to include them in the regression. Hence, I estimate the following panel count model

$$\begin{aligned} \mathrm{PAT}_{G,it} =& \exp\big\{\gamma_{G,1}\tilde{u}^*_{1t} + \gamma_{G,3}\tilde{u}^*_{3t} + \gamma_{G,4}\tilde{u}^*_{4t} + \beta^*_{G,2}\ln \mathrm{K}_{G,it-1} + \beta^*_{G,3}\ln \mathrm{TPAT}_{it-1} \\ &+ \boldsymbol{G,} \boldsymbol{b}^*\boldsymbol{x}_{it-1} + \lambda^*_G t\big\}\eta^*_{G,1} + u^*_{G,it}, \end{aligned} \tag{5.4}$$

where $\tilde{u}^*_{jt} = \frac{1}{12}\sum_{s=1}^{12}\hat{u}^*_{jst}$ for $j = 1, 3, 4$ is the average of the monthly structural residuals for year t. In the following, I refer to these yearly averages as structural oil market shocks if not otherwise stated.

[115] Besides the challenges related to the identifying assumptions and the role of measurement error in the oil inventories data, a highly debated decision relates to an appropriate measure of global economic activity (y_s). Kilian (2009) and Kilian and Murphy (2014) use a measure based on the real costs of bulk dry cargo shipping. Recently, Hamilton (2021) argue that this measure has several drawbacks and a measure of world industrial production is preferable, while Kilian (2019) defends the measure based on the real costs of shipping. Baumeister and Hamilton (2019) rely on a measure of global industrial production (OECD+6 industrial production).

[116] As Baumeister and Hamilton (2019) use Bayesian techniques, the "point estimate" of the structural residuals is understood here as the median draw from the posterior distribution.

5.4 Data and Descriptive Statistics

5.4.1 Data

This section presents the data used in the empirical approach. The main data set covers the period 1990–2015 for 27 OECD countries. Appendix table D1 contains the full list of countries included in the sample.[117] The country coverage contains both net oil-importing and net oil-exporting countries.[118] An overview of all data sources can be found in appendix table D3.

5.4.1.1 Dependent Variable

The main data to capture green technical change are patent data drawn from the World Patent Statistical Database (PATSTAT)[119] maintained by the European Patent Office (EPO). To classify patents to green technologies, I rely on the "Y02" tagging scheme, which has been implemented within the CPC by the EPO (Angelucci et al., 2018), and which is also used by the OECD (Haščič and Migotto, 2015).

Specifically, in the main estimation, I consider three technology categories that are linked to oil prices. The first category are climate change mitigation technologies (CCMT) in energy generation, transmission and distribution (clean energy technologies). It is important to emphasize here that oil is not directly relevant for electricity generation for most countries included in this sample (e.g., Cheon and Urpelainen, 2012). However, oil prices are still frequently considered to be an important determinant of innovation in renewable energy technologies (e.g., Palage et al., 2019; Nunes and Catalão-Lopes, 2020). A potential reason for this importance is the high integration of oil and natural gas markets. Jadidzadeh and Serletis (2017) show that close to 50% of the variation of the real price of natural gas in the US can be attributed to structural shocks in the global oil market. Hence, oil shocks are relevant as they signal changes in the markets of other fossil fuels. However, to get a comprehensive view, I consider two further technology categories

[117] The time period is determined by the availability of the EPS indicators (Botta and Koźluk, 2014) at the time of data collection. The estimation sample starts in the year 1991 since there is no lagged value of the EPS indicator for that year. Additionally, since the EPS indicator was not available post 2012 for some countries, the estimation sample is unbalanced.

[118] Drawing on Chen and Hsu (2012), I define net oil exporters as those countries which had an oil export surplus on average during the whole sample period. Data on oil imports and exports are obtained from the U.S. Energy Information Administration. The oil exporting countries are Denmark, Canada, Mexico, Norway, and UK. I implement robustness exercises for when the oil exporting countries are excluded from the sample.

[119] The PATSTAT autumn 2021 version is used.

that are more directly related to oil prices. Lee and Ni (2002) document for the US economy that historically oil demand has been especially important for transportation, specific industrial sectors, and residential and commercial use. Hence, I consider climate change mitigation technologies (CCMT) in the building sector (clean building technologies) as second technology. Finally, I consider biofuel technologies as they provide a direct substitute for oil-based fuel products (Guillouzouic-Le Corff, 2018). Specifically, Guillouzouic-Le Corff (2018) documents that the boom in biofuel innovation in the 2000s was spurred by increasing oil prices. Biofuels are a subcategory of the first category, clean energy technologies. A detailed classification of the three technology fields can be found in appendix table D2.

Additionally, general propensity to patent is captured by total patents counts, which refer to all patent applications regardless of CPC class. Based on the identified patent applications, I count the technology-specific green technologies between 1980–2015 at the country level, to have 10 years of presample information for the construction of knowledge stocks and presample means, which is explained in detail later. To distribute patent applications to countries, I use the inventor's country of residence. In case of inventors from multiple countries, patents are distributed according to the fractional counts (e.g., Kruse and Wetzel, 2016; Wurlod and Noailly, 2018).

There are several advantages of using patents as a measure of technical progress in green energy technologies.[120] First, patents have a wide and detailed data provision (Haščič and Migotto, 2015). Second, this especially extends to detailed information regarding specific technology classes, which is generally not available for R&D investment data and of high importance in the empirical study at hand. Third, most economically significant inventions seem to have been patented (Dernis and Khan, 2004).

However, there are potential limitations in the use of patent data. First, the specific value of patents is very heterogeneous and many patents have considerably low value (Aghion et al., 2016). To mitigate this problem, I follow the common approach to rely on patent applications at the EPO (Johnstone et al., 2010; Kruse and Wetzel, 2016), rather than patent applications at national authorities. Because of the relatively high application costs, patent applications at the EPO are often of high value (Johnstone et al., 2010). Additionally, I only count the first patent of the DOCDB patent family. This patent family is a collection of single patents that cover the same single invention. Focusing on the first

[120] Extensive discussions on advantages and limitations of the use of patent data are provided by Griliches (1990) and OECD (2009).

patent of the patent family further ensures that only high value patents are selected (e.g., Probst et al., 2021). Second, to capture research effort as timely as possible, I collect patent applications filed at the EPO based on the priority date, which corresponds to the first date of the invention worldwide (OECD, 2009). This date is generally strongly related to actual inventive activity (OECD, 2009).[121]

Knowledge stocks are constructed from the patent counts with the perpetual inventory method (e.g., Cockburn and Griliches, 1988; Peri, 2005; Aghion et al., 2016; Kruse and Wetzel, 2016). Specifically, the end-of-period t knowledge stock in country i and green technology G is calculated as

$$\mathrm{K}_{G,it} = \mathrm{PAT}_{G,it} + (1-\delta)\mathrm{K}_{G,it-1}, \tag{5.5}$$

where δ is the depreciation rate of existing knowledge and $PAT_{G,it}$ is the amount of new green patent applications in year t. In line with the literature, the depreciation rate is assumed to be 10% (Verdolini and Galeotti, 2011; Kruse and Wetzel, 2016). Following Kruse and Wetzel (2016), the initial knowledge stock is calculated as $K_{G,it_0} = PAT_{G,it_0}/(\delta+\gamma)$, where PAT_{G,it_0} is the initial patent count. To mitigate the influence of the initial observation, I construct the knowledge stocks from 1980 onward, using 10 years of presample observations. The parameter g is the pre-1980 growth rate in knowledge stocks and δ the depreciation rate from above, which are set to 0.15 and 0.1, respectively (Kruse and Wetzel, 2016).

5.4.1.2 Oil Market Variables

This paper focuses on the price component that emerges from the global commodity markets, such that the focus is on the real price of crude oil. The advantage on relying on oil prices is that the oil market is globally determined and the oil price consequently mostly exogenous to single country actions (Cheon and Urpelainen, 2012). Furthermore, as discussed by Sato et al. (2019), a potential problem with the use of energy price indicators is that they depend on the sectoral (or national) fuel mix. The fuel mix is, however, potentially endogenous to commodity prices or technological change within sectors.

[121] Note that by focusing on EPO applications and only counting the priority filing, excluding patents that are not the first patent in the patent family does not change patent counts much.

Oil price data on yearly frequency are obtained from the World Bank Commodity Prices. I use a simple average of West Texas Intermediate (WTI) and Brent crude oil spot prices. Real oil price series are obtained by deflating the crude oil price series with the OECD-wide CPI, drawn from the OECD Consumer price indices database.[122] To capture the structural shocks to the global oil market, I use the monthly structural residuals estimated and provided by Baumeister and Hamilton (2019).

5.4.1.3 Further Controls

To capture environmental policy support, I use the OECD Environmental Policy Stringency (EPS) Indicator (Botta and Koźluk, 2014). The indicator can be regarded as displaying the overall policy mix, comprising the stringency of different market based policies and command-and-control regulations. Unfortunately, the indicator is only available until 2012 for several OECD countries, while being available until 2015 only for Australia, Canada, France, Germany, Italy, Japan, Korea, Türkiye, the UK and the US.[123] Hence, the sample reduces to the period dictated by the availability of the EPS indicator in specifications where it is employed.

Finally, in the robustness sections, I use several further control variables. First, data on real GDP is obtained from the World Bank World Development Indicators. It is given in constant 2015 US $, converted using 2015 exchange rates. Second, data on total final energy consumption (in Terajoule) is obtained from the Sustainable Energy For All database provided by the World Bank. Third, the share of renewable energy consumption in total final energy consumption is obtained from the same data base. Population data to construct per capita series are obtained from the World Bank World Development Indicators. Finally, I use the index of global economic conditions calculated and provided by Baumeister et al. (2022).

5.4.2 Descriptive Statistics

This section contains several descriptive statistics for the main variables used in the empirical analysis. Table 5.1 presents some basic summary statistics. Some remarks are in order. First, the three considered patent classes are considerably different in terms of mean application, with biofuels displaying the smallest numbers given that it is a

[122] Given that short-run fluctuations in CPI inflation are generally negligible (Alquist et al., 2013), the exact deflation method can be considered as not decisive for the calculations.

[123] At the time of data collection.

subclass of clean energy patents. Second, the different structural oil shocks averaged to yearly frequency have different standard deviations, which is important to take into account when interpreting the estimated coefficients in the results sections.

Table 5.1. Descriptive statistics

Variable	Obs.	Mean	S.D.	Min.	Max.
Clean energy patents	702	114.61	257.08	0	1,775.45
Biofuels patents	702	5.40	16.82	0	175.55
Clean building patents	702	30.39	58.80	0	351.37
Total patents	702	3,592.03	6,729.53	0	36,567.35
Log real oil price	702	4.63	0.49	3.70	5.39
EPS	652	1.76	0.94	0.21	4.13
Log clean energy stock	702	4.08	2.18	-1.39	8.85
Log biofuel stock	702	1.92	1.69	-2.17	6.55
Log buildings stock	702	3.48	2.15	-1.61	7.66
Oil supply shocks	702	-0.06	0.39	-1.04	0.64
Oil demand shocks	702	-0.07	1.03	-1.80	2.82
Precautionary demand shocks	702	-0.05	0.18	-0.47	0.31

Note: Descriptive statistics for the main variables used in the empirical analysis for the period 1990–2015.

Figure 5.1 provides an overview of the development of patent applications for total patents, clean building patents, clean energy patents, and biofuels. It plots the cross-sectional mean of each class in all sample years. For better comparability, patent averages are normalized to 1 in the year 2005. Comparing the evolution of all three classes, a pronounced burst in green patents starting at around 2003 is evident. This development peaks at around 2010 and is followed by a remarkable decline in renewable energy patents, which appears to stop at the current margin of the sample. This decline is extensively discussed by Popp (2019), Sterlacchini (2020), and Probst et al. (2021). Potential explanations include a drop in energy prices, which is illustrated later in this section. Finally, this development appears to be an exclusive phenomenon for environmental technologies, as total patents display a steady development, remaining on similar levels after roughly 2000.

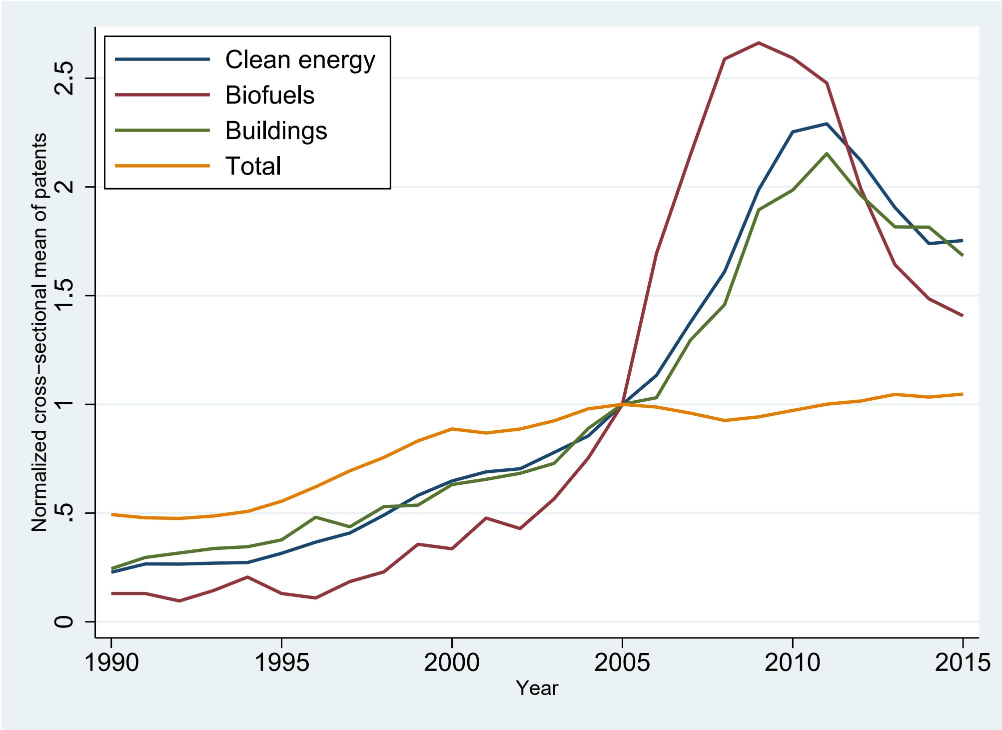

Figure 5.1. Green patents over time. Cross-sectional average of the main categories of green patent applications for the whole sample. For better comparability, patent averages are normalized to 1 in the year 2005. Mexico and Hungary are excluded, since their RE patent counts contain too many zeros to allow for normalization. Source: Own calculations based on the PATSTAT database.

Figures 5.2 and 5.3 plot the two explanatory variables of main interest, the global real price of oil and the yearly structural oil shocks, respectively. As noted above, a possible explanation for the boom and decline in green patents is that these technologies closely follow energy price developments. Indeed, the global real oil price appears to closely mirror the development especially in clean energy technologies. Finally, figure 5.3 shows that the three shock series are characterized by pronounced variation around zero. Any value below zero implies that the average of the original monthly structural shocks in that year is negative. Hence, the focus of this paper is not the volatility of the monthly structural shocks per se, as negative and positive realizations might cancel. As discussed by Baumeister and Hamilton (2019), negative oil supply shocks lead to a persistent increase in the real price of oil, such that the price is higher even 15 months after the shock. Indeed, as shown in appendix table D4, positive structural shocks to oil supply (unexpectedly high oil production growth) reduce the contemporaneous growth rate of the real price of oil. Using this simple regression, oil supply shocks explain roughly one third of the contemporaneous growth rate of the real oil price.

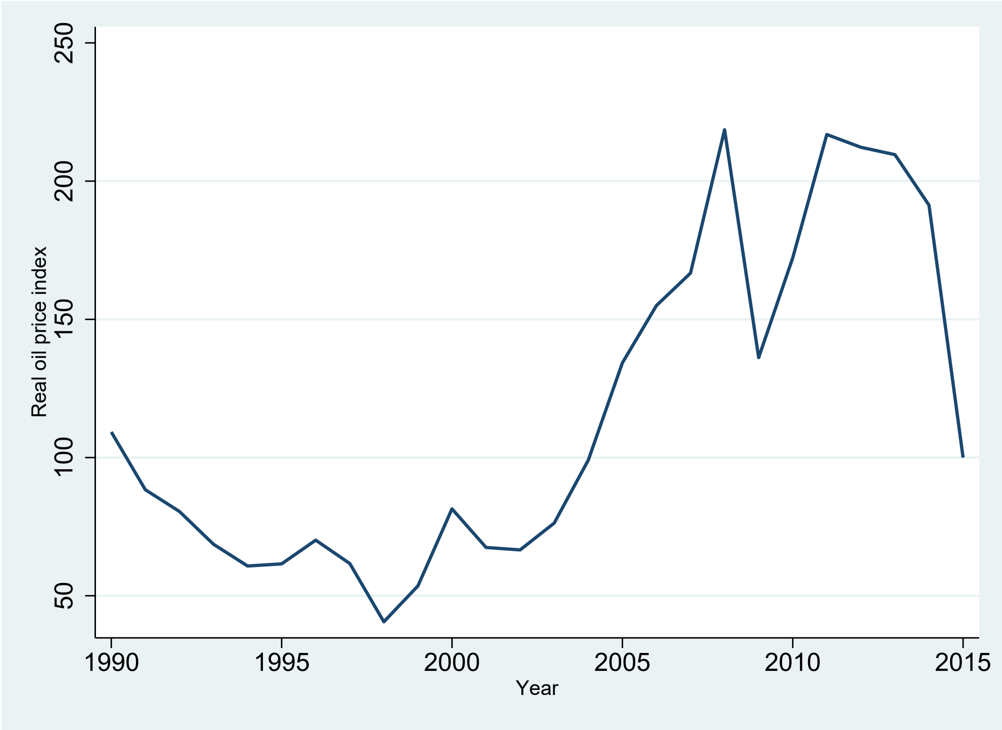

Figure 5.2. Real oil price. The real oil price (blue solid line) is expressed as an index (2015=100). Simple average of Brent and WTI spot prices deflated by the OECD-wide CPI. Source: On calculations based on data from the World Bank Commodity Prices and the OECD Consumer price indices database.

Figure 5.3. Structural shocks at yearly frequency. Structural residuals identified from the global oil market VAR obtained from Baumeister and Hamilton (2019) annualized to yearly frequency. Source: Own calculation based on data by Baumeister and Hamilton (2019).

As discussed by Baumeister and Hamilton (2019), oil supply shocks contribute strongly to the evolution of the real oil price in their estimation. For example, they attribute parts of the run-up in the oil price until 2008 (see figure 5.2) to unexpectedly low oil supply. This is also reflected in the structural shock series: from 2003 onward, the structural shock series is declining, with on average negative structural shocks for the years 2004, 2005, and 2006. Finally, appendix table D4 also shows that the shock series estimated by Baumeister and Hamilton (2019) attribute a more important role to oil supply shocks than the shocks estimated from the original decomposition proposed by Kilian (2009). Details are provided in the appendix.

5.5 Results

5.5.1 Benchmark Estimation

The benchmark results for the real oil price are shown in table 5.2. All columns use the method to control the country-specific fixed effect proposed by Hausman et al. (1984). Column 1 uses clean energy patents, column 2 uses clean building patents, and column 3 uses biofuel patents. The results are generally in line with previous empirical literature. First, the lagged knowledge stock has a pronounced effect on patent applications for the three considered technology classes, in line with the technology-push hypothesis (e.g., Kruse and Wetzel, 2016). The estimated elasticities imply that a 10% increase in the knowledge stock is associated with a roughly 3.1–5.7% increase in patent activity, depending on the technology class, which is broadly comparable to previous research (e.g., Aghion et al., 2016; Kruse and Wetzel, 2016). Second, the country-specific policy support, measured by the EPS index, is only significantly associated with patent activity in the case of biofuels. This is comparable to the findings by Kruse and Wetzel (2016), who document that public R&D support is only positively associated with green patent activity for specific technology classes, including biofuels. Third, the coefficient for the Kyoto dummy is significantly positive for all technology classes, indicating that the expected patent count is higher in the periods after the Kyoto protocol was signed.

The coefficient for the variable of main interest, the real oil price, is significantly positive for all green patent classes. The estimated elasticities imply that a 10% increase in the global price of real oil is associated with a roughly 3.3–11.5% increase in expected patent counts, depending on the technology class. The estimated elasticity is most pronounced for biofuels, in line with the argument that biofuels are close substitutes to conventional fuels. In terms of magnitude, the estimate is similar to the one reported by

Guillouzouic-Le Corff (2018), who documents that biofuel patents are elastic to oil price changes. Overall, the results imply that expected green patent counts in the different classes are strongly associated with changes in the level of the real oil price.

Table 5.2. Regression of green patents on the real oil price

	Dependent variable: CE patents	Dependent variable: Building patents	Dependent variable: Biofuel patents
	HHG	HHG	HHG
	(1)	(2)	(3)
Knowledge stock	0.566***	0.310**	0.450***
	(0.106)	(0.126)	(0.159)
Real oil price	0.345***	0.325***	1.149***
	(0.085)	(0.049)	(0.137)
Total patents	0.251	0.337**	0.200
	(0.198)	(0.166)	(0.346)
EPS	0.047	0.125	0.177**
	(0.085)	(0.087)	(0.070)
Kyoto dummy	0.571***	0.262***	2.073***
	(0.153)	(0.092)	(0.474)
Observations	641	641	641
Countries	27	27	27

Note: Asterisks indicate significance at * 10%; ** 5%; *** 1%. Standard errors in parentheses are of robust sandwich type. All models include two unreported dummies for no lagged knowledge stock and no lagged total patents. Common time effects are controlled for through an unreported linear time trend. HHG denotes the method to control for the fixed effect by Hausman et al. (1984).

Appendix table D5 presents the results for the benchmark model when different panel count techniques are applied. First, columns 1, 3, and 5 account for potential overdispersion of the dependent variable and use a negative binomial (NegBin) specification (Hausman et al., 1984). Second, columns 2, 4, and 6 account for potential weak exogeneity of the explanatory variables by using the method by Blundell et al. (1995, 1999), henceforth BGVR. The results are very similar to these alternative estimation approaches. This includes the coefficient of the real oil price, which is comparable in terms of magnitude and estimation precision across all approaches for each technology class. An interesting difference can be observed for the coefficient of the knowledge stock, which is generally smaller in magnitude and significance for the NegBin approach, but much more pronounced for the BGVR method. A similar observation is made by Aghion et al. (2016) when applying the BGVR approach. They argue that a potential reason for this observation is that the presample mean is not able to fully capture the country-specific fixed effects (Aghion et al., 2016).

In summary, table 5.2 offers evidence that oil price developments are positively related to the expected value of patents in the three considered technology classes. This result motivates further to consider the origin of real oil price changes and, thus, the structural shocks that lie behind them in the following sections.

5.5.2 Structural Oil Shocks

The main results for the structural oil shocks are shown in table 5.3. All columns use the method to control the country-specific fixed effect proposed by Hausman et al. (1984). Column 1 uses clean energy patents, column 2 uses clean building patents and column 3 uses biofuel patents.[124] The coefficient of the lagged knowledge stock is somewhat more pronounced in this estimation, which is likely a result of the absence of the real oil price level in this specification. Apart from this difference, the coefficients of the control variables are broadly consistent with the benchmark approach.

Turning to the structural oil market shocks, table 5.3 reports that positive oil supply shocks, i.e., unanticipated increases in oil supply, reduce the expected value of green patents for each considered technology. This effect is most pronounced for biofuel patents, and not very pronounced and imprecisely estimated for building patents. To put the estimated coefficient into perspective, the effect of a one standard deviation increase in the continuous oil supply shock series is associated with an approximate 8.8% decrease in patent applications in the following year for biofuels and an approximate 2.1% decrease in patent applications for clean energy technologies.[125] Positive oil demand shocks increase expected patent applications mostly in the case of general clean energy technologies. A one standard deviation increase in the oil demand shock series is associated with an approximate 4.4% increase in expected patent applications in the following year.[126] Finally, precautionary demand shocks are only precisely related to green patent activity in the case of biofuels, and the effect is particularly pronounced: a one standard deviation in-

[124] It is important to emphasize that the standard errors for the structural shocks should be treated with due caution. Since the shocks are estimates themselves, estimation uncertainty should include uncertainty from the structural shock estimation. Yet, controlling for this fact is very difficult due to the different time structure of the data (Kilian, 2009) and because of the use of Bayesian estimation techniques by Baumeister and Hamilton (2019). Hence, I follow the bulk of empirical literature and report standard errors that do not control for the generated regressors problem (e.g., Kilian, 2009; Chen and Hsu, 2012; Ahmadi et al., 2019; Phan et al., 2019; Jibril et al., 2020; Maghyereh and Abdoh, 2020). Although I do not strongly rely on the significance, it gives at least a good indication of the relative precision of estimation comparing the different generated shocks.

[125] Calculated as $\gamma_{G,1} \times 100 \times 0.39$.

[126] Calculated as $\gamma_{G,3} \times 100 \times 1.03$.

crease in the precautionary demand shock series is associated with an approximate 15.5% increase in biofuel patent applications in the following year.[127]

Table 5.3. Regression of green patents on oil shocks

	Dependent variable: CE patents	Dependent variable: Building patents	Dependent variable: Biofuel patents
	HHG	HHG	HHG
	(1)	(2)	(3)
Knowledge stock	0.608***	0.316***	0.741***
	(0.139)	(0.118)	(0.196)
Oil supply shocks	-0.054**	-0.039	-0.225***
	(0.024)	(0.029)	(0.049)
Oil demand shocks	0.043***	0.021	0.014
	(0.013)	(0.017)	(0.024)
Precautionary demand shocks	-0.002	0.007	0.861***
	(0.148)	(0.086)	(0.237)
Total patents	0.179	0.326*	0.014
	(0.252)	(0.172)	(0.423)
EPS	0.050	0.140	0.211**
	(0.100)	(0.100)	(0.084)
Kyoto dummy	0.377***	0.065	1.330***
	(0.135)	(0.097)	(0.432)
Observations	641	641	641
Countries	27	27	27

Note: Asterisks indicate significance at * 10%; ** 5%; *** 1%. Standard errors in parentheses are of robust sandwich type. All models include two unreported dummies for no lagged knowledge stock and no lagged total patents. Common time effects are controlled for through an unreported linear time trend. HHG denotes the method to control for the fixed effect by Hausman et al. (1984).

These results are well in line with the conceptual considerations. As estimated by Baumeister and Hamilton (2019), the real oil price is mostly driven by oil supply and oil-specific demand shocks. A positive structural oil supply shock reduces the real oil price, thus reducing green innovation incentives. On the other hand, a positive shock to oil-specific demand increases the real oil price and hence increases green innovation incentives. These results are also in line with preliminary evidence reported by Hu et al. (2022), who estimate a similar empirical setup at the firm level in the US. Interestingly, the effect of oil demand shocks is not very pronounced for biofuel patents. A possible explanation is contained in the preliminary results by Hu et al. (2022). They find that the effect of oil demand shocks is even negative for green innovation incentives of oil-producing firms. Thus, the effects might cancel in the case of biofuel patents if a sufficient share is issued by oil-producing firms. Precautionary demand shocks are highly relevant in the baseline estimation for biofuel patents. This is interesting against the background that

[127] Calculated as $\gamma_{G,4} \times 100 \times 0.18$.

precautionary demand shocks, as discussed by Baumeister and Hamilton (2019), play only a minor role in explaining real oil price movements in their estimation. This can also been seen in the effect on contemporaneous real oil price growth reported by appendix table D4. As discussed by Kilian and Murphy (2014), precautionary demand shocks are designed to capture expected future oil supply shortfalls, speculation, or other shocks related to the expectations of oil market participants. Hence, precautionary demand shocks might contain information regarding future oil uncertainties, which encourage patenting activity for technologies that are close substitutes for conventional fuels, such as biofuels. Finally, all shock series display only limited relevance for patent applications in the building sector. This observation might be related to the relatively broad classification of clean building patents.

In summary, the results of the structural shock analysis imply the following. First, positive structural oil supply shocks are associated with a reduction in patent applications for all considered technology classes, while the effect is most pronounced for biofuels and smallest in terms of magnitude and precision for clean building patents. Second, oil-specific demand shocks are mostly relevant for overall clean energy technologies. Third, precautionary demand shocks are relevant only for biofuel patents.

5.5.3 Robustness and Extensions

This section contains several robustness tests and extensions. First, appendix table D6 presents the results for the benchmark model when different panel count techniques are applied. The results for the structural shocks are very similar to these alternative estimation approaches in terms of magnitude and precision of the estimates. Second, appendix table D7 drops the net oil-exporting countries from the sample. Again, the results are very similar compared to the main estimation and support the main insights.

5.5.3.1 Additional Controls

The main estimation approach broadly follows Kruse and Wetzel (2016) and includes important explanatory variables while being as parsimonious as possible. However, since the structural oil shocks are global and, thus, the same for each country each year, a relevant concern might be the omission of important variables. This section considers several different specifications including different sets of control variables. This includes additional country-specific controls as well as additional common factors. The country-specific controls include the following. First, GDP per capita is added as an additional control for changing economic conditions over time (e.g., Aghion et al., 2016; Guillouzouic-Le Corff, 2018). Second, since energy patent activity might be influenced by the country-specific trend in energy demand (Sterlacchini, 2020), energy use per capita is added. Third, the technological innovation capacity of a country might not be fully captured by the lagged knowledge stocks. Cheon and Urpelainen (2012) use the renewable energy share in electricity generation as an alternative measure. Hence, I control for the share of renewable energy use in total energy use as a measure of the importance of renewable energy technologies. The additional common factors control for the state of the global business cycle, as patenting behavior might be different in periods of global crisis. First, the remaining structural shocks from the decomposition by Baumeister and Hamilton (2019), aggregate demand shocks, are added. These contain unexpected shifts in global industrial production growth and, hence, unexpected economic downturns. Second, following Hu et al. (2022), the index of global economic conditions developed by Baumeister et al. (2022) is added. This index is a combination of 16 subindicators, designed to capture economic conditions that are well suited to forecast energy prices.

Table 5.4 adds the different country-specific controls to the benchmark estimation. Columns 1, 4, and 7 add GDP per capita, columns 2, 5, and 8 add energy use per capita, and columns 3, 6, and 9 add the renewable energy share. The main results are generally robust when adding these country-specific controls.

Table 5.5 adds the two additional global factors at a time. Columns 1, 3, and 5 add the remaining structural shocks from the decomposition by Baumeister and Hamilton (2019), aggregate demand shocks. Columns 2, 4, and 6 add the indicator of global economic conditions. Interestingly, both global economic variables are related negatively with patent applications for all three technology areas. A possible explanation is the severe downturn of economic conditions during the financial crisis 2007–2009, during which patent activity has not dropped (see figure 5.1). Importantly, however, the results for the main results remain robust against the inclusion of the measures of global economic conditions, and are even somewhat more pronounced in general. In summary, tables 5.4 and 5.5 document that the main results are robust against adding different further country-specific and aggregate controls.

Table 5.4. Additional country-specific controls

	Dependent variable: CE patents			Dependent variable: Building patents			Dependent variable: Biofuel patents		
	HHG (1)	HHG (2)	HHG (3)	HHG (4)	HHG (5)	HHG (6)	HHG (7)	HHG (8)	HHG (9)
Knowledge stock	0.610***	0.606***	0.606***	0.312***	0.317***	0.286***	0.697***	0.731***	0.729***
	(0.154)	(0.130)	(0.141)	(0.113)	(0.116)	(0.085)	(0.200)	(0.210)	(0.190)
Oil supply shocks	-0.047**	-0.053**	-0.054**	-0.040	-0.038	-0.038	-0.158***	-0.175***	-0.224***
	(0.021)	(0.024)	(0.024)	(0.031)	(0.033)	(0.029)	(0.051)	(0.048)	(0.048)
Oil demand shocks	0.048***	0.043***	0.043***	0.020	0.022	0.021	0.051	0.040	0.015
	(0.014)	(0.010)	(0.013)	(0.014)	(0.015)	(0.016)	(0.034)	(0.036)	(0.024)
Precautionary demand shocks	-0.006	-0.005	-0.001	0.008	0.004	-0.025	0.691***	0.687***	0.818***
	(0.144)	(0.120)	(0.146)	(0.089)	(0.077)	(0.098)	(0.151)	(0.186)	(0.238)
Total patents	0.087	0.169	0.182	0.337	0.315*	0.323**	-0.385	-0.218	0.028
	(0.354)	(0.315)	(0.259)	(0.238)	(0.176)	(0.154)	(0.534)	(0.510)	(0.430)
EPS	0.056	0.052	0.051	0.138	0.142	0.125	0.219**	0.267***	0.191**
	(0.104)	(0.113)	(0.099)	(0.098)	(0.107)	(0.093)	(0.099)	(0.085)	(0.080)
Kyoto dummy	0.390***	0.376***	0.378**	0.061	0.066	0.019	1.081***	1.236***	1.253***
	(0.131)	(0.130)	(0.133)	(0.099)	(0.095)	(0.098)	(0.298)	(0.381)	(0.444)
GDP p.c.	0.649			-0.093			5.331**		
	(0.629)			(0.637)			(2.151)		
Energy use p.c.		0.088			0.077			3.178**	
		(0.879)			(0.595)			(1.599)	
RE share			0.002			-0.022*			-0.028
			(0.007)			(0.012)			(0.022)
Observations	631	641	641	631	641	641	631	641	641
Countries	27	27	27	27	27	27	27	27	27

Note: Asterisks indicate significance at * 10%; ** 5%; *** 1%. Standard errors in parentheses are of robust sandwich type. All models include two unreported dummies for no lagged knowledge stock and no lagged total patents. Common time effects are controlled for through an unreported linear time trend. HHG denotes the method to control for the fixed effect by Hausman et al. (1984).

Table 5.5. Additional common factors

	Dependent variable: CE patents		Dependent variable: Building patents		Dependent variable: Biofuel patents	
	HHG	HHG	HHG	HHG	HHG	HHG
	(1)	(2)	(3)	(4)	(5)	(6)
Knowledge stock	0.594***	0.559***	0.311***	0.320***	0.694***	0.506***
	(0.137)	(0.113)	(0.119)	(0.118)	(0.186)	(0.159)
Oil supply shocks	-0.106***	-0.158***	-0.093***	-0.132***	-0.349***	-0.492***
	(0.032)	(0.034)	(0.036)	(0.036)	(0.056)	(0.071)
Oil demand shocks	0.049***	0.037***	0.027	0.017	0.027	0.021
	(0.011)	(0.012)	(0.017)	(0.016)	(0.027)	(0.026)
Precautionary demand shocks	0.060	0.086	0.073	0.098	0.980***	0.990***
	(0.156)	(0.129)	(0.085)	(0.070)	(0.247)	(0.224)
Total patents	0.202	0.255	0.332*	0.316**	0.001	0.067
	(0.249)	(0.199)	(0.169)	(0.153)	(0.432)	(0.361)
EPS	0.050	0.041	0.144	0.130	0.220***	0.182***
	(0.100)	(0.071)	(0.102)	(0.083)	(0.082)	(0.063)
Kyoto dummy	0.354***	0.224**	0.052	-0.031	1.276***	0.893***
	(0.132)	(0.105)	(0.096)	(0.090)	(0.415)	(0.324)
Aggregate demand shocks	-0.226***		-0.229***		-0.406***	
	(0.055)		(0.060)		(0.100)	
Economic conditions		-0.355***		-0.313***		-0.661***
		(0.037)		(0.040)		(0.091)
Observations	641	641	641	641	641	641
Countries	27	27	27	27	27	27

Note: Asterisks indicate significance at * 10%; ** 5%; *** 1%. Standard errors in parentheses are of robust sandwich type. All models include two unreported dummies for no lagged knowledge stock and no lagged total patents. Common time effects are controlled for through an unreported linear time trend. HHG denotes the method to control for the fixed effect by Hausman et al. (1984).

5.5.3.2 Lag Structure

This section considers the possibility that the association between the structural shocks and the patent count changes with more time lag. Specifically, table 5.6 adds a second lag for each structural shock series to the main regression.

Table 5.6. Additional lag included

	Dependent variable: CE patents	Dependent variable: Building patents	Dependent variable: Biofuel patents
	HHG (1)	HHG (2)	HHG (3)
Knowledge stock	0.642***	0.348***	0.820***
	(0.171)	(0.130)	(0.169)
Oil supply shocks (1. lag)	-0.059*	-0.040	-0.305***
	(0.032)	(0.031)	(0.053)
Oil supply shocks (2. lag)	-0.080***	-0.052*	-0.261**
	(0.029)	(0.027)	(0.107)
Oil demand shocks (1. lag)	0.070***	0.046**	0.038
	(0.014)	(0.019)	(0.036)
Oil demand shocks (2. lag)	0.037***	0.040***	-0.014
	(0.010)	(0.012)	(0.015)
Precautionary	-0.066	-0.058	1.075***
demand shocks (1. lag)	(0.177)	(0.098)	(0.295)
Precautionary	0.150	0.126*	1.262***
demand shocks (2. lag)	(0.131)	(0.074)	(0.216)
Total patents	0.074	0.258	-0.453
	(0.304)	(0.191)	(0.502)
EPS	0.043	0.132	0.232**
	(0.095)	(0.095)	(0.095)
Kyoto dummy	0.395***	0.080	1.187***
	(0.128)	(0.103)	(0.369)
Observations	615	615	615
Countries	27	27	27

Note: Asterisks indicate significance at * 10%; ** 5%; *** 1%. Standard errors in parentheses are of robust sandwich type. All models include two unreported dummies for no lagged knowledge stock and no lagged total patents. Common time effects are controlled for through an unreported linear time trend. HHG denotes the method to control for the fixed effect by Hausman et al. (1984).

In general, the main insights remain robust to adding a second lag. Some remarks are in order. First, for both clean energy technologies in general and clean building technologies, the second lag of oil supply shocks is more significantly related to patenting activity. This might indicate that the response is somewhat slower for these technology areas. Second, when allowing for the second lag, the positive association of clean building patents to oil demand shocks is more precisely estimated than in the main approach.

Third, both clean energy and clean building patents are related positively to the second lag of precautionary demand shocks, although the precision of the estimate is quite low. Again, this might indicate that the response in these two technology areas is slower. However, in general the results reported in table 5.6 support the insights from the main estimation.

5.6 Conclusions

In this paper I have estimated the impact of different structural shocks in the global oil market on country-specific green innovation. Based on the observation that oil price shocks are frequently related to incentives to develop green innovation, I argue that it is important to consider the structural nature of the shocks. In a benchmark estimation it is confirmed that the technology classes under consideration are strongly associated with changing levels of the real oil price, which further motivates to consider the origin of oil price shifts. To identify the global oil shocks, I draw on the estimated shock series provided by Baumeister and Hamilton (2019). I use patent data in three technology areas that might be related to oil prices and hence to structural oil market shocks, namely general clean energy technology, clean building technologies, and biofuel technology. The key insight is that the type of oil market shocks matters for patent activity in green technologies. First, positive oil supply shocks, i.e., unanticipated increases in global oil supply growth, are associated with negative patent applications in the following year for all three technology areas, yet with different magnitude and significance. The effect is most pronounced for biofuels, which provide a direct substitute for oil-derived fuels (e.g., Guillouzouic-Le Corff, 2018). Second, oil demand shocks play a much more limited role, being only associated with higher patent applications for clean energy technologies in general. Third, precautionary demand shocks, which are related to expectations and uncertainty of oil market participants, are strongly associated with higher patenting activity for biofuels.

These results have importing implications for policy. First, since oil supply shocks are robustly associated with green patenting activity, the results are consistent with the hypothesis that technological disruptions in global energy markets, such as the shale gas boom, can hinder green technological progress (e.g., Lazkano and Ayasli, 2022). On the other hand, they are also consistent with the view that supply shortages because of scarce oil stocks increase the incentives for green innovation (e.g., Hassler et al., 2021). Second, since green innovation responds differently to different structural oil market shocks (at least in the short run), a better knowledge of the effects of underlying structural shocks appears to be important to design a resilient green innovation system. Third, the particularly strong effect of precautionary demand shocks for biofuel patents points to the need to consider uncertainty in the energy market as relevant incentive for green innovation.

However, the aggregate nature of the analysis comes with some limitations. First, because the oil market shocks are the same for all countries in the sample, it is not possible to focus on country-specific variation in order to mitigate the potential for omitted variable bias. Second, the oil market shocks depend naturally on the specific method to extract them. Although I relied on recent advances in the literature on oil market modeling, different decompositions might lead to somewhat different results.

These limitations directly indicate avenues for further research. First, more fine-grained micro level studies might add to the causal interpretation of the structural oil market shocks and to country-, sector-, or firm-specific transmission channels which are beyond the scope of this paper. Secondly, additional studies might use different methods to identify the oil market shocks to get comprehensive view.

Appendix D

Part I: Data and Descriptive Statistics

Table D1. List of the sample countries

Australia	Hungary	Slovak Republic
Austria	Ireland	Spain
Belgium	Italy	Sweden
Canada*	Japan	Switzerland
Czech Republic	Korea	Türkiye
Denmark*	Mexico*	United Kingdom*
Finland	Netherlands	United States
France	Norway*	
Germany	Poland	
Greece	Portugal	

Note: The OECD countries included in the sample. Asterisks indicate net oil-exporting countries. Calculated based on data from the U.S. Energy Information Administration.

Table D2. Green patent classifications

Technology field	Description	CPC class
Renewable energy	Reduction of greenhouse gas [GHG] emissions, related to energy generation, transmission or distribution	Y02E
Buildings	Climate change mitigation technologies related to buildings, e.g., housing, house appliances or related end-user applications	Y02B
Biofuels	Technologies for the production of fuel of non-fossil origin; specifically biofuels	Y02E50/10

Table D3. Data sources

Data series	Source
Yearly frequency	
Patent data	EPO PATSTAT 2021 autumn
Crude oil spot price Brent and WTI	World Bank, Commodity Prices database "pink sheet", `https://www.worldbank.org/en/research/commodity-markets`
CPI total OECD	OECD, Consumer price indices (CPIs) - Complete database
Environmental Policy Stringency	OECD, Botta and Koźluk (2014)
Total final energy consumption (TFEC) in TJ	World Bank, Sustainable Energy For All database (1.1_TOTAL.FINAL.ENERGY.CONSUM)
Renewable energy share of TFEC (%)	World Bank, Sustainable Energy For All database (2.1_SHARE.TOTAL.RE.IN.TFEC)
GDP in constant 2015 US $	World Bank World Development Indicators (NY.GDP.MKTP.KD)
Population	World Bank World Development Indicators (SP.POP.TOTL)
Crude oil including lease condensate imports and exports	U.S. Energy Information Administration (EIA)
Monthly frequency	
Crude oil spot price Brent and WTI	World Bank, Commodity Prices database "pink sheet", `https://www.worldbank.org/en/research/commodity-markets`
CPI total OECD	OECD, Consumer price indices (CPIs) - Complete database
Index of global real economic activity	Federal Reserve Bank of Dallas, available at `https://www.dallasfed.org/research/igrea.aspx`. Originally developed by Kilian (2009)
Global crude oil including lease condensate production	U.S. Energy Information Administration (EIA)
Global economic conditions indicator	Baumeister et al. (2022) available at `https://sites.google.com/site/cjsbaumeister/datasets?authuser=0`
Structural oil shocks	Baumeister and Hamilton (2019) available at `https://sites.google.com/site/cjsbaumeister/datasets?authuser=0`

Part II: Structural Shocks

Table D4. Contemporaneous effect of structural shocks on real oil price growth

	Dependent variable: Real oil price growth				
	Shocks Baumeister and Hamilton (2019)			Shocks Kilian (2009)	
	(1)	(2)	(3)	(4)	(5)
Supply shock	-4.452***			-0.767	
	(0.371)			(0.551)	
Demand shock		1.813***			7.830***
		(0.090)			(0.327)
Precautionary demand shock			0.799*		
			(0.450)		
Observations	311	311	311	311	311
R^2	0.318	0.566	0.010	0.006	0.650

Note: Asterisks indicate significance at * 10%; ** 5%; *** 1%. Standard errors in parentheses.

Table D4 presents a comparison between the structural shocks provided by Baumeister and Hamilton (2019) and the shocks obtained from the original approach by Kilian (2009). To estimate the shocks with latter approach, I use the code files provided in the supplementary material to Kilian (2009). Following Kilian (2009), I use $p = 24$ lags. In order to have residual observations from the first month in 1990 onward, the structural VAR is estimated for the period 1988-2015 on a monthly base. The three variables of the model are: first, the growth rate of global oil production (including lease condensate). Second, the index of global economic activity based on shipping costs developed by Kilian (2009). Third, real crude oil prices constructed as the average of Brent and WTI deflated by the OECD CPI. Details on the data sources are provided in table D3.

Interestingly, despite fundamental differences in model specification, econometric technique/identification, and data choices, the correlation between the structural shocks is decent. In particular, the correlation coefficient of structural supply shocks at monthly frequency is 0.631 and the correlation coefficient between the oil-specific demand shocks at monthly frequency is 0.699. However, in line with the discussions by Kilian (2009) and Baumeister and Hamilton (2019), structural supply shocks play a greater role in explaining contemporaneous real oil price growth rates in the estimation by Baumeister and Hamilton (2019).

Part III: Additional Estimation Results

Table D5. Regression of green patents on the real oil price, alternative estimators

	Dependent variable: CE patents		Dependent variable: Building patents		Dependent variable: Biofuel patents	
	Negbin	BGVR	Negbin	BGVR	Negbin	BGVR
	(1)	(2)	(3)	(4)	(5)	(6)
Knowledge stock	0.461***	0.948***	0.199***	0.754***	0.041	0.964***
	(0.055)	(0.099)	(0.071)	(0.097)	(0.097)	(0.064)
Real oil price	0.385***	0.321***	0.346***	0.330***	1.057***	0.987***
	(0.057)	(0.083)	(0.064)	(0.054)	(0.140)	(0.167)
Total patents	-0.004	0.093	0.234***	0.266***	0.122	0.109*
	(0.064)	(0.116)	(0.076)	(0.075)	(0.100)	(0.057)
EPS	0.045	0.054	0.168***	0.069	0.167**	0.058
	(0.031)	(0.072)	(0.037)	(0.062)	(0.074)	(0.056)
Kyoto dummy	0.611***	0.725***	0.279***	0.350***	1.461***	2.358***
	(0.078)	(0.133)	(0.084)	(0.066)	(0.193)	(0.319)
Observations	641	641	641	641	641	641
Countries	27	27	27	27	27	27

Note: Asterisks indicate significance at * 10%; ** 5%; *** 1%. Standard errors in parentheses are clustered at the country level for BGVR. The Negbin models include two unreported dummies for no lagged knowledge stock and no lagged total patents. The dummies are dropped for BGVR to ensure convergence of the likelihood function. Common time effects are controlled for through an unreported linear time trend. Negbin accounts for overdispersion of the patent count variable. BGVR is the method by Blundell et al. (1999).

Table D6. Regression of green patents on oil shocks, alternative estimators

	Dependent variable: CE patents		Dependent variable: Building patents		Dependent variable: Biofuel patents	
	Negbin (1)	BGVR (2)	Negbin (3)	BGVR (4)	Negbin (5)	BGVR (6)
Knowledge stock	0.517***	0.967***	0.199***	0.756***	0.205**	1.051***
	(0.057)	(0.095)	(0.074)	(0.093)	(0.100)	(0.086)
Oil supply shocks	-0.087**	-0.051**	-0.059	-0.038	-0.278***	-0.207***
	(0.036)	(0.025)	(0.041)	(0.031)	(0.085)	(0.050)
Oil demand shocks	0.043***	0.042***	0.021	0.023	-0.013	0.017
	(0.013)	(0.013)	(0.015)	(0.016)	(0.033)	(0.022)
Precautionary demand shocks	0.087	0.060	0.009	0.053	0.662***	0.897***
	(0.081)	(0.133)	(0.091)	(0.094)	(0.195)	(0.159)
Total patents	-0.078	0.070	0.224***	0.265***	-0.025	0.079
	(0.066)	(0.112)	(0.079)	(0.073)	(0.099)	(0.056)
EPS	0.053*	0.057	0.189***	0.079	0.220***	0.100
	(0.032)	(0.081)	(0.038)	(0.071)	(0.077)	(0.066)
Kyoto dummy	0.358***	0.502***	0.057	0.131*	0.692***	1.469***
	(0.072)	(0.080)	(0.076)	(0.068)	(0.178)	(0.234)
Observations	641	641	641	641	641	641
Countries	27	27	27	27	27	27

Note: Asterisks indicate significance at * 10%; ** 5%; *** 1%. Standard errors in parentheses are clustered at the country level for BGVR. The Negbin models include two unreported dummies for no lagged knowledge stock and no lagged total patents. The dummies are dropped for BGVR to ensure convergence of the likelihood function. Common time effects are controlled for through an unreported linear time trend. Negbin accounts for overdispersion of the patent count variable. BGVR is the method by Blundell et al. (1999).

Table D7. Regression of green patents on oil shocks, net oil-importing countries

	Dependent variable: CE patents	Dependent variable: Building patents	Dependent variable: Biofuel patents
	HHG	HHG	HHG
	(1)	(2)	(3)
Knowledge stock	0.534***	0.330***	0.682***
	(0.152)	(0.125)	(0.215)
Oil supply shocks	-0.049*	-0.041	-0.242***
	(0.027)	(0.031)	(0.046)
Oil demand shocks	0.042***	0.024	0.011
	(0.014)	(0.018)	(0.028)
Precautionary demand shocks	-0.032	-0.021	0.843***
	(0.161)	(0.093)	(0.285)
Total patents	0.301	0.324*	0.063
	(0.282)	(0.177)	(0.504)
EPS	0.050	0.131	0.310***
	(0.118)	(0.110)	(0.101)
Kyoto dummy	0.313**	0.056	1.284***
	(0.149)	(0.101)	(0.495)
Observations	522	522	522
Countries	22	22	22

Note: Asterisks indicate significance at * 10%; ** 5%; *** 1%. Standard errors in parentheses are of robust sandwich type. All models include two unreported dummies for no lagged knowledge stock and no lagged total patents. Common time effects are controlled for through an unreported linear time trend. HHG denotes the method to control for the fixed effect by Hausman et al. (1984).

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Personal Contributions to the Papers of the Cumulative Dissertation

Convergence in Resource Productivity

This paper is joint work with Tobias Wendler. Tobias Wendler and I contributed similarly to roughly each step in the process, including conceptualization, methodology, data preparation, formal analysis, and writing.

Institutions and the Nexus of Economic Growth and Natural Resource Use

This paper is joint work with Martin Kalthaus and Tobias Wendler. It is largely based on my own work. Martin Kalthaus mainly contributed to conceptualization, literature research, and writing. Tobias Wendler mainly contributed to conceptualization, literature research, writing, and data preparation. I contributed to all steps in the process and especially the empirical analysis was mostly conducted by me.

Green Technologies and Growth: Evidence from European Regions

This paper is joint work with Torben Klarl and Tobias Wendler. It is largely based on my own work. Torben Klarl mainly contributed to conceptualization and provided the theoretical foundation. Tobias Wendler mainly contributed to conceptualization, literature research, writing, and data preparation. I contributed to all steps in the process and especially the empirical analysis was mostly conducted by me.

Oil Shocks and Green Energy Technical Change

This is a singled-authored paper which is based exclusively on my own work.

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Erklärung

Erklärung über die Anfertigung der Dissertation ohne unerlaubte Hilfsmittel

Ich erkläre hiermit, dass diese Arbeit ohne unerlaubte Hilfe angefertigt worden ist und keine anderen als die angegebenen Quellen und Hilfsmittel benutzt wurden.

Ich erkläre ferner, dass die den benutzten Werken wörtlich und inhaltlich entnommenen Stellen als solche kenntlich gemacht wurden.

Eine Überprüfung der Dissertation mit qualifizierter Software im Rahmen der Untersuchung von Plagiatsvorwürfen ist gestattet.

Bremen, April 6, 2023 Philip Kerner

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Remark

Compared to the submitted version of the dissertation, small changes to this published version have been made. These include the correction of minor errors and typos, some formal changes and small language changes or additions for clarification.